The Effects of Biased Labor Market Expectations on Consumption, Wealth Inequality, and Welfare

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Abstract

Idiosyncratic labor market risk is a prevalent phenomenon with important implications for individual choices. In labor market research it is commonly assumed that agents have rational expectations and therefore correctly assess the risk they face in the labor market. We analyze survey data for the U.S. and document a substantial optimistic bias of households in their subjective expectations about future labor market transitions. Furthermore, we investigate the heterogeneity in the bias across different demographic groups and we find that high-school graduates tend to be strongly over-optimistic about their labor market prospects, whereas college graduates have rather precise beliefs. In the context of a quantitative heterogeneous agents life cycle model we show that the optimistic bias has a quantitatively sizable negative effect on the life cycle allocation of income, consumption and wealth and implies a substantial loss in individual welfare compared to the allocation under full information. Moreover, we establish that the heterogeneity in the bias leads to pronounced differences in the accumulation of assets across individuals, and is thereby a quantitatively important driver of inequality in wealth.

Keywords: Subjective expectations, labor markets, consumption, asset accumulation, wealth inequality.
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"Optimism is the madness of insisting that all is well when we are miserable."
— Voltaire

1 Introduction

Idiosyncratic labor market risk is a prevalent phenomenon with important implications for individual choices such as wage bargaining (Mortensen and Pissarides (1994)), consumption and saving (Krusell et al. (2010)), job search and job acceptance (Rogerson et al. (2005)), portfolio choice (Den Haan et al. (2017)), and human capital accumulation (Krebs (2003)). Through its influence on individual behavior, labor market risk may affect the processes which shape macroeconomic outcomes such as aggregate employment, physical and human capital accumulation, the distribution of wages, aggregate consumption and inequality in wealth. In labor market research it is common to make use of the rational expectation assumption by imposing that economic agents possess all relevant knowledge about the stochastic processes governing the idiosyncratic risk in the labor market. In this paper, we document in U.S. micro data that agents' subjective probabilities over labor market outcomes systematically differ from their actual ones, and we explore theoretically and quantitatively how this bias in subjective labor market expectations affects both individual decision making and macroeconomic outcomes. Importantly, we report the extent of heterogeneity in the expectation bias across different demographic groups and show that it is a quantitatively important driver of the observed inequality in wealth.

In the first part of the paper, we use data from the Survey of Consumer Expectations (henceforth SCE) to document the subjective expectations of U.S. households about future transitions between the three labor market states employment, unemployment, and out-of-the-labor-force. Most importantly, we find that these subjective transition probabilities differ substantially from the actual probabilities. Specifically, we establish that, on average, households in the U.S. are strongly over-optimistic about their own labor market prospects. That is, households' subjective probability exceeds the respective statistical probability of experiencing a transition into a favorable labor market state – such as finding a job, or remaining employed. At the same time, households tend to underestimate the probability of transitioning into a bad state – such as remaining unemployed, or leaving the labor force. For example, according to our results, unemployed workers overestimate the probability to be employed in four months by 18.8 percentage points, while employed workers underestimate the likelihood of leaving the labor force by 1.9 percentage points. Individuals who are not in the labor force overestimate the probability of entering the labor force by 11.2 percentage points.

Furthermore, we document the heterogeneity in the optimistic bias in expectations across different demographic groups. Most importantly, in this context, we find a strongly negative relation between education and the size of the bias. Accordingly, the optimistic bias is largest for high-school educated individuals, while college-educated individuals – who are still over-optimistic

– have more accurate beliefs. For example, unemployed job seekers with a high-school degree overestimate the probability to be employed in fours months by 21.7 percentage points, whereas this number is 10.6 percentage points for job seekers with college degree . Similarly, inactive individuals with a high-school education overestimate the likelihood of entering the labor force by 13.8 percentage points, where it is 6.6 percentage points for college-educated individuals.

In the second part of the paper, we perform a theoretical and quantitative analysis. The purpose of this analysis is to explore the extent to which the optimistic bias in labor market expectations affects household life cycle consumption behavior and wealth accumulation and thereby shapes macroeconomic outcomes such as wealth inequality.[1] As part of this analysis, we first use a tractable two-period model to explore in closed form how the bias in expectations distorts the inter-temporal consumption decision of households. In the context of this model, we show analytically that agents with over-optimistic expectations obtain a lower level of lifetime utility than with rational expectations because they save less and, thus, they achieve a lower level of lifetime consumption, and they are overly exposed to random fluctuations in income. Moreover, we show that heterogeneity in the optimistic bias causes differences in savings behavior across agents and thereby leads to inequality in wealth.

In the quantitative analysis, we assess to what extent the empirically observed expectation bias matters for individuals' life cycle consumption, income and wealth, as well as the aggregate distribution of wealth. As part of this analysis, we explore the welfare effects of over-optimism and we briefly discuss the implications of our results for economic policy. As a framework for the quantitative analysis we use a heterogeneous agents life cycle model with incomplete insurance markets, various sources of idiosyncratic risk, and households with different levels of human capital. Crucially, we incorporate households that have a subjective probability distribution over future labor market transitions and we allow the subjective distribution to differ from the actual distribution. Moreover, guided by our empirical findings, we incorporate heterogeneity in the bias across households with different human capital. We calibrate the model to U.S. data and show that the quantitative model matches very well several important data outcomes at the individual and aggregate level. This includes, for example, the life cycle profile of income, consumption and assets for individuals with different levels of human capital, as well as the high degree of inequality in the distribution of wealth in the U.S.

In the final step of our analysis we examine in a counterfactual experiment the quantitative importance of biased expectations on allocations. In this experiment, we eliminate the bias altogether and assume that all agents in the economy have rational expectations. Then, we compare the characteristics of the implied full information equilibrium with the equilibrium of the baseline economy. The optimistic bias distorts the individuals' inter-temporal consumption

[1] In related work, we use a general equilibrium labor market matching model to study quantitatively the implications of biased labor market expectations on choices of the household related to labor market outcomes. This includes, for example, the decisions of employed workers to leave a job, or of job seekers to search for employment and wage bargaining outcomes (see Balleer et al. (2021b)).

allocation and it discourages individual asset accumulation. This effects is particularly pronounced for individuals with low human capital who are more over-optimistic. This effect is quantitatively sizable. For example, the savings rate for high-school educated individuals is, on average, 8 percentage points lower in the economy with biased expectations, whereas for individuals with a college education it is essentially the same as in the economy with full-information. As a result, high-school graduates accumulate less wealth over the life cycle and enter retirement with approximately 33% fewer assets than in the economy without biased expectations. Due to the lack in assets, they attain a lower life cycle path of consumption which implies a welfare loss relative to the full-information case of 5.4% (in terms of equivalent variation in expected lifetime consumption). Naturally, these effects are less pronounced for college-educated individuals who have a much smaller optimistic bias than high-school graduates. As a result, the heterogeneity in the optimistic bias across individuals has a substantial effect on wealth inequality. Without the bias in expectations the wealth Gini coefficient would be 7 percentage points lower. This is an important finding as it suggests that a substantial part of U.S. inequality in wealth distribution is due to the bias in individuals' labor market expectations.

This paper contributes to a growing body of research which collects and uses subjective expectations data to study decision making under uncertainty. See Manski (2004) for an early survey of this literature. Broadly, this literature can be divided into two strands. The first strand examines individual expectations about aggregate variables. This includes individuals' inflation expectations (see e.g. the work by Broer et al. (2021), Carroll (2003), Andolfatto et al. (2008), Malmendier and Nagel (2015), and Coibion et al. (2018), house price expectations (see e.g. Piazzesi and Schneider (2009), Case et al. (2012), and Kuchler and Zafar (2019)), expectations about aggregate unemployment (see Broer et al. (2021), and Kuchler and Zafar (2019)), or expectations about financial market outcomes such as credit spreads, and bond and stock market returns (see Piazzesi et al. (2015), Bordalo et al. (2018), and Vissing-Jorgensen (2003)).

The second strand of literature analyses subjective expectations about individual level variables such as income (see Rozsypal and Schlafmann (2020) and Exler et al. (2020), survival (Grevenbrock et al. (2021)), retirement (Haider and Stephens (2007)), social security benefits (Dominitz et al. (2003)), returns to education (Attanasio and Kaufmann (2014)), and portfolio returns (Vissing-Jorgensen (2003)). As part of this second strand, recent work has started to utilize newly available data to study subjective expectations of individual labor market outcomes. This includes, for example, expectations about job loss, wage offers, and job finding. See Mueller and Spinnewijn (2021) for a recent survey of this literature. Within this literature, several papers are related to ours. First, Mueller et al. (2021) use data from the SCE to compare the perceived and actual job finding for unemployed individuals. Like us, they find that job seekers in the U.S. substantially over-estimate their job finding probability. Moreover, they show in a model of job search how the bias in beliefs induces individuals to engage less in job search and can thereby help understand the slow exit out of unemployment for certain job seekers. In the same vein, Conlon et al. (2018) use the SCE to analyze individuals' expectations

and realizations about future wage offers. In particular, they study how individuals update their expectations in response to deviations of realized from expected offers. They embed their empirical findings into a model of job search and show that learning is key feature to understand the observed patterns of reservation wages. Spinnewijn (2015) analyzes survey data from Price et al. (2006) and finds a substantial optimistic bias of unemployed job seekers. He then studies the implications of this bias for the optimal design of unemployment insurance. Jäger et al. (2021) measure bias in beliefs about outside options of workers and argue that this increases labor market segmentation and lower wages for slow-wage workers. Our work is complementary to these papers in that we analyze not only the job finding expectations of unemployed individuals or employed job seekers, but jointly address the expectations of employed and unemployed workers, as well as non-participants about finding a job or becoming unemployed, or to move out of the labor force. This allows us to obtain a more complete picture of the expectation structure of the working-age population. Moreover, while the aforementioned papers focus on the search behavior of job seekers, we study individual choices with respect to consumption and asset accumulation.
Another related paper is Broer et al. (2021) which proposes a model of information choice to study the effects of biased expectations on macroeconomic volatility and wealth inequality. A key difference to our paper is their focus on expectations about aggregate variables such as inflation and aggregate unemployment. In contrast, we study households' expectations about individual labor market outcomes including job finding, job loss, and transitions to inactivity. Another difference is that while they document the expectations across wealth quintiles, we explore the variation in the expectation bias across different demographic groups (e.g. education groups) and show that it is a key element for understanding aggregate wealth inequality. Moreover, while they employ a model with infinitely lived agents, we consider a life cycle model with retirement. This allows us to study the effect of biased expectations on the life cycle path of consumption and assets, and on retirement savings.

Our paper also contributes to the literature studying the determinants of inequality in wealth. See De Nardi and Fella (2017) for a recent survey of this literature. According to De Nardi and Fella (2017) it remains a challenge in this literature to reconcile the predictions of the canonical Bewley model (Bewley (1977)), which serves as the workhorse model to study wealth inequality, with the empirically observed patterns of individual saving behavior and wealth accumulation. Specifically, while in the U.S. wealthy individuals save considerable amounts of their income, the Bewley model counterfactually predicts savings rates to decrease with wealth and to even turn negative if net worth is sufficiently large relative to labor earnings.[2] As a result, a number of additional savings motives were introduced to improve the empirical fit of the model. The set of savings motives includes, for example, bequests, preference heterogeneity, entrepreneurship, or medical expense risk. Our analysis adds to this literature by showing (i) that the bias in subjective labor market expectations is a quantitatively important determinant of individual

[2] In the Bewley model, agents engage in precautionary savings in the presence of idiosyncratic income shocks. Thus, the ability to self-insure increases with wealth and the precautionary savings motive looses relevance.

saving behavior, and (ii) that the empirically observed heterogeneity in the bias across individuals generates differences in the saving behavior, which are in line with those observed in the data. More concretely, in the presence of the expectation bias our quantitative model generates a strong positive association between wealth and saving rates. Furthermore, our analysis helps to understand the determinants of wealth inequality. As mentioned above, we establish in the quantitative analysis that a substantial part of the significant inequality in U.S. wealth distribution is due to the optimistic bias in individuals' labor market expectations. As an important corollary, we show that without biased expectations the model cannot generate the high dispersion of wealth observed in the data.

