Perceived and Actual Labor Market Risk

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Abstract

Labor market risk is a prevalent phenomenon with important implications for individual decision making. A common approach is to assume that agents have rational expectations and therefore correctly assess the risk they face in the labor market. We use survey data for the U.S. on subjective expectations to establish that – in contrast to the common wisdom – the perceived individual labor market risk systematically differs from the actual risk and that, on average, individuals in the U.S. are vastly over-optimistic about their own labor market prospects. We use a quantitative heterogenous agents lifecycle model to assess the impact of agents' bias in the subjective labor market expectations on the lifecycle path of individual consumption, income and wealth, as well as aggregate wealth inequality. Moreover, we quantitatively explore the welfare effects of over-optimism and we derive implications for economic policy.

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"Optimism is the madness of insisting that all is well when we are miserable."

— Voltaire

1 Introduction

Labor market risk is a prevalent phenomenon with important implications for individual decision making. Labor market risk as described by the probability to experience a labor market transition (for example, to lose a job or to find employment) shapes the behavior of economic agents with respect to a number of choices, including wage bargaining (see Mortensen and Pissarides (1994)) or the consumption-savings allocation (see Krusell et al. (2010)), but also job search intensity (see for example Rogerson et al. (2005)), portfolio composition (see Den Haan et al. (2017)) or human capital accumulation (see Krebs (2003)). Through its effect on individual behavior, labor market risk therefore has important consequences for aggregate outcomes such as employment, physical capital accumulation, wage growth and wealth inequality. A common approach in the literature is to assume that agents have rational expectations and therefore correctly assess the risk they face in the labor market. This implies, for example, that employed workers' expected probability to lose their job should, on average, be equal to the realized job loss rate. In this paper, we investigate whether subjective labor market transition probabilities differ from the actual probabilities and how the potential misperception of individual labor market risk affects both individual and macroeconomic outcomes.

In the first part, we empirically investigate how accurately individuals in the U.S. can assess their own labor market risk. We use survey data from the New York-Fed's Survey of Consumer Expectations (SCE) to measure workers' subjective probability distribution over future labor market outcomes. Examples for such outcomes include changes in an individual's labor market states, such as finding a new job, becoming unemployed, or leaving the labor force. Then, we compare the workers' subjective probability distribution with the actual probability distribution of labor market outcomes that we compute with data on individual labor market transitions from the Current Population Survey (CPS). Most importantly, we find that the perceived individual labor market risk systematically differs from the actual risk. More concretely, we establish that, on average, individuals in the U.S. are vastly over-optimistic about their own labor market prospects. That is, individuals' tend to over-estimate the probability of experiencing a favorable labor market event – such as finding a job, or remaining employed – and they underestimate the probability of experiencing an adverse labor market event – such as becoming unemployed, or leaving the labor force. Moreover, we find this pattern to be robust and wide ranging, holding for different demographic groups, in terms of age, gender, race, education and income. Interestingly, in this context, we find that individual over-optimism is negatively related to education. College-educated individuals are still over-optimistic but they have a more precise perception of their labor market risk than, for example, high-school educated individuals. Our findings largely contradict the common approach in the theoretical and quantitative literature to assume that agents' subjective probability distribution over labor market events is identical to the actual probability distribution. The empirical prevalence of labor market misperception - measured by the difference between worker's subjective and the respective actual probability of labor market events - raises the question about its economic implications.

In the second part, we perform a theoretical and quantitative analysis to shed light on this question. In particular, we explore how misperception shapes individuals' life cycle choices of consumption and asset holdings and thereby affects individual welfare as well as macroeconomic outcomes such as aggregate wealth inequality. In the first step of the analysis, we use a tractable two-period model to illustrate how agents' inter-temporal consumption-savings trade-off is affected by misperception. We reproduce a standard result in expected utility theory that over-optimism induces agents to save less which leads to a higher ex-post exposure to individual income fluctuations. Moreover, we show within the simple framework that differences in the population in terms of the degree of over-optimism – as in the data – leads to aggregate wealth inequality.
Then we turn to the quantitative analysis. The goal of the analysis is to assess the impact of agents' bias in the subjective labor market expectations on the lifecycle path of individual consumption, income and wealth, as well as aggregate wealth inequality. Moreover, we quantitatively explore the welfare effects of over-optimism and we derive implications for economic policy. As a framework we use a heterogenous agents lifecycle model that features incomplete insurance markets, various sources of idiosyncratic risk (but no aggregate risk) and different education groups. Crucially, we introduce misperception of idiosyncratic labor market risk into the model by allowing the subjective probability distribution over labor market events to differ from the actual distribution. Motivated by our empirical evidence, we the allow for different degrees of misperception across education groups. We calibrate the model to match various features of the U.S. economy. The quantitative model matches remarkably well several prominent characteristics of outcomes at the individual and aggregate level. This includes, for example, the individual life cycle profiles of income, consumption and assets, as well as the high degree of inequality in the distribution of wealth in the U.S. The splendid empirical fit of the model is not self-evident as the calibration does not target features in the data related to individual life cycle outcomes or aggregate inequality.

In our main quantitative experiment we compare the calibrated baseline economy – in terms of individual and aggregate outcomes – with a counterfactual economy in which all agents have correct expectations. Most importantly, we find worker's over-optimism is an important driver of aggregate wealth inequality. Over-optimism generally discourages individual asset accumulation but more so for the low-skilled individuals who are more over-optimistic and who save substantially less than they would if they knew the correct expectations. The lack in buffer stock savings, leads to a higher exposure of individuals to income fluctuations and thereby reduces welfare.

Related literature ... to be completed

The remainder of the paper is structured as follows. Section 2 contains the empirical analysis and shows the facts about individual misperception in the U.S. labor market. Section 3 uses a simple two period model to illustrate the channels through which misperception affects individual decision making. In Sections 4 and 5 we develop and calibrate the quantitative model. In Section 6 we first explore the quantitative properties of the calibrated model and then we perform the main quantitative experiment. Section 7 discusses briefly the policy implications of our findings and Section 8 concludes. An appendix contains details of the data work and the computational algorithm, as well as additional results.

2 Facts

In the first step, we use data from the New York-Fed's *Survey of Consumer Expectations* to measure the subjective probabilities of U.S. individuals to experience a change in their labor market state. The SCE, which launched in 2013, is a nationally representative survey of a rotating panel of approximately 1,300 households, and it focuses primarily on subjective expectations about a number of macroeconomic and household-level variables[1]. The SCE has several components. We make use of the data provided by the 2014-2018 waves of the *Labor Market Survey*[2]. In this survey, respondents are asked to report their expectations about several labor market outcomes that pertain to them. The questions that are relevant for our purpose ask about the respondent's perceived probability of being in a given labor market state at a specific point in time in the future. More precisely, the survey question reads:[3]

"What do you think is the percent chance that four months from now you will be ...

- *employed,*
- *unemployed and looking for work,*
- *unemployed and not looking for work?*

Active job search is the key characteristic that distinguishes unemployed individuals from non-participants. Hence, we classify the second item (*unemployed and looking for work*) as the state of unemployment and the third item (*unemployed and not looking for work*) as the state of not in the labor force. The labor market states among the response options are mutually exclusive and exhaustive. This implies that for each respondent the sum over the subjective probabilities adds up to 1. We exclude those observations for which the sum is not equal to one. A key feature of the SCE is its reliance on a probabilistic question format. This allows us to aggregate the individual answers and report the subjective probabilities for different demographic groups. As our baseline sample, we select individuals aged 25-60, who do not attend school or college. The baseline sample consists of 10,196 observations. In the first step,

[1] For an introduction into the SCE see Armantier–Topa–Klaauw–Zafar 2017.

[2] The 2018 wave is the most recent one since the SCE Labor Market Survey microdata is released with a 18-month lag

[3] The list of possible answers also includes additional employment states: *"employed and working for the same employer", "employed and working for a different employer", "self-employed"*, which we aggregate into one state of employment.

we compute the subjective probabilities separately for employed and unemployed individuals, as well as for non-participants[4]. The results are in Table 1 in the columns labelled "*Subjective*". The rows in the table represent the current labor market state of an individual and the columns represent the future (expected) labor market states. According to our results, employed workers expect to be employed with 96.0%, unemployed with 2.6%, and not in the labor force with 1.4% probability in four months after the interview.

	Subjective			Actual			Subjective-Actual		
	E	U	N	E	U	N	E	U	N
E	96.0	2.6	1.4	94.2	1.7	4.1	1.8	0.9	-2.7
U	61.0	33.2	5.8	46.2	25.1	28.7	14.8	8.1	-22.9
N	10.5	13.9	75.6	12.9	3.5	83.7	-2.4	10.4	-8.1

Source: SCE and CPS; Sample: age 25-60 years, non-school or college

Table 1: 4-months subjective and actual transition probabilities

Given the focus of the paper, we are primarily interested in how these subjective probabilities compare to the actual probabilities. To shed light on this question, use observations from the Current Population Survey (CPS) on individual labor market transitions to compute the implied actual labor market transition probabilities[5]. A meaningful comparison of the actual and perceived probabilities is possible only when both concepts are closely linked to each other. To achieve a high degree of consistency, we apply the same sample selection criteria across the two datasets and use the same definitions of labor market states and transitions. To be concrete, we compute the actual transition probability between labor market states s and s' as the fraction of individuals who where in state s in a given month and are in state s' four months later.[6]. As before we consider the three states: employment, unemployment and not in the labor force. Moreover, to be consistent with the subjective probability measure we do not consider labor market transitions in the CPS that take place in between a four months period. This is because the SCE asks explicitly about the probability to be in a given state in four months and NOT about the probability to experience a labor market transition within the next four months.

The results for the actual labor market transition probabilities are in Table 1 in the columns labelled "*Actual*". In addition, we also report the absolute difference between subjective and actual probabilities. A number of observations are worth highlighting. First, employed workers tend to over-estimate the probability of remaining employed. The subjective probability of being employed in four months of 96% whereas the actual probability is 94.2%. The stan-

[4]The details of these calculations, including sample selection are in the Appendix

[5]Our choice to use the CPS as the main datasource is motivated mainly by sample size. In principle, we could have used the SCE to compute the actual probabilities. However, in comparison to the expectational data, the number of observations in the SCE to compute the actual probabilities would be substantially lower since the calculation requires individuals to stay in the survey for at least 4 months. As a result the standard errors get very large. This becomes a severe limitation especially when we consider different demographic groups, as below. Though, qualitatively the patterns for the actual probabilities are very similar between the CPS and the SCE.

[6]For the details of the calculation see Appendix.

dard errors around the two probabilities are very small; hence, the difference of 1.8 percentage points between the subjective and the actual probability is statistically significant at the 1% level. We report the standard errors in the Appendix. Moreover, the results in Table 1 indicate that in case of job loss, workers underestimate the likelihood of leaving the labor force by 2.7 percentage points. Also this difference is highly significant. Another important finding is that unemployed individuals vastly over-estimate their re-employment prospects. Job seekers expect to be employed in four months with a 61% probability. This is 14.8 percentage points above the actual employment probability. At the same time, the unemployed substantially underestimate the likelihood of leaving the labor force by a remarkable 22.9 percentage points. Furthermore, our results show that individuals who are not in the labor force, generally over-estimate the probability of entering the labor force by 8.1 percentage points. In particular, they strongly over-estimate the likelihood of starting to look for a job.

