Self-Insurance in Turbulent Labor Markets *

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Abstract

We investigate the welfare consequences of turbulence risk—the risk of skill loss coinciding with involuntary layoffs—on individual and aggregate labor market outcomes. Motivated by new empirical evidence on the link between wealth and labor market outcomes after job loss, we build a tractable dynamic heterogeneous agents model with directed search, imperfect financial markets, and uninsurable persistent labor market risk. We calibrate our model to the US economy, matching new empirical facts on the joint impact of turbulence risk and wealth on re-employment wages, occupational mobility, and unemployment duration. We use the estimated model to conduct counterfactual experiments. We find that in the model economy, the incidence of shocks matters for the link between risk and wealth inequality. Moreover, we show that the main mechanism in the paper - wealth-driven occupational reallocation - shapes the sensitivity of macroeconomic aggregates to increases in idiosyncratic level risk.

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1 Introduction

The negative impact of involuntary job loss on future earnings has been well documented (Jacobson, LaLonde and Sullivan, 1993; Davis and Von Wachter, 2011; Jarosch, 2021). This effect is particularly sizable when accompanied by occupational displacement (Kambourov and Manovskii, 2008, 2009; Huckfeldt, 2021; Postel-Vinay and Sepahsalari, 2021), suggesting that the reallocation of workers across occupations following displacement is a major source of long-lasting earning losses. In this paper we ask, theoretically and empirically: how do workers use wealth to self-insure from job loss? How does wealth interact with occupational displacement following job loss, and what are the implications for welfare and macroeconomic aggregates?

With the objective to answer these questions, we proceed in two steps and make two contributions. First, we study how and wether wealth affects the consequences of job loss, with a focus on re-employment wages and unemployment duration. Then, we introduce a new model that replicates these new and salient micro-facts on unemployment transitions and use the model to study the interaction between wealth and occupational mobility, as well as the resulting macroeconomic implications.

The first contribution is empirical. We start the analysis by documenting new stylised facts on the impact of wealth on unemployment duration and reemployment wages. To do this, we use the NLSY79 monthly worker panel and restrict our attention to the transitions from employment to unemployment and back to employment. This panel is particularly well-suited for our analysis because it contains information on workers' labor market experiences and asset holdings. Following Fujita (2018), we identify *turbulent* workers as those suffering job loss together with occupational displacement, conditional on having long tenure in an occupation. We document those turbulent workers experience nearly 12% fall in wages and 60% longer unemployment duration relative to *tranquil* workers, namely, workers who did not switch their occupation.

Additionally, we document that longer unemployment duration and higher reemployment wages are positively associated with initial wealth upon unemployment, though this association is considerably larger for turbulent workers. These fact suggest that workers use both precautionary savings and search as insurance devices.

We dig deeper into this association between wealth and labor market outcomes and analyze whether wealth matters for the consequences of job loss, focusing both on the impact of the latter on wages and the persistence of wage losses. We find that the scarring effect of unemployment (Jarosch, 2021) is concentrated on poor turbulent workers, who lose 11% after 5 years following job loss; rich turbulent workers suffer roughly half of these losses, equal to 5%. This is new evidence pointing that wealth matters for the consequences of job loss on top of occupational switching, as emphasized by the literature (Huckfeldt, 2021). The key finding of this analysis is that it is *poor* occupational switchers that experience the largest earning losses following job loss.

Next, we build a stochastic dynamic heterogenous-agent model with imperfect financial markets, labor market frictions, and skill dynamics. We consider two types of exogenous and uninsurable earnings risks: (i) the risk of a *transitory* earnings loss associated with unemployment, and (ii) a risk of a *persistent* earnings loss associated with skill obsolescence. Following Ljungqvist and Sargent (1998, 2007, 2008) we label the persistent risk as *turbulence risk*. Our framework embeds two mechanisms that allow workers to cope with these risks. First, workers engage in *precautionary savings* by accumulating a risk-free asset. This allows them to smooth consumption across different employment status. Second, workers to apply for low paying jobs which offer them higher likelihood of getting reemployed; this mechanism is labeled *precautionary search* (Eeckhout and Sepahsalari (2019)). We augment the typical mechanism of precautionary search in that we consider also heterogeineity on the job side: to retain simplicity, we consider an economy in which workers can direct their search in two 'isands' (A and B), or major occupational groups. Workers can reallocate across islands when unemployed after paying a monetary cost. Therefore, workers can self-ensure by reallocating across islands, which differ by returns and risks: matches in island A produce more, but these matches are harder to form. This trade-off between wage and unemployment duration caused by asset depletion is key for understanding the change in wages for both turbulent and tranquil workers, and we show that the mechanism we introduce can replicate the micro-facts that we uncover in the first part.

At the core of the mechanism is the interaction between precautionary motives and the endogenous occupational choice. It is precisely this interaction that generates displacement effects similar to the data: poor workers cannot afford to pay the cost of reallocation and direct their search towards the low productivity island (or occupational group), where jobs are easier to find. This in turn depresses their wage and future wealth accumulation, generating long-lasting effects that go well beyond the original displacement event. Rich occupational switchers, on the contrary, can better self-insure and do not incur in the low wealth- low productivity trap as their poor counterparts.

Last, we use a calibrated version of the model to conduct a novel quantitative analysis to examine and quantify the macroeconomic effects of idiosyncratic turbulence risk. We find that in this economy, the *incidence* of turbulence shocks matters: whether turbulence (or the risk of skill obsolescence) increases in high returns, high risk occupational groups or low return, low risk occupational groups matters greatly; in fact, an increase in skill obsolescence in high returns occupational groups decreases wealth inequality in this economy. The opposite happens if turbulence risk increases in low returns ococupations, closer to a standard incomplete markets model. This is a novel result that highlights the important of considering wealth and occupational reallocation when examining the effects of these risks.

These results are particularly relevant when thinking about displacing effects of technological change: a large literature analyzes how new technologies can exacerbate inequality (Krusell, Ohanian, Ríos-Rull and Violante, 2000; Acemoglu and Restrepo, 2022). The theoretical results of this paper underscore the importance of distinguishing between technological change that affects low productivity occupations (such as the arrival of labor-replacing machines) and technological change that affects high productivity occupations (for example, the most recent advances in AI technologies). These types of technological changes can have different macro implications since workers are heterogeneous in their ability to cope with the arrival of these new techonologies (and their associated risks) in the presence of financial and labor market frictions. The implication is that taking into account these frictions *jointly* is crucial to analyze the optimal policy response to technology-induced displacement (as done recently, for example, in Beraja and Zorzi (2022)).

We also examine the effects of increases in layoff (or separation) risk in the economy: in a counterfactual economy in which we shut down reallocation of workers across occupational groups (islands), we find that ouput and unemployment are significantly more sensitive to increases in separation risk. This last exercise shows that the model can have implications for the study of business cycles; more precisely, the exercise puts forward the idea that occupational mobility and the resulting allocation of workers to jobs with different levels of security might be important to study the amplification of recessions following an increase in separation risk, a major driver of cyclical unemployment fluctuations (see for example, Shimer (2005) and Krusell and Şahin (2017)). This is because in this model, the allocation of workers to occupation with more (or less) security is endogenous and depends on the wealth distribution. An increase in layoff risk therefore affects unemployment and output through its direct effect and through an equilibrium effect that operates through workers' wealth and the endogenous occupation choice, the central theme of this paper.

Finally, we briefly touch on the policy and welfare implications of the quantitative results, with the goal of expanding the section to study the different component of the welfare costs of unemployment transitions. Simulating an increase in unemployment benefits in this economy, it emerges that - through the aforementioned endogenous reallocation of workers across islands - unemployment insurance can have output and mobility effects above and beyond those studied in the literature. This suggests the need to explore further the welfare implications of the mechanism put forward in this paper, something we plan to address in the near future.

Overall, the paper puts forward the idea that occupational displacement - and the associated negative effects on wages - are mediated by wealth. We do so by exploring this new link empirically, at the *micro* level. We also examine this link theoretically, focusing on the *macro* implications of increases in turbulence risk. Exploring how market incompleteness can interact with secular trends related to technological change and labor market outcomes is the next step in our research agenda.

Related Literature. Our work contributes to several strands of the macro labor literature.

On the empirical front, we show that the duration of unemployment spells and the subsequent reemployment wages vary significantly across two margins: (i) the type of unemployment transition (tranquil or turbulent) and (ii) the position in the wealth distribution. Moreover, we show that these two margins interact and reinforce each other.

In this respect, our findings bridge two literatures. On the one hand, we speak to the literature that explores human capital depreciation as a determinant of labor market experiences. Following the evidence pointing towards occupational tenure as the key instance of human capital (Kambourov and Manovskii, 2009; Fujita, 2018; Huckfeldt, 2021; Jarosch, 2021; Postel-Vinay and Sepahsalari, 2021) , we confirm that the loss of occupational tenure—a turbulence shock—generates sizeable losses in reemployment wages and excess unemployment duration. On the other hand, we speak to the empirical literature documenting the effect of asset holdings on job search behavior (Rendón, 2006; Lise, 2012; Herkenhoff, Phillips and Cohen-Cole, 2016). In line with this literature, we find that lower asset holdings upon unemployment decrease unemployment duration on average. Our key contribution is to consider jointly these two margins and show that the negative effects of losing occupational tenure are amplified for workers at the bottom of the wealth distribution, and viceversa, that the effects of lower assets on job search behavior are stronger for workers that go through a turbulence transition.

With regards to the theory, our model combines elements from various strands of the literature. First, we borrow from the turbulence literature (Ljungqvist and Sargent, 1998, 2007, 2008; den Haan, Haefke and Ramey, 2005; Baley, Ljungqvist and Sargent, 2021) and consider that upon layoff workers face the the risk of losing their occupational experience. Additionally, we introduce search frictions and incomplete markets (Danforth, 1979; Hopenhayn and Nicolini, 1997; Shimer and Werning, 2007, 2008). Our framework closely follows the general equilibrium model by Krusell, Mukoyama and Sahin (2010); instead of random search, we use the directed search protocol (Shi, 2009; Menzio and Shi, 2011). Directed search allows us to explain the observed heterogeneity in unemployment duration, and moreover, renders a tractable block-recursive model. Our model is also close to Eeckhout and Sepahsalari (2019), who investigate the interaction between precautionary savings and job search behavior in a framework with sorting. While we abstract from sorting by assuming homogenous jobs, our model introduces two dimensions of worker heterogeneity (wealth and skills). Lastly, our model relates to the work by Krusell, Luo and Ríos Rull (2021) and Chaumont and Shi (2018). While those papers consider on-the-job search, we abstract from this dimensions but introduce skill dynamics.

Michelacci and Ruffo (2014), Griffy (2021), Bartal (2020) and Hubmer (2018) focus on the life cycle aspects of skills dynamics. Michelacci and Ruffo (2014) mostly focus on the optimal UI in a market with risk and hazard of job finding and loosing are exogenous. Griffy (2021), shows differences in initial wealth cause larger differences in life time earnings than initial human capital or ability. Bartal (2020) offers and explanation for why highly constrained workers suffer persistent income loss after displacement. Hubmer (2018) looks at the impact of job ladder on the earning risk. Instead, our main focus of attention is on characterising the interaction between wealth, job search and skill dynamics. This allows us to carefully quantify the main channels through which an unemployment transition results in welfare loss.

2 Empirical Facts

This section presents new facts on the effects of turbulence and asset holdings in explaining the duration of unemployment spells and the changes in earnings upon re-employment.

2.1 Data and variables

Sources. We use the cross-sectional sample of the National Longitudinal Survey of Youth for the 1979 Cohort (NLSY79). This dataset is particularly suited for the purposes of this study because it contains information on individuals' labor market history, including wages and occupation for each employer, as well as detailed information on asset holdings.[1] As in Baley, Figueiredo and Ulbricht (2022), we first use the Work History Data file to build a monthly panel and then we identify workers making employment to unemployment to employment transitions (EUE). This sample covers the years 1979 to 2016. We use the CPI reported by the BLS to convert the market value of wages and assets to 2000 dollars.[2]

Turbulent transitions. We identify a EUE transition if the worker was non-employed in month T_0 (i.e., reported to be not working, unemployed or out of the labor force), after being

[1]The Survey of Income and Program Participation (SIPP) also has information on respondents' assets and employment history. However, the NLSY79 provides consistent job identifiers across waves, which allows us to build employment spells for each job reported by the respondent. In contrast, the SIPP resets employment records for individuals who leave employment for an entire wave.

[2]The Data Appendix provides further details on the construction and definition of the variables as well as on the characteristics of the sample (race, gender, education, among other).

previously employed, and employed in month T_1. Additionally, we define a worker making an occupational switch when the occupation at month T_1 is different from the one in the last reported job. We use Dorn (2009)'s three-digit occupational classification system, which has the advantage of being consistent over time. We follow the view that human capital is largely occupation specific and thus labor market turbulence—the risk of skill depreciation—is linked to occupational mobility upon job switches. Following Kambourov and Manovskii (2008, 2009) and Fujita (2018), we use occupational switching and occupational tenure to measure the loss of human capital occurred when a worker experiences a EUE transition.[3] In this spirit, we define "turbulent" workers as those individuals that switch their occupation upon re-employment and had an occupational tenure longer than k years:

$$\text{turbulent} = \mathbb{1}_{\{\text{occupational tenure} \geq k \text{ years} \times \text{occupational switch}\}}. \tag{1}$$

Workers with an occupational tenure above k years but that after an EUE transition are reemployed in the same occupation are labeled as "tranquil":

$$\text{tranquil} = \mathbb{1}_{\{\text{occupational tenure} \geq k \text{ years} \times \text{no occupational switch}\}}. \tag{2}$$

Finally, workers with occupational tenure below the threshold of k years are labeled as "non-tenured":

$$\text{non-tenured} = \mathbb{1}_{\{\text{occupational tenure} < k \text{ years}\}}. \tag{3}$$

For our baseline results, we follow the literature, namely Fujita (2018), and focus on an occupational tenure threshold of $k = 2$ years, which is the average tenure in an occupation in the sample of EUE transitions (the Appendix shows robustness for alternative thresholds k).

Outcomes. Our two key outcomes of interest are the changes in the wages in a transition and the unemployment duration. We define Δw as the log difference between pre-unemployment and post-employment real wage (in 2000 dollars) and τ as the length of the unemployment spell measured in months, where T_0 is the month entering unemployment and T_1 is the

[3]This is in line with Kambourov and Manovskii (2008, 2009), who envision the notion of occupation as a label for the kind of work individuals do and not as a label for the wage they receive. They show that once occupational tenure is taken into account, tenure in an industry or with an employer has relatively little importance in accounting for wage differences across workers.

month in which the worker gets reemployed:

$$\Delta w \equiv \log(w_1/w_0), \quad (4)$$

$$\tau \equiv T_1 - T_0. \quad (5)$$

Liquid wealth. While the NLSY survey includes information on all assets of the workers, we focus on liquid wealth, since, by definition, it allows workers to better insure against shocks given the relative ease to sell and purchase these assets. Concretely, following Lise (2012), we define *Liquid Wealth* as the sum of financial assets (saving accounts, stocks, bonds and mutual funds), farm and business assets, vehicles, and then subtract all the debts in these categories. With this definition, liquid wealth does not take into account the value of housing—a highly illiquid asset. Respondents report the expected market value of their assets at the moment of the interview.