The remainder of the paper is structured as follows. In Section 2 we document the facts about subjective labor market expectations in the U.S. In Section 3.1 we present a simple two-period model to illustrate how biased expectations affect individual decision making regarding consumption and savings. In Sections 3.2 and 4.1 we set up and calibrate the quantitative model. In Section 4.2 we first explore the quantitative properties of the calibrated model and then we perform the main quantitative experiment. Section 4.5 discusses the robustness of our results, and Section 5 concludes.

2 Facts about biased labor market expectations

2.1 Aggregate

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. It focuses primarily on subjective expectations about a number of macroeconomic and household-level variables.[3] The SCE has several components. We make use of the data provided by the 07/2014-11/2019 waves of the *Labor Market Survey.* In this survey, respondents are asked to report their expectations about several labor market outcomes that pertain to them. More precisely, the question in the survey that is relevant for our purpose reads: *"What do you think is the percent chance that four months from now you will be ...*

[1] employed and working for the same employer

[2] employed and working for a different employer

[3] self-employed

[4] unemployed and looking for work

[5] unemployed and not looking for work?

We aggregate [1]-[3] into one state of employment. Moreover, corresponding to the usual notion of unemployed and non-participants used in the literature, active job search is the key characteristic that distinguishes unemployed individuals from non-participants. Hence, we classify [4] as

[3]For an introduction to the SCE see Armantier et al. (2016).

the state of unemployment and [5] as the state of not in the labor force. The labor market states among the response options are mutually exclusive and exhaustive. Indeed, for the majority of respondents the sum of probabilities across the three states adds up to 1. We exclude the few observations (22) 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 answers across individuals and report the average subjective probability for specific sample of individuals. We select individuals aged 25-60 years who do not attend school or college. The baseline sample then consists of 12,392 observations. See Table 16 in Appendix A for the descriptive statistics of the sample. In the first step, 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". We also report in the table the implied standard errors. 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 a probability of 96.1%, unemployed with 2.5%, and not in the labor force with 1.4% in four months after the interview.

We now compare these subjective probabilities to the actual probabilities. To shed light on this question, we use observations from the Current Population Survey (CPS) on individual labor market transitions to compute the implied actual labor market transition probabilities.[5] To achieve a high degree of consistency between subjective and actual probabilities from the two datasets, we apply the same sample selection criteria to the two datasets and use the same definitions of labor market states and transitions. Appendix A.2 contains the details. As before we consider the three states: employment, unemployment, and not in the labor force. 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. 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.

Clearly, for the comparison of the actual and the subjective transition probabilities to be meaningful, we require the composition of the two samples (taken from the CPS and SCE) to be similar in terms of demographic characteristics. Even though both surveys are designed to be nationally representative, the two samples may differ in terms of composition due to, for example, different sampling or non-random attrition. Consequently, if we used the sample weights provided by each survey to aggregate the individual responses then the implied results would be subject to a composition bias. To avoid such bias, we use the sample weights provided by the

[4]The details of these calculations, including the definition of labor market states and sample selection criteria are in Appendix A.1.

[5]The CPS data are extracted from the IPUMS data repository; see Flood et al. (2020).

CPS to aggregate the individual observations from the SCE. The details of these calculations can be found in Appendix A.2.[6]

	Subjective			Actual			Subjective - Actual		
	E	U	N	E	U	N	E	U	N
E	96.1	2.5	1.4	95.2	1.5	3.3	0.9	1.0	-1.9
	(0.17)	(0.11)	(0.10)	(0.03)	(0.02)	(0.02)	(0.17)	(0.11)	(0.11)
U	61.3	32.1	6.6	42.5	32.2	25.3	18.8	-0.1	-18.7
	(2.24)	(1.83)	(1.22)	(0.31)	(0.30)	(0.28)	(2.27)	(1.85)	(1.25)
N	10.7	14.2	75.1	10.7	3.0	86.3	0.0	11.2	-11.2
	(0.80)	(1.04)	(1.40)	(0.08)	(0.04)	(0.08)	(0.80)	(1.04)	(1.41)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. E: employment, U: unemployment, N: not in the labor force. Example: "UE" represents the expectation of unemployed workers to be employed in four months.

Table 1: 4-Months subjective and actual transition probabilities

The results for the actual labor market transition probabilities together with the implied standard errors are in Table 1 in the columns labelled "Actual". In addition, we also report in the table the difference between subjective and actual probabilities. We will refer to this differences as the individuals' bias in their subjective labor market expectations. 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 is 96.1% whereas the actual probability is 95.2%. The standard errors around the two probabilities are very small; hence, the difference of 0.9 percentage points between the subjective and the actual probability is statistically significant at the 1% level. Moreover, the results in the table indicate that in case of job loss, workers underestimate the likelihood of leaving the labor force by 1.9 percentage points. This difference is highly significant. Another important finding is that unemployed individuals vastly over-estimate their re-employment prospects.[7] Job seekers expect to be employed in four months with a probability of 61.3%. This is 18.8 percentage points above the actual employment probability. At the same time, unemployed workers substantially underestimate the likelihood of leaving the labor force by a remarkable 18.7 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 11.2 percentage points. While they correctly assess the probability of employment, they strongly over-estimate the likelihood of starting to look for a job. The pattern emerging from Table 1 suggests that individuals in the U.S. are generally over-optimistic about their own labor market prospects. More specifically, individuals tend to underestimate the likelihood of experiencing a transition into bad labor market states (for example, $E \rightarrow N$, $U \rightarrow N$) and they overestimate the likelihood of moving to good states ($U \rightarrow E$,

[6] In Table 18 we report the results obtained when the weights from the SCE are used. The patterns are qualitatively the same as in the baseline case; even quantitatively the differences are small.

[7] This result is in line with Mueller et al. (2021) who also find evidence of an optimistic bias of unemployed workers. Likewise, Conlon et al. (2018) find in the SCE that job seekers are generally over-optimistic about future wage offers.

$N \to \neg N$).[8]

At this point it is important to discuss the robustness and the generality of these findings. In our baseline, we compute the actual transition probabilities from the CPS and not the SCE. This choice is mainly motivated by sample size. The CPS is a large-scale survey with monthly information on roughly 120,000 respondents. As a result, we observe a large number of individual labor market transitions and this allows us to obtain precise estimates of the transition probabilities. In contrast, in the SCE we observe a much lower number of individual labor market transitions than in the CPS, and thus, the implied estimates of actual transition probabilities obtained from the SCE are somewhat imprecise.[9] Table 19 reports the results when the actual transition probabilities are computed from the SCE. The smaller number of observed transitions in the SCE is reflected by the sizable standard errors. Reassuringly, the qualitative patterns for the bias in expectations are very similar to those obtained in the baseline.

An often-raised concern regarding data on subjective expectations addresses the reliability of such data due to both systematic and differential difficulties in in the cognitive ability of individuals to deal with probabilities. First, if the assessment of probabilities is systematically biased in a certain way, e.g. if subjective probabilities are generally over-estimated, it is still valid to investigate the comparison of the relative bias across groups. Second, to address this concern, we use a set of control questions in the SCE, which are meant to assess the respondents' ability to calculate and process probabilities.[10] More concretely, we calculate the bias in subjective expectations separately for those individuals who answer correctly to all control questions, and those individuals who give a wrong answer to at least one question. The results are in Table 20. The qualitative patterns are very similar between the two groups and any differences in the value of the bias are minor. Generally, these findings alleviate the concern that individuals who are better able to deal with probabilities also have a more precise perception of their labor market risk.

Lastly, we address the important question of whether U.S.-workers' over-optimism is a stable phenomenon over time or it applies only to specific years. As a first step, we compute the actual and the subjective transition probabilities separately for each year from 2014-2019. The results in Table 21 confirm that the baseline findings also hold year-by-year. As to whether over-optimism is a long-run phenomenon, the SCE cannot provide a definitive statement due to its

[8] The only exception from this pattern is the transition from employment to unemployment, about which workers are overly pessimistic. In Balleer et al. (2021a) we use data from the German Socio-Economic Panel to document the expectations of employed workers and unemployed job seekers in Germany. Like in the U.S., workers are overly pessimistic when transitioning from employment to unemployment, but unlike in the U.S. this pessimism also applies when transitioning from employment to non-participation. For job seekers we find an optimistic bias in their job finding expectations, which is similar to the pattern in the U.S.

[9] Notice that the number of transitions observed in the SCE (6,180) is also significantly below the number of observations from which we compute the subjective transition probabilities (12,392). This is because the calculation of the actual probabilities requires us to observe individuals in two consecutive waves of the labor market module.

[10] See Appendix B for the list of control questions in the survey.

relatively short time frame. However, we can resort to earlier data on labor market expectations from the U.S. Survey of Economic Expectations (SEE), which was conducted between 1994-2002. Even though the SEE differs from the SCE in terms of design and survey questions, we can nevertheless compare individuals' subjective expectations about job loss with the actual counterparts. See Appendix C for the details. Reassuringly, we find that workers' over-optimism has been present consistently throughout during the entire time period covered by the SEE. Interestingly, this time frame also includes a period of an economic downturn (in year 2001), during which, however, we do not observe a reversal in the observed bias in subjective labor market expectations.

2.2 Heterogeneity

In the next step, we explore whether the findings of the previous section generally hold across different population groups or whether there is noteworthy heterogeneity in the population in terms of the sign and the degree of the bias in expectations. To this end, we consider different demographic groups. In particular, we disaggregate the data according to gender, age, education, and income and compute the subjective and the actual transition probabilities for each group separately (see Tables 22 - 25 in Appendix D). The results for gender do not indicate any systematic differences between men and women. If anything, women tend to be slightly more over-optimistic than men. With respect to age, we find some evidence for a decrease in the level of the bias with age, indicating that young workers have a less accurate perception of their labor market situation than prime-age workers. However, this pattern is not significant, primarily because the small number of observations for each age group implies large standard errors around the subjective transition probabilities.

	EE	EU	EN	UE	UU	UN	NE	NU	NN
All	0.9 (0.17)	1.0 (0.11)	-1.9 (0.11)	18.8 (2.27)	-0.1 (1.85)	-18.7 (1.25)	0.0 (0.80)	11.2 (1.04)	-11.2 (1.41)
High school or less	1.8 (0.45)	0.7 (0.29)	-2.5 (0.26)	21.7 (4.26)	-2.8 (3.27)	-18.9 (2.44)	1.3 (1.40)	12.4 (1.88)	-13.8 (2.51)
Some college	0.9 (0.26)	0.8 (0.15)	-1.6 (0.19)	21.4 (2.78)	0.1 (2.56)	-21.5 (1.15)	-0.3 (0.92)	10.4 (1.01)	-10.2 (1.48)
College and higher	0.3 (0.13)	1.2 (0.09)	-1.5 (0.09)	10.6 (2.67)	4.8 (2.52)	-15.4 (1.01)	-2.8 (1.15)	9.4 (1.07)	-6.6 (1.70)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. E: employment, U: unemployment, N: not in the labor force. XY: Transition from current labor market state X to future state Y. Example: "UE" represents the bias of unemployed workers' expectation to be employed in four months.