The pattern that emerges from Table 1 is that individuals in the U.S. are generally are over-optimistic about their own labor market prospects. More specifically, they tend to underestimate the likelihood of moving to bad labor market states (for example, $E \rightarrow N$, $U \rightarrow N$) and overestimate the likelihood of moving to good states ($U \rightarrow E$, $N \rightarrow \neg N$). An important follow up question in this context is whether these findings hold generally across different population groups or there is noteworthy heterogeneity in the population in terms of the sign and the degree of misperception. To address this question, we consider different demographic groups. In particular, we disaggregate the data according to gender, education, age, and income and compute the misperception for each group separately. The results for gender do not indicate any systematic differences in misperception for men and women. If anything, women tend to be slightly more over-optimistic than men. See the Appendix for the details. With respect to age, we find evidence for a decrease in the level of misperception with age, indicating that workers at young ages have a less accurate perception of their labor market situation than during their prime age. As interesting as it may be to follow up on this matter, we nevertheless sideline it for now because the relatively large standard errors challenge the robustness of the observed age-pattern.

	EE	EU	EN	UE	UU	UN	NE	NU	NN
All	1.8	0.9	-2.7	14.8	8.1	-22.9	-2.4	10.4	-8.1
High school or less	2.9	0.6	-3.5	17.5	6.4	-23.9	-0.6	11.2	-10.6
Some college	2.0	0.6	-2.6	18.2	7.4	-25.6	-2.9	10.0	-7.1
College and higher	0.7	1.3	-2.9	5.4	12.3	-17.7	-6.0	9.4	-3.5

Table 2: Misperception for different education groups

More worthwhile to follow up are the results we find for different education groups. We split the sample into three education groups: low-skilled, medium-skilled or high-skilled individuals. We define low-skilled individuals as those who have at least a high school degree, middle-skilled as those with a high school degree, but no college degree, and high-skilled as those with at least a college degree. To keep the exposition concise, we report for each education group only the difference between the subjective and the actual transition probabilities. The results are in Table 2. To clarify, the first (second) letter in the labels indicates the current (future) labor market state. For example, *UE* denotes the combination of unemployment as the current state and employment as the future state. Quite interestingly, we find that the level of over-optimism is decreasing in the skill level. In other words, high-skill individuals have a more precise perception of their labor market risk than the low-skilled. This pattern applies to almost every labor market transition and it is particularly pronounced for unemployed and non-participants. For example, the misperception of the reemployment probability – as measured by the difference between the subjective and the actual probability to be employed – is more than three times as high for job seekers who are low-skilled than for those who are high skilled (17.5% versus 5.4%). We find the same pattern for non-participants, where the low-skilled are much more over-optimistic about entering the labor force than the high-skilled. Similarly, we find that among the employed workers the low-skilled are overly optimistic about being employed four months later than the high-skilled for whom we find that the subjective probability is much closer to the actual probability. The finding that the low-skilled are generally more over-optimistic about their labor market prospects is a key aspect that we will investigate further in our quantitative analysis.

Lastly, we also explore the relationship between individual income and misperception. Typically, an individual's level of income is closely linked to the educational attainment. Hence, not surprisingly, we obtain very similar patterns of misperception for different income groups than for education groups. That is, low income individuals are generally more over-optimistic and high-income individuals. See the appendix for the results.

We end this section with a brief discussion on whether over-optimism is a specific feature of the U.S. labor market or whether it is a general phenomenon adhering also to other outcomes at the individual level. Recent research in economics has found evidence for individual over-optimism in the U.S. along several dimensions, including future income expectations, the timing of retirement and individual survival. At the same time, there is evidence that over-optimism does not generally extend to other countries. In follow-up work in Balleer et al. (2021) we use data from the German Socio Economic Panel to show that, in contrast to the U.S., workers in Germany are overly pessimistic about their individual labor market prospects.

Motivated by our empirical findings, we proceed to explore the effects of individuals' over-optimism on individual and macroeconomic outcomes. In the first step of our analysis, we lay out a stylized two period consumption/savings model in order to illustrate how misperception shapes individual choices of consumption and asset accumulation, and aggregate wealth inequality. The purpose of the simple model is to provide a conceptual framework that allows for an analytical characterization of the main forces at work. The main insights we derive here will be useful for the interpretation of the results of the quantitative model in Section 4.

3 Two-period model

The model economy is populated by a unit mass of risk averse individuals who live for two periods. In the first period, every individual is employed and receives deterministic income $0 < y_1 < \infty$. Income in the second period, y_2 depends on an individual's labor market state. With (true) probability $p > 0$, an individual is employed and receives income $y_2 = \bar{y}$. With (true) probability $1 - p$ the individual has no job in the second period and receives income $y_2 = \underline{y} > 0$; where $\underline{y} < \bar{y}$. Individuals know the values of $\underline{y}$ and $\bar{y}$ but they have subjective expectations about the realizations of the labor market states. These subjective expectations are given by $(p - \Delta)$ and $(1 - p + \Delta)$, respectively. Δ denotes the degree of an individuals misperception. Moreover, assume that individuals start with zero initial assets but they can save part of their first-period income and consume it in the second period. The period budget constraints are

$$c_1 + k = y_1 \qquad\qquad c_2 = y_2 + rk$$

where c_1 and c_2 denote period consumption, k is savings and r is the interest rate. Since agents live for two periods, they do not leave any capital for after their demise. Let $u(c)$ denote the agent's period utility function and assume that it satisfies the usual regularity and Inada conditions. To endogenize the interest rate, we assume that there is a firm which - in the second period only - rents capital and produces output. All markets are competitive. Using the period budget constraints and assuming time-separable utility, we can formulate the agent expected utility maximization problem

$$\max_{0 \leq k \leq y_1} u\big(y_1 - k\big) + \beta(p - \Delta)u\big(\underline{y} + rk\big) + \beta(1 - p + \Delta)u\big(\bar{y} + rk\big)$$

where $0 < \beta < 1$ is the personal discount factor. The associated Euler equation reads

$$\beta r\Big[(p - \Delta)u'(\underline{y} + rk) + (1 - p + \Delta)u'(\bar{y} + rk)\Big] = u'(y_0 - k)$$

A unique interior k with $0 < k < y_1$ exists iff $\beta r\big((p-\Delta)u'(\underline{y}) + (1-p+\Delta)u'(\bar{y})\big) > u'\big(y_1\big)$. This condition holds and agents' savings are positive if, for example, the interest rate is sufficiently large relative to agents' impatience $r > 1/\beta$, or the bad outcome $\underline{y}$ is sufficiently small which induces agents to self-insure. Next, we use the Euler equation to demonstrate how the optimal savings choice is affected by individual misperception. To this end, we compute $\frac{dk}{d\Delta}$, keeping the interest rate r constant. After a few lines of algebra, we obtain

$$\frac{dk}{d\Delta} = \frac{u'(\underline{y} + rk) - u'(\bar{y} + rk)}{u''(y_0 - k)/(\beta r) + r(p - \Delta)u''(\underline{y} + rk) + r(1 - p + \Delta)u''(y_0 + rk)}$$

Since $\underline{y} < \bar{y}$, $u' > 0$ and $u'' < 0$, we get that $\frac{dk}{d\Delta} < 0$. This is a standard result in expected utility theory and it says that over-optimism induces agents to build up less precautionary savings.

An immediate implication is that over-optimistic agents - i.e. those who underestimate the risk of becoming unemployed - engage less in self-insurance and are more exposed to income fluctuations than rational agents. Next, we derive the implications for the equilibrium interest rate. For concreteness, we assume that a fraction ϕ of the population is over-optimistic and has $0 < \Delta < p$, whereas the remaining fraction $(1-\phi)$ of the population has correct beliefs $(\Delta = 0)$. Therefore, aggregate capital, K, in the economy is given by

$$K = (1-\phi)k^r + \phi k^o$$

where k^r and k^o are the capital holdings by the realist and the optimist individual, respectively. The result from above implies that $k^r > k^o$. Let $F(K)$ denote the production technology of the firm with $F'(K) > 0$ and $F''(K) < 0$. With competitive pricing, we obtain the usual interest rate rule $r = F'(K)$. To explore the aggregate effects of misperception, suppose for a moment that $\Delta = 0$ for both types of agents. An increase in Δ for the optimist leads to a reduction in k^o. This reduces aggregate capital K and leads to an increase in the interest rate r. A higher interest rate affects agents' savings choice. The sign of $\frac{dk}{dr}$ depends on the functional form of $u(\cdot)$. For example, with *log*-utility we get that $\frac{dk}{dr} > 0$, which implies that both types of agents save more and this partly offsets a lower capital choice of the optimist agent.

To sum up, our analysis reveals the following insights: First, over-optimistic agents hold fewer assets than rational agents; hence, misperception per se leads to wealth inequality. Less individual savings imply a lower aggregate capital stock and a higher equilibrium interest rate. Looking ahead to the full model, these results imply that wealthier individuals enjoy higher asset returns and, hence, they can benefit from the misperception of the optimistic agents. This channel further amplifies aggregate wealth inequality. A similar effect materializes when wages are endogenous. A lower aggregate capital stock lowers the marginal product of labor and thereby depresses wages. This hits primarily the asset-poor individuals whose primary income source is labor earnings. Lastly, our findings imply that less self-insurance due to over-optimism impedes individual's ability to smooth consumption across states and over the life cycle. The last point suggests that there is potentially room for welfare improving policies which counteract the lack of private insurance either by providing public insurance or by stimulating individual self-insurance.

4 Quantitative model

In the next step, we use a calibrated general equilibrium model to perform a quantitative analysis. The goal is to explore the quantitative implications of over-optimism on individual asset accumulation, welfare and aggregate wealth inequality. Moreover, we will use the framework to discuss the implications of over-optimism for policy. Our theoretical framework builds on the canonical Bewley-Huggett-Aiyagari (BHA) model, and it shares many features of the stationary version of the model in Krueger, Mitman and Perri (2016); henceforth KMP. In a nutshell, the agents in our model economy have a life-cycle including working-age and retirement, they have different levels of human capital, and face various sources of idiosyncratic labor market risk. Insurance markets are incomplete and agents accumulate assets to self-insure against labor market risk and longevity risk, and to save for retirement. Agents have a subjective probability distribution over individual labor market states and this can differ from the actual probability distribution. Aggregate output is produced by a representative firm that rents capital and labor from households at competitive factor prices. The features of the model imply that in equilibrium, individuals' asset holdings are characterized by a stationary non-degenerate distribution function.

Life cycle

We follow KMP and assume that individuals are either working-age (denoted by W) or retired (denoted by R). The age of an individual is denoted by $j \in \{W, R\}$. With the constant probability $1-\theta$ working-age individuals retire, and with probability $1-\nu$ retired individuals die. Deceased individuals are replaced by new working-age individuals. Stochastic aging and death imply that the population shares of both types of individuals are given by:

$$\Pi_W = \frac{1-\nu}{1-\theta+1-\nu} \qquad \Pi_R = \frac{1-\theta}{1-\theta+1-\nu}$$

Preferences and assets

We assume that individuals' preferences are described by a CRRA utility function over current consumption:

$$u(c) = \frac{c^{1-\sigma}-1}{1-\sigma}$$

where $\sigma > 0$. As is standard, we assume that insurance markets are incomplete, but as a means of self-insurance, agents can accumulate assets $a > \bar{a}$ which yield a non-state-contingent return denoted by r. $\bar{a} \geq 0$ is a borrowing constraint. Individuals are born with zero initial assets.

Human capital

Motivated by our empirical findings that agents' misperception is linked to education, we assume that individuals are ex-ante heterogeneous with respect to human capital. A worker's level of human capital is denoted by h and we allow for three levels of human capital: low-skill, medium-skill, and high-skill. h is assumed to stay constant over time and, hence, there is a constant population share for each h-type, given by $P(h)$, with $\sum_h P(h) = 1$. At birth, workers draw their human capital level according to the stationary probabilities $P(h)$.