One challenge with the asset data in NLSY is that it is not observed at the same frequency as the labor market data; asset data are collected at interview dates, providing at most one observation on assets per year. In spite of this limitation, we consider the closest observation of wealth as a proxy of the wealth level upon a transition. In this way, we construct the initial log of assets upon unemployment a_0, as the asset holds observed immediately *before* a worker enters into unemployment. In order to take logs, we first add a constant to all asset holdings equal to one minus the minimum asset level (which is negative).

2.2 Summary statistics

Table 1 shows key summary statistics about labor market experiences for EUE transitions in our NLSY sample. Column 1 considers the entire sample of EUE transitions, while Columns 2, 3 and 4 show statistics for the subsamples of non-tenured, tranquil and turbulence transitions, which represent 69.4%, 19.0% and 11.6% of transitions, respectively. We observe that, on average, tenured workers (both experiencing turbulent and tranquil transitions) are older, wealthier, and more experienced—both in terms of their tenure in their previous job, their occupation, and their labor market participation—compared to non-tenured workers. For turbulent workers, a EUE transition entails an average earning loss of 12% and an average unemployment duration of 12 months; for tranquil workers, there is an average earning change of 0% and an average unemployment duration of 4 months.

2.3 Reemployment wages and unemployment duration

As a first step in the analysis, we construct *residual* unemployment duration and reemployment wage change in order to clean the data from sources of heterogeneity that may

Table 1: Summary Statistics of EUE Transitions

Transitions	All	Untenured	Tranquil	Turbulent
Observations	37,324	25,910	7,102	4,212
% of total transitions	100	69.4	19.0	11.6
Worker characteristics at separation				
Age	29.7	26.8	36.6	36.0
Job tenure	1.4	0.5	3.0	3.6
Occupational tenure	2.5	0.7	7.2	5.8
Total experience	8.3	5.7	14.8	13.5
Liquid wealth (000's, 2000 dollars)	28.9	20.1	43.0	35.2
Outcomes at reemployment				
Wage growth (%, 1st job)	1%	4%	0%	-12%
Unemployment duration (months)	7.7	8	4	12

Source: NLSY79.

Notes: NLSY data. EUE transitions running over the period from 1979 and 2016. Turbulent refers to transitions in which the worker switches occupation upon reemployment and had tenure in the previous occupation above or equal to 2 years.

potentially contaminate our assessment of the role of turbulence and liquid wealth. To do this, we regress the two key outcomes $y \in \{\tau, \Delta w\}$ on a set of individual and aggregate controls, including age, labor market experience, race, gender, educational attainment, ability, occupation, industry, as well as year and month fixed effects.[4] Additionally, we control the log wage in the last job held by the worker w_0.[5]

The specification is as follows:

$$y = \gamma_0 + \gamma_1 \cdot controls + \varepsilon^y. \tag{6}$$

Then the residual earning loses and unemployment duration are recovered as ε^y. These residuals ε^y capture the expected outcomes conditional on the set of individual and aggregate controls.[6]

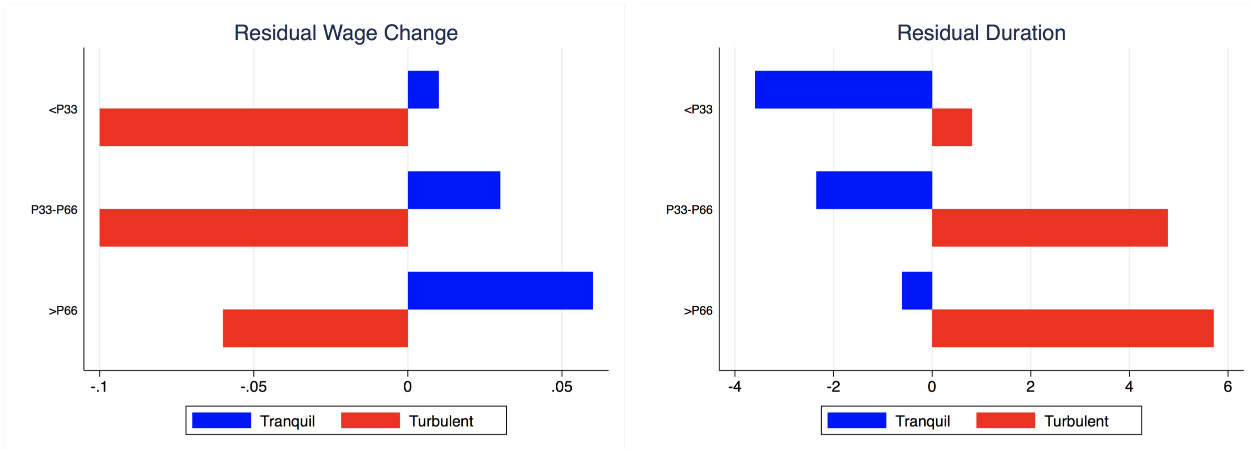
Once we have cleaned the data from observed heterogeneity, we turned the attention to the effect of wealth and turbulence. Figure 1 plots the residuals for wage growth $\varepsilon^{\Delta w}$ in Panel

[4]Labor market experience refers to the cumulative number of months an individual has worked since her first job. Ability is proxied through the individual's scores in the ASVAB test.

[5]Including the previous wage is important to account for omitted variable bias: As the previous wage is positively correlated with wealth (correlation between these two variables is around 0.2), not including it in the vector of controls would lead to a downward bias when estimating the effect of wealth on wage growth. This is because the wage in the previous job is negatively associated with wage growth upon reemployment after a non-employment spell.

[6]Table A.1 in the Data Appendix reports the estimated coefficients for the controls. For instance, being female or black is associated with a lower effect on reemployment wages and a higher unemployment duration; in contrast, a college degree is associated with a wage gain and lower unemployment duration.

Figure 1: Residual Wage Change and Unemployment Duration: By Turbulence and Wealth



Notes: NLSY79 data. Residual re-employment wage growth ($\epsilon^{\Delta w}$) is the log difference of pre-unemployment and current real wage and residual unemployment duration (ϵ^{τ}) is the length of the unemployment spell in months. The left and right panel plot, respectively, the mean of $\epsilon^{\Delta w}$ and ϵ^{τ} for *Turbulent* and *tranquil* workers at different parts of the liquid wealth distribution. P33, P33-P66 and >P66 correspond to percentiles of the (household) liquid wealth distribution at the start of the unemployment spell.

A and the residuals of unemployment duration ε^{τ} in Panel B. We split the residual sample along the transition type—turbulent or tranquil—and the position in the wealth distribution at the moment of falling into unemployment: We split the distribution of liquid wealth at the start of the unemployment spell into three equal sized groups: below the 33^{rd} percentile, between the 33^{rd} and 66^{th} percentile, and above the 66^{th} percentile.[7]

With respect to the residual wage change, we observe wage loses for turbulent workers and wage gains for tranquil workers across all wealth levels. However interestingly, the loses and gains are both increasing in initial wealth. There is a larger wage loss for turbulent workers in the bottom of the wealth distribution than the wage loss of workers at the top of the distribution; similarly, for tranquil workers, the wage gain is increasing in wealth. Regarding the residual duration, we observe that the turbulent workers have longer duration than tranquil workers, and that this additional duration is increasing in their wealth, ranging from 1 month for turbulent workers in the bottom of the wealth distribution to 6 months at the top of the wealth distribution. For tranquil workers residual duration also increases in wealth. Therefore, turbulence and wealth increase unemployment duration on their own and also they interact positively. Overall, higher initial wealth upon unemployment amplifies the wage changes and increase unemployment duration for all workers.

Effects of turbulence and initial wealth on labour market outcomes. We proceed to quantify the role played by turbulence and initial wealth upon unemployment on the residual

[7]The average wealth (in 2000 dollars) for workers below the 33^{rd} percentile is -$2,368, while the average wealth for workers above the 66^{th} percentile is $80,000.

duration and residual wage changes. To do so, we run a regression of the residuals from equation (6) on the dummy variable *turbulent* in (1), the dummy variable *tranquil* in (2), and two dummy variables indicating the position of the worker on the distribution of liquid log wealth at the start of the unemployment spell: $a_{0,m} = 1$ if the worker is between the 33^{rd} and 66^{th} percentile and $a_{0,h} = 1$ if the worker is at the top of the initial wealth distribution. The baseline groups in the regression are the *non-tenured* in (3) and the workers with assets below the 33^{rd} percentile; therefore, regression results should be interpreted relative to these groups.

Let $y \in \{\epsilon^{\Delta w}, \epsilon^{\tau}\}$ denote the wage and duration residuals, respectively, then we estimate:

$$y = \beta_0 + \beta_1\, turbulent + \beta_2\, tranquil + \beta_3 a_{0,m} + \beta_4 a_{0,h} + \eta. \tag{7}$$

The results are given in Table 2. Column 1 shows that turbulent workers suffer a large and statistically significant decrease in real earnings (around $-12\% = -9\% - 3\%$) when compared to tranquil workers, in line with Fujita (2018)'s findings.[8] Liquid wealth at the start of the unemployment spell generates, on average and conditional on finding a job, a wage gain for those at the top of the wealth distribution. The point estimate (β_4) implies that, when compared to workers at the bottom of the initial wealth distribution, wage growth is 4% higher for workers at the top of the wealth distribution.

Now let us focus on the effects of turbulence and initial wealth on residual unemployment duration. Our findings in Column 2 show that, all else equal, unemployment spells of turbulent workers are around 6 months larger when compared to tranquil workers, and that liquid wealth is positively associated with the duration of unemployment: in comparison to poor workers, unemployment durations is larger in 1.8 months and 2.3 months for workers with medium and high wealth, respectively. In summary, unemployment duration is positively and significantly related to turbulence and initial wealth.

Robustness. In order to assess the validity of our results, the Data Appendix conducts a series of robustness exercises. Table A.1 introduces two additional controls, namely the unemployment benefit and spousal income. Table A.2 consider different thresholds on occupational tenure $k = \{1, 2, 3\}$ to define turbulent workers. As expected, the larger is the tenure threshold, the larger are wage loses upon reemployment and the longer the unemployment duration, consistent with a larger loss of experience upon a layoff. Table A.3

[8]While our specification is inspired by Fujita (2018), it differs in two dimensions: First, we take into account the role of individual wealth at the start of the unemployment spell, and second, we control for the previous wage. For completeness, we also estimate Fujita (2018)'s specification, i.e., a regression of wage growth on the turbulence dummy, controlling for age, gender and unemployment duration, and we replicate his findings: Earnings losses of 13% for turbulent workers.

Table 2: Labor Market Outcomes: By Turbulence and Wealth

	Residual Wage Change	Residual Duration
	(1)	(2)
turbulent	-0.089***	5.974***
	(0.013)	(0.413)
non-turbulent	0.032***	-0.082
	(0.007)	(0.196)
$a_{0,m}$	0.009	1.877***
	(0.008)	(0.269)
$a_{0,h}$	0.038***	2.352***
	(0.009)	(0.260)
Observations	14042	14639
R^2	0.010	0.031

Notes: The table reports coefficients from an OLS regression with robust standard errors reported in parentheses. Dependent variable: Columns 1 to 2 is the residual wage growth ($\epsilon^{\Delta w}$); Columns 3 to 4 is the residual duration of non-employment in months (ϵ^{τ}) . The omitted categories are $a_{0,l}$ and *non-tenured*. The sample includes all EUE transitions between 1979 and 2016. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

excludes short-term unemployment spells from the main sample to address the potential concern that EUE transitions with very short jobless spells may be, in fact, transitions of job-changers taking a short break between jobs. Lastly, following Koehne and Kuhn (2015), we consider various definitions of liquid wealth. Our results are robust to all these different specifications.

2.4 Scarring Effects

In this section, we examine the effect of job loss and EUE transitions on wages, with a special emphasis on the dynamics of job loss and mobility over time. We focus, in line with the objective of the paper, on the relationship between wage losses, occupational mobility and wealth. We proceed in two steps. First, we replicate in our NLSY sample the recent findings in the literature on the scarring effects of job loss. In particular, we confirm that job losses are mostly concentrated among occupational switchers ((Huckfeldt, 2021)). To keep the analysis consistent with our focus on turbulent vs tranquil workers, we analyze wage losses of these two group of workers. Second, we examine the heterogeneity of job losses *among switchers* by wealth level upon separation.

The full econometric specification is standard in the literature and is as follows:

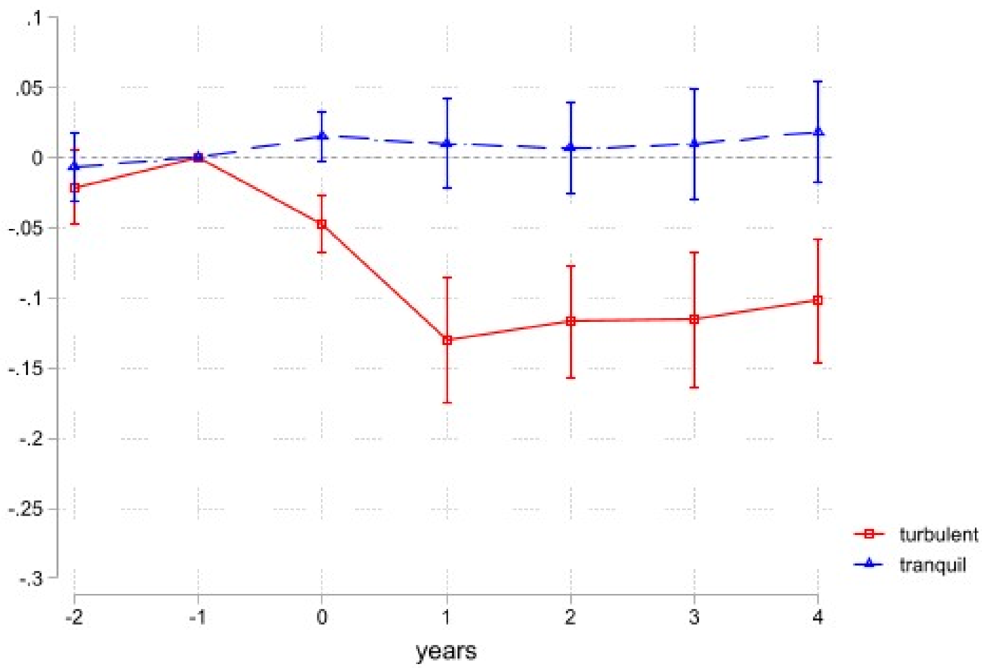


Figure 2: Scarring Effects

$$\log w_{it} = \sum_{k=-24}^{62} \delta^k_{tranq} \mathbf{1}^k_{tranq} + \sum_{k=-24}^{62} \delta^k_{turb,p} \mathbf{1}^k_{turb} + \lambda_t + \beta' X_{it} + \epsilon_{it} \tag{8}$$

The coefficients of interest are $\delta^k_{tranq,p}$ and $\delta^k_{tranq,p}$, that measure the effect of job loss on wages for each lag k and wealth tercile p. As mentioned, first we report the results of this analysis without distinguishing for wealth terciles, as a benchmark specification. This is reported in Figure 2. The Figure clearly shows that the empirical patterns documented in the literature with other datasets (PSID) hold in NLSY. Turbulent workers, or workers who are tenured and switch occupations, suffer large and persistent wage losses following displacement. In our sample, tenured workers that do not switch occupations barely suffer any losses at all.

$$\log w_{it} = \sum_{p \in \{<33, >66\}} \sum_{k=-24}^{62} \delta^k_{tranq,p} \mathbf{1}^k_{tranq,p} + \sum_{p \in \{<33, >66\}} \sum_{k=-24}^{62} \delta^k_{turb,p} \mathbf{1}^k_{turb,p} + \lambda_t + \beta' X_{it} + \epsilon_{it} \tag{9}$$

In Figure 3, we report the results of the specification in 9. As the specification makes clear, the objcetive is to analyze whether and how much there is heterogeneity in the impact of job loss *by wealth*. An interesting result emerges from the Figure: wage losses following displacement are concentrated among *poor* occupational switchers (turbulent), while rich turbulent workers suffer much lower losses. The difference is economically significant: In our sample, wage losses for rich turbulent workers are still 11% 4 years after losing the job; for rich turbulent workers, the losses are only equivalent to 5%.