Table 2: Expectation bias in 4-months transition probabilities (by education)

Interestingly, we find a systematic relationship between education and the level of workers' over-optimism.[11] More concretely, we split the sample into three education groups: low-skilled,

[11] This result is complementary to previous findings in the literature showing that the accuracy of beliefs is

medium-skilled and 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 in Table 2 for each education group only the difference between the subjective and the actual transition probabilities. The probability levels and the standard errors can be found in Table 22 in Appendix D. Importantly, the results in the table reveal that the level of over-optimism is decreasing in the skill level. In other words, high-skill individuals tend to have a more precise perception of their labor market perspectives than low-skill individuals. This pattern applies to almost every labor market transition and it is particularly pronounced for unemployed workers and non-participants. For example, job seekers who are low-skilled overestimate the probability to be employed in four months by 21.7 percentage points. In contrast, for the high-skilled the difference between the subjective and the actual reemployment probability is only half of that and equal to 10.6 percentage points. We find a similar pattern among non-participants, where all skill groups, but particularly the low-skilled individuals, are over-optimistic about entering the labor force. The low-skilled over-estimate the probability by 13.8 percentage points, whereas the number for the high-skilled is only half of that and equal to 6.6 percentage points. Lastly, among employed workers, the low-skilled overestimate the probability of being employed four months later by 1.8 percentage points, whereas for the high-skilled the subjective reemployment probability is almost in line with the actual probability.[12]

The expectation biases reported in Table 2 are based on the average expectations of all individuals belonging to the same education group. One may be concerned that these biases are blurred by compositional differences across education groups, or by potential dependencies between education and other individual characteristics. We address this concern in the following empirical analysis. In the first step of this analysis, we estimate the Probit model, $P(Y_i = 1|x_i) = \Phi(x_i'\beta_Y)$, in order to predict the probability of an individual to experience a given labor market transition, Y, conditional on the observable variables x. The set of possible transitions includes $Y \in \{EE, EU, EN, UE, UU, UN, NE, NU, NN\}$. As an example, consider the UE-transition. The outcome variable Y is equal to one, if we observe an individual moving from unemployment to employment, and it is equal to zero otherwise. The characteristics we include in x control for age, gender, race, income, and year fixed effects. Moreover, we include in x a set of dummy variables to represent our education groups from above. We use data from the CPS on actual individual labor market transitions to estimate the coefficients β_Y separately

positively associated with individual income, wealth, or experience. For example, Exler et al. (2020) show in SCF data that financially less literate individuals have less precise expectations about future income, and they tend to underestimate the probability of experiencing bad income realizations. Broer et al. (2021) find in the SCE that wealthier households in the U.S. have more precise expectations about inflation and aggregate unemployment. Another example is Vissing-Jorgensen (2003) who find that investors are generally optimistic about stock market returns but the bias in beliefs is smaller for more wealthy investors. She finds the same pattern for investors' age, where the young are more optimistic than experienced investors.

[12] We also explore the relationship between individual income and the bias in subjective expectations. Not surprisingly, since income and educational attainment are strongly correlated, we find very similar patterns for income groups as for education groups. That is, individuals with low income are strongly over-optimistic, whereas high-income individuals have more precise expectations. See Table 25 for the results.

for each type of transition. The estimated coefficients are used to compute for each individual observed in the SCE the predicted actual labor market transition probability. That is, we evaluate the estimated Probit model using in X the individual's characteristics, and obtain the predicted probability as the fitted value from the model. Next, we subtract the predicted actual probability from the individual's reported subjective transition probability to compute the individual's expectation bias. Lastly, we estimate by OLS the linear model $z_{iY} = x_i'\gamma_Y$, where z_{iY} is the expectation bias of individual i with respect to the transition Y. The vector x_i contains the same control variables as in the Probit estimation.

In Table 3 we report the implied expectation bias by education group. The bias is computed as the average marginal effect for each education group, where all other control variables are set to their respective mean value.[13] Clearly, the expectation biases would be identical to those

	EE	EU	EN	UE	UU	UN	NE	NU	NN
High school or less	2.4	0.5	-2.8	23.7	-2.4	-21.5	1.3	11.9	-13.1
	(0.42)	(0.27)	(0.26)	(3.42)	(2.72)	(1.81)	(1.28)	(1.63)	(2.15)
Some college	1.0	0.6	-1.7	22.3	0.1	-22.4	0.3	10.1	-10.4
	(0.25)	(0.14)	(0.18)	(2.70)	(2.45)	(1.17)	(0.92)	(0.97)	(1.43)
College and higher	0.2	1.4	-1.6	13.0	4.0	-17.0	-0.8	11.7	-10.9
	(0.17)	(0.12)	(0.10)	(2.78)	(2.60)	(0.99)	(1.28)	(1.37)	(1.96)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. E: employment, U: unemployment, N: not in the labor force. XY: Transition from current labor market state X to future state Y. Example: "UE" represents the bias of unemployed workers' expectation to be employed in four months.

Table 3: Expectation bias in transition probabilities (conditional, by education)

in Table 2 when we included in X only the education dummies. Hence, any difference to the previous results conditions on other variables, e.g. controls for compositional differences of age, race, income or year between the education groups. Most importantly, the expectation biases we obtain after controlling for worker observables are very similar to those in Table 2. Specifically, we can confirm the positive expectation bias among individuals, as well as the robustly negative relationship between the level of over-optimism and education.

2.3 Learning

Lastly, we address the question whether and to what extent individuals learn over time and form increasingly accurate labor market expectations. While this is certainly a relevant question to ask in the context of expectation biases, there are several reasons why it is not straightforward to address it. First, the SCE offers a relatively short panel dimension and follows an individual for a maximum of 12 months. Within this narrow time frame, respondents are asked only every four months to report their subjective transition expectations. At the same time, the attrition of survey participants is high. As a result, we observe for only 17% of individuals in our sample

[13] Appendix E provides further details of the empirical procedure.

more than two interviews in which respondents report their transition expectations. With such limited information at hand we refrain from analyzing expectation updating at the individual level. An alternative way to explore learning is to make use of the time dimension embedded in cross-sectional information. For example, learning may be inferred from the variation in the expectation bias across individuals with different job tenure, or unemployment duration. A decline in the (absolute value of the) bias with increasing duration may be interpreted as individual learning. We proceed along these lines and extend the previous empirical analysis to include in the regression as additional control variables individual job tenure, unemployment duration, and duration of non-participation. In Table 4, we report the implied conditional expectation biases for all nine labor market flows and different durations.[14]

Ten	EE	EU	EN	U_{dur}	UE	UU	UN	N_{dur}	NE	NU	NN
< 3 m	5.3 (1.04)	-0.6 (0.77)	-4.7 (0.55)	0-3 m	16.6 (3.52)	-1.4 (2.25)	-15.0 (3.06)	0-12 m	-15.6 (2.37)	9.9 (2.15)	6.1 (3.12)
3-6 m	2.3 (0.84)	0.4 (0.77)	-2.7 (0.22)	4-6 m	23.7 (7.65)	-4.3 (5.05)	-19.6 (4.03)	>12 m	7.7 (1.89)	14.0 (1.80)	-21.7 (2.63)
6-12 m	1.6 (0.58)	-0.2 (0.32)	-1.4 (0.41)	7-12 m	36.1 (2.89)	-7.6 (3.93)	-29.0 (1.91)				
1-5 y	0.3 (0.21)	0.8 (0.14)	-1.0 (0.13)	>12 m	32.8 (6.99)	-1.0 (4.88)	-34.0 (3.05)				
>5 y	-0.5 (0.16)	1.2 (0.10)	-0.7 (0.10)								

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. E: employment, U: unemployment, N: not in the labor force. XY: Transition from current labor market state X to future state Y. Example: "UE" represents the bias of unemployed workers' expectation to be employed in four months. Ten: Tenure of current job, in months (m) and years (y). U_{dur}: Duration of current unemployment spell, in months (m). N_{dur}: Duration of current non-employment spell, in months (m).

Table 4: Conditional expectation bias, by duration

The results in the table reveal a somewhat mixed pattern. The expectation bias of employed workers to stay employed (EE) and to leave the labor force (EN) decreases with job tenure. Since, generally, job security increases with job tenure and hence EE flows are more and EN flows are less likely, this suggests constant beliefs about labor market transitions out of employment of employed workers. However, there is no clear relationship between job tenure and the expectation bias of becoming unemployed (EU). For unemployed workers, the expectation bias to become employed (UE) and to leave the labor force (UN) increase with unemployment duration. The pattern is less clear for remaining unemployed (UU). This result is consistent with the findings of Mueller et al. (2021) who use a different question in the SCE and establish that unemployed workers are generally over-optimistic about their job finding prospects and that they do not revise their beliefs downward when remaining unemployed. Since, as is well known, the job finding hazard gradually declines with unemployment duration, this, again, suggests constant beliefs about labor market transitions of job seekers. The learning pattern

[14] A detailed description of the analysis is in Appendix F.

for individuals who are out of the labor force is generally ambiguous. While the beliefs about finding employment (NE) become more precise, the expectation bias related to entering job search (NU) increases with duration. Overall, non-participants tend to form increasingly less accurate beliefs about remaining out of the labor force (NN).

In the last step, we consider individuals' age as the relevant time dimension and we explore whether individuals learn as they grow older. For this purpose, we make use of the Probit analysis from above to compute the conditional expectation bias for different age groups. We report the results in Table 32. As before, the pattern is not clear-cut. For some labor market transitions (EE, EN, NE, NU) the bias tends to decline with age, but for other transitions (EU, UE, UN) the bias increases or shows no systematic variation. In Appendix G, we use yet another set of expectation questions from the SCE to provide more analysis of learning, and we obtain qualitatively similar findings.

Taken together, our analysis reveals no clear-cut evidence of individuals systematically learning about the relevant labor market transitions. As a consequence, we choose not to incorporate the feature of learning into our theoretical framework. Looking ahead, in the quantitative analysis we are primarily interested in the implications of biased labor market expectations on aggregate long-run outcomes, such as the distribution of wealth. For this purpose, it is rather inconsequential whether and to what extent individuals update their expectations over time.

3 Model

Motivated by our empirical findings, we proceed to explore the effects of individuals' over-optimism on individual decision making and macroeconomic outcomes. In the first step of our analysis, we lay out a stylized two-period general equilibrium model in order to illustrate theoretically how a positive bias in subjective labor market expectations shapes individual choices of consumption and asset holdings, and thereby affects 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 of this analysis will be useful for the interpretation of the results of the quantitative analysis that we perform in Section 3.2. In this analysis we use a calibrated general equilibrium model to explore to what extent the observed differences between subjective and actual labor market expectations matter quantitatively for individual life cycle profiles of asset accumulation and consumption, as well as welfare and wealth inequality.

3.1 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 the individual's bias in expectations and $\Delta > 0$ represents the case of over-optimism. Moreover, we 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. Agents live for two periods, hence, 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. 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's expected utility maximization problem

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

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

$$\beta r\Big[(p+\Delta)u'(\bar{y}+rk) + (1-p-\Delta)u'(\underline{y}+rk)\Big] = u'(y_1-k)$$

A unique interior k with $0<k<y_1$ exists iff $\beta r\big((p+\Delta)u'(\bar{y}) + (1-p-\Delta)u'(\underline{y})\big) > u'\big(y_1\big)$. 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 realization of income $\underline{y}$ 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 the bias in expectations Δ. To this end, we compute $\frac{dk}{d\Delta}$, keeping the interest rate r constant. After a few lines of algebra, we obtain

$$\frac{dk}{d\Delta} = \frac{u'(\underline{y}+rk) - u'(\bar{y}+rk)}{u''(y_1-k)/(\beta r) + r(p+\Delta)u''(\bar{y}+rk) + r(1-p-\Delta)u''(\underline{y}+rk)}$$

Since $\underline{y} < \bar{y}$, $u' > 0$ and $u'' < 0$, we obtain that $\frac{dk}{d\Delta} < 0$. This is a standard result in expected utility theory going back to the work by Bernoulli (1738) and Savage (1954). It says that over-optimism, represented by $\Delta > 0$, induces agents to build up less precautionary savings. An immediate implication is that over-optimistic agents - i.e. those who underestimate the probability of receiving a bad income realization - engage less in self-insurance and are more exposed to income fluctuations than rational agents (for whom $\Delta = 0$). This is reflected by the fact that the difference in second-period utilities between the good state and the bad state, $u(\bar{y}+rk) - u(\underline{y}+rk) > 0$ is increasing with Δ. Moreover, it is straightforward to show that, if an interior solution exists, consumption in the second period, c_2, and total lifetime consumption (c_1+c_2) decrease with Δ irrespective of the realization of income in the second period. That is, individuals with a positive bias in their subjective expectations enjoy a lower level of total consumption and of welfare as measured by the discounted sum of lifetime utility.