Idiosyncratic employment risk

We assume that a working-age individual can be either employed, unemployed, or not in the labor force. Idiosyncratic transitions between labor market states are stochastic and governed by transition probabilities that are denoted by $p_h(s'|s)$. In particular, $p_h(s'|s)$ is the actual per-period probability that a worker with human capital level h will transit from state s to state s', where $s \in \{\mathbf{e}(mployed), \mathbf{u}(nemployed), \mathbf{n}(ot\ in\ the\ labor\ force)\}$ denotes the labor market state. The invariant distribution of s among workers with human capital h is given by $P_h(s)$, with $\sum_s P_h(s) = 1$.

Two aspects of our modeling of the labor market deserve further explanation. First, we allow the transition probabilities to differ across workers with different levels of human capital. This choice is motivated by the empirical observation that actual labor market transition rates differ substantially across workers with different levels of education. We want the model to be flexibel enough to match this empirical feature. Second, we depart from the conventional way to consider only employment and unemployment as labor market states, and instead we also allow individuals to be not in the labor force. This approach has several advantages: (i) in the data the flows in and out of the labor force are just too big to ignore; (ii) having three labor market states allows for a precise mapping of the model to the data on individual labor market expectations which features the same three states; (iii) being out of the labor force is a fundamentally different state for an individual in terms of income and job finding prospects than being in unemployment. Hence, we want the model to be able to capture the potential individual misperception of the probability of being in this (bad) labor market state.

Idiosyncratic labor productivity

We follow KMP and introduce idiosyncratic labor productivity risk. An individual's labor productivity, z, is stochastic and governed by a first-order Markov process. $\pi_h(z'|z)$ is the conditional probability that a worker with human capital h will transit from state z today to state z' tomorrow. The invariant distribution of z for workers with human capital h is $\Pi_h(z)$. Given the focus of our analysis it is useful to include productivity risk into the model because it allows us to obtain a realistic representation of individual labor income processes and, thus, we are able to match the degree of actual labor market risk that individuals face. Moreover, as shown by KMP, idiosyncratic productivity is the key feature for matching the observed wealth distribution.

Production

A representative firm rents capital from households and hires labor to produce output with the production function:

$$F(K, N) = K^\alpha N^{1-\alpha}$$

where $\alpha \in [0, 1]$. K denotes aggregate capital (defined below). N denotes total labor in efficiency units which is computed as the sum of all employed workers' effective labor supply

$$N = \Pi_W \sum_h P_h P_h(e) \sum_z \Pi_h(z) hz$$

where Π_W is the total mass of working-age individuals, P_h is the fraction individuals with human capital h, $P_h(e)$ is the fraction individuals with human capital h who are employed, and $\Pi_h(z)$ is the fraction of workers with human capital h that have productivity z. Hence, since, $\sum_z \Pi_h(z) = 1$, the term $\Pi_W \sum_h P_h P_h(e)$ is equal to aggregate employment.

Factor markets are competitive, hence the firm's first order conditions lead to the usual marginal product pricing

$$r = F_K\big(K, N\big) = \alpha \left(\frac{K}{N}\right)^{\alpha-1} \qquad w = F_N\big(K, N\big) = (1-\alpha)\left(\frac{K}{N}\right)^{\alpha} \tag{1}$$

w is the wage per efficiency unit of labor.

Optimization problem of a retired individual

Retirees earn income on their asset holdings and they collect social security payments. In particular, we assume that social security benefits, denoted by $b_{ss}(h)$, are a fixed fraction $\rho_{ss} \in [0, 1]$ of the average wage of a worker with the same human capital.

$$b_{ss}(h) = \rho_{ss} w h \sum_z \Pi_h(z) z$$

That is, pension benefits depend only on the individual's human capital but not on her actual history of past contributions [7] Moreover, we follow KMP and assume that households have access to perfect annuity markets which implies that the assets of the deceased individuals are used to pay an extra return of $1/\nu$ to the retired survivors. A retired individual with asset holdings a and human capital h chooses current-period consumption c and next-period's assets a' to solve the inter-temporal utility maximization problem

$$W_R(a, h) = \max_{a'} u(c) + \nu\beta W_R(a', h) \tag{2}$$

subject to

$$c + a' = (1 + r - \delta)\frac{a}{\nu} + b_{ss}(h) \qquad \text{and} \qquad a' \geq \underline{a}$$

Retirees die with probability $1 - \nu$; hence, the effective discount factor is $\nu\beta$. Since, we exclude utility from leaving bequests, the payoff in the case of death is zero. $\delta \in [0, 1]$ is the depreciation rate of physical capital; hence, $r - \delta$ is the net return on asset holdings. Retired individuals do not participate in the labor market and, hence, they do not face employment or productivity risk.

[7] The decoupling of benefits from actual contributions helps to keep the state space at a manageable size.

Optimization problem of the working-age individual

A working-age individual with assets a, human capital h, labor market state s, and productivity z, chooses consumption and next period's assets to solve:

$$\begin{aligned} W_W(a,h,s,z) = \max_{a'} u(c) \quad & +\beta\theta \textstyle\sum_{s'}\sum_{z'} \widehat{p}_h(s'|s)\pi_h(z'|z)W_W(a',h,s',z') \\ & +\beta(1-\theta)W_R(a',h) \end{aligned} \tag{3}$$

subject to

$$c + a' = (1+r-\delta)a + y \qquad \text{and} \qquad a' \geq \underline{a}$$

With probability $1-\theta$, the working age individual retires and obtains the value of retirement, W_R, next period. An individual expects to move from its current labor market state s to s' with the subjective probability $\widehat{p}_h(s'|s)$. Lastly, individual labor productivity, z, can change as captured by $\pi_h(z'|z)$. In this context, it is important to mention that we assume $\widehat{p}_h$ to be constant over time. In other words, we do not allow for changes in individual labor market expectations, for example, due to learning. This assumption may seem restrictive. However, in light of the limited and somewhat inconclusive evidence of our empirical analysis about individual learning, we choose not to consider this feature in the baseline version of the model. As the SCE is an ongoing survey with more data coming up regularly, we hope to be able to address this aspect at some point in future work.

y denotes labor earnings which depend on the individual's labor market state

$$y = \begin{cases} (1-\tau-\tau_{ss}) \cdot w \cdot z \cdot h & \text{employed} \\ (1-\tau) \cdot b(z,h) & \text{unemployed} \\ T & \text{not in the labor force} \end{cases}$$

When employed, a worker with human capital h and productivity z earns $z \cdot h \cdot w$, where w is the wage per efficiency unit of labor and $z \cdot h$ is the worker's labor supply in efficiency units. Labor earnings are subject to a proportional labor income tax τ and a social security tax τ_{ss}. Unemployed workers receive benefits $b(z,h)$ which are taxed at rate τ but exempt from social security taxes. We follow KMP and assume that benefits are a constant fraction ρ^u of the individual's potential wage, that is $b(z,h) = \rho^u z \cdot h \cdot w$. Furthermore, individuals who are not in the labor force receive welfare transfers, denoted by T. We model T as a constant fraction $\rho^n \in [0,1]$ of average labor earnings per worker in the economy[8]. T is an unconditional transfer and does not depend on worker's characteristics, hence, all individuals who are not in the labor force receive the same welfare benefits.

As usual, we impose that individuals take factor prices (w,r) and taxes (τ,τ_{ss}) as given when

[8] Average labor earnings are computed as $w\frac{\sum_h P_h P_h(e) \sum_z \Pi_h(z)zh}{(\sum_h P_h P_h(e))}$, which is the wage per efficiency unit of labor times the efficiency labor per employed worker.

they optimize. Lastly, we make the following assumptions about the timing of events at birth. A newborn individual first draws its human capital level according to $P(h)$, and conditional on the realization of h, she draws the employment status according to $P_h(s)$ and the initial labor productivity level according to $\Pi_h(z)$.

Government policy

Government policy in our model economy consists of three parts: unemployment insurance, welfare transfers and social security. Unemployment benefits and welfare transfers are financed by the revenues accruing from the labor income tax τ. We assume government budget balance which requires the following condition to hold:

$$\tau \sum_h \sum_z P_h \Pi_h(z) \Big[P_h(e) wzh + P_h(u) b(z,h) \Big] = \underbrace{\sum_h \sum_z P_h P_h(u) \Pi_h(z) b(z,h)}_{\text{Unemployment benefits}} + \underbrace{\sum_h \sum_z P_h P_h(n) \Pi_h(z) T}_{\text{Welfare benefits}} \tag{4}$$

We use the definitions of $b(z,h)$ and T and rewrite this expression to obtain the budget balancing tax rate

$$\tau = \frac{\sum_h \sum_z P_h \Pi_h(z) \Big(P_h(u) \rho^u zh + P_h(n) \rho^n z \bar{h} \Big)}{\sum_h \sum_z P_h \Pi_h(z) zh \Big(P_h(e) + P_h(u) \rho^u \Big)},$$

which is equal to total benefits (for UI and welfare) divided by total before-tax labor income (worker's earnings and unemployment income).

The social security program is run as a balanced budget PAYGO system. Pension benefits are financed by the receipts of the payroll tax τ_{ss} which is levied on the labor earnings of employed workers. Hence, the budget constraint of the social security program is:

$$\Pi_R \sum_h P_h b_{ss}(h) = \tau_{ss} \Pi_W \sum_h P_h P_h(e) wh \sum_z \Pi_h(z) z \tag{5}$$

Using the definition of $b_{ss}(h)$, we can express the social security tax rate as:

$$\tau_{ss} = \rho_{ss} \cdot \frac{\Pi_R}{\Pi_W} \cdot \frac{\sum_h \sum_z P_h h \Pi_h(z) z}{\sum_h \sum_z P_h P_h(e) h \Pi_h(z) z}$$

Recursive competitive equilibrium

The model does not feature aggregate risk and hence, the state space of the economy is described by a time-invariant cross-sectional distribution, Φ, of individuals across age $j \in \{W, R\}$, employment status $s \in \{e, u, n\}$, labor productivity $z \in Z$, human capital $h \in \{h_L, h_M, h_H\}$ and assets $a \in A$.

Definition 1 *The recursive competitive equilibrium in the model economy is defined as a collection of value functions* (W_W, W_R)*, policy functions* (c, a')*, factor prices* (r, w)*, and taxes* (τ, τ_{ss}) *such that*

- *given factor prices and taxes, the value functions are the solution to the individuals' optimization problems stated in Equations (2) and (3) and* (c, a') *are the optimal policy functions for consumption and next period's assets.*
- *the factor prices satisfy the firm's optimality conditions stated in (1)*
- *the government budget constraints in (4) and (5) are satisfied*
- *markets clear*

$$N = \Pi_W \sum_h P_h P_h(e) \sum_z \Pi_h(z) hz$$

$$K = \int a d\Phi$$

Lastly, it is important to mention that we assume a veil of ignorance to exist, implying that individuals have an incomplete model of the macroeconomy. That is, they do not know the equilibrium mapping between primitives and the aggregate state. If individuals knew the expectations of all others, they could infer that there is a discrepancy between the actual and the subjective probability distribution because the aggregate variables are not consistent with how the individuals perceive the economy.

5 Calibration

Next, we calibrate the model to U.S. data. Since we focus on transitions between labor market states, we use a quarterly frequency. The probability of retiring $1-\theta = \frac{1}{160}$ and the probability of dying $1-\nu = \frac{1}{60}$ are set so that individuals can expect 40 years of work life and 15 years in retirement. The probability that an individual is born with human capital level h is given by P_h. Since, death and retirement are random and independent of h, the probability P_h is equal to the population share of working-age individuals with human capital h. We exploit this feature and calibrate P_h to match the observed share of low-skilled, medium-skilled or high-skilled individuals in the working-age population. We define low-skilled individuals as those who have at least a high school degree, middle-skilled as those with a high school degree, but no college degree, and high-skilled as those with at least a college degree. To compute the population shares, we use the data from the 2014-2018 American Community Survey (ACS) and we restrict the sample to individuals aged between 25-60 years. The results are reported in Table 3.