To the best of our knowledge, this is the first paper to document the fact that wage losses following job loss are concentrated among poor occupational switchers. While previous empirical explorations and mechanisms in the literature have been focused on explaining why occupational switchers suffer such large losses - and more in general, the consequences of occupational mobility on human capital depreciation - this evidence calls for a framework that includes wealth as an active margin of occupational mobility. How does wealth upon job loss interacts with occupation switching, and what are the resulting effects on the human capital accumulation process of workers? The framework in the next Section has the objective of answering these questions.

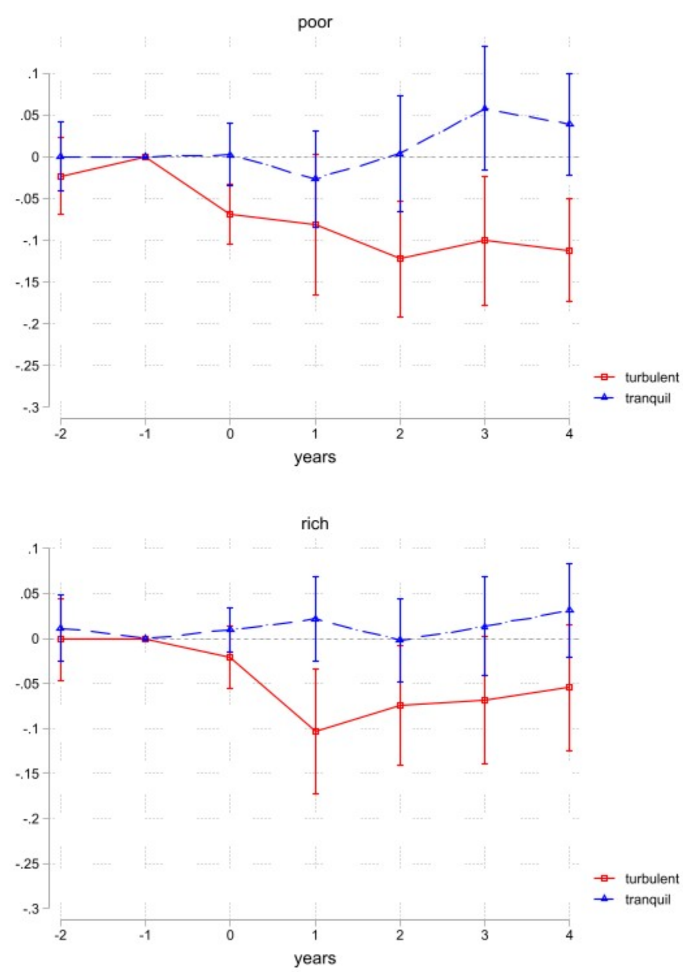


Figure 3: Scarring Effects by Wealth

3 Quantitative framework

In this section, we develop a Bewley-type model with uninsurable unemployment risk and human capital dynamics contingent on the job status and transitions between employment and unemployment. The three key elements of the model are (i) experience dynamics, (ii) imperfect financial markets, and (iii) directed search in the labor markets. Additionally, we consider job heterogeneity by positing that workers can search for jobs in two tiers, which can differ in productivity and job security. We show how the interaction of these elements gives rise to precautionary savings and precautionary search behavior, which in turn shapes the labor market experience of workers and their response to turbulence.

3.1 Environment

Time is infinite and discrete. There is a continuum of workers, a continuum of potentially operating firms, and a government.

Workers. Consider a continuum of risk-averse workers of measure one who are all ex-ante identical. Workers value consumption, with preferences ordered according to

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(c_t), \tag{10}$$

where future utilities are discounted at a rate $\beta \equiv \hat{\beta}(1-\rho_r)$, which consists of a subjective time discount factor $\hat{\beta} \in (0,1)$ and a constant probability of retirement $\rho_r \in (0,1)$. Workers can be employed or unemployed. If unemployed, they receive unemployment benefits b that are linked to the wage on the previous job and they search for a new job in a frictional labour market. If employed, they supply one unit of labour inelastically, receive a wage, and pay a proportional tax on wages τ. Besides employment status, workers differ in three dimensions: the current experience level i, which can be either low (l) or high (h), the experience level j during the last employment spell that determines their benefit entitlement, and the asset holdings a. We assume that all workers jointly own all firms, and thus receive an equal share of dividends d every period.

Firms, vacancies and labour market. Worker-firm pairs are located in two tiers $k \in \{A, B\}$. Within tiers, firms are homogenous in every dimension. Across tiers, firms differ by productivity level y_k, where we assume without loss of generality that $y_A > y_B$. Moreover, worker-firm pair across tiers are also allowed to differ with respect to turnover rates (i.e., job risks and job find rates). Thus, matches in the two tiers differ in both returns and associated risks.

To enter a market, a firm posts a vacancy at the cost κ_k. The job search in the labour market is directed. At the beginning of each period firms simultaneously announce wages. Workers observe the bundle of wage and job finding probability for every tiers and decide to which combination of tiers and job they want to apply to. Then workers and firms form the submarket $\theta_k = v_k/u_k$. Within each submarket a worker finds a job with probability $m(\theta_k)$ which pays $w(\theta_k)$ and a firm fills a vacancy with probability $q(\theta_k) = m(\theta_k)/\theta_k$.

Worker-firm relationships and productivity processes. A worker-firm relationship produces output $y_k \cdot x_i$, that is indexed by the worker's experience level i as well as tier-specific productivity level. Workers gain or lose experience stochastically depending on their employment status and instances of layoffs. At the beginning of each period, a job is exogenously terminated with probability $\lambda_{i,k}$. If not terminated, an employed worker's experience may get upgraded from low to high with probability γ^u. In that case, they also get a wage increase equal to the difference between their wage and the wage they would have applied to if they were high skilled upon employment.

Following Ljungqvist and Sargent (1998, 2007, 2008), we define turbulence as the risk of losing experience after an exogenous job separation. Upon a layoff, experienced worker suffers an experience loss with probability γ^d. As in Baley, Ljungqvist and Sargent (2021), we label this risk, *layoff turbulence*. The experience dynamics mimic the loss of occupational specific experience (γ^d) for those workers with sufficiently long average tenure in that occupation (γ^u). We allow for γ^d and γ^u to be tier specific, i.e. $\gamma^d = \gamma^d_k$. This will be helpful in the calibration of the model, as shown in the next section.

In addition to the exogenous turbulence risk γ^d_k, workers can decide to search in a different tier k' than the one in which they lost the job (k) by paying a cost $\mathcal{M}_{kk'}$[9]. They can do so at the cost of losing skills but knowing they will find a job with higher probability than if they stay in the same tier (so for example, high-tenure workers workers employed in A that lose a job, can decide to pay the cost of switching across tiers $\mathcal{M}_{AB}$ and search for a job in B as a low skill). This is meant to capture the *endogenous* turbulence risk that workers faces. It follows that a worker's wealth level will impact her switching decisions (hence wealth affects occupational mobility), due to market incompleteness in the financial markets, as explained next.

Financial markets. We consider a small open economy with exogenous returns. Workers have access exclusively to a non-contingent risk-free bond that pays an exogenous gross

[9] $\mathcal{M}_{kk'}$ can be thought of a training cost, and captures the idea that workers skills and tenure are not immediately transferable across tiers.

return R per period. There is an exogenous borrowing constraint

$$a' \geq \underline{a}, \tag{11}$$

which reflects the severity of financial market imperfections. A retired worker exits the economy and is replaced by a newborn worker, who is born inexperienced. The assets of retired workers are being distributed equally among new-born workers.

3.2 Problems of workers and firms

Value of an unemployed worker. Let $U_k(a, x_{ij})$ be the value of an unemployed worker searching in tier k with assets a, and an experience type x_{ij}, which includes her current experience x_i and the experience in previous job x_j. The experience in the previous job enters the worker's state as it determines her benefit entitlement. Let $E_k(a, w, x_{ij})$ be the value of an employed worker in tier k with assets a, wage w, and type x_{ij}.

An unemployed worker in tier k chooses asset holdings for next period a' and a submarket θ[10] to maximize:

$$\begin{aligned} U_k(a, x_{ij}) &= \max_{a',\theta} u(c) + \beta \left[m(\theta) E_k(a', w(\theta), x_{ij}) + (1 - m(\theta)) \mathcal{U}_k(a', x_{ij}) \right] \\ \text{s.t.} \quad c &= Ra + b_j - a' + d, \qquad a' \geq \underline{a}, \quad \text{and } \ i, j \in \{l, h\}, \end{aligned} \tag{12}$$

that is, with some (endogenous) probability $m(\theta)$, the worker becomes employed in the same tier she is searching for or remains unemployed next period with probability $1 - m(\theta)$.

Workers draw independent Type I extreme value tier shocks (i.e., one for each tier) with a scale parameter ν for every period they spend as unemployed. We interpret these shocks as preference shocks to work in different tiers, and besides making the model closer to reality, they will help in the solution of the model. [11] Unemployed workers choose a tier in which to search during the next period by maximizing expected utility, taking into account preference shocks and the cost of switching tiers:

$$\mathcal{U}_k(a, x_{ij}) = \mathbb{E} \left[\max_{k'} U_{k'}(a' - \mathcal{M}_{kk'}, x_{ij}) + \nu \epsilon_{k'} \right] \tag{13}$$

$$= \nu \log \sum_{k'} \exp \left(\frac{1}{\nu} \cdot U_{k'}(a' - \mathcal{M}_{kk'}, x_{ij}) \right). \tag{14}$$

[10]To save on notation, we omit the subscripts k and ij from market tightness θ.

[11]See Giannone, Li, Paixao and Pang (2023) for a recent contribution on solving dynamic programming model with preference shocks.

The second equality comes from the assumptions that idiosyncratic tier preference shocks are i.i.d. over time and distributed Type-I Extreme value with a zero mean (see also (McFadden, 1973)).[12]

An unemployed worker's submarket and tier choice depends on her experience type and asset level, i.e., $\theta(a, x_{ij})$. For instance, an unemployed worker with higher levels of asset holdings applies for better-paying jobs that are more difficult to get (with lower market tightness), everything else equal, compared to a poorer worker. Thus, a rich tenured worker is more likely to pay the cost $\mathcal{M}$ and switch tier for a given preference realization.

Value of an employed worker. Employed workers only make decisions about their saving. The value of being an inexperienced employed worker x_{lj} (previously non-tenured or turbulent), in tier k, who is subject to the risk of an experience upgrade with probability γ^u, is given by:

$$
\begin{aligned}
(15) \qquad E_k(a, w_l, x_{lj}) &= \max_{a'} \ u(c) \\
&+ \beta \lambda_{lk} \mathcal{U}_k(a', x_{ll}) \\
&+ \beta(1 - \lambda_{lk})[(1 - \gamma^u) E_k(a', w_l, x_{lj}) + \gamma^u E_k(a', w_l + \Delta_k, x_{hl})] \\
\text{s.t.} \quad c &= Ra + w_l(1 - \tau) - a' + d \quad \text{and} \ a' \geq \underline{a}
\end{aligned}
$$

An employed worker with low experience is subject to the risk of experience upgrade, γ_k^d. In that case not only her experience increases, but also she gets a rise in her wage proportional to the tier-specific productivity, as well as the difference in productivity between high and low skilled workers, $\Delta_k \equiv y_k \cdot (x_h - x_l)$. Note that, wages of inexperienced workers are increasing in the upgrade probability γ^u but bounded above by the wage of the experienced workers, as we show below.[13] Moreover, expression (15) shows that upon an experience upgrade the benefit entitlement also changes and it is linked to the current experience level. This captures the idea that benefits are proportional to the average wage of the experience group (which takes into account the upgrade probability, as just explained).

The value for an experienced employed worker with benefit entitlement j takes into account turbulent risk. With probability γ_k^d she suffers an experience downgrade after an

[12]A complete proof is provided in A.3 of Appendix.

[13]We check that ex-post all matches have positive surplus and that the value of employment is higher that the value of unemployment, i.e. $E > U$, so that workers do not want to quit to increase their wage.

exogenous layoff. This value is given by:

$$
\begin{aligned}
(16) \qquad E_k(a, w_h, x_{hj}) &= \max_{a'} \; u(c) \\
&+ \beta\lambda_{hk}[\gamma_k^d \mathcal{U}_k(a', x_{lj}) + (1-\gamma_k^d)\mathcal{U}_k(a', x_{hj})] \\
&+ \beta(1-\lambda_{hk})E_k(a', w_h, x_{hj}) \\
\text{s.t.} \quad c &= Ra + w_h(1-\tau) - a' + d, \;\; a' \geq \underline{a}, \;\; \text{and} \;\; j \in \{l, h\}.
\end{aligned}
$$

We summarize workers endogenous and exogenous transitions in the Figure 4.