Next, we derive the implications for the equilibrium interest rate. For concreteness, we assume that a fraction $0 < \phi < 1$ of the population is over-optimistic and has $0 < \Delta < 1-p$, 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 a bias in expectations, suppose 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, a positive bias in expectations for some individuals per se leads to wealth inequality. Lower 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 bias of the optimistic agents. This channel further amplifies aggregate wealth inequality. A similar effect materializes in the full model where 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. Second, 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.

3.2 Full model

In this section, we present the full model that we use in our quantitative analysis. The theoretical framework builds on the canonical Bewley–Huggett–Aiyagari model, and it shares many features of the stationary version of the model in Krueger et al. (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 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 distribution 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. 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 an individual's preferences are given 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, denoted by $a > \bar{a}$, which yield a non-state-contingent return, denoted by r. $\bar{a} \geq 0$ is a borrowing constraint. Individuals are born with zero assets.

Human capital

Individuals are ex-ante heterogeneous with respect to human capital. We introduce differences in human capital across individuals because we want our model to capture the empirical finding of Section 2 that the size of the bias in subjective expectations varies substantially across education groups. A worker's level of human capital is denoted by h. We allow for three levels of human capital: low-skill, (h_L), medium-skill, (h_M), and high-skill, (h_H). 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 $s, s' \in \{\mathbf{e}(mployed), \mathbf{u}(nemployed), \mathbf{n}(ot\ in\ the\ labor\ force)\}$ 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 capture 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 expectation bias of the probability of being in this labor market state.

Idiosyncratic labor productivity

We follow KMP and introduce idiosyncratic labor productivity risk. An individual's labor productivity, denoted by 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

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

where Π_W is the total mass of working-age individuals, P_h is the fraction of individuals with human capital h, $P_h(e)$ is the fraction of 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. Since,

$\sum_z \Pi_h(z) = 1$, the term $\Pi_W \sum_h P_h P_h(e)$ represents aggregate employment.

Factor markets are competitive, which implies 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.[15] 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

$$W^R(a, h) = \max_{a'} \Big\{ u(c) + \nu\beta W^R(a', h) \Big\} \tag{2}$$

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 $\nu\beta$. Agents leave no bequests and, thus, the payoff in case of death is zero. $\delta \in [0, 1]$ is the depreciation rate of physical capital and $r - \delta$ 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.

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:

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

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

subject to

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

With probability $1 - \theta$, working age individuals retire and obtain 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 $\widehat{p}_h(s'|s)$. Crucially, we allow $\widehat{p}_h(s'|s)$, to differ from the actual probability, $p_h(s'|s)$. As before, in the context of the toy model, we refer to the difference between the subjective and the actual probability, $\Delta = \widehat{p}_h(s'|s) - p_h(s'|s)$, as the bias in individuals' expectations. The case $\Delta > 0$ reflects an optimistic bias and $\Delta < 0$ a pessimistic bias, and $\Delta = 0$ corresponds to rational expectations.

Lastly, individual labor productivity, z, can change as captured by $\pi_h(z'|z)$. Furthermore, guided by the findings of our empirical analysis 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.

Labor earnings, y, depend on the individual's labor market state as follows:

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

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.[16] 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 they optimize. Lastly, about the timing of events at birth we assume that a newborn individual first draws its human capital level according to $P(h)$, and conditional on the realization of h, she draws the labor market state according to $P_h(s)$ and the initial labor productivity level according to $\Pi_h(z)$.

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

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:

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

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

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

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 state space of the economy is described by a time-invariant cross-sectional distribution, Φ, of individuals across age $j \in \{W, R\}$, labor market 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 problem stated in Equations (2) and (3) and (c, a') are the optimal policy func-*

tions 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.

4 Quantitative analysis

4.1 Calibration

Next, we calibrate the full model to quarterly U.S. data. All calibrated values are reported in Table 5. 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 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 2014-2019 American Community Survey (ACS) and we restrict the sample to individuals aged between 25-60 years.[17]

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 borrowing limit $\underline{a}$ equal to zero, and the coefficient of relative risk aversion σ to unity, which implies log-utility.

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

[17] ACS data are extracted from the IPUMS data repository; see Ruggles et al. (2021).

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 average income of welfare recipients to average 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. 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. The details of the calculation are in Appendix H.1.

To calibrate $p_h(s'|s)$ and $\widehat{p}_h(s'|s)$ for all three skill groups, we use the values on the actual and the subjective labor market transition probabilities from Section 2, and we adjust these probabilities to fit the quarterly calibration.[18]
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 $w \cdot z \cdot h$ – because 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 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:

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

Here, 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 $\sigma^2_{\eta,h}$. Importantly, we allow the stochastic income process to be different across human capital types. Consequently, the parameters governing the process are indexed by 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 Appendix I for the details of the estimation procedure. Table 5 contains the estimated parameters.

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 calculating $\phi_h = \hat{\phi}_h^{\frac{1}{4}}$ 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 process for z with a discrete Markov chain with 21 states. More concretely, we approximate the persistent component of the process by a discrete

[18]The details of the adjustment procedure are in Appendix H.2.

seven-state Markov chain using the Rouwenhorst method (see Kopecky and Suen (2010)) and we discretize the transitory component using the Tauchen method (Tauchen (1986)) 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
Persistence of labor productivity	ϕ	0.9677	0.9614	0.9661	PSID
Variance of persistent component	σ_{η}^{2}	0.0126	0.0135	0.0147	PSID
Variance of transitory component	σ_{ϵ}^{2}	0.0640	0.0767	0.0847	PSID
Deterministic productivity level	h	1.00	1.29	1.76	PSID

L: Low-skill, M: Medium-skill, H: High-skill.

Table 5: 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 1968-2019 waves of the PSID to estimate a Mincer regression of log hourly earnings on age controls, education dummies and year fixed effects. For consistency, we apply the same sample selection criteria as before and apply our previous definition of education groups. In the regression, we use the low-skilled as reference group. The estimated coefficients on the education dummies imply values of $h_M = 1.29$ and $h_H = 1.76$.

4.2 Results

First, we report the quantitative properties of the equilibrium in terms of individual and aggregate outcomes.[19] Whenever possible, we compare the model outcome with the counterpart in the data to gauge the empirical fit of the model. Our calibration implies an equilibrium

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

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 $\tau = 2.3\%$ and $\tau_{ss} = 19.7\%$. Moreover, we obtain a quarterly capital to output ratio of K/Y=10.2 and an investment to output ratio of I/Y=0.26. These values are in line with those typically applied in the RBC/DSGE literature. For example, Cooley and Prescott (1995) obtain values of K/Y = 9.76 and I/Y=0.252.

In our calibration, we use the empirical labor market transition probabilities, $p_h(s'|s)$. Hence, not surprisingly, the model matches the observed 2014-2019 average employment-to-population ratio as well as the unemployment rate for each education group. Table 6 shows that the wealth distribution implied by the model matches very well the high degree of wealth inequality in the U.S. economy.[20] 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. The implied Gini coefficient of 0.74 is very close to that of the U.S. economy of 0.77. The model's success to account for the observed inequality in wealth is based on its ability to generate a realistic saving behavior across wealth quintiles. As shown by Dynan et al. (2004) there exists a strong positive association between wealth and saving rates in U.S. data. Our model can reproduce this pattern as shown in the column labelled s/y in Table 6.

	Wealth share		s/y
	Data	Model	Model
Q1	-0.9	0.2	4.1
Q2	0.8	1.5	7.3
Q3	4.4	5.1	13.1
Q4	13.0	15.3	20.8
Q5	82.7	77.9	34.3
90-95	13.7	17.5	
95-99	22.8	26.3	
Top 1%	30.9	15.1	
Gini	0.77	0.74	

Wealth share: Share of each quintile, or percentile in total wealth. **s/y**: Average savings rate, in %

Table 6: Wealth inequality – model and data

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

[20] The empirical wealth distribution is taken from Krueger et al. (2016) who compute the distribution from PSID data.

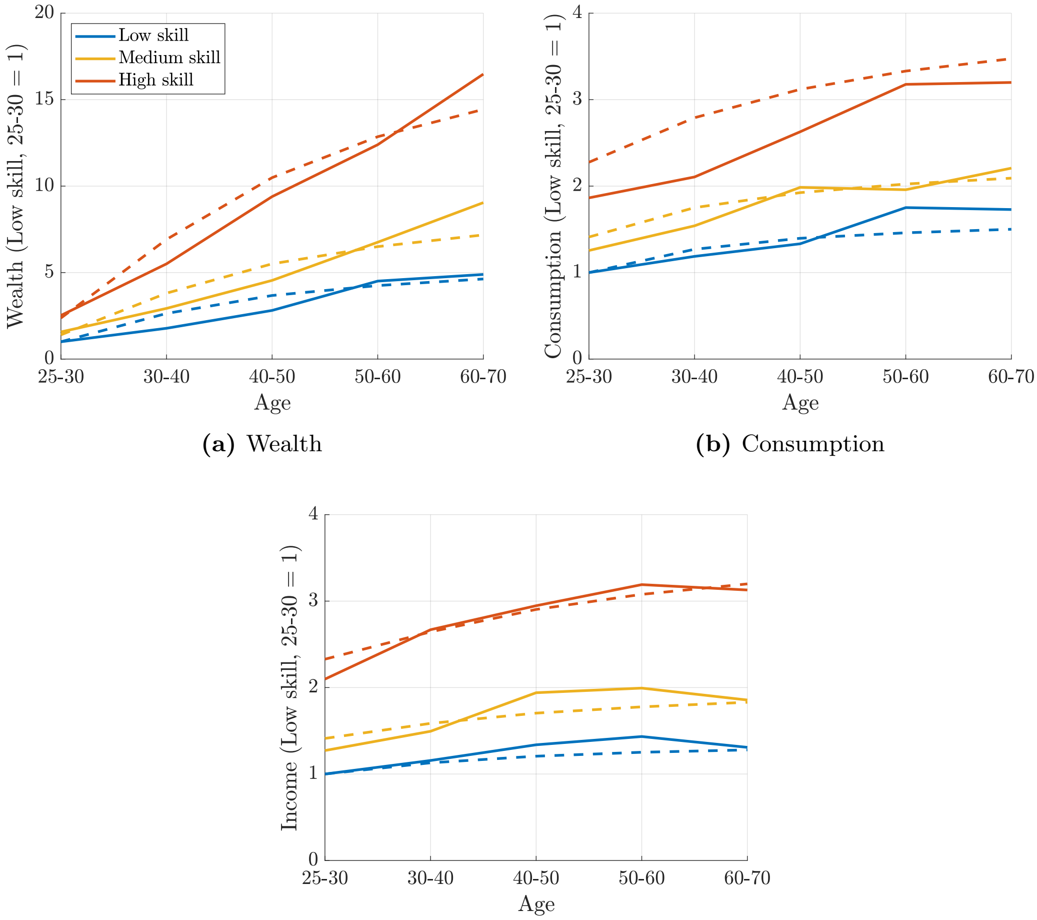
deterministic component of labor productivity h, and the process of the stochastic component of labor productivity z. As a result, the wealth holdings differ, on average, across education groups. Table 7 reports the share of wealth held by each education group. The first row shows that more than half 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 7 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	0.25	0.55
Share in wealth, 1^{st} quintile	0.53	0.25	0.22	0.46	0.29	0.25
Share in wealth, 5^{th} quintile	0.14	0.16	0.69	0.16	0.23	0.61

L: Low-skill, M: Medium-skill, H: High-skill.

Table 7: 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 life cycle in the model consists of two parts: 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 life cycle 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 life cycle 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 life cycle, which is implied by 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 life cycle path of individual income.



(a) Wealth

(b) Consumption

(c) Income

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

According to our calibration 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 8 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 1.80% 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.

	All	L	M	H
$\widehat{E}(y') - E(y')$	1.80	2.54	1.58	1.19
$\widehat{E}(c') - E(c')$	0.69	1.05	0.59	0.39

In percent of actual future income.
L: Low-skill, M: Medium-skill, H: High-skill.