The quarterly depreciation rate of physical capital δ is set equal to 2.5%. As is standard, we set $\alpha = 0.36$ which implies a capital share of 36%. We calibrate the personal discount factor to match a 4% annual net return to capital. The implied value of β is 0.9878. In the baseline calibration we set the coefficient of relative risk aversion σ to unity which implies log-utility. Also in line with the standard calibration, we set the borrowing limit $\underline{a}$ equal to zero.

Government policy in our model economy is parameterized by the three replacement rates $\rho_u, \rho_{ss}, \rho_n$. We follow KMP and set the replacement rate for retirement benefits, ρ_{ss}, to 0.40 and the replacement rate for unemployment benefits ρ^u to 0.5. We calibrate the replacement rate for welfare benefits ρ^n to match the ratio of total welfare income to total labor earnings in the U.S. economy. We compute this ratio from the 2015-2019 waves of the March supplement of the Current Population Survey. Total welfare income includes income from public assistance, survivor's and disability benefits, worker's compensation (due to job-related injury or illness), educational assistance, or child support. We define the sample of welfare recipients as non-retired individuals who did not work and were not looking for work and who reported to have received no labor earnings or retirement income.

To calibrate $p_h(s'|s)$ and $\widehat{p}_h(s'|s)$ we use the values on the actual and the perceived labor market transition probabilities from Section 2, and we adjust these probabilities to fit the quarterly calibration[9].

$$\widehat{p}_l = \begin{pmatrix} 95.90 & 2.58 & 1.52 \\ 51.72 & 41.18 & 7.10 \\ 6.71 & 12.86 & 80.43 \end{pmatrix} \quad \widehat{p}_m = \begin{pmatrix} 96.83 & 1.98 & 1.19 \\ 54.64 & 42.55 & 2.80 \\ 6.45 & 12.24 & 81.31 \end{pmatrix} \quad \widehat{p}_h = \begin{pmatrix} 97.34 & 1.96 & 0.70 \\ 48.85 & 47.72 & 3.43 \\ 7.29 & 11.02 & 81.69 \end{pmatrix}$$

$$p_l = \begin{pmatrix} 93.75 & 2.10 & 4.15 \\ 37.12 & 34.76 & 28.12 \\ 8.28 & 2.89 & 88.83 \end{pmatrix} \quad p_m = \begin{pmatrix} 95.35 & 1.55 & 3.10 \\ 39.56 & 34.91 & 25.53 \\ 9.79 & 3.46 & 86.75 \end{pmatrix} \quad p_h = \begin{pmatrix} 96.89 & 0.90 & 2.21 \\ 45.30 & 35.48 & 19.22 \\ 12.73 & 2.92 & 84.35 \end{pmatrix}$$

Next, we calibrate the Markov process that governs the evolution of idiosyncratic labor productivity. This involves finding values for the levels of labor productivity z and the transition probabilities $\pi_h(z'|z)$. It is important to notice that, idiosyncratic labor productivity z is the only source of changes in individual labor earnings (given by $w \cdot z \cdot h$), since worker's human capital h and the wage per efficiency unit w are both constant in equilibrium. Following much of the related literature, we exploit this feature and use data on individual labor earnings processes to calibrate the process of z. In particular, we follow KMP and assume that individual labor earnings follow a continuous stochastic process with a transitory and a persistent component

$$\log(z_t) = p_t + \epsilon_t \qquad p_t = \phi_h p_{t-1} + \eta_t$$

where ϕ governs the persistence of the process. ϵ_t and η_t are the innovations of the persistent and the transitory shocks, respectively, with variances $\sigma^2_{\epsilon,h}$ and $\sigma^2_{\eta,h}$. Notice that we allow the stochastic income process to be different across human capital types. Consequently, the parameters governing the process are indexed by an h. We estimate the parameters $(\phi_h, \sigma^2_{\epsilon,h}, \sigma^2_{\eta,h})$, with data on annual individual labor earnings from the Panel Study of Income Dynamics (PSID). See the Appendix for the details of the estimation procedure. The estimated parameters are in

[9]The details of the adjustment procedure are in the Appendix

Table 3. Overall, we find that the estimated income processes are very similar for different education groups. The persistent parameters, ϕ_h, are not statistically different from each other and, if anything, the variance of the transitory and the persistent component, $\sigma^2_{\epsilon,h}$ and $\sigma^2_{\eta,h}$ slightly increase with education. The parameter estimates in the table are at an annual frequency. To make the estimates consistent with the quarterly calibration, we convert the values to quarterly frequency by using $\phi_h = \hat{\phi}_h^{\frac{1}{4}}$ as well as $\frac{\sigma^2_\eta}{1-\phi^2} = \frac{\hat{\sigma}^2_\eta}{1-\hat{\phi}^2}$. Next, we use our estimates to approximate the continuous stochastic z-process with a discrete Markov chain with 21 states. More concretely, we approximate the persistent component of the process by a discrete seven-state Markov chain using the Rouwenhorst method and we discretize the transitory component using the Tauchen method with three grid points.

Explanation	Parameter	Value			Source/Target
Life cycle					
Probability of retiring	$1-\theta$	0.0063			40 years of work life
Probability of dying	$1-\nu$	0.0167			15 years in retirement
Technology					
Depreciation rate	δ	2.5%			
$Y = K^\alpha N^{1-\alpha}$	α	0.36			Capital share of 36%
Preferences					
Personal discount factor	β	0.9878			4% annual net return
Coefficient of RRA	σ	1			log utility
Borrowing limit	$\underline{a}$	0			No borrowing
Government policy - replacement rates					
Retirement benefits	ρ_{ss}	0.40			KMP
Unemployment benefits	ρ^U	0.50			KMP
Welfare benefits	ρ^N	0.022			CPS
Human capital specific parameters		L	M	H	
Probability of being born with h	P_h	0.37	0.30	0.33	ACS
Deterministic productivity level	h	1.00	1.29	1.75	PSID
Persistence of labor productivity	ϕ	0.9677	0.9614	0.9661	PSID
Variance of persistent component	σ^2_η	0.0126	0.0135	0.0147	PSID
Variance of transitory component	σ^2_ϵ	0.0640	0.0767	0.0847	PSID

L: High-school or less; M: Some college; H: College and higher.

Table 3: Calibrated parameter values

Lastly, we calibrate the deterministic part of individual labor productivity h. We normalize the value of h for the lowest education group to $h_L = 1$. Since the wage w is the same across skill groups, h_M and h_H determine the education premium of earnings of medium-skilled workers and high-skilled workers, respectively. We exploit this feature to calibrate h_M and h_H. More concretely, we use data from the PSID to run a Mincer regression of log hourly earnings on age controls, education dummies and year fixed effects. We apply our previous definition of education groups and use the low-skilled as reference group in the regression. The estimated coefficients on the education dummies imply values of $h_M = 1.29$ and $h_H = 1.75$.

6 Results

We start this section by reporting the quantitative properties of the equilibrium.[10] We focus on a number of individual and aggregate outcomes and, whenever possible, we compare the model outcome to the empirical counterpart in the data. Our calibration implies an equilibrium quarterly net interest rate of $r - \delta = 1.02\%$, as well as unit wage equal to $w = 2.37$. The tax rates that balance the government budget constraints (4) and (5) are equal to $\tau = 2.4\%$ and $\tau_{ss} = 19.8\%$. Moreover, the equilibrium implies a quarterly capital to output ratio of K/Y=10.2 and an investment to output ratio of I/Y=0.26.

In our calibration, we use the empirical labor market transition probabilities, $p_h(s'|s)$. Hence, not surprisingly, the model can match very well the observed 2014-2018 average employment-to-population ratio as well as the unemployment rate for each education group. Table 4 shows that the wealth distribution implied by the model matches very well the high degree of wealth inequality in the U.S. economy[11]. Wealth in the model is given by asset holdings. In particular, the model can account for the empirical feature that individuals in the first two quintiles essentially hold no significant amount of wealth and that most of the wealth is concentrated in the top quintile. As a result, the implied Gini coefficient of 0.74 is very close to that of the U.S. economy of 0.77.

	Data	Model
Q1	-0.9	0.2
Q2	0.8	1.6
Q3	4.4	5.1
Q4	13.0	15.3
Q5	82.7	77.8
90-95	13.7	17.5
95-99	22.8	26.3
Top 1%	30.9	15.1
Gini	0.77	0.74

Table 4: Wealth inequality – Model and data

In the model, there are four sources of inequality given by differences across individuals in terms of the deterministic and the stochastic component of labor productivity h and z, labor market states s, and the subjective probability distribution of labor market transitions $\widehat{p}_h$. We assess the importance of each of these components for aggregate inequality in wealth holdings by performing a counterfactual exercise in which we shut down each of these components and calculate the change in the wealth distribution. The key insight of this exercise is that stochastic labor

[10]The equilibrium of the model is solved numerically. See the Appendix for the details of the numerical algorithm.

[11]The empirical wealth distribution is taken from Krueger et al. (2014) who compute the distribution from PSID data.

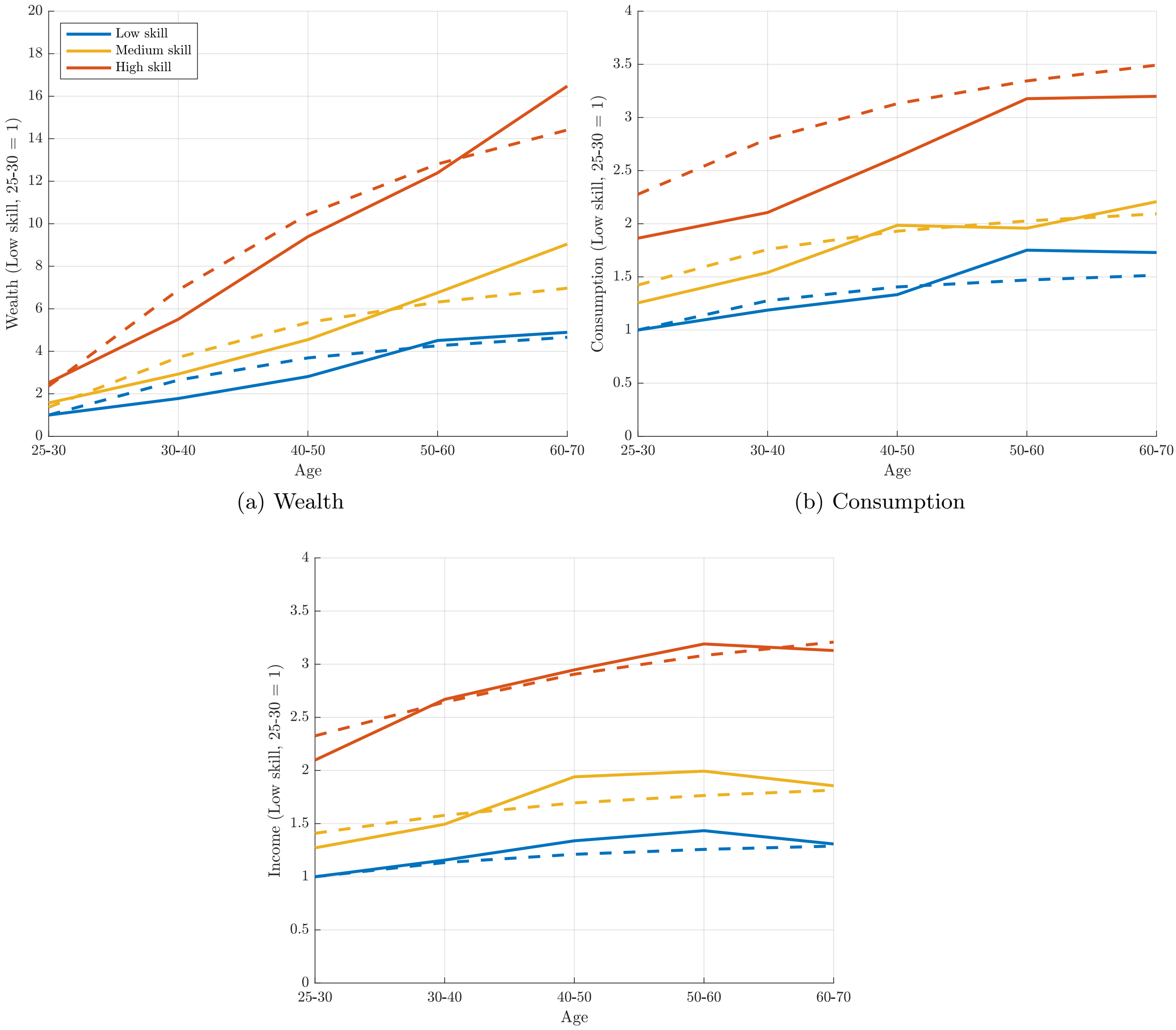
productivity and individuals' misperception of labor market transitions are the main drivers of aggregate wealth inequality. Instead, differences in labor market states and deterministic productivity are of minor importance.