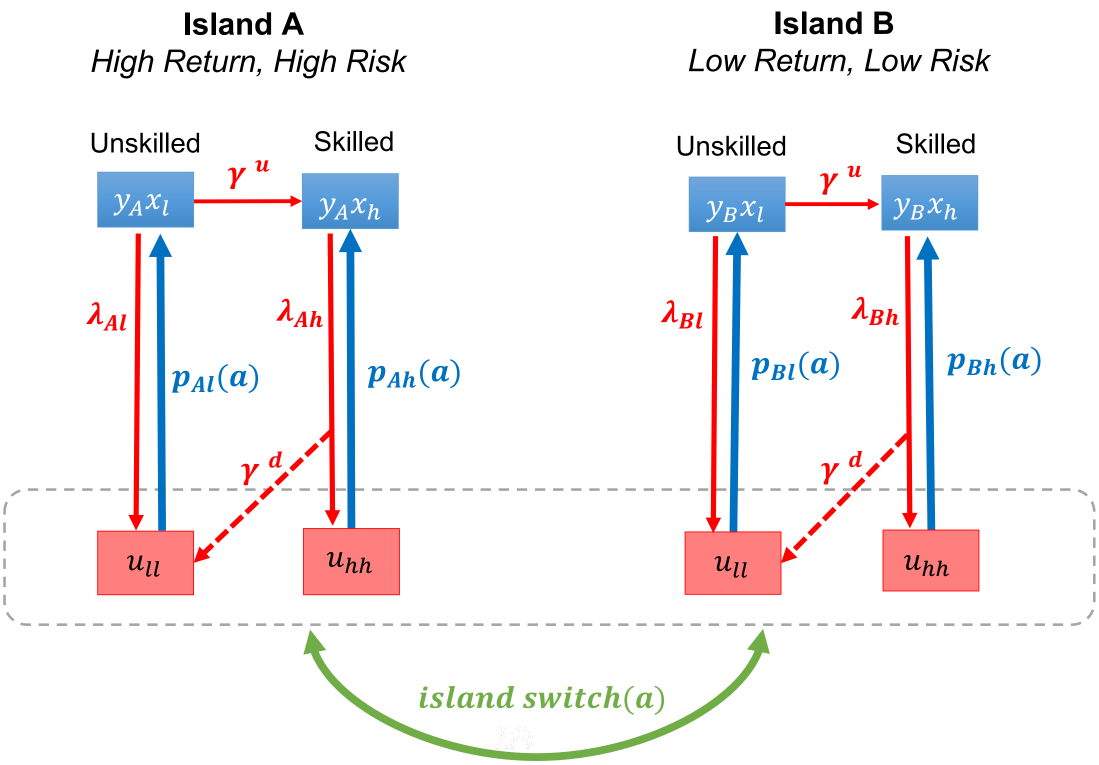


Figure 4: Employment and skill dynamics

Value of a vacant job. Firms pay a per period cost of vacancy κ to open a vacancy. A vacancy posted in the submarket θ for experience x_i and in tier k is given by

$$
(17) \qquad V_k(x_i) = -\kappa_k + \beta \max_{\theta} \left\{ q_k(\theta) J_k(w(\theta), x_i) + (1 - q_k(\theta)) V_k(x_i) \right\} \qquad \forall i.
$$

Since firms are all ex-ante identical, the tradeoff between the market tightness (affecting the probability of filling a vacancy) and the wage offered to the workers makes them indifferent to hire workers with different levels of assets, benefits, or experiences.

Value of a filled job. A worker-firm relationship produces output proportional to the worker's experience x_i. The value of a filled job with a worker with experience x_i in tier k is given respectively by:

$$
\begin{aligned}
J_k(w, x_h) &= f(y_k, x_h) - w + \beta[\lambda_{kh} V_k + (1-\lambda_{kh})J(w, x_h)] \\
J_k(w, x_l) &= f(y_k, x_l) - w + \beta[\lambda_{kl} V_k + (1-\lambda_{kl})(\gamma^u J(w', x_h) + (1-\gamma^u)J(w, x_l)]
\end{aligned}
$$

where $w' = w + \psi_k(x_h - x_l)$. Note that the match value of hiring an experienced worker can only be affected by exogenous separation, λ. However, if a firm hires an inexperienced worker, it takes into account the likelihood with which the experience of workers is upgraded from low to high. As a result, this firms also factors in the rise in the productivity of match in that case, as well as the change in the wage it is paying to the worker.

Worker distributions. Let $\Gamma^{e_{ij}}(a, w)$ be the joint distribution of employed workers over asset and wages and $\Gamma^{u_{ij}}(a)$ be the distribution of unemployed workers over assets, conditional on the worker type (i, j). Then employment and unemployment masses by experience/benefit type are computed as

$$
e_{ij} \equiv \int_a \int_w d\Gamma^{e_{ij}}(w, a), \quad u_{ij} \equiv \int_a d\Gamma^{u_{ij}}(a). \tag{18}
$$

3.3 Stationary Equilibrium

The next step is to characterise the model at the steady state. We use the same tools as Shi (2009) and Menzio and Shi (2011) to solve for a Block-Recursive Equilibrium in which policy functions and prices do not depend on the distribution of workers across submarkets.

Equilibrium. *Given an exogenous interest rate R, a steady-state equilibrium consists of consumption $c(a, x_{i,j})$ and saving $a'(a, x_{i,j})$ policies for all workers; submarket choice for the unemployed workers $\theta(a, x_{i,j})$, a wage-tightness profile (w, θ), an income-tax rate ν, and a distribution of employed and unemployed workers over wages, assets, and types, $\Gamma^{e_{ij}}(w, a)$ and $\Gamma^{u_{ij}}(a)$ such that:*

1. *Consumption and saving policies maximize workers' utility;*
2. *Unemployed workers chose the submarket $\theta(a, x_{i,j})$ that maximizes their utility;*
3. *Free entry condition holds for firms;*
4. *The distributions $\Gamma^{u_{ij}}(a)$ and $\Gamma^{e_{ij}}(w, a)$ are stationary and consistent with policies.*

3.4 Characterization

The directed search protocol, together with the free entry condition, implies that we can solve for the firms' problem independently of the workers' problem and the distribution of workers over asset holdings and experience. Using this block-recursive structure, we find a relationship between wages and market tightness using firms' Bellman equations at the steady-state. Then, using this relationship, we solve for the policy functions of workers, and finally, we can back out the distributions of households over assets and wages after solving for the Bellman equations.

Free entry condition and wage-tightness profile Free entry of firms implies that the steady state value of posting a vacancy in all submarkets is equal to zero $V_k(x_i) = 0$ for all i and tiers k. This implies that since all firms are identical, they are indifferent between hiring different types of workers ex-ante. This is because of the trade-off between the probability of filling the vacancy and the wages firms offer. Thus we obtain the following zero profit condition:

$$J_k(w, x_i) = \frac{\kappa_k}{\beta q_k(\theta)} \quad \text{where} \quad \theta = \theta(a, x_{ij}). \tag{19}$$

Now, using the definition of $J_k(w, x_i)$, we express the value of a filled job $J(w, x_i)$ in terms of wages:

$$J_k(w, x_h) = \frac{y_K k \cdot x_h - w_h}{1 - \beta(1 - \lambda_{hk})} \tag{20}$$

$$J_k(w, x_l) = \frac{y_k \cdot x_l - w_l + \hat{\gamma}_k^u (y_k \cdot x_h - \psi_k(x_h - x_l))}{1 - \beta(1 - \lambda_{lk})(1 - \gamma^u)} \tag{21}$$

where $\hat{\gamma}_k^u \equiv \frac{\beta(1-\lambda_{lk})\gamma^u}{1-\beta(1-\lambda_{hk})}$. Substituting (19) into the values of filled jobs and solving for wages we get the firm indifference conditions that relate tightness θ and wages w:

$$w_k(x_h) = y_k \cdot x_h - \frac{\kappa_k^h}{q_k(\theta)} \tag{22}$$

$$w_k(x_l) = \left[x_l + \hat{\gamma}_k^u (y_k \cdot x_h - \psi_k(x_h - x_l)) - \frac{\kappa_k^l}{q_k(\theta)} \right] \tag{23}$$

(24)

which can be rearranged as:

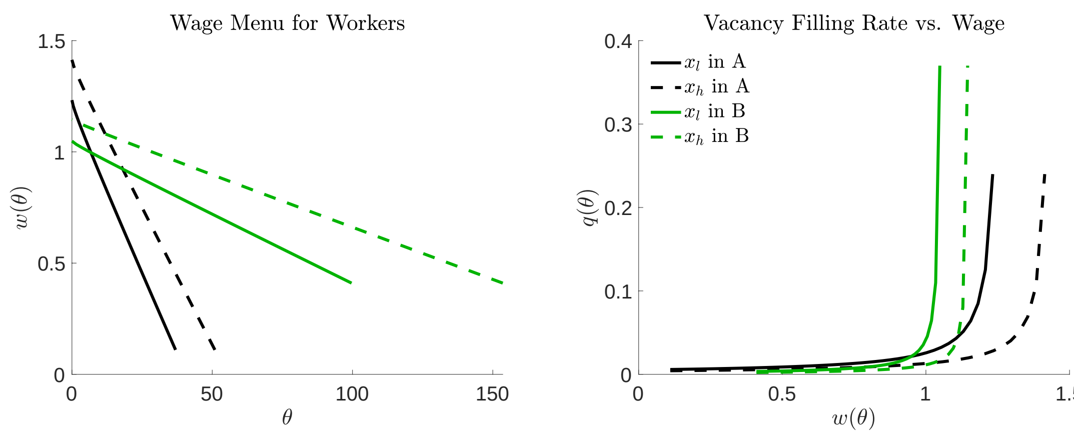
$$(25) \qquad q_k(\theta_h) = \frac{\kappa[1-\beta(1-\lambda_{hk})]}{\beta(x_h - w_h)}$$

$$(26) \qquad q_k(\theta_l) = \frac{\kappa[1-\beta(1-\lambda_{lk})(1-\gamma^u)]}{\beta\left[x_l - w_l + \hat{\gamma}^u_k(x_h - w_l - \Delta_{lj})\right]}$$

where $\tilde{\kappa}^h_k \equiv \frac{(1-\beta(1-\lambda_{hk}))\kappa_k}{\beta}$ and $\tilde{\kappa}^l_k \equiv \frac{\left(1-\beta(1-\lambda_{lk})(1-\gamma^u)\right)\kappa_k}{\beta}$.

Figure 5 shows the wage and job filling probabilities profiles that arises from the firms' free entry condition for each tier and skill level.[14] The job finding probability $m(\theta)$ is decreasing in the wage, or from the firms' perspective, the job filling rate $q(\theta)$ is increasing in the wage. Firms are indifferent between paying high wages and hiring fast and paying low wages but hiring slow. Recall that there are many labour markets, indexed by the workers' experience, benefit entitlement, and level of asset holdings. Workers optimally choose the submarket where they apply for jobs given their type, as explained below. Each figures also makes clear that the menu of choices and wages available for each worker as function of market tightness θ is tier-specific.

Figure 5: Wage-Job Finding Rate Profile

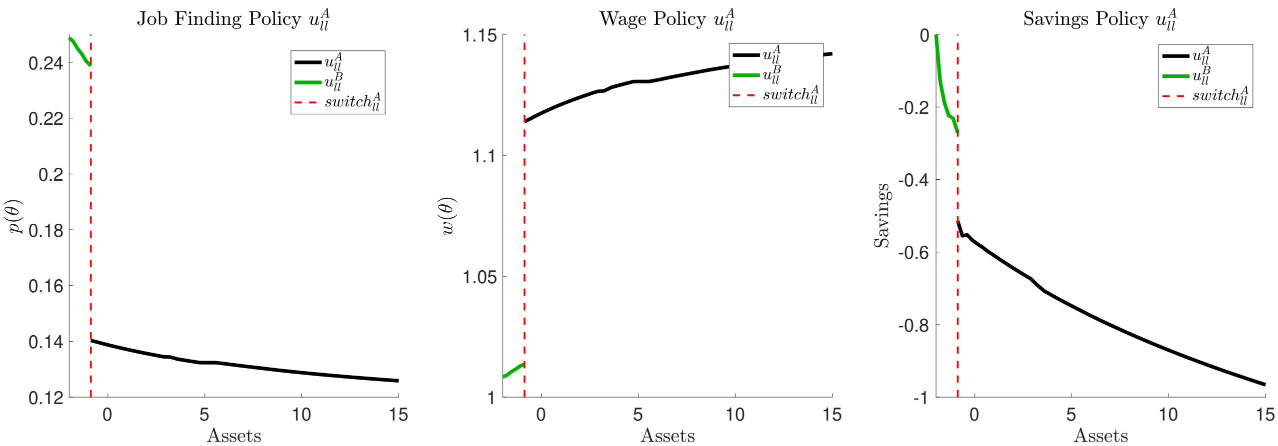


Tier choice From the assumption on the distribution of preference shocks (McFadden, 1973), the proportion of unemployed workers that switch from tier k to tier k', can be expressed is endogenous and depends on the savings choice of the workers:[15]

$$(27) \qquad \mu_{kk'}(a', x_{ij}) = \frac{\exp\left(\frac{1}{\nu}\cdot U_k(a' - \mathcal{M}_{kk'}, x_{ij})\right)}{\sum_{k'}\exp\left(\frac{1}{\nu}\cdot U_{k'}(a' - \mathcal{M}_{kk'}, x_{ij})\right)}.$$

[14]Figures consider the steady state calibration described in Section 4, unless noted otherwise.
[15]Derivation for this expression is reported in Section A.2 of Appendix.

Figure 6: Job search, wage, and savings policies as a function of current assets



Notes: Equilibrium search and wage policies for each type of unemployed worker.

Intuitively, for a given preference for working in a given tier, it is more likely that a worker will switch occupation if she is richer, and the cost of switching to that particular tier is lower.

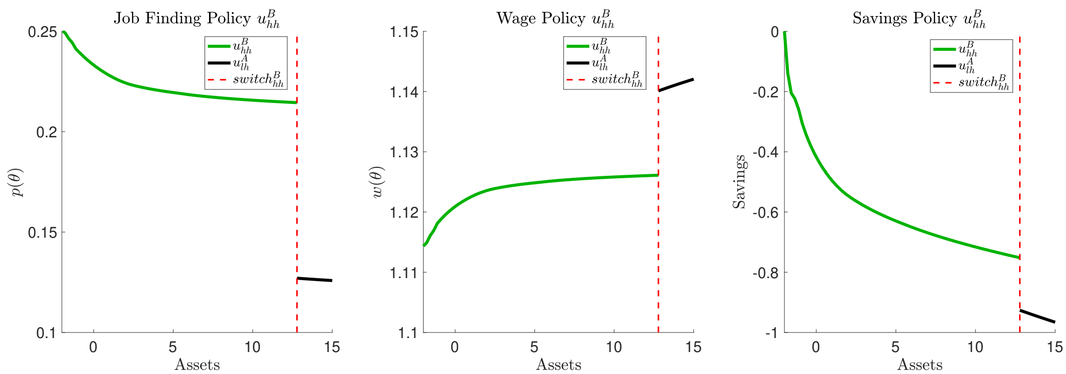
Job search choice. Now we turn into the job search policies of the unemployed workers as a function of their wealth and experience. Figure 6 plots the equilibrium job search choice—wage and job finding probability—as a function of their current level of assets and their type (i, j), for workers who downgrade from A to B. It is important to note that while assets are not directly observable by firms, workers with the same level of skills and benefits sort monotonically into different submarkets depending on their asset holdings.

For workers that downgrade (i.e., workers who at some asset level, decide to switch tier), the job finding probability policy is decreasing in asset level, both within tier, and overall. The discontinuity (denoted by the vertical, dashed line) is precisely given by the fact that rich enough workers can afford to search for a job in tier A where the job finding probability is significantly lower, but the wage is significantly higher.