Table 8: Bias in expected income and consumption (model)

It is of interest to explore the extent to which these model predictions are confirmed by data. Unfortunately, the exact empirical counterparts of the model variables are not available in the SCE. Nevertheless, we resort to data outcomes which are arguably closely related in order to gauge the empirical validity of the model predictions - at least qualitatively. Concretely, we use information on individual's expected earnings, household income and consumption expenditure growth from the SCE and compute a 4-months growth rate of these measures. Moreover, we use the information from the SCE on individuals' expected inflation to obtain the growth rate of real variables.[21] The results of these calculations are in Table 9 in the rows labelled "Expected". We report the expected growth rates for the full sample and separately by skill group and labor market status. In order to assess the expectation bias, the table also shows the realized growth rates of the respective variables ("Actual"). We compute these growth rates using panel data from the PSID on individual earnings, household income and expenditures. For consistency, we deflate all nominal variables to express growth in real terms.

	All	L	M	H	E	(U,N)
Earnings (real, 4-months growth, in %)						
Actual	0.67	0.36	0.70	0.89		
Expected	1.39	1.40	1.16	1.51		
Income (real, annual growth, in %)						
Actual	1.15	0.03	1.36	2.05	1.36	-0.81
Expected	1.55	1.30	1.46	1.95	1.80	1.36
Expenditures (real, annual growth, in %)						
Actual	0.05	-0.10	-0.36	0.39	0.13	-0.65
Expected	0.89	0.95	0.85	0.90	0.94	0.90

L: Low-skill, M: Medium-skill, H: High-skill.

Table 9: Bias in expected earnings, income and expenditures (data)

Clearly, there are conceptual differences between the measures of labor income and consumption expenditures in the model and the data-outcomes reported in the table. For example, in the

[21] In Appendix K we describe the calculation of expected and actual growth of individual income, earnings, and expenditures.

model, the expectation of employed individuals concerning future labor income includes their perception of idiosyncratic productivity changes, as well as the effect on earnings of potential intermittent periods of non-employment. In the data, individuals' earnings expectations may be based also on additional factors which are not present in the model, for example their expectations of future changes in hours worked. Moreover, income and expenditures in the model are measured at the individual level whereas in Table 9 these variables are measured at the household level. A discrepancy may arise because in the data the expectation about future household income (or expenditures) may reflect not only how individuals perceive their own future income but also that of other household members. These conceptual differences should be kept in mind in the following comparison.

For all three variables displayed in Table 9 we find a substantial positive expectation bias. That is, individuals' expected growth of earnings, income and consumption expenditures consistently exceeds the realized growth. As such, these findings are in line with the model's prediction of over-optimism concerning future income and consumption expenditures. Moreover, according to the results, the expectation bias differs substantially across skill groups and it is largest for the low-skilled whereas, high-skilled individuals tend to have more accurate expectations. For example, low-skilled individuals expect real income to grow at 1.3% p.a., whereas realized growth is only 0.03% p.a. This difference amounts to a substantial positive expectation bias of 1.27%. Instead for middle- and high-skilled individuals, the difference between expected and actual income growth is substantially smaller and equal to 0.10% (in absolute value). This pattern is consistent with the predictions of our quantitative analysis that low-skilled individuals are strongly over-optimistic about favorable labor market transitions and, hence, they tend to overestimate future income and consumption. In contrast, the high-skilled have more precise labor market expectations and, as a result, they have a smaller expectation bias about income and consumption. Lastly, it is worthwhile to notice that the optimistic bias in the data is particularly pronounced for jobless individuals. This is qualitatively consistent with the model because there unemployed individuals and non-participants overestimate the probability of finding employment or to enter the labor force. Both transitions are associated with an increase in income. Thus, the over-optimism regarding the favorable labor market transition translates into an optimistic bias regarding future income and consumption.

4.3 Eliminating the expectation bias

Given the focus of the paper, we are primarily interested in exploring how the bias in labor market expectations affects individual and macroeconomic outcomes. To address this question, we run the experiment in which we eliminate the bias 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. All other model parameters are as before.

When agents have correct beliefs, they assign higher probabilities to the transition into bad states and they expect good states to realize with a lower probability than in the baseline case.

By labor market state			By skill		
	Baseline	$\widehat{p} = p$		Baseline	$\widehat{p} = p$
E	37.3	40.1	L	28.0	36.1
U	19.3	29.3	M	29.7	33.6
N	-55.5	-45.2	H	33.6	33.6

L: Low-skill, M: Medium-skill, H: High-skill. E: Employed. U: Unemployed. N: Not in labor force.

Table 10: Saving rate with and without expectation bias

As Table 10 shows, over-optimism in the subjective probabilities implies that agents save more and build up more asset holdings than in the baseline case. This is in line with the toy model in Section 3.1. The left-hand panel in Table 10 shows the average 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 when out of the labor force, agents run down their assets less quickly because they expect to remain longer in this state than in the baseline case. The right-hand panel in Table 10 reports the savings rate by skill level. Since low-skilled individuals are relatively more over-optimistic in the baseline case than medium- and high-skilled, they experience the largest change in their expectations and, thus, they increase their savings rates by more than the other skill groups. As a consequence, asset holdings increase for all education groups but more so for the low skilled. This is shown in Table 11 which reports the change in the life cycle 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 49% whereas that of the high-skilled increase by 14%.

Age		[25-30)	[30-40)	[40-50)	[50-60)	At retirement
	L	46%	49%	49%	48%	49%
Δ Assets	M	34%	31%	26%	22%	23%
	H	21%	14%	6%	1%	1%

L: Low-skill, M: Medium-skill, H: High-skill.

Table 11: Change in asset holdings (in %) after elimination of expectation bias

As low-skill individuals are primarily concentrated at the lower end of the wealth distribution (see Table 7), the relatively larger increase of their asset holdings implies that wealth is distributed more equally and aggregate wealth inequality is lower than in the baseline economy.[22] Table 12 shows that the Gini coefficient of 0.67 in the economy without the bias in expectations

[22] More asset accumulation implies a higher equilibrium capital stock in the counterfactual economy. The K/Y ratio increases 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 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 lower interest rate.

is substantially lower than that in the baseline economy. This result has two important implications. First, the finding suggests that a substantial part of the inequality in U.S. wealth holdings is due to individuals having biased labor market expectations. Second, the bias in expectations is a key feature that allows the quantitative model to match the observed inequality in the data. In contrast, the version of the model with rational expectations fails to generate the high wealth concentration at the top.[23]

	Data	Baseline	$\widehat{p} = p$
Q1	-0.9	0.2	0.7
Q2	0.8	1.5	3.2
Q3	4.4	5.1	7.9
Q4	13.0	15.3	18.3
Q5	82.7	77.9	69.9
90-95	13.7	17.5	16.1
95-99	22.8	26.3	22.6
Top 1%	30.9	15.1	12.3
Gini	0.77	0.74	0.67

Table 12: Wealth inequality with and without expectation bias

4.4 Welfare effects of biased expectations

Next, we evaluate the welfare effects of the bias in subjective expectations. First, 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 as well off in the baseline economy than in the counterfactual economy. However, it is important to notice that the welfare calculations are based on the equivalent variation that is computed from the actual expected lifetime consumption. That is, we calculate the expected value E_0 using the actual labor market transition probabilities $p_h(s'|s)$. The compensating variation expressed in this way hence describes the benefit from removing the expectation bias, which is structural in this model, from the viewpoint of the social planner. More concretely, we compute for a new born agent with human capital h the value of ϕ that satisfies

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

The first row in Table 13 shows that $\phi > 0$ for all education groups. That is, agents attain a

[23]To allow for a fair comparison with the rational expectations approach, we also consider the case where we eliminate the expectation bias and recalibrate β (which is the only parameters calibrated internally). We obtain a similar result than before that the model with rational expectations cannot match the empirical wealth concentration.

higher level of welfare in the counterfactual economy. On average, the welfare gain is equal to 4.1%. This result is equivalent to that obtained in the context of the simple model in Section 3.1: without the bias in expectations agents have higher asset holdings and this allows them to sustain a higher path of lifetime consumption. To build up the higher level of assets, agents consume less in the initial phase of their life cycle and this has a negative effect in terms of utility. However, this negative effect is more than offset by the positive effect that results from higher levels of consumption in the later periods of life. As expected, the welfare gain is largest and equal to 5.4% for low-skill individuals who experience the largest adjustment in their savings behavior.

If instead of a social planner, we adopt the viewpoint of the agent in our model, then we should compute the expected value using the subjective labor market probabilities. In other words, we ask the agent in our model to report the value of ϕ that makes her indifferent between the baseline and the counterfactual economy. The results for this case are in the second row of Table 13. Not unexpectedly, we obtain that $\phi < 0$ 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 the transitions into bad states.

	All	ϕ_L	ϕ_M	ϕ_H
E_0	0.041	0.054	0.038	0.028
$\widehat{E}_0$	-0.199	-0.281	-0.186	-0.110

First (second) row: the expected value, E_0 ($\widehat{E}_0$), is computed with the actual (subjective) transition probabilities p_h ($\hat{p}_h$).

Table 13: Consumption equivalent variation

In our model 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 the bias in expectations individuals have higher buffer stock savings, which generally leads to better self-insurance than in the baseline economy. To quantify the degree of individual consumption smoothing, we simulate the equilibrium of the model and we use the simulated data on individual income and consumption to estimate the following model

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

Δc_{it} is the log-difference of individual i's consumption between periods t and $t-1$ and Δy_{it} is the log-difference of the individual's 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 and show the results for b in Table 14.

	Baseline			$\widehat{p} = p$		
	L	M	H	L	M	H
b	0.133	0.095	0.075	0.077	0.071	0.069

Table 14: Consumption smoothing with and without expectation bias

All coefficient estimates reported in the table are statistically significant at the 1% level. The values indicate that both, in the baseline and in the counterfactual economy, less-skilled individuals are more exposed to income fluctuations and thus achieve a lower degree of smooth consumption. In the counterfactual economy without the bias in expectations, all agents hold more assets and, thus, they can 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 individuals.

Generally, according to our results, over-optimism induces agents to hold less private insurance against adverse labor market shocks than in an economy without biased expectations. This suggests that there is potentially room for welfare improving policies which counteract the lack of private insurance. However, arguably simply substituting public insurance for private insurance, for example by providing higher public benefits (for unemployment or retirement) would be ineffective as such measures would just crowd out private insurance. Likely more effective are incentives that improve private insurance via stimulating savings.

4.5 Robustness and extensions

In this section we consider extensions to the baseline economy and modifications of the quantitative analysis in an effort to assess the robustness of our main findings. The results of the robustness checks are succinctly summarized in Table 12. Each column in the table corresponds to a specific robustness exercise. For comparability, we include in the column labelled "Benchmark" the outcomes of the baseline economy. The subcolumns "w" and "w/o" refer to the economy with and without expectation bias, respectively.

In the first step, we use in the quantitative analysis the subjective and the actual transition probabilities which are both computed from the same sample of individuals taken from the SCE. This is different from the baseline case where we compute the actual transition probability matrix from the CPS. As mentioned in Section 2 the SCE and the CPS generate qualitatively very similar patterns for the bias in expectations. There are, however, subtle differences in terms of magnitudes across the two datasets (see Table 19). For example, according to the results obtained from the SCE, job seekers underestimate the probability of dropping out of the labor force by 14.7 percentage points, which is 4 percentage points higher than the number computed from the CPS. Given these differences, we now want to assess whether the choice of the CPS instead of the SCE for computing the actual probabilities matters quantitatively through the lens of our model. Reassuringly, we can observe from the column labelled "*SCE*" in Table 15 that the properties of the equilibrium are very similar to the ones of the baseline case. Importantly, this includes the life cycle profile of individual consumption and asset accumulation and the aggregate wealth distribution. Moreover, when we eliminate the bias in subjective expectations we obtain very similar results than from the same counterfactual exercise conducted in the baseline case. In view of these findings, we conclude that the choice of the CPS, instead of the SCE, as a dataset for calculating the actual transition probabilities has no significant relevance for our main findings.