In the model, we distinguish between three education groups: low-, medium-, and high-skilled individuals. According to our calibration, these groups differ in terms of various dimensions that matter for individual asset accumulation. This includes, for example, the value of the deterministic component of labor productivity h or the stochastic process governing the evolution of the stochastic component of labor productivity z. Hence, quite naturally, the level of wealth will be different across education groups. Table 5 reports the share of wealth held by each education group. The first row shows that more than half of aggregate wealth is held by high-skilled individuals whereas the low-skilled account for only about one fifth. This pattern is quite different across the quintiles of the wealth distribution. In the first quintile, the largest share is held by the low-skilled (second row) whereas the asset rich individuals are predominately high skilled (third row). To compute the empirical analogue of these statistics, we use data from the 2017-wave of the PSID on individual net worth. Table 5 shows that overall, the model can replicate the pattern in the data remarkably well, even though in our calibration we did not target any data moments related to aggregate inequality or asset holdings by education group.

	Data			Model		
	L	M	H	L	M	H
Share in wealth, total	0.18	0.18	0.64	0.20	0.24	0.56
Share in wealth, 1^{st} quintile	0.53	0.25	0.22	0.45	0.30	0.25
Share in wealth, 5^{th} quintile	0.14	0.16	0.69	0.16	0.22	0.62

Table 5: Share of wealth by education group – Model and data

Next, we explore the model fit in terms of outcomes at the individual level. In particular, we focus on the life-cycle pattern of individual (pre-tax)income, asset holdings and consumption. The individual lifecycle in the model consists of two parts only: working-age and retirement. To compute individual life-cycle patterns, we simulate the equilibrium of the model over a long time horizon and for a large number of individuals. In this simulation, we keep track of each individual's age, as well as her income, assets and consumption in each period of its life cycle. This procedure allows us to compute individual lifecycle statistics that we can compare to the data. To compute the data counterparts, we use information on individual income, consumption expenditures and net worth from the 2017-wave of the PSID. Figure 1 shows the results for the five age groups [25-30), [30,40), [40,50), [50,60), [60,70). Newborn individuals in the model correspond to age 25 in the data. In each of the panels, we normalize the series by the value for the low-skilled individuals belonging to age group [25-30). Generally, the model (dashed line) can match very well the observed lifecycle profiles of individual income, asset holdings and consumption for the different education groups. Again, this is not evident, as our calibration did not target any data moment related to individual life-cycle outcomes. In particular, the model can account for the very large - almost 8-fold increase - in asset holdings for high-skilled individuals and the comparatively modest increase for the low-skilled. Individual consumption rises much less than asset holdings over the lifecycle, which is a feature of the consumption-smoothing motive. By and large, the increase in individual consumption is similar across education groups but, of course, there are important differences in the level - both in the model and in the data. Lastly, the model also gets very close in matching the slope and the level differences across education groups in the empirical lifecycle path of individual income.



(a) Wealth

(b) Consumption

(c) Income

Figure 1: Lifecycle path of income, wealth and consumption;
Model (dashed) and Data (solid)

Our calibration implies that individuals tend to over-estimate the probability of favorable labor market events (such as remaining or becoming employed) and under-estimate the probability of adverse events (leaving or remaining out of the labor force). As a result, individuals systematically, over-predict their future income. For example, an unemployed individual expects to become employed and to earn labor income next period with a probability that is higher than the actual probability. Since labor earnings are generally higher than unemployment benefits, the individual over-predicts its next period's income. The same logic also applies to next period's consumption. In the absence of complete markets, the level of consumption in each period depends on the individual's period income. As a consequence of higher expected income, individuals also over-predict their future consumption. Table 6 shows by how much individuals over-predict their next-period's income and consumption. The findings in the table imply that, on average, individuals' expected future income is 1.82% higher than their actual future income. As before, the low-skilled are more over-optimistic which is reflected by their higher forecast error with respect to future labor income and consumption.

It would be useful to relate these numbers to their empirical counterparts; that is, to compare the model-implied income expectations and the associated forecast error with the actual outcomes in the data. While those concepts are straightforward to compute in the model, there are certain data limitations that prevent a meaningful comparison to the data.

	Total	L	M	H
$\widehat{E}(y') - E(y')$	1.82%	2.50	1.77	1.09
$\widehat{E}(c') - E(c')$	0.69%	1.00	0.66	0.38

Table 6: Forecast error of future labor income and consumption

Individual and aggregate effects of misperception

Given the focus of the paper, we are primarily interested in exploring how individual misperception of labor market transitions affects individual and macroeconomic outcomes. To address this point, we run the experiment in which we eliminate misperception altogether and assume that all individuals know the correct labor market transition probabilities. That is, we set $\widehat{p}_h(s'|s) = p_h(s'|s)$ for every h. It is important to notice that in this experiment we do not recalibrate any of the other model parameters.

When agents have the correct expectations then, in comparison to the baseline case, they assign higher probabilities than before to the transition into bad states and they expect good states to realize with a lower probability. As shown within the toy model of Section 3, this adjustment in the subjective probabilities implies that, for each given individual state (s, z, h, a), agents will save more and build up more asset holdings than in the baseline case. This effect will particularly be pronounced for the low-skill agents who experience the largest adjustment in the subjective probabilities. Table 7 confirms this notion. The upper panel shows the average individual savings rates conditional on the labor market state. Employed agents and especially job seekers save more in the counterfactual economy than in the baseline economy. Moreover the results imply that while being out of the labor force, agents run down their assets less

	Baseline			$\widehat{p} = p$		
	By labor market state					
E	0.37			0.40		
U	0.19			0.30		
N	-0.56			-0.45		
	By labor market state and skill level					
	h_L	h_M	h_H	h_L	h_M	h_H
E	0.38	0.36	0.38	0.45	0.41	0.38
U	0.21	0.16	0.21	0.35	0.29	0.24
N	-0.67	-0.64	-0.40	-0.34	-0.50	-0.54

Table 7: Savings rate

quickly because they expect to remain longer in this state than in the baseline case. The lower panel of the table reports the savings rate also by skill level. As expected, the adjustment in the individuals' savings choice is largest for low skill agents who increase their savings rates by relatively more than the high-skilled.

As consequence, asset holdings increase for all education groups but more so for the low skilled. This is shown in Table 8 which reports the change in the lifecycle path of asset holdings with respect to the baseline economy. For example, for the age group]30-40) years the asset holdings of the low-skilled increase, on average, by 47% whereas that of the high-skilled increase by 12%.

		[25-30)	[30-40)	[40-50)	[50-60)	At retirement
	L	1.44	1.47	1.46	1.44	1.47
Δ Assets	M	1.36	1.33	1.28	1.23	1.26
	H	1.20	1.12	1.05	0.99	1.00

Table 8: Change in asset holdings relative to the baseline economy

Since the low-skilled are typically at the lower end of the wealth distribution, the relatively larger increase of their asset holdings, implies that wealth will be distributed more equally across agents and aggregate wealth inequality will be lower than in the baseline economy. Table 9 shows that indeed the Gini coefficient is substantially lower than in the baseline economy and equal to 0.67. An important driver of the decline in inequality is the increase in asset holdings of the poorest quintiles. For example, the lowest 40% more than double their share in total assets from 1.8% to 3.9%.

Quite naturally, the increase in individual asset accumulation implies a higher equilibrium capital stock in the counterfactual economy. The K/Y ratio goes up from 10.2 in the baseline to 10.9. Since aggregate labor is unchanged, the equilibrium quarterly net interest rate drops from $r - \delta$=1.02% to 0.81% and the unit wage rises from $w = 2.37$ to 2.45. The change in the factor

	Data	Baseline	$\widehat{p} = p$
Q1	-0.9	0.2	0.7
Q2	0.8	1.6	3.2
Q3	4.4	5.1	7.9
Q4	13.0	15.3	18.3
Q5	82.7	77.8	69.8
90-95	13.7	17.5	16.0
95-99	22.8	26.3	22.6
Top 1%	30.9	15.1	12.3
Gini	0.77	0.74	0.67

Table 9: Wealth inequality

prices adds to decline in aggregate inequality. Labor earnings are the primary source of income for asset poor individuals and, hence, they gain from the increase in the wage rate. In contrast, asset income plays an important role for the rich and thus, they loose from the drop in the interest rate.

Next, we make a step towards evaluating the welfare effects of individual misperception. First, note that in our economy assets serve as a means of self insurance against adverse shocks. Hence, the stock of assets of an individual determines its ability to smooth consumption during bad states. Our previous findings imply that without misperception individuals have higher buffer stock savings and that generally leads to better self-insurance than in the baseline economy. To quantify the degree of individual consumption smoothing, we simulate the equilibrium of model and we use the simulated data on individual income and consumption to estimate the following model

$$\Delta c_{it} = a + b \cdot \Delta y_{it} + e_{it}$$

c_{it} is the log of consumption of individual i in period t and y_{it} is the log of individual after-tax labor earnings. Of interest to us is the estimate of b which measures how changes in labor income translate into changes in consumption. Large values of b indicate a high dependence of period consumption on period income and thus reflect a low degree of consumption smoothing. We estimate the equation separately for each education group. Table 10 reports the results.

	Baseline			$\widehat{p} = p$		
	h_L	h_M	h_H	h_L	h_M	h_H
b	0.131	0.101	0.074	0.077	0.071	0.069

Table 10: Consumption smoothing

All coefficient estimates reported in the table are statistically significant at the 1% level. The values indicate that in both versions of the model, less-skilled agents are more exposed to income fluctuations and thus achieve a lower degree of smooth consumption. This result is a consequence of lower precautionary savings of the low-skilled. In the counterfactual economy without misperception, all agents hold more assets and can thus better self-insure against bad shocks. This particularly applies to low skilled individuals who experience the largest drop in b and attain a level of consumption smoothing that is comparable to that of the high-skilled agents.

Lastly, we address the question whether the optimist agents in our baseline economy would be better off being realists. That is, we compute the equivalent variation in expected lifetime consumption that would make a new-born agent indifferent between the baseline economy and the counterfactual economy without misperception. More concretely, we compute for a new born agent with skill h the value of ϕ that satisfies

$$\underbrace{E_0\left[\sum_t \beta^t u\big((1+\phi)c_{it}\big)\right]}_{\text{Economy w/ misperception}} \quad = \quad \underbrace{E_0\left[\sum_t \beta^t u\big(\bar{c}_{it}\big)\right]}_{\text{Economy w/o misperception}}$$

The first row in Table 11 shows that $\phi > 0$ for all agents. That is, agents would attain a higher level of welfare in the counterfactual economy. This can be explained by the higher asset holdings in the counterfactual economy, which allows agents to sustain a higher path of lifetime consumption. As expected the welfare gain is largest and equal to 5.2% for the low-skill agent. However, it is important to notice that the welfare calculations and the resulting welfare gains are purely hypothetical because we computed the equivalent variation using the actual expected lifetime consumption. That is, we calculated the expected value E_0 using the actual labor market transition probabilities. Hence, the welfare is computed from the viewpoint of, say, a social planner. If instead, we wanted to adopt the viewpoint of the agent in our model, then we should compute the expected value using the perceived labor market probabilities. The results for this case are in the second row of Table 11. Not unexpectedly, $\phi < 0$ for all agents. The reason is simple: agents are over-optimistic in the baseline, hence, the counterfactual economy seems unattractive to them since there they face labor market transition probabilities which put more weight on bad states.