Figure 7 shows the equivalent policies for upgrading workers. Analogously to workers who downgrade, it's the asset level of the worker that determines both the job finding and wage policy, within and across tiers. As shown in the picture, it is only the rich tenured workers who switch tier and search for a high paying, low finding probability job.

Savings choice. In the presence of incomplete financial markets, risk-averse agents engage in precautionary savings to smooth their consumption. For all workers, regardless of their job status, the asset choice yields standard Euler equations that link consumption across

Figure 7: Job search, wage, and savings policies as a function of current assets



Notes: Equilibrium search and wage policies for each type of unemployed worker.

consecutive periods.

Given $m(\theta)$ and $\mu_{kk'}$, the FOC with respect to assets a' in (12) yields:

$$u'(c^{U_k}) = \beta m(\theta)u'(c^E) + \beta(1-m(\theta))\sum_{k'}\mu_{kk'}\left[u(c^{U_{k'}})\right]. \tag{28}$$

Equation 28 has a clear interpretation. Ss in a standard Euler equation, current marginal utility is equated to future marginal utility. The latter is a combination of marginal utilities, with the associated (endogenous) probabilities. If a worker stays in unemployment next period, she will choose the tier in which to look for a job, depending on assets, preferences, and job prospects. Importantly, both the probability that the worker finds a job and the probability to switch tier are endogenous in this model.[16]

Figures 6 and 7 (right panel) plot the saving policy $(a'-a)$ for unemployed and employed workers against current asset holdings. Workers borrow when unemployed, and even more so when they switch tier. Inexperienced employed workers save more than experienced ones during employment. This is because they have lower wages and know that upon unemployment, they will receive lower benefits. Therefore, they build a bigger buffer for the rainy days. Among the unemployed workers, experienced ones borrow the most. Although tranquil and turbulent workers receive the same benefits, they will receive higher wages when they get employed because of their higher experiences. Therefore, they borrow more while unemployed to smooth consumption.

[16]As will be explained in more detail in the quantitative section, this Euler equation can be exploited to significantly improve the computation time of the equilibrium of the model. In fact, given job finding and tier switching probabilities $m(\theta)$ and $\mu_{kk'}$, the solution for consumption can be found by iteratively looking for the consumption decision that is consistent with the Euler equation 28. The additional difficulty is that this require doing so for a given $m(\theta)$ and $\mu_{kk'}$, which are endogenous, and hence require an additional step in which we solve for them. This could be avoided if the model had a deterministic life cycle structure, as shown in Giannone, Li, Paixao and Pang (2023).

4 Quantitative Analysis

In this section, we explore quantitatively the performance of the model. We first calibrate the steady state to match aggregate moments as well as statistics from the micro-data. Next, we report some non-targeted moments in particular those related to reemployment wages and unemployment duration for turbulent and tranquil workers. This is to study the ability of the model to account for the empirical evidences we document in the first section.

4.1 Calibration

In the first step of the quantitative analysis, we set externally the value of several parameters, including data moments from the NLSY and other values which are standard in the literature. In the subsequent step, the remaining parameters are jointly calibrated though a simulated method of moments.

Externally calibrated parameters. One period is set to be a month. Given the model time period, we specify a discount factor $\hat{\beta} = 0.9955$ and a retirement probability $\rho^r = 0.0021$, which together imply an adjusted discount factor of $\beta = \hat{\beta}(1 - \rho^r) = 0.9934$. The retirement probability implies an average time of 40 years in the labour force. The utility function is CRRA, $u(c) = (c^{1-\sigma})/(1 - \sigma)$. We set the coefficient of relative risk aversion σ to 2, which is a standard value in the literature. The interest rate is set to $r = 0.0035$, which yields an annual risk-free rate of 4%. Following Menzio and Shi (2011), we pick a CES contact rate function, which implies a job finding probability of $m(\theta) = \chi\theta(1+\theta^{\alpha})^{\frac{-1}{\alpha}}$ and a vacancy filling probability $q(\theta) = m(\theta)/\theta$.

Other externally calibrated parameters are set using the NLSY. We set exogenous layoffs for high and low skilled workers in each island to match the employment duration from the NLSY data, 8.3 and 1.8 years for the high and low experienced workers respectively, obtaining $\lambda_h^A = 0.0066$, $\lambda_h^B = 0.0094$, $\lambda_l^A = 0.0242$ and $\lambda_l^B = 0.045$. Importantly, this implies that low skilled workers have lower job security (with respect to their skilled counterpart) regardless of the island they are in. For comparison, Shimer (2005) reports a monthly separation probability of 0.035 for all workers, which is similar to the values in NLSY. Following our empirical definition of turbulent workers—workers switching occupations following an EUE transition with occupational experience of more than 2 years—we set a probability of upgrading experience to $\gamma^u = 0.0417$ so that employed workers take on average 2 years to move from low to high experience, in line consistent with Fujita (2018).

Internally calibrated parameters. We use the simulated method of moments to calibrate the remaining seven parameters to match a set of targets. All the parameters are jointly estimated in equilibrium using indirect inference but we can provide a heuristic argument of which parameter is most related to which target. In each island, we target the experience premium, namely the ratio of average wages between experienced and inexperienced workers which is equal to $\mathbb{E}[w_h]/\mathbb{E}[w_l] = 1.14$ in island A and $\mathbb{E}[w_h]/\mathbb{E}[w_l] = 1.07$ in B, respectively. This informs the skill differences across workers x_l, x_h in both islands as well as the step of the wage upgrade, ψ. To estimate the elasticity of matching function, α, we target the monthly elasticity of job finding to market tightness reported by Shimer (2005).

To discipline turbulence risk γ^d, we target the fraction of EUE transitions in the NLSY that are considered to be turbulent according to our definition, equal to 21% and 11% in A and B, respectively. To discipline the matching efficiencies, we target the excess unemployment duration of turbulent workers to tranquil and non-tenured in NLSY, as well as the average unemployment duration. These will help us to both replicate the level of unemployment duration as well as its relative difference across different unemployment groups. The median asset to income ratio from PSID (2007) helps us to inform the estimation of vacancy cost since this cost directly affects wages. Next, we estimate the borrowing constraint parameter by matching the share of workers with negative asset in the model with the figure we observe in NLSY. The switching rates between island inform the switching costs $\mathcal{M}_{kk'}$. Finally, island-specific home production values b_K help target the island-specific asset distributions. Table 3 shows the baseline parameterization.

Table 4 shows the model fit by comparing model generated moments versus data. The overall fit of the model is quite satisfactory, except for a few targets: in particular, the targets referring to excess duration across workers of different tenure. This is not very surprising since there is a common within-island match efficiency, but all workers with different skill face the same labor market efficiency parameter χ. This was assumed to simplify the model and not add too many parameters to be estimated; however, as recently highlighted in (**?**), there are large differences in the job search processes of different workers. Without imposing such differences or an underlying theory of different search processes in the labor, it's hard to perfectly match these targets.

4.2 Additional Model Outcomes

Here we report additional, non-targeted model outcomes to inspect the properties of the calibrated version of the model.

Wage Distributions We plot the wage distributions in Figure 8. From the wage distributions in the calibrated model, it is immediately clear (and not surprising) that wages are on average much higher in the more productive island, A. There is another fact to be noted,

Table 3: Summary of Parameters

Parameter	Definition	Value	Source
pre-calibrated			
$\hat{\beta}$	discount factor	0.9965	monthly frequency
ρ_r	retirement probability	0.0021	avg. worklife = 40 years
$\beta \equiv \hat{\beta}(1-\rho_r)$	adjusted discount	0.9944	—
σ	relative risk aversion	2	standard in the literature
r	interest rate	0.003	yearly risk-free rate = 4%
λ_h^A	separation tenured, island A	0.0073	NLSY
λ_h^B	separation tenured, island B	0.0124	NLSY
λ_l^A	separation untenured, island A	0.0221	NLSY
λ_l^B	separation untenured, island B	0.0466	NLSY
γ^u	experience upgrade	0.0417	experience = 2 years
calibrated			
α	matching elasticity	0.7	
γ_A^d	experience depreciation in A	0.4	
γ_B^d	experience depreciation in B	0.6	
χ_A	matching efficiency in A	0.24	
χ_B	matching efficiency in B	0.37	
κ_A	vacancy creation cost in A	0.10	
κ_B	vacancy creation cost in B	0.40	
y_A	productivity in A	1.15	
y_B	productivity in B	1	normalization
$\mathcal{M}_A$	switching cost to A	0.75	
$\mathcal{M}_B$	switching cost to B	0	normalization
b_A	home production/benefits in A	0.1	
b_B	home production/benefits in B	0.4	
$\underline{a}$	borrowing constraint	−8	

Table 4: Model Fit

Moment	Source	Data	Model
Island wage premium tenured $\mathbb{E}[w_h^A]/\mathbb{E}[w_h^B]$	NLSY	1.22	1.17
Island wage premium untenured $\mathbb{E}[w_l^A]/\mathbb{E}[w_l^B]$	NLSY	1.14	1.16
Wage ratio in A $\mathbb{E}[w_h^A]/\mathbb{E}[w_l^A]$	NLSY	1.14	1.15
Wage ratio in B $\mathbb{E}[w_h^B]/\mathbb{E}[w_l^B]$	NLSY	1.07	1.08
Observed Job finding / Aggregate unempl. in A	NLSY	7.2%	3.8%
Observed Job finding / Aggregate unempl. in B	NLSY	24.2%	17.2%
Proportion of employed agents B	NLSY	60 %	71.2%
Proportion of turbulent transitions EUE'	NLSY	0.12	0.13
Elasticity of job finding to tightness	Shimer (2005)	0.72	0.75
Excess duration $\mathbb{E}[\tau_{lh}]/\mathbb{E}[\tau_{hh}]$	NLSY	3	1.1
Excess duration $\mathbb{E}[\tau_{lh}]/\mathbb{E}[\tau_{ll}]$	NLSY	1.5	1.1
Switching rate B to A	NLSY	30%	14%
Avg. unemployment duration (months)	NLSY	7.7	5.2
Fraction with negative assets	NLSY	0.16	0.16

Notes: Data from NLSY. Model calibrated at monthly frequency. Unless otherwise specified, aggregate moments refer to a weighted average of island-specific moments.

however: the wage difference between high and low skilled in the two islands is higher. This reflects the steeper wage profile in island A. This contributes to the persistence of the adverse effects (in terms of wages) of switching to island B, where it is more difficult to climb the ladder towards a high wage (in other words, the wage profile is less steep). In turn, these differences of wage profiles across islands are important to help the model generating persistent scarring effects for switchers (or turbulent) workers, as we will show in the next section.

Asset Distributions Next, we plot the asset distributions in Figure 9. Employed workers are significantly richer in island A. The same is true for unemployed workers, but the difference is somewhat less pronounced. Once again, this reflects the different wage profiles across islands and different opportunities faced by employed workers across islands.

The asset distributions of unemployed workers also show that turbulent workers (in red) are poorer than their tenured counterparts (in blue) but significantly richer than non-tenured workers (in black). This is important to notice because these wealth differences will result in different search policies and as such, different wage profiles faced by the workers (in expectations) when they look for a job. This is crucial when analyzing the dynamic effects on wages and durations of unemployment transitions.

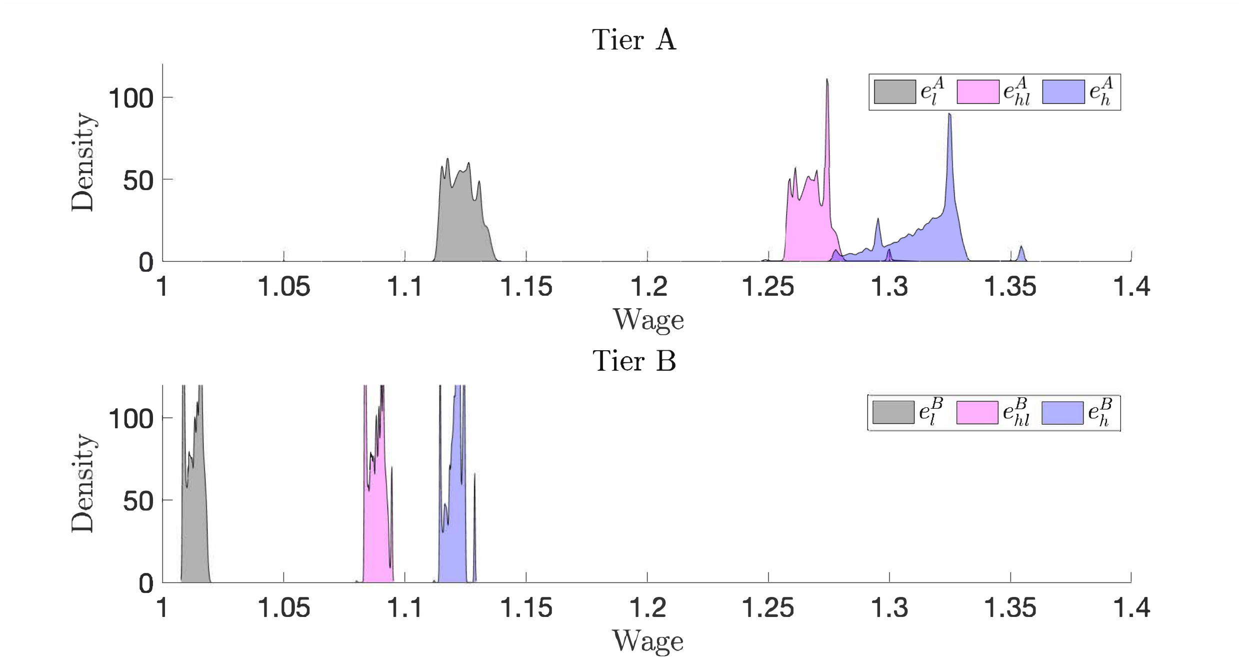


Figure 8: Wage Distributions

Figure 9: Asset Distributions

4.3 Untargeted: Scarring effects in the model

Despite being non-targeted, it is particularly interesting to check whether and how the model replicates one of the main findings of the empirical section, which is that the scarring effects of unemployment are concentrated among turbulent workers, particularly the poor ones.