In the baseline, we the coefficient of relative risk aversion, $\sigma = 1$, implies log-utility. Quite naturally, in the context of our model, agents' attitude towards risk arguably plays an important role. Thus we consider in the quantitative analysis the alternative value of $\sigma = 2$ to test the robustness of the baseline results with respect to the degree of the risk aversion. The results are reported in the column labelled "σ=2" in Table 15. As can be observed from the table a higher value of risk aversion leads to more asset accumulation. This is in line with standard intuition. Interestingly, for a higher value of σ the elimination of the bias in expectation leads to a larger adjustment in individual savings than in the baseline and to a larger reduction in aggregate wealth inequality. Also the implied effect of expectation bias on welfare is higher because due to higher asset holdings, individuals in the counterfactual scenario are able to sustain a higher level of consumption.

Next, we extend the baseline economy to include an endogenous labor supply choice by employed individuals. The purpose of this extension is twofold. First, we want to study whether the observed bias in subjective labor market expectations per se has a sizable quantitative effect on individual labor supply. Second, we want to generally assess whether the baseline results of Section 4.2 are robust to allowing for an endogenous labor choice. We assume additively separable preferences in consumption and leisure. As in the baseline economy, transitions between the labor market states are governed by the Markov process but, unlike before, employed individuals can optimally choose the amount of hours to work. See Appendix L for the full description of the framework and the calibration of the extended model. The results are reported in the column labelled "Labor" in Table 15. The pattern for individual labor supply shown in Panel (d) of the table are in line with basic intuition: over-optimism induces individuals to work less hours because they expect to stay employed for longer, and in case of job loss, they expect to be reemployed faster than it is actually the case. Generally, the low-skilled individuals hold little assets and thus, when the bias in subjective expectations is eliminated, they react more strongly and increase their hours by more than the high skilled. This is particularly the case for younger individuals who hold little wealth. While the increase in hours worked for the low-skilled is, on average, relatively modest and equal to $34.5 - 33.8 = 0.7$ percentage points, it is much more pronounced and equal to 3.7 percentage points for the age group 25-30 years.
Importantly, as can be seen from the table the results obtained for our baseline economy are

	Benchmark		SCE		$\sigma = 2$		Labor		Bias for E, U, or N		
	w	w/o	w	w/o	w	w/o	w	w/o	E	U	N
	Panel (a): Savings rate, in %										
L	28.0	36.1	26.5	37.3	28.9	38.8	29.7	35.6	32.7	34.9	32.6
M	29.7	33.6	30.9	34.3	30.1	36.1	30.3	33.3	32.1	32.4	32.7
H	33.6	33.6	33.6	31.1	34.0	35.9	34.4	34.3	32.9	33.7	34.5
	Panel (b): Assets at retirement entry										
L	23.3	34.6	20.9	35.1	24.5	38.8	9.7	13.3	29.5	32.7	29.4
M	35.9	43.9	40.8	48.2	37.0	49.2	13.7	16.2	40.7	41.5	41.9
H	70.0	70.8	77.8	69.7	71.8	79.1	25.9	26.3	68.2	71.0	73.7
	Panel (c): Consumption at retirement entry										
L	2.2	2.7	2.2	2.7	2.3	2.9	0.9	1.1	2.4	2.6	2.5
M	2.9	3.3	3.1	3.5	3.1	3.6	1.2	1.3	3.2	3.2	3.2
H	4.8	5.1	5.2	5.1	5.0	5.5	1.8	2.0	4.9	5.1	5.1
	Panel (d): Labor supply, in %										
L							33.8	34.5			
M							32.5	33.0			
H							30.6	31.1			
	Panel (e): Gini coefficient										
	0.74	0.67	0.74	0.68	0.71	0.64	0.75	0.68	0.70	0.68	0.69
	Panel (f): Consumption smoothing										
b_{all}	0.10	0.07	0.10	0.09	0.09	0.07	0.06	0.04	0.09	0.08	0.07
	Panel (g): Welfare, in %×100										
ϕ_L	5.37		5.95		12.1		5.29		3.77	4.89	4.35
ϕ_M	3.81		2.94		9.94		3.63		2.48	3.25	3.26
ϕ_H	2.80		1.62		7.74		2.55		1.40	2.35	2.36

SCE: Actual and subjective transition probabilities are computed from SCE; $\sigma = \mathbf{2}$: Coefficient of relative risk aversion is set equal to 2.0; **Labor**: Model economy with endogenous labor supply; **Bias for E, U, or N**: Only employed individuals (E), or unemployed individuals (U), or non-participants (N) have biased expectations
w (w/o): subjective expectations in the model are with (without) bias; $\mathbf{L}, \mathbf{M}, \mathbf{H}$: Low-, middle-, high-skilled.
Panel (a): Average savings rate of working-age individuals. **Panels (b,c)**: Average level of assets and consumption of newly retired individuals. **Panel (d)**: Average labor supply by employed working-age individuals. **Panel (f)**: Coefficient estimate of b from $\Delta c_{it} = a + b \cdot \Delta y_{it} + e_{it}$. **Panel (g)**: Consumption equivalent variation required to make a new-born individual in the economy with the bias as well off as in the economy without the bias.

Table 15: Results of robustness analysis

generally robust to the inclusion of an endogenous labor supply choice. If anything, the welfare effects are slightly lower which can be explained by the higher labor supply in the counterfactual economy that implies larger disutility of working.

Lastly, An important empirical finding of Section 2 was that employed and unemployed individuals, as well as non-participants all have biased expectations about labor market transitions.

Now, we want to understand whether the expectation bias of one of these three groups is quantitatively more important than that of the others for explaining the results. To this end, we re-run the quantitative analysis but allow only a given labor market group to have biased subjective expectations. The two other groups are assumed to have the correct expectations.[24] In the column labelled "Bias for E, U, or N" in Table 15 we report the properties of the implied equilibria when only the employed individuals (column E), or the unemployed individuals (U), or the non-participants (N) have a bias in their expectations. Clearly, the equilibrium values of these hypothetical scenarios lie in between the values of the baseline economy where all individuals have biased expectations (column "Baseline w") and the counterfactual economy where no group has a bias (column "Baseline w/o"). According to the findings in the table none of the three groups stands out particularly prominently but the bias of each groups is quantitatively important.

5 Conclusion

In this paper we use survey data from the U.S. Survey of Consumer Expectations to document household expectations about individual labor market transitions. We find evidence for a substantial optimistic bias in expectations. Households tend to overestimate the probability of experiencing a transition into a favorable labor market state (finding a job, remaining employed) and they underestimate the probability of transiting into a bad state (leaving the labor force). Furthermore, we document the heterogeneity in the bias across different demographic groups and we find a strongly negative relation between education and the degree of over-optimism. Individuals with a high-school degree (or less) tend to be strongly over-optimistic about their labor market prospects. In contrast, college educated individuals – who are still over-optimistic – have substantially more precise beliefs.

We explore the implications of biased labor market expectations on individual choices and aggregate outcomes – first, within a stylized two-period model, and then in the context of a calibrated quantitative life cycle model. We show that the optimistic bias generally discourages individual savings and thereby dampens wealth accumulation. The effect on life cycle consumption allocation is quantitatively sizable and implies a substantial loss in welfare of individuals compared to the allocation under full information. As a key result, we establish that the heterogeneity in the bias leads to pronounced differences in the accumulation of assets across individuals, and is thereby a quantitatively important driver of inequality in wealth.

Our results have important implications for economic policy. Generally, in the presence of positively biased expectations, agents hold less private insurance (in the form of wealth) than under full information, which impedes their ability to smooth consumption over the life cycle

[24] We also consider the alternative approach, where we turn-off the bias for one group but keep it for the other two. This approach leads to very similar conclusions.

and against income fluctuations. Providing (more) public insurance to compensate for the lack in private insurance would not be an adequate policy measure because of crowding out. An arguably more promising approach is to provide incentives to increase private insurance by stimulating savings and wealth accumulation. We consider the analysis of such policies a promising avenue for future research.

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Appendix

A Descriptive statistics and calculation of subjective and actual probabilities

A.1 Subjective probabilities

We use the "Labor Market Module" of the Survey of Consumer Expectations (SCE). This supplement is conducted every four months. The question of interest was first introduced into the survey in July 2014; thus, our dataset covers the period from July 2014 until November 2019, which is the date with the most recent available data (as of writing). We consider the sample of individuals aged 25 to 60 year, who report not to be enrolled in school or college. We define individuals as employed, if they report as their current employment status either "Working full-time", "Working part-time", or "sick or other leave". Unemployed individuals are those who report to be (i) "temporarily laid off", or (ii) "not working, but would like to work" and who state that they have "done something in the last 4 weeks to look for work". Lastly, individuals are defined as non-participants if they report to be "Permanently disabled or unable to work", "Retiree or early retiree", "Student, at school or in training", or "Homemaker". In addition, we classify individuals as non-participants if they report that they would like to work but haven't searched for employment during the last 4 weeks. 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 observations for which we cannot determine the labor market status.

Table 16 reports the number of observations in the sample for different demographic groups and labor market states. The first two columns represent the sub-sample of individuals for which we have information about the individual actual labor transitions. Columns three and four represent the sample of individuals from which we compute the subjective expectations.

A.2 Actual probabilities

The actual transition probabilities are computed from CPS data on individual labor market transitions.The CPS is a monthly, nationally representative survey of around 60,000 households. It is conducted by the Bureau of Labor Statistics and its primary purpose is to evaluate the current state of the U.S. labor market. Every individual in the CPS is interviewed for 4 successive months and, after a break of 8 months, it is interviewed again for 4 months. This structure implies that we can directly observe 1–3 months as well as, 9–15 months labor market transition rates. To stay as close as possible to the SCE, we consider the same sample restrictions and period of time. That is, we consider individuals who are 25-60 years old, who are not enrolled in school or college, and who are not a member of the armed forces. We use waves from July 2014 to November 2019. The last two columns of Table 16 report the characteristics of the CPS-sample for different demographic groups. We compute the average m-month transition rate as the share of individuals who report to be in state s in one month and in state s' m months later. We use the CPS-survey weights to aggregate the individual observations. To obtain the 4-months transition probabilities, we interpolate linearly between the values for the

	SCE				CPS	
	Actual		Subjective			
	Obs	%-share	Obs	%-share	Obs	%-share
Men	3044	49.27	6044	48.52	1821125	49.04
Women	3136	50.73	6348	51.48	1967713	50.96
25–29	750	11.62	1534	12.16	496254	14.56
30–39	1606	25.07	3279	25.48	1041851	27.65
40–49	1716	28.21	3419	28.15	1010370	26.54
50–54	914	15.06	1841	14.96	555329	14.16
55–60	1194	20.04	2320	19.26	685034	17.09
$\leq$HS	649	33.48	1327	33.82	1386627	36.91
C	1926	29.44	3966	29.99	1038170	26.91
$\geq$Bachelor	3605	37.07	7096	36.18	1364041	36.18
White	5046	80.63	10104	80.72	3035009	76.92
Non-white	1134	19.37	2289	19.28	753829	23.08
Single	2085	34.10	4175	33.85	1512200	40.78
Married	4095	65.90	8218	66.15	2276638	59.22
$<$30,000	947	22.91	1905	22.51	753842	20.05
30,000–49,000	946	16.52	1928	17.17	660401	17.57
50,000–99,000	2243	31.74	4461	31.81	1264007	32.84
$\geq$100,000	2021	28.83	4052	28.51	1110588	29.54
E	5256	81.19	10553	81.54	2920734	77.00
U	188	3.38	365	3.37	111747	3.05
N	736	15.43	1475	15.09	756357	19.95

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Obs: Number of observations. %-share: Population shares in sample.

Table 16: Descriptive statistics for subjective and actual transition rates

4-months, and the 9-months transition probabilities.