	ϕ_L	ϕ_M	ϕ_H
E_0	0.052	0.041	0.027
$\widehat{E}_0$	-0.278	-0.195	-0.105

Table 11: Consumption equivalent variation

7 An exploratory look at policy

In the last part we contemplate briefly the implications of our results for policy. Our previous analysis reveals two potentially policy-relevant findings. First, the low-skilled agents who should save the most - because they face the highest labor market risk - actually save the least. As a result, the lack of precautionary savings impedes their ability to smooth consumption and thereby leads to a high exposure to income fluctuations. Second, as shown in Table 8 the general lack in savings implies that agents accumulate too little wealth for their old age. Hence, the lack of (private) insurance against bad labor market states or retirement opens room for potentially welfare-improving policy measures. However, simply substituting public insurance for private insurance, for example by increasing the unemployment or retirement benefits would be ineffective as such measures would just crowd out private insurance.

Likely more effective are incentives which increase the amount of private insurance – especially for asset-poor individuals – for example by stimulating their private savings.[12] To illustrate the effectiveness of such incentives we consider a simple version of a means-tested savings subsidy on the rate of return r. In particular, we assume that an agent's effective rate of return is equal to

$$r \times \Big(1 + \tau_s \cdot max\big[1 - p/\bar{p}, 0\big]\Big)$$

where $\tau_s > 0$ is the subsidy, p denotes the percentile of the agent in the wealth distribution and $\bar{p}$ is the highest percentile in the wealth distribution for which agents receive the subsidy. This specification implies that the effective subsidy is highest and equal to τ_s for individuals without assets for which $p = 0$ and it gradually declines and reaches zero for individuals who are at or above the $\bar{p}^{th}$-percentile in the asset distribution. Moreover, we assume that the subsidy is not paid to retirees and that it is financed through the labor income tax τ. In the following numerical exercise we set $\bar{p} = 20$ – that is, only the poorest 20% receive the subsidy – and we consider different values of $\tau_s \in \{0.01, 0.02, 0.05, 0.10\}$. For each of these cases, we compute the general equilibrium. Table 12 reports the results for different individual and aggregate outcomes. Panel (a) in the table shows the implied budget-balancing tax rate. τ increases by roughly 1 percentage point when the subsidy is raised from the value of 0 in the baseline model to 10%.

Panel (b) shows the savings rate across skill groups. Since low-skill agents are more likely to be asset-poor (see Table 5), they are more likely to receive the subsidy. Hence, the average savings rate of the low-skilled increases more than that of the other skill groups. Middle-skill and especially high-skill agents are less likely to obtain the subsidy and, at the same time, they face a higher tax burden due to the increase in τ. This reduces their disposable income. As a result, the savings subsidy differentially affects the asset holdings across skill groups. Panel (c)

[12] At this point we refrain from implementing a fully-fledged analysis of (optimal) policy. Mainly because it is not the main focus of the paper and moreover, the model does not feature certain trade-offs which are central for policy analysis - including, for example, a labor-leisure trade-off. In future work we will address the question of optimal policy in the presence of individual misperception of labor market risk.

shows the change in average asset holdings with respect to the baseline economy. A subsidy of $\tau_s = 0.1$ leads to a 3.5% increase in average asset holdings of low-skilled and to a 0.2% reduction of asset holdings of the high-skilled. As a consequence, wealth inequality is lower than in the baseline case and the Gini coefficient drops by two points to 0.72; see Panel (d). Moreover, higher asset holdings of the poor lead to better insurance against income shocks. Panel (e) shows that the estimated coefficient of consumption smoothing declines substantially for the low-skilled. Lastly, Panel (f) reports the welfare effects of the savings subsidy for the different skill groups. As before, we measure welfare in terms of the equivalent variation in (actual) expected lifetime consumption. Generally, low-skill and medium-skill agents benefit from the savings subsidy whereas the high-skilled agents are worse off than in the baseline economy. For a level of the subsidy of $\tau_s = 0.1$, the low-, and medium-skilled agents experience a welfare gain of roughly 1% and 0.5% respectively, whereas the high-skilled face have a small welfare loss of 0.03%. The heterogenous welfare effects across agents are intuitive as the high-skilled are least likely to receive the subsidy but they cover the majority of the higher tax burden.

τ_s	0.00	0.01	0.02	0.05	0.10
	Panel (a): Budget-balancing tax				
τ	0.024	0.025	0.026	0.029	0.034
	Panel (b): Savings rate, in %				
L	22.4	22.5	22.6	22.7	23.0
M	23.8	23.8	23.8	24.0	24.1
H	27.9	27.9	27.9	27.9	27.9
	Panel (c): Change in assets, in %				
L		0.39	0.73	1.80	3.51
M		0.27	0.49	1.19	2.25
H		0.02	-0.02	-0.05	-0.18
	Panel (d): Wealth-Gini coefficient				
	0.74	0.74	0.74	0.73	0.72
	Panel (e): Consumption smoothing				
b	0.131	0.128	0.125	0.117	0.105
	Panel (f): Welfare, in %×100				
ϕ_L		0.08	0.18	0.46	0.92
ϕ_M		0.05	0.11	0.27	0.53
ϕ_H		~ 0	~ 0	-0.01	-0.03
Average assets are compute for the working-age population					

Table 12: Results with a savings subsidy

8 Conclusion

To be written

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Appendix

A CPS Welfare Benefits

As described in the main text, we calibrate the replacement rate for welfare benefits to match the ratio of total welfare income to total labor earnings in the U.S. economy. This section provides more details on the computation of this ratio.

We use the March supplement of the Current Population Survey (ASEC), waves 2015–2019. In this supplement, individuals report their total income as well as their income from various sources during the preceding 12 months. This information allows us to elicit the income from what we broadly call welfare benefits in the model. We apply the same sample restrictions as in our main CPS sample and construct two sub-samples.

For the sample of welfare recipients, we consider all non-retired individuals who did not work nor searched for a job. In particular, we exclude all individuals who received wage or business income or income related to retirement. We define the individual total welfare income as the sum of income from public assistance, survivor's and disability benefits, worker's compensation (due to job-related injury or illness), educational assistance, child support, veteran's benefits, and income or assistance from other sources. This represents a conservative measure in the sense that we overestimate the welfare benefits, making non-participation and hence misperception less severe.

To compute total labor earnings we restrict the original sample to individuals with positive wage income. Additionally, we consider only individuals who worked full-time, were formally employed for the whole year, and did not received any income from self-employment or retirement. For this group, we define total labor earnings as wage and salary income.

Next, we compute for each wave the ratio of average total welfare income from the first sample to the average total labor earnings from the second sample. Finally, we compute the average ratio across all waves to account for inflation.

B Calibration

We construct the 3-months transition matrices for the three skill groups as follows. Regarding the CPS, we follow the same procedure as described in Section D.2 with the difference that we do not interpolate between the 3-months and 9-months transition rates, and just use the former. Similar to the probabilities reported in Table 16, we use the values for the different education groups, which we label low, medium, and high skilled in the main model. Finally, we round the values, s.t. the row sums equal 100% and the rounding error is minimal.
Since we only observe the subjective expectations on the four month horizon, we need to impose additional assumptions to compute 3-months counterparts. We assume that the transition probabilities follow a Markov Chain in the sense that the four months transition matrix is identical to multiplying the 1-month (unobserved) transition matrix four times with itself. Using the implying 1-month transition matrix then allows us to compute the 3-months counterpart by multiplying it 3 times with itself. Numerical, we first solve

$$vec(p_h)^4 - P_h^{SCE}(4m) = 0$$

for p_h and then we compute p_h^3. Finally, we round again in the same fashion as before.

C Computation

To find the general equilibrium of the quantitative model, we employ the following algorithm which mimics the standard procedure to solve Bewley-Huggett-Aiyagari-type models:

1. Choose a grid for assets and discretize the productivity shocks.
2. Given the labor market transition probabilities, compute the total labor supply in efficiency units and the mass of agents in each employment state. Using these quantities, compute the tax rates.
3. Guess the interest rate r.
4. Use the first-order conditions of the firm to compute the wage w.
5. Solve the worker's optimization problem using the endogenous grid point method.
6. Solve for the cross-sectional distribution of assets, productivities, and labor market states using the eigenvector method.
7. Compute the implied capital stock and interest rate r'.
8. If r' is sufficiently close to r, stop. Otherwise, update r using the bisection algorithm and continue with step 4.

We use the Tauchen-method with three grid points and the Rouwenhorst-method with 7 grid points to discretize the transitory and permanent component of productivity, respectively. Together with the three labor market states and the retirement state, this yields a Markov chain with $7 \times 3 \times 3 + 1 = 64$ states.

For the policy functions in the endogenous grid point method, we use 301 exponentially spaced points between $\underline{a} = 0$ and $\overline{a} = 10,000$. Before we compute the stationary distribution, we interpolate the policy functions linearly to get a finer grid of 1,000 points. In the last iteration, we further extent this grid to 5,000 points. Note that we exploit the sparsity of the transition matrix to speed up the code, as we need to repeatedly solve for the largest eigenvector of a $192,000 \times 192,000$ or $320,000 \times 320,000$ matrix for each h-type.
Finally, we directly use the cross-sectional distribution for most statistics. Especially, for statistics relating to the age of agents, we track $200,000$ newly-born agents for up to 401 periods (quarters) or until they leave the model.

D Calculation of subjective and actual probabilities

D.1 Subjective probabilities

As discussed in the main text, we use the "Labor Market Module" of the Survey of Consumer Expectations (SCE) to compute expectations of individuals about their future employment status. This supplement is conducted every four months. Since the main question we consider was first introduced in July 2014, we restrict the whole dataset to July 2014 until November 2018 – the newest available month as of writing. Furthermore, we focus on individuals aged 25 to 60, who are not in school. We classify individuals into employed (E), unemployed (U), and non-participant (N) according to the following iterative procedure:
First, we define all individuals as currently employed, if they include "Working full-time", "Working part-time", or "sick or other leave" in their answers regarding their current employment status. Second, among all others, we define an individual to be unemployed in two cases: either they report to be "temporarily laid off", or are "not working, but would like to work" and state that they have "done something in the last 4 weeks to look for work". Third, from all the remaining workers, those which include "Permanently disabled or unable to work", "Retiree or early retiree", "Student, at school or in training", or "Homemaker" are assigned to be non-participants. Additionally, individuals who report that they haven't searched in the last 4 weeks, but include that they would like to work are defined as non-participants. Note that the question about the past job search is only available every four months as part of the Labor Market Module. We exclude all entries where we cannot determine an employment status. For the computation of the subjective transition rates, we only consider answers where the assigned probabilities across all states equals 1.
Based on the reported employment status and the expectations about future states, we compute average actual 4-months transition rates as well as average subjective expectations about each possible transition. Since we need to two consecutive answers of one individual to the Labor Market Module to compute actual transitions, the number of observations is much lower for this sub-sample. Since most individuals are interviewed only twice in the Labor Market Module (with only very few individuals being interviewed three times, if the first SCE-interview happens to align with the Labor Market Module and they stay in the survey for the full year), we observe only one actual transition for most respondents. On the contrary, we can exploit the information

	SCE				CPS	
	Actual		Subjective		Actual	
	N	%-share	N	%-share	N	%-share
Men	2494	48.53	4954	47.68	1508613	49.01
Women	2645	51.47	5242	52.32	1631247	50.99
25–29	621	11.09	1266	12.05	411121	14.48
30–39	1325	24.25	2672	25.37	859211	27.49
40–49	1472	28.89	2847	28.45	837801	26.61
50–54	803	15.73	1546	15.29	465389	14.33
55–60	1046	20.04	1865	18.85	566338	17.09
≤HS	561	33.77	1104	34.04	1156710	37.18
C	1674	30.04	3269	30.25	864866	27.10
≥Bachelor	3032	36.20	5819	35.71	1118284	35.72
white	4292	80.48	8289	80.53	2516282	77.09
non-white	975	19.52	1907	19.47	623578	22.91
single	1775	34.32	3424	33.70	1248517	40.57
married	3492	65.68	6772	66.30	1891343	59.43
<30K	848	23.80	1605	23.19	644567	20.75
30K–49K	821	16.61	1616	17.25	555096	17.81
50K–99K	1893	31.38	3657	31.51	1046786	32.83
≥100K	1682	28.21	3276	28.04	893411	28.61
E	4476	81.26	8665	81.20	2411875	76.67
U	164	3.40	320	3.54	96233	3.18
N	608	15.34	1211	15.26	631752	20.15

Sample: 25-60, non-school. N: number of observations.
Shares factor in the weights supplied by the respective dataset.