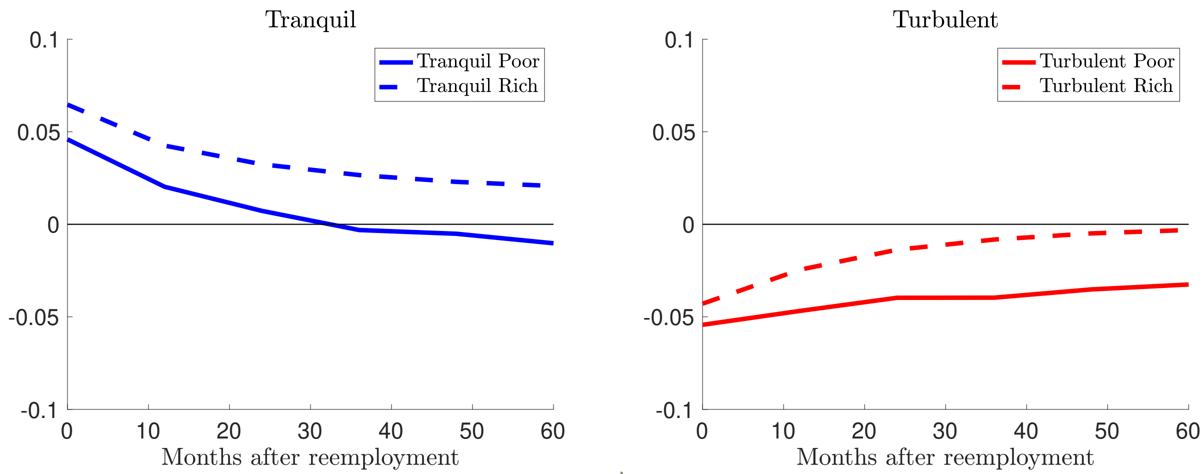
The model equivalent result of the empirical evidence is reported in 10. Several interesting patterns emerge. First, the model replicates the stayer vs. switcher effects of unemployment, regardless of wealth. In fact, stayers in the model barely suffer any losses (they gain a bit), while switchers suffer large and persistent wage losses.

The second observation is that the model does a decent job of replicating the patterns of the unemployment scar by wealth, especially for the switchers (red dashed and continuous line). In the model, the poor switchers suffer larger losses than rich switchers on impact; perhaps even more importantly, rich switchers fully recover from losing their job after four years; poor switchers, instead, have wages that on average, are still lower than their rich counterparts after four years, in line with the data.

This property of the model is particularly valuable since it has been shown that standard search models have difficulty in replicating the large and persistent scarring effects of unemployment (Davis and Von Wachter (2011)), and additional mechanisms are needed to capture the persistence (one such mechanism is proposed in Jarosch (2021)). In line with our new evidence, this model goes one step further to replicate the fact that these large losses are concentrated among *poor* workers, and it is therefore grounded in micro-level evidence that we have uncovered in the previous section.

Having checked the model performance in replicating this important micro-fact previously discussed, we now turn to the macroeconomic implications of the different idiosyncratic risks embedded in the model.

Figure 10: Scarring Effects in the Model



5 Macro Implications

Having explored, empirically and theoretically, the micro effects of turbulence risk, we now study the macro implications of turbulence risk in the model economy. We conduct several exercises to illustrate the model implications and discuss future steps.

5.1 Implications for technological change

We first draw an implication of the model relating to the risks associated with technological change. A large literature has emphasized the benefits and the associated risks, especially for low and middle-income workers, of Skill Biased Technical Change (Heathcote, Storesletten and Violante, 2010). We use the model structure to show that the *incidence* of shocks, and in particular shocks that displace workers, can have very important effects on a macroeconomic scale; as the next results make clear, it will be important to distinguish what we have called turbulence risk (in the model, γ_d) and whether this risk occurs in low risk-low returns occupations (γ_d^B, capturing in reduced form, the effects of low-skill displacing technological change) or in high-returns high-risk occupations (γ_d^A, possibly capturing the displacing effects of newer technologies, such as AI, that also affect occupations and sectors populated mostly by high skilled workers). Figures 11 and 12 make this point.

In Figure 11, we simulate an increase in the parameter γ_d^B from its value in the benchmark economy. The Figure plots the resulting outcomes in these alternative economies, where the risk of losing skills after job displacement in B is progressively higher. As typical in economies with idiosyncratic level risk, workers save more to face the increased risk (especially in B), thus increasing overall wealth and inequality. Output and unemployment rate are mildly affected, because of two opposing forces at the island-level: as workers increasingly switch

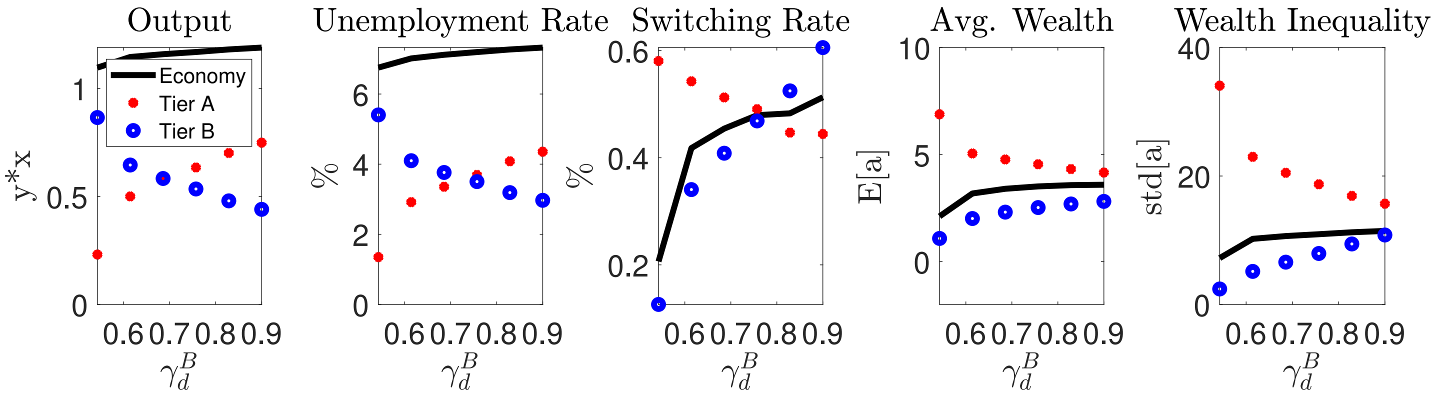


Figure 11: Increase in turbulence risk in B

from B to A, both unemployment and ouput decrease in B (and viceversa for A). The key message is that when turbulence risk increases in low returns occupations, wealth inequality increases, a standard prediction even in a one-sector economy with idiosyncratic risk.

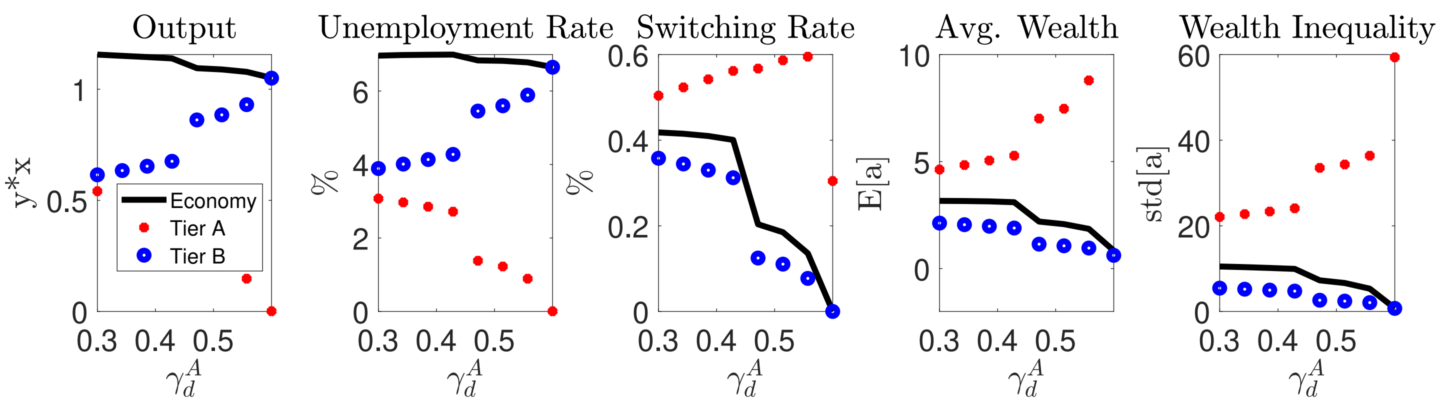


Figure 12: Increase in turbulence risk in A

In Figure 12 instead, we simulate an increase in the parameter γ_d^A from its value in the benchmark economy, leaving all other parameters unchanged. As turbulence risk increases in A, workers in A tend to leave that island and workers in B tend to stay more in their island. Opposing forces are at work when it comes to the effects on wealth and wealth inequality: on the one hand, risk increases, leading to more precautionary savings; on the other, workers are more concentrated in the least productive island B, thus lowering their income and savings (as well as total output). The key result is that, compared to the results in Figure 11, here an increase in risk does *not* lead to an increase in wealth inequality (in fact, it decreases). This implies that the incidence of shocks matters in this economy when evaluating the macroeconomic effects of increases in turbulence risk.

Shutting down reallocation To better understand the results of increasing turbulence risk and isolate the channels at work, we consider a similar comparative statics exercise as the one in Figure 11 and Figure 12, but now considering two economies: a first economy in which turbulence risks γ_d^A and γ_d^B are increased (or decreased) simultanously by a factor ϕ. Hence we move γ_d^A and γ_d^B proportionally from their baseline levels. We compare these results to those in which we move these parameters in the same way, but in an economy in which we shut down reallocation[17]. We plot the results in Figure 13.

There are several difference between the two economies. Clearly, in the no-reallocation economy, the switching rate is fixed at zero, while the switching rate in the baseline economy goes up in response to an increase in turbulence risk, as a precautionary mechanism. What does this difference imply for the rest of the macroeconomic aggregates? First, output decreases in the no-reallocation economy, and increases in the baseline. This is because workers can freely reallocate and this increases aggregate productivity. This also translates into a higher increase in wealth and wealth inequality, as agents are on average richer in the baseline economy. The increase in these last aggregates in the no reallocation economy is much less pronounced. The key takeaway form this exercise is that the ability to reallocate across major occupational groups (islands) matters greatly for the macroeconomic effects of increases in idiosyncratic level risk.

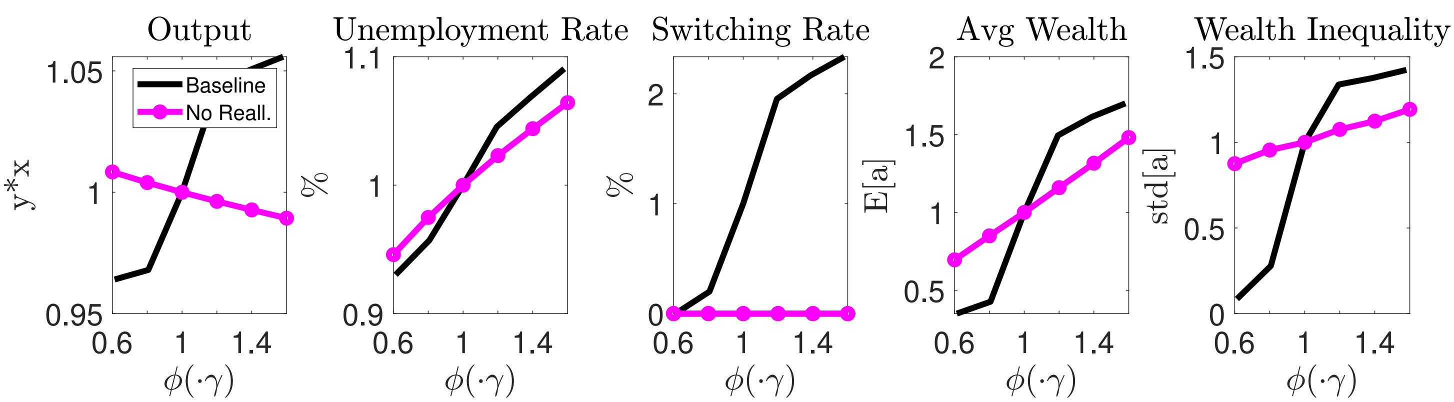


Figure 13: Increase in turbulence risk with and without reallocation

5.2 Implications of increases in layoff risk

So far, we have focused our analysis of the macroeconomic implications of increases in risk on the effects of increases in turbulence risk, γ_d. However, there is another important source of risk in the model, namely layoff risk λ. While turbulence risk is perhaps more important to discuss the implications for long term skill obsolescence, the risk of layoff (or separation risk) is also very important to examine the macro implications of this model

[17]To do so, we consider a baseline economy in which heterogeneity between islands is shut down; effectively this implies the model economy is composed by only one island.

at shorter frequencies (e.g, business cycles). To examine these implications, we conduct a similar exercise than before and consider an increase (and decrease) in generalized layoff risk λ (i.e., a proportional increase in $\lambda_h^A, \lambda_h^B, \lambda_l^A, \lambda_l^B$ from their baseline values) by a factor ϕ. The results are depicted in Figure 14.

Looking at the macroeconomic aggregates, an interesting pattern emerges. Following a proportional increase in separation risk in this economy, both output and unemployment rate change more sharply in the no reallocation economy (to facilitate comparison, we normalized the value of each aggregate in the baseline parametrization at 1). This happens because, in the baseline economy, workers can cope with an increasing risk not only by saving, but also by reallocating and switching sectors. Thus, the allocation of workers to jobs is endogenous and this can affect the response of the economy to increases in separation risk, which is commonly thought of as an important driver of recession. This is an important result and, while it is beyond the scope of this paper to examine the business cycle implications of this model, it might represent an important avenue for future research.

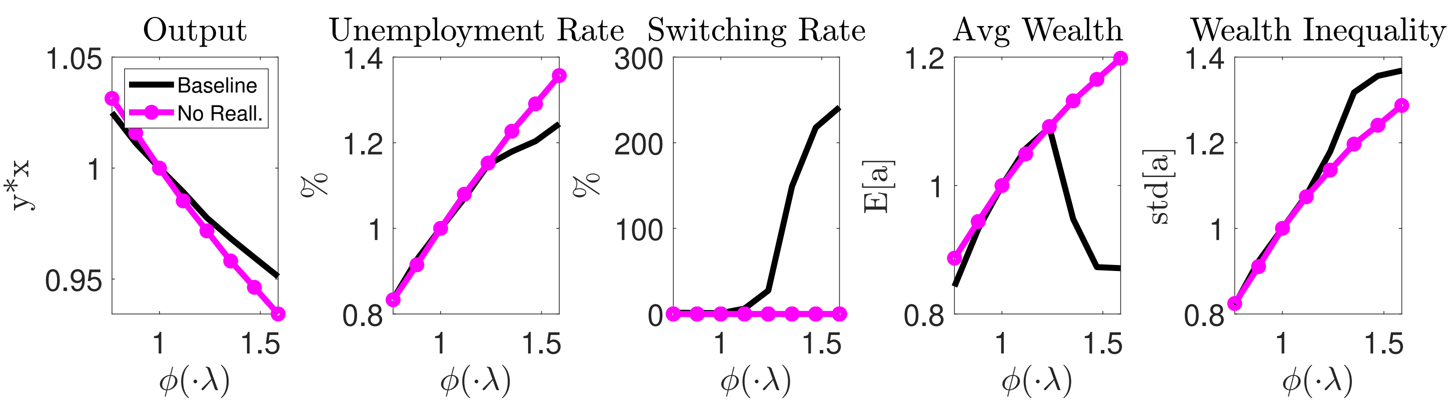


Figure 14: Increase in layoff risk

6 Conclusion

In this paper, we have explored the role of turbulence risk in shaping aggregate economic outcomes. Using a panel of workers' labour market experiences, we provide novel evidence that turbulence risk associated to losing occupational experience substantially decreases reemployment wages and increases unemployment duration. Moreover, workers' initial level of wealth upon entering unemployment dampens the decrease in the wage but amplifies the increase in unemployment duration. Then, we set up an environment with search and financial frictions in which agents exploit two insurance tools to smooth their consumption: precautionary savings and precautionary search. We quantify the relative role of these mechanisms and find welfare loses from increased turbulence risk and welfare gains from a more generous unemployment insurance policy.