Both, the SCE and the CPS are designed to be nationally representative. However, Table 16 documents a number of differences in the composition of both samples. For example, the share of married individuals is higher in the SCE. This can be explained by the fact that respondents in the SCE are asked whether they are married or live together, whereas in the CPS the legal status of the respondent matters. Furthermore, individuals in the SCE are, on average, slightly older, better educated, and more likely to be employed than out of the labor force. The difference to the CPS could be due to the survey design of the SCE which requires respondents to have access to internet and to be able to fill out an online-questionnaire. A noteworthy feature of the SCE is that the labor market status is not considered in the construction of the sample weights. Consequently, there are notable differences between the SCE and the CPS in the joint distribution of age and education conditional on the labor market state. See Table 17 for an illustration of this discrepancy between the two datasets. To correct for these compositional differences, we use the CPS sample weights – listed in Table 17 – to re-normalize the weights from the SCE for each education-age-labor cell.

		SCE			CPS		
State		E	U	N	E	U	N
Age	Education						
25–29	≤HS	0.78	2.20	0.41	3.72	8.89	5.15
25–29	C	2.71	2.75	2.65	3.77	4.85	3.13
25–29	≥Bachelor	9.93	3.57	2.85	5.03	3.70	2.58
30–39	≤HS	2.15	4.40	2.85	8.23	14.57	11.25
30–39	C	6.92	6.59	6.45	7.54	8.65	6.10
30–39	≥Bachelor	18.86	13.46	7.12	12.21	6.42	6.23
40–49	≤HS	2.68	3.85	5.83	8.95	11.54	12.00
40–49	C	8.86	11.26	10.04	7.59	6.68	5.98
40–49	≥Bachelor	16.81	11.26	6.45	11.55	6.49	5.53
50–54	≤HS	1.77	1.37	3.05	5.23	6.18	8.88
50–54	C	5.53	8.24	8.01	4.22	3.80	4.00
50–54	≥Bachelor	7.47	6.59	4.14	5.60	3.73	2.95
55–60	≤HS	1.79	3.30	8.48	5.96	6.24	14.22
55–60	C	5.86	9.62	18.59	4.64	4.28	6.95
55–60	≥Bachelor	7.88	11.54	13.09	5.76	3.97	5.05
Total		100	100	100	100	100	100

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019.

Table 17: Sample composition conditional on labor market state

The standard errors for the subjective transition probabilities – reported in Tables 1, 2, 20, 18, 22, 23, 24, 25, 19 – are expressed as so-called linearized Taylor standard error and they are computed with the Stata command ”svy” (with ”pweights”). We use the same method to compute the standard errors for the actual 3-months and 9-month transition probabilities from the CPS. Then, we interpolate linearly between those two to obtain an approximation of the standard error for the 4-months transition probability.

Panel (a): Baseline (CPS-weights)

	Subjective			Actual			Subjective - Actual		
	E	U	N	E	U	N	E	U	N
E	96.1	2.5	1.4	95.2	1.5	3.3	0.9	1.0	-1.9
	(0.17)	(0.11)	(0.10)	(0.03)	(0.02)	(0.02)	(0.17)	(0.11)	(0.11)
U	61.3	32.1	6.6	42.5	32.2	25.3	18.8	-0.1	-18.7
	(2.24)	(1.83)	(1.22)	(0.31)	(0.30)	(0.28)	(2.27)	(1.85)	(1.25)
N	10.7	14.2	75.1	10.7	3.0	86.3	0.0	11.2	-11.2
	(0.80)	(1.04)	(1.40)	(0.08)	(0.04)	(0.08)	(0.80)	(1.04)	(1.41)

Panel (b): Survey-specific weights

	Subjective			Actual			Subjective - Actual		
	E	U	N	E	U	N	E	U	N
E	96.1	2.5	1.4	95.2	1.5	3.3	0.9	1.0	-1.9
	(0.16)	(0.10)	(0.10)	(0.03)	(0.02)	(0.02)	(0.16)	(0.10)	(0.10)
U	59.5	34.1	6.4	42.5	32.2	25.3	17.0	1.9	-18.9
	(2.10)	(1.81)	(1.10)	(0.31)	(0.30)	(0.28)	(2.12)	(1.83)	(1.14)
N	10.0	12.6	77.3	10.7	3.0	86.3	-0.7	9.6	-9.0
	(0.72)	(0.79)	(1.17)	(0.08)	(0.04)	(0.08)	(0.72)	(0.79)	(1.17)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. Panel (a): Observations from the SCE and CPS are both aggregated using sample weights from the CPS. Panel (b): Observations from the SCE (CPS) are aggregated using sample weights from the SCE (CPS).

Table 18: 4-Months subjective and actual transition probabilities (with survey-specific weights)

Actual transition probabilities calculated from CPS

	Subjective			Actual (CPS)			Subjective - Actual		
	E	U	N	E	U	N	E	U	N
E	96.1	2.5	1.4	95.2	1.5	3.3	0.9	1.0	-1.9
	(0.17)	(0.11)	(0.10)	(0.03)	(0.02)	(0.02)	(0.17)	(0.11)	(0.11)
U	61.3	32.1	6.6	42.5	32.2	25.3	18.8	-0.1	-18.7
	(2.24)	(1.83)	(1.22)	(0.31)	(0.30)	(0.28)	(2.27)	(1.85)	(1.25)
N	10.7	14.2	75.1	10.7	3.0	86.3	0.0	11.2	-11.2
	(0.80)	(1.04)	(1.40)	(0.08)	(0.04)	(0.08)	(0.80)	(1.04)	(1.41)

Actual transition probabilities calculated from SCE

	Subjective			Actual (SCE)			Subjective - Actual		
	E	U	N	E	U	N	E	U	N
E	96.1	2.5	1.5	96.7	1.8	1.6	-0.6	0.7	-0.1
	(0.23)	(0.14)	(0.15)	(0.38)	(0.27)	(0.28)	(0.44)	(0.30)	(0.32)
U	57.0	37.3	5.7	38.2	41.4	20.4	18.8	-4.1	-14.7
	(2.93)	(2.60)	(1.06)	(4.46)	(4.67)	(4.37)	(5.34)	(5.35)	(4.50)
N	10.5	12.2	77.3	6.8	2.6	90.6	3.7	9.6	-13.3
	(1.03)	(1.06)	(1.67)	(1.19)	(0.80)	(1.40)	(1.57)	(1.33)	(2.18)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. Panel (a): Baseline case, actual transition probabilities computed from the CPS. Panel (b): Actual transition probabilities computed from the SCE.

Table 19: 4-Months subjective and actual transition probabilities. (actual probabilities computed from CPS and SCE)

B Ability to process probabilities in SCE

The following three questions in the SCE ask the respondents to calculate and process probabilities

- **QNUM3**: *"In the BIG BUCKS LOTTERY, the chances of winning a $10.00 prize are 1%. What is your best guess about how many people would win a $10.00 prize if 1,000 people each buy a single ticket from BIG BUCKS?"*
- **QNUM5**: *"If the chance of getting a disease is 10 percent, how many people out of 1,000 would be expected to get the disease?"*
- **QNUM6**: *"The chance of getting a viral infection is 0.0005. Out of 10,000 people, about how many of them are expected to get infected?"*

The fraction of individuals in our sample who answer correctly is equal to: 83% for QNUM3, 89% for QNUM5, and 78% for QNUM6. We want to explore whether the bias in subjective expectations is significantly different for those individuals who are less able to deal with probabilities. To this end, we first split the sample into two groups: one group is composed of those individuals who gave an incorrect answer to at least one of the three control questions. The second group consists of the remaining 58% of individuals who answered all questions correctly. Then, we calculate the subjective probabilities for each group and compare them to the actual probabilities to assess the bias in expectations. For the actual probabilities we consider two cases. In the first case, we use – as in the baseline – the transition probabilities calculated from the CPS. In the second case, we account for the fact that the two groups of individuals could in principle differ in terms of the actual transition probabilities. Thus, we calculate the actual probabilities from the SCE. Hence, in this second case, the subjective and the actual probabilities for both groups are calculated from the same sample of individuals. Table 20 shows the results.

Actual probabilities calculated from CPS

	Subjective E	Subjective U	Subjective N	Actual (CPS) E	Actual (CPS) U	Actual (CPS) N	Subjective-Actual E	Subjective-Actual U	Subjective-Actual N
Panel (a): Wrong answer to at least one control question									
E	94.8	3.2	2.1	95.2	1.5	3.3	-0.4	1.7	-1.2
	(0.35)	(0.22)	(0.20)	(0.03)	(0.02)	(0.02)	(0.35)	(0.22)	(0.20)
U	60.0	31.5	8.5	42.5	32.2	25.3	17.5	-0.7	-16.8
	(3.35)	(2.64)	(1.88)	(0.31)	(0.30)	(0.28)	(3.36)	(2.66)	(1.90)
N	11.5	16.4	72.1	10.7	3.0	86.3	0.8	13.4	-14.2
	(1.17)	(1.59)	(2.09)	(0.08)	(0.04)	(0.08)	(1.17)	(1.59)	(2.09)
Panel (b): All control questions answered correctly									
E	97.0	2.0	1.0	95.2	1.5	3.3	1.8	0.5	-2.3
	(0.15)	(0.10)	(0.10)	(0.03)	(0.02)	(0.02)	(0.15)	(0.10)	(0.10)
U	63.5	32.9	3.6	42.2	32.8	25.0	21.3	0.1	-21.4
	(2.43)	(2.23)	(0.85)	(0.31)	(0.30)	(0.28)	(2.45)	(2.25)	(0.89)
N	9.4	11.1	79.4	10.6	3.0	86.4	-1.2	8.1	-7.0
	(1.01)	(1.07)	(1.64)	(0.08)	(0.04)	(0.08)	(1.01)	(1.07)	(1.64)

Actual probabilities calculated from SCE

	Subjective E	Subjective U	Subjective N	Actual (SCE) E	Actual (SCE) U	Actual (SCE) N	Subjective-Actual E	Subjective-Actual U	Subjective-Actual N
Panel (c): Wrong answer to at least one control question									
E	94.4	3.3	2.3	95.2	2.6	2.2	-0.8	0.7	0.1
	(0.51)	(0.31)	(0.30)	(0.76)	(0.55)	(0.54)	(0.91)	(0.63)	(0.61)
U	54.4	38.5	7.0	33.7	45.1	21.2	20.7	-6.6	-14.1
	(4.35)	(3.86)	(1.58)	(5.97)	(6.56)	(5.87)	(7.39)	(7.61)	(6.08)
N	11.9	14.6	73.5	7.2	3.7	89.1	4.7	10.9	-15.6
	(1.51)	(1.64)	(2.49)	(1.80)	(1.35)	(2.18)	(2.35)	(2.13)	(3.31)
Panel (d): All control questions answered correctly									
E	97.0	2.0	1.0	97.5	1.3	1.2	-0.5	0.7	-0.2
	(0.20)	(0.11)	(0.15)	(0.40)	(0.27)	(0.31)	(0.45)	(0.29)	(0.34)
U	61.2	35.2	3.6	45.5	35.5	19.0	15.7	-0.3	-15.5
	(3.13)	(2.89)	(0.88)	(6.40)	(5.91)	(6.43)	(7.12)	(6.58)	(6.49)
N	8.6	8.8	82.6	6.2	1.1	92.7	2.4	7.7	-10.1
	(1.32)	(1.06)	(1.94)	(1.40)	(0.40)	(1.46)	(1.92)	(1.14)	(2.42)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. Panel (a): Baseline case. Panel (b): Subjective expectations of individuals who answered wrongly to at least one control question. Panel (c): Subjective expectations of individuals who answered correctly to all control questions.

Table 20: 4-months subjective and actual transition probabilities (control questions)

C Results from the Survey of Economic Expectations

The Survey of Economic Expectations (SEE) was conducted as national telephone survey by the University of Wisconsin Survey Center (UWSC) during the period from 1994-2002. The purpose of the SEE was to elicit probabilistic expectations of significant personal events. For example, respondents were asked to report expectations for crime victimization, health insurance, employment, and income. In addition, in some waves, respondents were asked about returns on mutual-fund investments and about their future Social Security benefits. See Dominitz and Manski (2020) for an introduction into the SEE. We consider the sample of individuals with 25-60 years of age. The survey question of interest to us asks employed respondent to report their expectations of future job loss. The specific survey question reads: *"I would like you to think about your employment prospects over the next 12 months. What do you think is the PERCENT CHANCE that you will lose your job during the next 12 months?"*. For the period 1994-2002, the average value of the subjective (12-months) probability of job loss is 14.6%.