Table 13: Descriptive statistics for different samples.

about the subjective expectations in every interview.

Table 13 lists the number of observations as well as the shares of different demographic groups and labor market states across different samples. The first two columns show the sub-sample where we have information about the actual transitions. In columns 3 and 4, we consider all entries for individuals with subjective expectations about their employment status in 4 months. Our choice for the education as well as income groups is motivated by the fact that the SCE weights are based on these groups, and it is therefore not possible to compute nationally representative results for different groups.

Not surprisingly, Table 13 shows that both SCE samples are very similar in terms of composition. Mainly, the number of observations is much lower for the actual transitions in the SCE compared to the subjective expectations as discussed above.

Regarding the subjective expectations sample, especially the number of unemployed workers is very low. Despite having only 320 observations, we can still compute meaningful UE, UN, and

	Actual			Perceived		
	E	U	N	E	U	N
E	96.97	1.63	1.40	96.02	2.57	1.40
	(0.38)	(0.26)	(0.28)	(0.19)	(0.12)	(0.11)
U	36.04	43.96	20.00	59.09	35.30	5.61
	(4.59)	(5.05)	(4.74)	(2.26)	(1.96)	(0.98)
N	6.72	3.03	90.25	9.72	12.35	77.93
	(1.29)	(0.94)	(1.56)	(0.78)	(0.82)	(1.26)

Source: SCE; Sample: 25-60, non-school.
Standard errors are in parenthesis.

Table 14: 4-months actual and perceived transition probabilities in SCE.

UU expectations. Since every respondent assigns a probability to each potential future state, we have 320 subjective probabilities for each of the three transitions. Sadly, we cannot compute precise average actual transition rates, as first, we lose nearly 50% of the observations, and second, these 164 observations are split into UE, UN, and UU. This means, that we have even less realizations for each flow.
Nevertheless, Table 14 compares the actual and perceived labor market transition rates for these two samples as a point of reference. In this table, the columns represent the current state, and the row the future state. Note, that we use the Stata command "svy" to compute "linerarized Taylor" standard errors. This is the case for all tables if not stated otherwise.
As expected due to the low sample size, the standard errors for actual flows out of unemployment are very large. Therefore, we make use of the "Current Population Survey" to construct the actual transition probabilities, as discussed in the next section.

D.2 Actual probabilities

The "Current Population Survey" (CPS) is a monthly, nationally representative survey of around 60,000 households. It is conducted for the Bureau of Labor Statistics in order to evaluate the current state of the labor market. Every individual in the CPS answers questions about the current employment status for 4 successive months. After a break of 8 months, they answer the same questions again for 4 months until they rotate out. This implies that we can directly observe the 1–3, as well as, 9–15 months labor market transition rates.
To stay as close to the SCE as possible, we consider the same sample restrictions and time span. This means we consider 25–60 year old individuals, who are not in school, but also exclude members of armed forces. In general, we consider the same months from July 2014 to November 2018. Including members of the armed forces or focusing only on household heads has very little effect. We use the "empstat" variable to elicit the current employment status.
We compute average m-month transition rates by counting all individuals who report to be in state s in one month and in state s' m months later. We divide this number by the amount of individuals who report to be in state s and are still in the sample m months later. For this calculation, we consider somebody who, for example, reports to be employed in November 2018

		SCE			CPS		
State		E	U	N	E	U	N
Age	Education						
25–29	≤HS	0.80	2.19	0.33	3.72	9.05	5.16
25–29	C	2.79	3.13	2.56	3.78	4.93	3.13
25–29	≥Bachelor	9.90	3.76	2.73	4.98	3.54	2.56
30–39	≤HS	2.09	4.08	3.14	8.26	14.70	11.23
30–39	C	6.73	6.58	6.53	7.55	8.64	6.09
30–39	≥Bachelor	18.82	12.85	7.02	12.02	6.25	6.12
40–49	≤HS	2.70	3.76	6.20	9.05	11.68	12.10
40–49	C	9.20	10.97	10.50	7.63	6.65	5.99
40–49	≥Bachelor	16.71	11.60	6.61	11.43	6.40	5.49
50–54	≤HS	1.81	1.57	3.39	5.33	6.21	9.09
50–54	C	5.60	7.84	8.35	4.29	3.80	4.04
50–54	≥Bachelor	7.57	6.90	4.46	5.59	3.61	2.92
55–60	≤HS	1.84	3.13	8.18	5.97	6.29	14.19
55–60	C	5.69	9.40	17.36	4.67	4.33	6.9
55–60	≥Bachelor	7.75	12.23	12.64	5.74	3.92	4.97

Sample: 25-60, non-school, non-army (CPS).
Shares factor in the weights supplied by the respective dataset.

Table 15: Distributions conditional on employment state

and to be unemployed one month later. Furthermore, we use the weight ”WTFINL” to account for the design of the survey. Finally, for the 4 months transition rates, we interpolate linearly between the values for the three month transition rates and their 9 month counterparts.

The last two columns of Table 13 represent the sample from the CPS and enables a comparison of the demographic composition between the SCE and CPS.

Since the weights in the SCE are constructed to make the dataset match key demographic characteristics (income, age, education, and census regions [13]) of the American Community Survey (ACS), it is not surprising that there are no large differences. The single largest difference arises for the share of married individuals caused by the fact that the SCE asks about being married or living together, while the CPS only considers the legal status. Otherwise, it is notable, that in the SCE individuals are slightly older, better educated, and more often employed. This difference might be a consequence of the different survey design of the SCE. Respondents in the SCE need to express their access to internet and their ability to fill out an online-questionnaire. Furthermore, note that employment status is not considered for the construction of weights in the SCE.

To highlight the compositional differences given the employment status, Table 15 shows the joint distribution of age and education conditional on employment status for the CPS and the SCE sample, which we use to compute subjective expectations.

To account for the slightly different composition across the samples, we use the CPS shares listed in Table 15 to re-normalize the weights from the SCE for each education-age-employment cell.

Finally, Table 16 and Table 17 show the actual transition rates from the CPS, as well as the

[13] See [Armantier–Topa–Klaauw–Zafar 2017] for details.

subjective expectations from the SCE with and without the additional CPS weights described above.

For the actual and the subjective transition rates in the SCE, we use the Stata command "svy" with "pweights" to compute the "linearized Taylor standard error". We do the same for the 3 and 9 months transition rates in the CPS. Then, we interpolate linearly between those two rates to obtain estimates for the 4 months transition rate. The standard errors in this case should only give a very rough idea. For the SCE dataset with CPS weights, we use the same approach as with the other SCE estimates, but we re-normalize the weights before computing the standard error.

The re-normalization of SCE weights with the CPS shares, has a notable effect on the magnitude of the subjective expectations, especially for flows out of unemployment. However, it never affects the sign of the difference between the actual and perceived flows qualitatively.

E PSID: Estimation of labor income process

F PSID: Lifecycle path of income, consumption and wealth

The taxable income series is constructed by adding, for each household and from all members, income from assets, earnings, and net profits from farm or business (ER71330, ER71398), transfers (ER71391, ER71419), and social security (ER71420, ER71422, ER71424). The codes in brackets refer to the variable name in the 2017 wave of the PSID.

Consumption expenditures includes expenditures on cars and other vehicles purchases, food at home and away (ER71487), clothing and apparel (ER71525), child care (ER71516), health care (ER71517), housing including rent and imputed rental services for owners (ER71491), utilities and transportation expenses (ER71503), education (ER71515), trips and recreation (ER71527, ER71526), electronics and IT equipment (ER71522). Imputed rents for home owners were computing using the value of main residence (ER66031) times an interest rate of 4%.

All observations are aggregated using sample weights

Net worth is defined as the value of households' assets minus debt. Assets include the value of farms and businesses (ER71429), checking and saving accounts (ER71435), stocks or bonds (ER71445), real estates (ER71481,ER71439) , vehicles (ER71447), individual retirement accounts (ER71455), other assets (ER71451). Debt include the value of debt on real estate and farms or businesses (ER71431, ER71441), student loans (ER71463), medical debt (ER71467), credit card debt (ER71459), legal debt (ER71471) and other debt (ER71475, ER71479)

G CPS: Welfare benefits

As described in the main text, we calibrate the replacement rate for welfare benefits to match the ratio of total welfare income to total labor earnings in the U.S. economy. This section provides more details on the computation of this ratio.

We use the March supplement of the Current Population Survey (ASEC), waves 2015–2019. In this supplement, individuals report their total income as well as their income from various sources during the preceding 12 months. This information allows us to elicit the income from what we broadly call welfare benefits in the model. We apply the same sample restrictions as in our main CPS sample and construct two sub-samples.

For the sample of welfare recipients, we consider all non-retired individuals who did not work nor searched for a job. In particular, we exclude all individuals who received wage or business income or income related to retirement. We define the individual total welfare income as the sum of income from public assistance, survivor's and disability benefits, worker's compensation (due to job-related injury or illness), educational assistance, child support, veteran's benefits, and income or assistance from other sources. This represents a conservative measure in the sense that we overestimate the welfare benefits, making non-participation and hence misperception less severe.

To compute total labor earnings we restrict the original sample to individuals with positive wage income. Additionally, we consider only individuals who worked full-time, were formally employed for the whole year, and did not received any income from self-employment or retirement. For this group, we define total labor earnings as wage and salary income.

Next, we compute for each wave the ratio of average total welfare income from the first sample to the average total labor earnings from the second sample. Finally, we compute the average ratio across all waves to account for inflation.