Our theoretical framework assumes exogenous job and occupational displacement. Theories that rationalize these rates include dual markets (Huckfeldt, 2021), life-cycle dynamics (Jung and Kuhn, 2019), job security (Jarosch, 2021), and learning about worker skills (Baley, Figueiredo and Ulbricht, 2022). Moving forward, it would be interesting to assess welfare when these various margins are considered.

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Wealth and Inequality in Turbulent Labor Markets

Isaac Baley and Alireza Sepahsalari

Theory Appendix

A Proofs

A.1 Optimality conditions

Assets The FOC for assets (a') are given by

$$\begin{aligned}\frac{\partial u(c^u_{ij})}{\partial c} &= \beta R\left[m(\theta)\frac{\partial u(c^{e}_i{}')}{\partial c} + (1-m(\theta))\frac{\partial u(c^{u}_{ij}{}')}{\partial c}\right] + \nu^{u_{ij}} \\ \frac{\partial u(c^e_l)}{\partial c} &= \beta R\left\{\lambda\frac{\partial u(c^{u}_l{}')}{\partial c} + (1-\lambda)\left[\gamma^u\frac{\partial u(c^{e}_h{}')}{\partial c} + (1-\gamma^u)\frac{\partial u(c^{e}_l{}')}{\partial c}\right]\right\} + \nu^{e_l} \\ \frac{\partial u(c^e_h)}{\partial c} &= \beta R\left\{\lambda\left[\gamma^d\frac{\partial u(c^u_{lh})}{\partial c} + (1-\gamma^d)\frac{\partial u(c^u_{hh})}{\partial c}\right] + (1-\lambda)\frac{\partial u(c^e_h)}{\partial c}\right\} + \nu^{e_h}\end{aligned}$$

where $\nu^{x_{ij}}$ measures the shadow value of the borrowing constraint if it is binding.
Proof. The FOC for an unemployed worker with type i, j is given by:

$$\frac{\partial u(c^u_{ij})}{\partial c} = \beta\left\{m(\theta)\frac{\partial E_i}{\partial a'} + (1-m(\theta))\frac{\partial U_{ij}}{\partial a'}\right\} + \nu^{u_{ij}} \tag{A.1}$$

The envelope condition for U is $\frac{\partial U_{ij}}{\partial a} = R\frac{\partial u(c^u_{ij})}{\partial a} + \beta\left[\frac{\partial m(\theta)}{\partial \theta}\frac{\partial \theta}{\partial a}(E_i - U_{ij})\right] = R\frac{\partial u(c^u_{ij})}{\partial a}$, since by optimality, $\frac{\partial \theta}{\partial a} = 0$, and the envelope condition for E_i is $\frac{\partial E_i}{\partial a} = R\frac{\partial u(c^e_i)}{\partial a}$. Substituting the envelope conditions, evaluated at $t+1$, we obtain the standard Euler equation:

$$\frac{\partial u(c^u_{ij})}{\partial c} = \beta R\left[m(\theta)\frac{\partial u(c^{e}_i{}')}{\partial c} + (1-m(\theta))\frac{\partial u(c^{u}_{ij}{}')}{\partial c}\right] + \nu^{u_{ij}} \tag{A.2}$$

where $\nu > 0$ measures the shadow value of the borrowing constraint when it is binding.

For a low-skilled employed worker the FOC reads:

$$\frac{\partial u(c^e_l)}{\partial c} = \beta\lambda\left\{\frac{\partial U_l}{\partial a'} + (1-\lambda)\left[\gamma^u\frac{\partial E_h}{\partial a'} + (1-\gamma^u)\frac{\partial E_l}{\partial a'}\right]\right\} + \nu^{e_l} \tag{A.3}$$

Substituting using the envelope conditions:

$$\frac{\partial u(c^e_l)}{\partial c} = \beta R\lambda\left\{\frac{\partial u(c^{u}_l{}')}{\partial c} + (1-\lambda)\left[\gamma^u\frac{\partial u(c^{e}_h{}')}{\partial c} + (1-\gamma^u)\frac{\partial u(c^{e}_l{}')}{\partial c}\right]\right\} + \nu^{e_l} \tag{A.4}$$

Finally, the FOC for a high skilled employed worker reads:

$$\text{(A.5)} \qquad \frac{\partial u(c_h^e)}{\partial c} = \beta \left\{ \lambda \left[\gamma^d \frac{\partial U_{lh}}{\partial a'} + (1-\gamma^d) \frac{\partial U_{hh}}{\partial a'} \right] + (1-\lambda) \frac{\partial E_h}{\partial a'} \right\} + \nu^{e_h}$$

Substituting the envelope conditions:

$$\text{(A.6)} \qquad \frac{\partial u(c_h^e)}{\partial c} = \beta R \left\{ \lambda \left[\gamma^d \frac{\partial u(c_{lh}^u)}{\partial c} + (1-\gamma^d) \frac{\partial u(c_{hh}^u)}{\partial c} \right] + (1-\lambda) \frac{\partial u(c_h^e)}{\partial c} \right\} + \nu^{e_h}$$

■

Submarket choice The FOC for tightness (θ) is given by

$$\underbrace{\mathcal{E}_{m,\theta}}_{\text{increase in finding prob}} \underbrace{\frac{E-U}{E}}_{\text{gains from leaving unemp.}} = \underbrace{-\mathcal{E}_{w,\theta}}_{\text{wages lost}} \underbrace{\mathcal{E}_{E,w}}_{\text{sensitivity of utility to wages}}$$

Proof.

$$\begin{aligned} m'(\theta)\,(E-U) + m(\theta) \frac{\partial E}{\partial w} \frac{\partial w}{\partial \theta} &= 0 \\ \frac{m'(\theta)}{m(\theta)} (E-U) + \frac{\partial E}{\partial w} \frac{\partial w}{\partial \theta} &= 0 \\ \frac{m'(\theta)}{m(\theta)} \theta \left(\frac{E-U}{E} \right) + \frac{\partial E}{\partial w} \frac{\partial w}{\partial \theta} \frac{\theta}{w} \frac{w}{E} &= 0 \\ \mathcal{E}_{m,\theta} \left(\frac{E-U}{E} \right) = -\mathcal{E}_{w,\theta} \mathcal{E}_{E,w} & \end{aligned}$$

where $\mathcal{E}_{m,\theta} \equiv \frac{m'(\theta)}{m(\theta)} \theta$ denotes the elasticity of the finding probability with respect to tightness, $\mathcal{E}_{w,\theta} \equiv \frac{\partial w}{\partial \theta} \frac{\theta}{w}$ the elasticity of the wage profile with respect to tightness, and $\mathcal{E}_{E,w} \equiv \frac{\partial E}{\partial w} \frac{w}{E}$ the elasticity of the utility of being employed with respect to the wage. ■

Tightness choice in CES case. Start from the finding probability $m(\theta) = \theta(1+\theta^{\alpha})^{-1/\alpha}$ and the filling probability $q(\theta) = m(\theta)/\theta = (1+\theta^{\alpha})^{-1/\alpha}$. The derivative with respect to tightness is given by:

$$\begin{aligned}
\frac{\partial m(\theta)}{\partial \theta} &= (1+\theta^{\alpha})^{-1/\alpha} + \theta\left[\frac{-1}{\alpha}\frac{(1+\theta^{\alpha})^{-1/\alpha}}{(1+\theta^{\alpha})}\alpha\theta^{\alpha-1}\right] \\
&= (1+\theta^{\alpha})^{-1/\alpha}\left[1-\frac{\theta^{\alpha}}{1+\theta^{\alpha}}\right] \\
&= (1+\theta^{\alpha})^{-1/\alpha}\left[\frac{1}{1+\theta^{\alpha}}\right]
\end{aligned}$$

Then the elasticity of the finding rate with respect to tightness is given by

$$\mathcal{E}_{m,\theta} \equiv \frac{\partial m(\theta)}{\partial \theta}\frac{\theta}{m(\theta)} = \frac{\theta(1+\theta^{\alpha})^{-1/\alpha}}{m(\theta)}\left[\frac{1}{1+\theta^{\alpha}}\right] = \frac{1}{1+\theta^{\alpha}}$$

The equilibrium wages for the experienced workers are

$$w(x_h) = x_h - \frac{\kappa_h}{q(\theta(x_h))} = x_h - \kappa_h(1+\theta^{\alpha})^{1/\alpha}$$

Then the elasticity of wages with respect to θ is given by:

$$\begin{aligned}
\mathcal{E}_{w,\theta} \equiv \frac{\partial w}{\partial \theta}\frac{\theta}{w} &= \left(-\frac{\kappa_h}{\alpha}(1+\theta^{\alpha})^{1/\alpha-1}\alpha\theta^{\alpha-1}\right)\frac{\theta}{w} \\
&= -\frac{\kappa_h}{(1+\theta^{\alpha})^{-1/\alpha}}\frac{\theta^{\alpha}}{w}\frac{1}{1+\theta^{\alpha}} \\
&= -\frac{\kappa_h}{q(\theta)}\frac{\theta^{\alpha}}{w}\mathcal{E}_{m,\theta}
\end{aligned}$$

Substituting these expressions into the FOC for tightness choice yields:

$$\begin{aligned}
\mathcal{E}_{m,\theta}\left(\frac{E-U}{E}\right) &= -\mathcal{E}_{w,\theta}\mathcal{E}_{E,w} \\
\mathcal{E}_{m,\theta}\left(\frac{E-U}{E}\right) &= \frac{\kappa_h}{q(\theta)}\frac{\theta^{\alpha}}{w}\mathcal{E}_{m,\theta}\mathcal{E}_{E,w} \\
\left(\frac{E-U}{E}\right) &= \frac{\kappa_h}{q(\theta)}\frac{\theta^{\alpha}}{w}\mathcal{E}_{E,w} \\
E-U &= \frac{\kappa_h}{q(\theta)}\theta^{\alpha}\frac{E}{w}\frac{\partial E}{\partial w}\frac{w}{E} \\
\frac{1}{k_h}\frac{E-U}{\partial E/\partial w} &= (1+\theta^{\alpha})^{1/\alpha}\theta^{\alpha} \\
\frac{1}{k_h}\frac{E-U}{\partial E/\partial w} &= \Omega(\theta)
\end{aligned}$$

where we define $\Omega(\theta) \equiv (1+\theta^{\alpha})^{1/\alpha}\theta^{\alpha}$. Since Ω is an increasing function of θ, then θ is increasing in the difference between the employment and unemployment value $E-U$ and decreasing in the sensibility of the employment value to wages $\partial E/\partial w$ and the vacancy creation cost κ.

A.2 Switching Probability: Derivation

In this section we derive the expression for the endogenous probability of switching tier, as expressed in (27).

Under the assumption that shocks are Type I - Extreme Value distributed, the probability that a worker of skill x_{ij} in tier k chooses to move to tier k', defined by $\mu_{kk'}(a', x_{ij})$, is:

$$\mu_{kk'}(a', x_{ij}) = Pr(U_k^x + \nu\epsilon_k^i > U_{k'}^x + \nu\epsilon_{k'}^i, \forall k') \tag{A.7}$$

$$= Pr((U_k^x - U_{k'}^x) + \nu\epsilon_k^i > \nu\epsilon_{k'}^i, \forall k') \tag{A.8}$$

$$= Pr(\frac{1}{\nu}(U_k^x - U_{k'}^x) + \epsilon_k^i > \epsilon_{k'}^i, \forall k') \tag{A.9}$$

Where $U_k^x = U(a - \mathcal{M}_{kk'}, x, k)$ The last expression is simply the cdf of $\epsilon_{k'}^i$ evaluated at $(U_k^x - U_{k'}^x) + \epsilon_k^i$. Since ϵ_k^i is iid across agents i, this cdf can be computed easily as

$$\mu_{kk'} = \int \prod_{k \neq k'} e^{-e^{-\left(\frac{1}{\nu}(U_k^i - U_{k'}^i) + \epsilon_k^i\right)}} d\epsilon_k^i \tag{A.10}$$

Calculating this integral gives

$$\mu_{kk'} = \frac{e^{\left(\frac{1}{\nu}U(a-\mathcal{M}_{kk'},x,k)\right)}}{\sum_r e^{\left(\frac{1}{\nu}U(a-\mathcal{M}_{kr},x,k)\right)}} \tag{A.11}$$

which is the expression in the main text.

A.3 Unemployed Value Function $\mathcal{U}$: Derivation

To derive equation 13, first note that if two indipendent random variables ϵ_1, ϵ_2 with distributions $G_1(x)$ and $G_2(x)$, the distribution of $max(\epsilon_1, \epsilon_2)$ is simply the product of the individual distributions, i.e. $G_1 \cdot G_2$.

In our case, we want to find the distribution of the maximum of the k' variables $U_{k'}(a' - \mathcal{M}_{kk'}, x_{ij}) + \nu\epsilon_{k'}$, call this $M(x)$. Given the assumption of Type I Extreme Value shocks, then the distribution of the random variable $x = \mathbb{E}\left[max(U_{k'}(a' - \mathcal{M}_{kk'}, x_{ij}) + \nu\epsilon_{k'})\right]$ is the product of the terms $U_{k'}(a' - \mathcal{M}_{kk'}, x_{ij}) + \nu\epsilon_{k'}$ for every possible value of k^j, $j = 1, 2, 3, ..:$ [18]

$$\begin{aligned}
M(x) &= exp(-exp(-(x - U_{k^1}(a' - \mathcal{M}_{kk^1}, x_{ij}) + \nu\epsilon_{k^1})))) && \text{(A.12)}\\
&\cdot exp(-exp(-(x - U_{k^2}(a' - \mathcal{M}_{kk^2}, x_{ij}) + \nu\epsilon_{k^2})))) && \text{(A.13)}\\
&\cdot exp(-exp(-(x - U_{k^3}(a' - \mathcal{M}_{kk^3}, x_{ij}) + \nu\epsilon_{k^3})))) \ldots && \text{(A.14)}\\
&= exp(-exp(x - \omega)/\nu)) && \text{(A.15)}
\end{aligned}$$

This is equivalent to say that $M(x) = max(U_{k'}(a' - \mathcal{M}_{kk'}, x_{ij}) + \nu\epsilon_{k'})$ is a random variable that is distributed according to a Type I Extreme value distribution, with mean $\omega = \nu \log \sum_{k'} \exp(\frac{1}{\nu} \cdot U_{k'}(a' - \mathcal{M}_{kk'}, x_{ij})$, which proves the result.