	Perceived			Perceived			Actual		
Sample	SCE			SCE			CPS		
Weights	SCE			SCE-CPS			CPS		
	E	U	N	E	U	N	E	U	N
All									
E	96.02	2.57	1.40	95.97	2.59	1.44	95.22	1.52	3.26
	(0.19)	(0.12)	(0.11)	(0.19)	(0.13)	(0.12)	(0.04)	(0.02)	(0.03)
U	59.09	35.30	5.61	60.98	33.18	5.83	42.20	32.78	25.03
	(2.26)	(1.96)	(0.98)	(2.43)	(2.00)	(1.11)	(0.42)	(0.40)	(0.37)
N	9.72	12.35	77.93	10.44	13.93	75.63	10.62	3.03	86.35
	(0.78)	(0.82)	(1.26)	(0.87)	(1.18)	(1.58)	(0.11)	(0.06)	(0.12)
Education									
High school or less									
E	94.94	3.05	2.00	94.93	3.07	1.99	93.49	2.14	4.37
	(0.52)	(0.33)	(0.31)	(0.52)	(0.33)	(0.30)	(0.07)	(0.04)	(0.06)
U	58.08	33.78	8.14	60.44	31.37	8.19	39.31	32.76	27.93
	(4.62)	(3.85)	(2.13)	(4.58)	(3.60)	(2.15)	(0.61)	(0.58)	(0.56)
N	9.87	11.99	78.13	10.44	14.48	75.08	9.05	2.88	88.07
	(1.37)	(1.42)	(2.19)	(1.53)	(2.15)	(2.83)	(0.14)	(0.08)	(0.15)
Some college									
E	96.14	2.38	1.49	96.08	2.37	1.54	95.13	1.59	3.28
	(0.27)	(0.17)	(0.18)	(0.27)	(0.17)	(0.19)	(0.07)	(0.04)	(0.06)
U	61.21	35.52	3.27	64.19	32.46	3.35	42.15	32.79	25.06
	(2.90)	(2.79)	(0.86)	(2.89)	(2.69)	(1.07)	(0.79)	(0.74)	(0.69)
N	9.16	13.04	77.80	10.13	13.88	76.00	10.93	3.42	85.65
	(0.89)	(1.04)	(1.48)	(0.94)	(1.10)	(1.59)	(0.21)	(0.12)	(0.24)
College and higher									
E	96.76	2.36	0.88	96.73	2.36	0.92	96.70	0.96	2.33
	(0.15)	(0.11)	(0.09)	(0.15)	(0.11)	(0.10)	(0.05)	(0.03)	(0.04)
U	57.51	38.04	4.45	58.26	37.70	4.03	47.83	32.80	19.37
	(2.67)	(2.47)	(0.92)	(2.72)	(2.56)	(0.87)	(0.86)	(0.80)	(0.69)
N	10.42	11.90	77.68	10.82	12.70	76.48	13.80	2.93	83.27
	(1.16)	(1.09)	(1.74)	(1.22)	(1.20)	(1.87)	(0.25)	(0.12)	(0.27)
Gender									
Male									
E	96.01	2.55	1.43	95.96	2.58	1.46	96.05	1.56	2.39
	(0.26)	(0.15)	(0.17)	(0.27)	(0.16)	(0.18)	(0.05)	(0.03)	(0.04)
U	61.26	35.92	2.82	63.71	33.71	2.58	43.96	35.05	20.99
	(3.49)	(3.39)	(0.68)	(3.64)	(3.49)	(0.75)	(0.59)	(0.56)	(0.49)
N	9.49	12.42	78.09	10.45	13.89	75.67	12.16	3.90	83.94
	(1.36)	(1.49)	(2.13)	(1.60)	(1.80)	(2.52)	(0.20)	(0.12)	(0.23)
Female									
E	96.03	2.60	1.37	95.98	2.60	1.42	94.27	1.48	4.25
	(0.27)	(0.19)	(0.15)	(0.28)	(0.20)	(0.16)	(0.06)	(0.03)	(0.05)
U	57.38	34.83	7.79	58.96	32.79	8.25	40.30	30.32	29.38
	(2.93)	(2.28)	(1.57)	(3.20)	(2.33)	(1.74)	(0.59)	(0.55)	(0.55)
N	9.83	12.32	77.85	10.44	13.94	75.61	9.92	2.64	87.44
	(0.95)	(0.99)	(1.55)	(1.04)	(1.50)	(1.98)	(0.12)	(0.07)	(0.14)
Race									
White									
E	96.40	2.40	1.20	96.37	2.41	1.22	95.55	1.41	3.03
	(0.19)	(0.13)	(0.12)	(0.19)	(0.13)	(0.12)	(0.04)	(0.02)	(0.03)
U	61.68	34.84	3.48	64.46	32.19	3.35	44.55	31.58	23.87
	(2.57)	(2.42)	(0.71)	(2.68)	(2.47)	(0.78)	(0.49)	(0.45)	(0.42)
N	8.59	9.79	81.62	9.17	10.74	80.08	10.38	2.77	86.85
	(0.86)	(0.78)	(1.26)	(0.97)	(1.07)	(1.45)	(0.12)	(0.06)	(0.13)
Non-White									
E	94.47	3.28	2.24	94.31	3.36	2.33	93.98	1.92	4.10
	(0.56)	(0.33)	(0.33)	(0.59)	(0.35)	(0.35)	(0.10)	(0.06)	(0.08)
U	52.06	36.58	11.37	51.96	35.75	12.29	36.98	35.45	27.57
	(4.31)	(3.17)	(2.71)	(4.60)	(3.18)	(2.94)	(0.80)	(0.78)	(0.73)
N	14.85	24.09	61.06	15.68	27.07	57.24	11.33	3.81	84.86
	(1.83)	(2.57)	(3.52)	(1.79)	(3.22)	(4.13)	(0.23)	(0.14)	(0.26)

Source: SCE and CPS; Sample: prime-age population aged, 25-60, non-school, non-army. Standard errors are in parenthesis.

Table 16: 4-months actual and perceived transition probabilities

	Perceived			Perceived			Actual		
Sample	SCE			SCE			CPS		
Weights	SCE			SCE-CPS			CPS		
	E	U	N	E	U	N	E	U	N
Age									
25–29									
E	96.08	2.62	1.30	95.89	2.69	1.43	93.86	2.05	4.10
	(0.42)	(0.27)	(0.23)	(0.51)	(0.33)	(0.27)	(0.12)	(0.07)	(0.10)
U	66.62	23.64	9.74	67.11	23.86	9.03	43.00	31.02	25.98
	(7.27)	(4.23)	(4.53)	(6.69)	(4.05)	(4.16)	(1.02)	(0.94)	(0.89)
N	11.87	20.33	67.79	9.95	23.19	66.86	16.13	5.21	78.66
	(2.35)	(3.60)	(4.56)	(2.84)	(6.45)	(7.83)	(0.38)	(0.23)	(0.42)
30–39									
E	96.26	2.49	1.25	96.23	2.50	1.27	95.25	1.60	3.15
	(0.32)	(0.22)	(0.19)	(0.33)	(0.23)	(0.20)	(0.07)	(0.04)	(0.06)
U	70.80	25.75	3.45	70.96	25.72	3.31	43.69	32.07	24.24
	(3.44)	(3.11)	(1.25)	(3.48)	(3.18)	(1.23)	(0.78)	(0.72)	(0.67)
N	16.24	16.14	67.62	16.00	15.97	68.03	12.97	3.68	83.35
	(2.59)	(2.56)	(3.78)	(2.55)	(2.53)	(3.73)	(0.23)	(0.13)	(0.26)
40–49									
E	96.17	2.71	1.12	96.16	2.73	1.12	95.82	1.42	2.77
	(0.37)	(0.24)	(0.19)	(0.38)	(0.24)	(0.19)	(0.06)	(0.04)	(0.05)
U	51.95	39.23	8.81	50.35	39.87	9.78	43.79	32.58	23.63
	(3.88)	(2.95)	(2.19)	(4.06)	(2.92)	(2.51)	(0.83)	(0.78)	(0.72)
N	10.56	14.88	74.56	11.11	16.09	72.79	10.91	2.92	86.17
	(1.51)	(1.63)	(2.57)	(1.44)	(1.59)	(2.45)	(0.22)	(0.12)	(0.24)
50–54									
E	96.76	2.17	1.07	96.77	2.17	1.06	95.76	1.27	2.97
	(0.33)	(0.21)	(0.22)	(0.32)	(0.20)	(0.22)	(0.09)	(0.05)	(0.07)
U	62.73	34.08	3.19	67.21	29.90	2.89	39.42	35.25	25.33
	(5.29)	(4.88)	(1.28)	(6.43)	(5.81)	(1.24)	(1.11)	(1.08)	(1.00)
N	8.46	12.57	78.97	7.86	11.88	80.26	8.55	2.47	88.98
	(1.51)	(1.93)	(2.59)	(1.53)	(2.00)	(2.69)	(0.24)	(0.13)	(0.26)
55–60									
E	94.54	2.84	2.62	94.52	2.84	2.63	94.77	1.33	3.90
	(0.66)	(0.41)	(0.47)	(0.65)	(0.41)	(0.46)	(0.09)	(0.05)	(0.08)
U	47.26	49.58	3.16	45.54	51.29	3.17	37.40	34.93	27.67
	(4.85)	(4.83)	(0.85)	(5.27)	(5.26)	(0.88)	(1.09)	(1.06)	(1.01)
N	6.40	7.67	85.93	6.64	7.54	85.82	6.52	1.75	91.73
	(1.14)	(1.09)	(1.72)	(1.18)	(1.09)	(1.77)	(0.17)	(0.09)	(0.19)
Family Income									
<$30K									
E	90.85	5.52	3.63	90.63	5.63	3.74	91.29	3.22	5.49
	(0.80)	(0.52)	(0.46)	(0.83)	(0.55)	(0.47)	(0.13)	(0.08)	(0.11)
U	58.61	35.52	5.88	61.76	32.17	6.08	37.50	34.74	27.76
	(3.46)	(3.10)	(1.43)	(3.56)	(2.97)	(1.60)	(0.64)	(0.62)	(0.59)
N	10.05	14.89	75.06	10.57	16.91	72.52	8.89	3.48	87.62
	(1.22)	(1.29)	(1.96)	(1.39)	(1.74)	(2.25)	(0.16)	(0.10)	(0.18)
$30K–$49K									
E	96.80	2.27	0.93	96.85	2.25	0.90	94.12	1.93	3.94
	(0.31)	(0.24)	(0.16)	(0.31)	(0.24)	(0.15)	(0.10)	(0.06)	(0.08)
U	54.28	38.90	6.82	55.98	37.02	6.99	42.17	32.81	25.02
	(4.71)	(3.73)	(2.29)	(5.40)	(4.22)	(2.51)	(0.94)	(0.89)	(0.82)
N	10.49	11.04	78.47	12.61	14.51	72.88	10.64	2.91	86.45
	(1.91)	(1.82)	(2.86)	(2.35)	(3.74)	(5.02)	(0.24)	(0.13)	(0.26)
$50K–$99K									
E	97.16	1.93	0.91	97.17	1.91	0.92	95.72	1.31	2.97
	(0.23)	(0.16)	(0.15)	(0.24)	(0.16)	(0.16)	(0.06)	(0.03)	(0.05)
U	65.21	31.22	3.57	65.72	30.56	3.72	47.24	29.70	23.07
	(3.47)	(2.91)	(2.04)	(3.75)	(3.02)	(2.31)	(0.86)	(0.77)	(0.73)
N	9.37	9.03	81.60	9.58	9.75	80.67	12.44	2.95	84.61
	(1.37)	(1.55)	(2.27)	(1.33)	(1.65)	(2.40)	(0.23)	(0.12)	(0.25)
≥$100K									
E	96.99	1.95	1.06	96.95	1.95	1.10	96.85	0.84	2.31
	(0.26)	(0.14)	(0.19)	(0.27)	(0.14)	(0.20)	(0.05)	(0.03)	(0.04)
U	63.99	31.74	4.26	61.45	33.98	4.57	47.73	32.24	20.04
	(5.06)	(4.50)	(1.51)	(5.39)	(4.86)	(1.66)	(1.13)	(1.05)	(0.92)
N	7.83	8.05	84.13	8.29	8.38	83.33	11.93	2.24	85.83
	(1.29)	(1.23)	(2.18)	(1.38)	(1.32)	(2.32)	(0.27)	(0.12)	(0.29)

Source: SCE and CPS; Sample: prime-age population aged, 25-60, non-school, non-army. Standard errors are in parenthesis.

Table 17: 4-months actual and perceived transition probabilities