[18]Recall the cdf $F(x)$ of the Type I Extreme Value distribution is simply $F(x) = exp(-exp(-(x - \mu)/\nu))$ where μ and ν are the location and scale parameters, respectively.

Self-Insurance and Welfare in Turbulent Labor Markets

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Data Appendix

A Data Description

For the empirical analysis, we use data from the NLSY79, a nationally longitudinal survey of 12,696 individuals who were between 14 and 22 years when they were first interviewed in 1979. We use the cross-sectional sample has 6,111 respondents and was designed to represent the non-institutionalized civilian segment of people living in the United States in 1979 with ages 14-22 as of December 31, 1978.

Worker's employment history The NLSY79 interviewed individuals on an annual basis in the years from 1979 to 1993, and on a biannual basis for the period 1994-2016. Information on labor force status is recorded at a weekly frequency throughout the sample period, even in the later period where interviews were at biannual frequency. Following Baley, Figueiredo and Ulbricht (2022), we use the NLSY79's Work History Data file to construct a monthly panel. This file is a week-by-week record of the working history for each respondent, which contains information about weekly labor status and hours worked. While an individual may hold more than one job, we focus on the primary job at a given month, which is defined as the one for which an individual worked the most hours in a given month. Using a mapping that links jobs across consecutive interviews, we build a panel report employment spells for the primary job and any individuals spent not working.

For each primary job, we retain information on the hourly wage, occupation and industry codes. Before merging occupation and industry information with the employment panel, we clean occupational and industry titles following Guvenen, Kuruscu, Tanaka and Wiczer (2018)'s approach: to each job, we assign the occupation and industry code that is most often observed during the employment spell. In the NLSY79, occupation titles are described by the three-digit Census occupation code. Because this classification system changed over time[19], before cleaning we converted all the occupational codes across the years into the *occ1990dd* occupation system developed by Dorn (2009), which has the advantage of being time-consistent.[20]

Wages correspond to the hourly wage, which include tips, overtime and bonuses, and are measured in 2000 dollars (we use the consumer price index from the BLS to deflate wages).

Labor market transitions Our empirical exercise focus only on employment to unemployment to employment transitions, which we label as EUE'. We identify a EUE' transition if the worker was non-employed in month T_0, the start of the unemployment spell, (i.e. re-

[19] Until 2000, NLSY79 reports occupation codes in the Census 1970 three-digit occupation code. After this year, occupation codes are reported in the Census 2000 three-digit occupation code.

[20] The crosswalk files between the Census classification codes and the *occ1990dd* occupation aggregates created by Autor and Dorn (2013) can be found at http://www.ddorn.net/data.

ported to be not working, unemployed or out of the labor force), after being being previously employed, and employed in month T_1, meaning that she reported a job. These transitions include *recalls*, workers that return to their previous employer after a jobless spell. Moreover, we define a worker making an occupational switch when the occupation upon reemployment at month t is different from the one reported in the previous job.

Assets The NLSY79 contains detailed questions on the asset holdings and liabilities at the household level, from 1985 onwards. The welth information is not observed at the same frequency as the labor market data; asset data are collected at interview dates, providing at most one observation on assets per year. All assets are defined by the NLSY79 as the amount the respondent would reasonably expect someone to pay if the asset were sold in its current condition. Respondents report the market value of their assets at the moment of the interview; this information is thus assigned to its particular calendar month, leaving blank all others. We use the CPI reported by the BLS to convert the market value of each asset to 2000 dollars. From the detailed information reported by NLSY, ee create five categories of net assets—residential property, financial assets, business assets, vehicles and others—as follows:

- Residencial Property = "Market value of residential property r/spouse own" - "Amount of mortgages and back taxes r/spouse owe on residential property"
- Financial assets = "Total market value of stocks/bonds/mutual funds" + "Total amount of money assets like savings accounts of r/spouse"+ "Total amount of money in assets like IRAS or KEOUGH of r/spouse"+"Total amount of money in assets like CDS, loans or mortages of r/spouse"'
- Business assets = "Total market value of farm/business/other property r/spouse own"- "Total amount of debts on farm/business/other property r/spouse owe"
- Vehicles = "Total market value of vehicles including automobiles r/spouse own"- "Total amount of money r/spouse owe on vehicles including automobiles"
- Others = "Total market value of all other assets each worth more than $500"-"Total amount of other debts over $500 r/spouse owe"

We then define *Liquid Wealth* as the sum of business assets, financial assets, vehicles, and other assets, all net of debts, minus all debts on residential property. Following Lise (2012), we trim the top and bottom one-half-of-one percent of the assets distribution to reduce the influence of outliers.

Table A.1: Wage Change and Unemployment Duration:

	Wage Change	Duration
	(1)	(2)
previous wage (log)	-0.349***	-0.177
	(0.009)	(0.146)
age	0.017***	0.414***
	(0.004)	(0.136)
age × age	-0.000***	0.004
	(0.000)	(0.003)
experience	0.001***	-0.154***
	(0.000)	(0.006)
black	-0.000	0.191
	(0.009)	(0.316)
hispanic	0.006	0.666*
	(0.010)	(0.378)
female	-0.026***	0.384**
	(0.006)	(0.168)
≥ college degree	0.058***	-1.167***
	(0.010)	(0.269)
ability	0.001***	-0.014***
	(0.000)	(0.003)
Observations	25101	26648
R^2	0.201	0.181

Notes: The table reports coefficients from an OLS regression with robust standard errors clustered level reported in parentheses.The sample includes all EUE' transitions between 1979 and 2016 . ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

B Robustness Checks

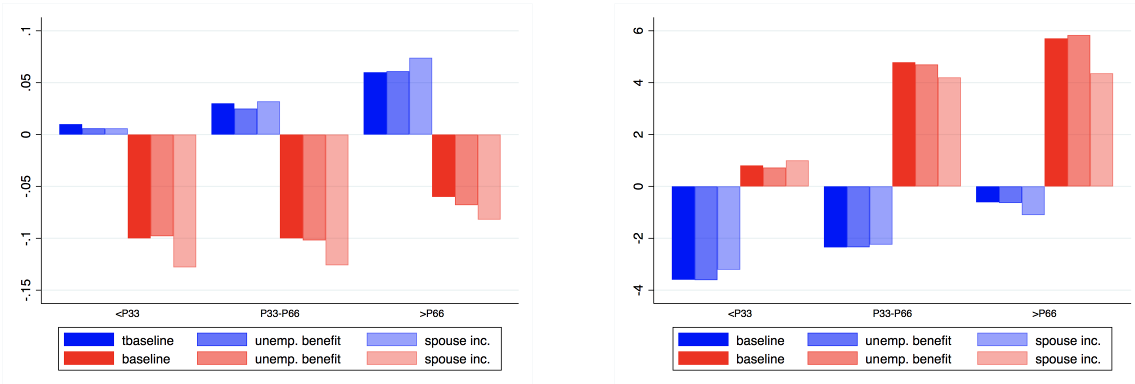
In this section, we show the empirical findings are robust to (i) adding additional controls when estimating equation 6 to recover residual wage change and residual unemployment (Figure A.1), namely the unemployment benefit received during the unemployment spell and spousal income, (ii) different thresholds on occupational tenure k to define turbulent workers (Figure A.2), $k = \{1, 3\}$, (iii) short unemployment spells (Figure A.3) and (iv) different definitions of liquid wealth (Figure A.4). Regarding the latter, we construct wealth measures following the definitions in Koehne and Kuhn (2015):

- L1 = "Total market value of stocks/bonds/mutual funds" + "Total amount of money assets like savings accounts of r/spouse"
- L2 = L1 + "Total market value of vehicles inc. autos r/spouse own"- "Total amount of money r/spouse owe on vehicles inc. autos"
- L3 = L2 + "Total amount of money in assets like IRAS or KEOUGH" + "Total amount of money in assets like CDS or loans"

Figure A.1: Labor Market Outcomes by Turbulence and Wealth: Additional Controls

(A) Residual Wage Change

(B) Residual Unemployment Duration

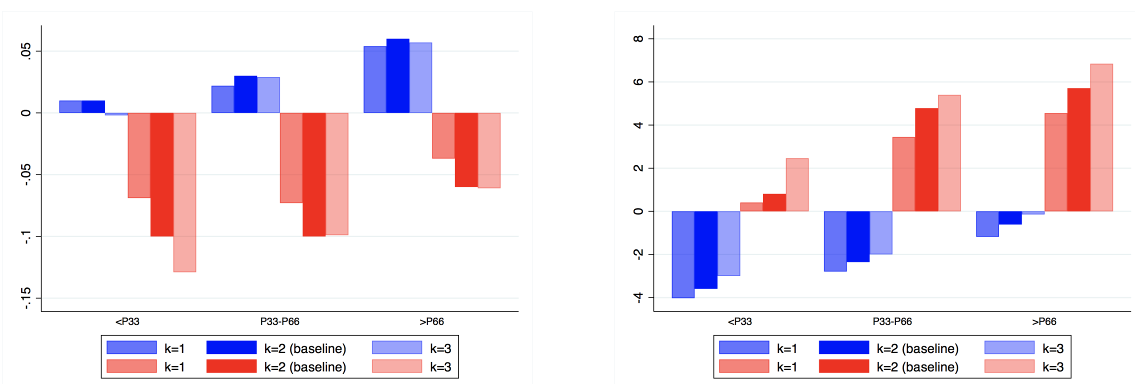


Notes: The left and the right panel plot, respectively, the average residual wage growth ($\hat{\varepsilon}^{\Delta w}$) and the average residual unemployment duration ($\hat{\varepsilon}^{\tau}$) for *turbulent* (red bars) and *tranquil* (blue bars) transitions at different parts of the liquid wealth distribution at the start of the unemployment spell. *unemp. benefit* and *spouse inc.* use, respectively, residuals from a specification that adds unemployment benefit eceived during the unemployment spell and spouce income as a control and *spouse inc.*. Sample includes all EUE' transitions observed over the period from 1979 to 2016 in NLSY79.

Figure A.2: Labor Market Outcomes by Turbulence and Wealth: Different thresholds

(A) Residual Wage Change

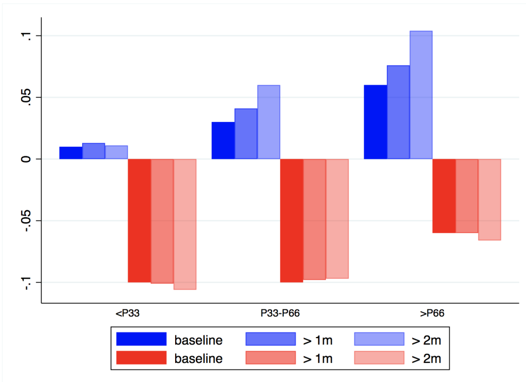
(B) Residual Unemployment Duration



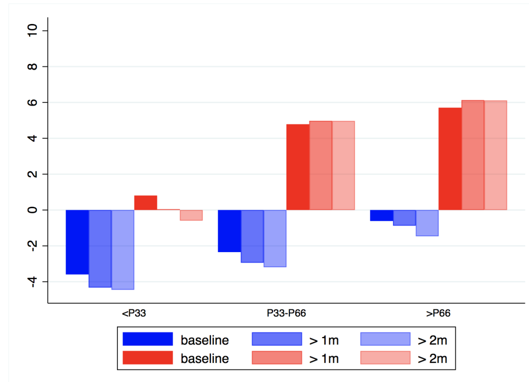
Notes: The left and the right panel plot, respectively, the average residual wage growth ($\hat{\varepsilon}^{\Delta w}$) and the average residual unemployment duration ($\hat{\varepsilon}^{\tau}$) for *turbulent* (red bars) and *tranquil* (blue bars) transitions at different parts of the liquid wealth distribution at the start of the unemployment spell. Turbulent workers are all workers that switch occupation upon reemployment with experience in the previous occupation larger than k years, while tranquil workers correspond to all transitions in which occupational tenure when entering unemployment was larger than k years and did not change occupation upon reemployment workers. Sample includes all EUE' transitions observed over the period from 1979 to 2016 in NLSY79.

Figure A.3: Labor Market Outcomes by Turbulence and Wealth: Short Unemployment Spells

(A) Residual Wage Change



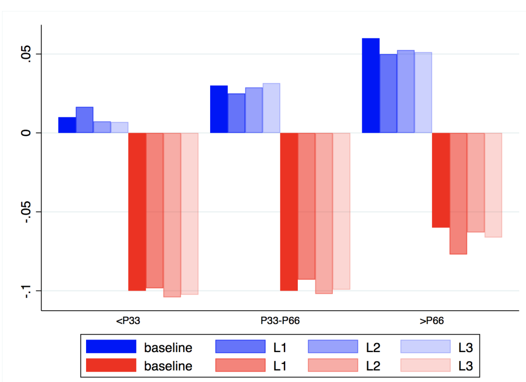
(B) Residual Unemployment Duration



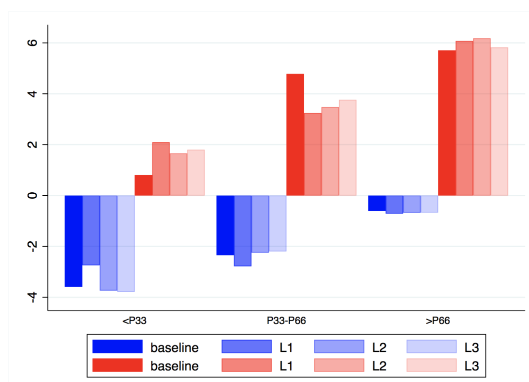
Notes: The left and the right panel plot, respectively, the average residual wage growth ($\hat{\varepsilon}^{\Delta w}$) and the average residual unemployment duration ($\hat{\varepsilon}^{\tau}$) for *turbulent* (red bars) and *tranquil* (blue bars) transitions at different parts of the liquid wealth distribution at the start of the unemployment spell. Sample includes all EUE' transitions observed over the period from 1979 to 2016 in NLSY79 or only those with with an unemployment spell higher than 1 and 2 months.

Figure A.4: Labor Market Outcomes by Turbulence and Wealth: Different Wealth Definitions

(A) Residual Wage Change



(B) Residual Unemployment Duration



Notes: The left and the right panel plot, respectively, the average residual wage growth ($\hat{\varepsilon}^{\Delta w}$) and the average residual unemployment duration ($\hat{\varepsilon}^{\tau}$) for *turbulent* (red bars) and *tranquil* (blue bars) transitions at different parts of the liquid wealth distribution. L1 = “Total market value of stocks/bonds/mutual funds” + “Total amount of money assets like savings accounts of r/spouse”; L2 = L1 + “Total market value of vehicles inc. autos r/spouse own”- “Total amount of money r/spouse owe on vehicles inc. autos”; L3 = L2 + “Total amount of money in assets like IRAS or KEOUGH” + “Total amount of money in assets like CDS or loans”. Sample includes all EUE' transitions observed over the period from 1979 to 2016 in NLSY79.