As before, we measure the bias in expectations by comparing the subjective probabilities with the actual probabilities. As in the baseline, we use the CPS to compute the actual transition probabilities (the SEE does not have a panel dimension). According to our interpretation, the survey question in the SEE asks respondents about their expectation of an involuntary layoff and not a voluntary quit. Identifying involuntary layoffs in the CPS is challenging because individuals are not asked about the reason of the job separation. Thus, we use as an indicator whether and for how long individuals move into unemployment after a job separation. The underlying idea is as follows. First, workers who get fired move to unemployment rather than leave the labor force. This allows us to distinguish involuntary job separations from voluntary quits, which are followed by a transition out of the labor force. Second, the duration of the spell of unemployment after a separation likely depends on the reason of separation. Voluntary quits, which are induced by a job-to-job transition likely result in no, or only short spells of unemployment, while involuntary layoffs likely results in longer spells.

We use the Annual Social and Economic Supplement to the CPS (ASEC) for the period from 1994-2003 and we apply the same sample restrictions than in the SEE. The ASEC is conducted every 12 months. This allows us to calculate the actual probability of job loss for the same 12-months horizon, for which we calculate the subjective probability from the SEE. More concretely, we calculate the actual probability as the share of individuals who are employed in period t and who report to have experienced at least x weeks of unemployment in the period t and $t + 12$ months. We consider different values of $x \in \{1, 3, 5, 10\}$ to account for more or less stringent definitions of job loss. For the case of $x = 1$, the sample likely contains also observations of job-to-job transitions, whereas individuals who have experienced $x = 10$ weeks and more in unemployment are likely to be displaced workers. Table 21 reports the results for the subjective probability of job loss and the actual probability for the different cases.

Probability of job loss (in %)										
		94-02	1994	1996	1997	1998	1999	2000	2001	2002
Actual (CPS)	$x = 1$	29.9	38.1	30.6	28.1	26.0	25.2	24.6	33.6	33.5
	$x = 3$	28.7	36.8	29.1	27.0	24.5	24.2	23.3	32.2	32.4
	$x = 5$	24.2	31.6	24.6	22.4	20.4	20.0	19.1	28.2	27.7
	$x = 10$	18.3	24.0	19.2	16.4	15.0	14.8	13.7	21.3	22.2
Subjective (SEE)		14.6	15.1	13.8	13.9	13.7	12.9	12.9	13.5	18.8

Sample: Individuals with age 25-60 years; Period: 1994-2002. Source: SEE and CPS.

Table 21: 12-Months subjective and actual probability of job loss

D Expectation bias for different demographic groups

Education

	Subjective E	Subjective U	Subjective N	Actual E	Actual U	Actual N	Subjective - Actual E	Subjective - Actual U	Subjective - Actual N
				High school or less					
E	95.28	2.87	1.85	93.46	2.16	4.38	1.82	0.71	-2.53
	(0.45)	(0.29)	(0.26)	(0.05)	(0.03)	(0.04)	(0.45)	(0.29)	(0.26)
U	61.35	29.03	9.61	39.63	31.85	28.52	21.72	-2.82	-18.90
	(4.23)	(3.25)	(2.41)	(0.45)	(0.43)	(0.42)	(4.26)	(3.27)	(2.44)
N	10.45	15.26	74.29	9.12	2.82	88.06	1.33	12.44	-13.77
	(1.39)	(1.88)	(2.51)	(0.10)	(0.06)	(0.11)	(1.40)	(1.88)	(2.51)
				Some college					
E	95.91	2.40	1.69	95.07	1.62	3.31	0.85	0.77	-1.62
	(0.25)	(0.15)	(0.18)	(0.05)	(0.03)	(0.04)	(0.26)	(0.15)	(0.19)
U	63.80	32.62	3.59	42.38	32.49	25.13	21.41	0.13	-21.54
	(2.72)	(2.50)	(1.03)	(0.58)	(0.56)	(0.52)	(2.78)	(2.56)	(1.15)
N	10.77	13.82	75.41	11.05	3.38	85.57	-0.28	10.44	-10.16
	(0.90)	(1.01)	(1.47)	(0.15)	(0.09)	(0.17)	(0.92)	(1.01)	(1.48)
				College or higher					
E	96.93	2.22	0.84	96.66	1.00	2.34	0.27	1.22	-1.49
	(0.13)	(0.09)	(0.08)	(0.03)	(0.02)	(0.03)	(0.13)	(0.09)	(0.09)
U	58.46	37.35	4.19	47.90	32.55	19.54	10.56	4.79	-15.35
	(2.60)	(2.45)	(0.87)	(0.63)	(0.60)	(0.50)	(2.67)	(2.52)	(1.01)
N	11.07	12.24	76.68	13.88	2.85	83.27	-2.81	9.39	-6.59
	(1.13)	(1.07)	(1.69)	(0.18)	(0.09)	(0.19)	(1.15)	(1.07)	(1.70)

Gender

	Subjective E	Subjective U	Subjective N	Actual E	Actual U	Actual N	Subjective - Actual E	Subjective - Actual U	Subjective - Actual N
				Male					
E	96.24	2.40	1.37	96.03	1.58	2.39	0.20	0.82	-1.02
	(0.23)	(0.13)	(0.15)	(0.03)	(0.02)	(0.03)	(0.23)	(0.13)	(0.15)
U	64.22	33.10	2.68	44.12	34.57	21.31	20.10	-1.47	-18.63
	(3.44)	(3.28)	(0.78)	(0.44)	(0.42)	(0.36)	(3.47)	(3.31)	(0.86)
N	10.44	13.13	76.43	12.41	3.88	83.71	-1.97	9.26	-7.28
	(1.42)	(1.57)	(2.26)	(0.15)	(0.09)	(0.17)	(1.43)	(1.57)	(2.26)
				Female					
E	96.00	2.56	1.44	94.23	1.51	4.26	1.76	1.05	-2.82
	(0.25)	(0.17)	(0.14)	(0.04)	(0.02)	(0.04)	(0.25)	(0.17)	(0.15)
U	59.50	31.41	9.09	40.73	29.65	29.62	18.77	1.76	-20.53
	(2.90)	(2.15)	(1.83)	(0.44)	(0.42)	(0.41)	(2.93)	(2.19)	(1.88)
N	10.77	14.68	74.55	9.94	2.56	87.50	0.83	12.12	-12.95
	(0.96)	(1.32)	(1.75)	(0.09)	(0.05)	(0.10)	(0.97)	(1.32)	(1.76)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses.

Table 22: 4-Months subjective and actual transition probabilities (by education, gender)

Age

	Subjective E	Subjective U	Subjective N	Actual E	Actual U	Actual N	Subjective - Actual E	Subjective - Actual U	Subjective - Actual N
25-29									
E	95.91	2.63	1.47	93.87	2.06	4.07	2.04	0.56	-2.60
	(0.46)	(0.29)	(0.25)	(0.08)	(0.05)	(0.07)	(0.47)	(0.30)	(0.26)
U	65.73	24.94	9.33	42.93	30.63	26.43	22.80	-5.70	-17.10
	(5.91)	(3.67)	(3.66)	(0.75)	(0.70)	(0.67)	(5.96)	(3.74)	(3.72)
N	11.13	22.72	66.15	16.36	5.20	78.44	-5.23	17.53	-12.29
	(2.38)	(4.99)	(6.10)	(0.27)	(0.17)	(0.30)	(2.40)	(4.99)	(6.10)
30-39									
E	96.33	2.39	1.28	95.23	1.61	3.16	1.10	0.78	-1.88
	(0.29)	(0.19)	(0.18)	(0.05)	(0.03)	(0.04)	(0.29)	(0.20)	(0.18)
U	69.27	24.70	6.03	44.08	31.49	24.43	25.19	-6.79	-18.40
	(3.60)	(2.93)	(2.71)	(0.58)	(0.54)	(0.50)	(3.65)	(2.98)	(2.76)
N	14.77	15.81	69.41	12.95	3.57	83.48	1.82	12.25	-14.07
	(2.34)	(2.44)	(3.50)	(0.17)	(0.09)	(0.19)	(2.34)	(2.44)	(3.51)
40-49									
E	96.35	2.61	1.05	95.80	1.44	2.75	0.54	1.16	-1.71
	(0.32)	(0.20)	(0.16)	(0.05)	(0.03)	(0.04)	(0.32)	(0.20)	(0.17)
U	54.06	36.72	9.22	43.97	31.99	24.04	10.09	4.73	-14.82
	(4.06)	(3.03)	(2.22)	(0.62)	(0.59)	(0.54)	(4.11)	(3.08)	(2.29)
N	12.73	16.21	71.06	11.01	2.87	86.12	1.73	13.34	-15.06
	(1.49)	(1.49)	(2.39)	(0.16)	(0.08)	(0.17)	(1.50)	(1.50)	(2.39)
50-54									
E	96.65	2.14	1.20	95.66	1.33	3.01	0.99	0.81	-1.80
	(0.32)	(0.20)	(0.21)	(0.06)	(0.04)	(0.05)	(0.33)	(0.20)	(0.22)
U	66.04	30.68	3.28	40.29	34.35	25.35	25.75	-3.68	-22.07
	(6.51)	(5.85)	(1.24)	(0.82)	(0.81)	(0.74)	(6.56)	(5.91)	(1.44)
N	7.80	13.82	78.38	8.71	2.41	88.88	-0.91	11.41	-10.51
	(1.41)	(2.44)	(2.89)	(0.17)	(0.09)	(0.19)	(1.42)	(2.44)	(2.90)
55-60									
E	95.04	2.59	2.37	94.72	1.35	3.93	0.32	1.24	-1.56
	(0.56)	(0.35)	(0.40)	(0.07)	(0.03)	(0.06)	(0.56)	(0.35)	(0.40)
U	47.81	49.09	3.09	37.68	34.39	27.93	10.13	14.70	-24.84
	(4.40)	(4.38)	(0.83)	(0.80)	(0.80)	(0.75)	(4.47)	(4.45)	(1.12)
N	6.68	7.70	85.63	6.61	1.70	91.69	0.07	6.00	-6.07
	(1.00)	(1.03)	(1.59)	(0.12)	(0.06)	(0.13)	(1.00)	(1.03)	(1.60)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019.
Source: SCE and CPS. Standard errors in parentheses.

Table 23: 4-Months subjective and actual transition probabilities (by age)

Year

	Subjective			Actual			Subjective - Actual		
	E	U	N	E	U	N	E	U	N
2014									
E	95.35	3.16	1.49	95.19	1.66	3.15	0.16	1.50	-1.66
	(0.46)	(0.33)	(0.24)	(0.08)	(0.05)	(0.06)	(0.47)	(0.33)	(0.25)
U	56.03	38.28	5.69	39.07	35.59	25.34	16.96	2.69	-19.65
	(5.38)	(4.44)	(1.47)	(0.80)	(0.80)	(0.73)	(5.44)	(4.51)	(1.64)
N	6.78	14.03	79.18	10.06	3.51	86.43	-3.27	10.52	-7.24
	(1.45)	(2.54)	(3.28)	(0.21)	(0.13)	(0.25)	(1.47)	(2.54)	(3.29)
2015									
E	95.57	2.54	1.90	95.08	1.63	3.28	0.48	0.90	-1.39
	(0.49)	(0.25)	(0.34)	(0.06)	(0.04)	(0.05)	(0.50)	(0.25)	(0.35)
U	55.97	38.29	5.74	40.47	34.63	24.90	15.50	3.67	-19.16
	(4.77)	(4.15)	(2.13)	(0.66)	(0.65)	(0.59)	(4.81)	(4.20)	(2.21)
N	8.89	15.72	75.38	10.52	3.33	86.15	-1.63	12.39	-10.76
	(2.36)	(2.88)	(3.37)	(0.17)	(0.10)	(0.19)	(2.37)	(2.88)	(3.38)
2016									
E	96.03	2.81	1.16	95.15	1.58	3.27	0.88	1.22	-2.11
	(0.42)	(0.34)	(0.19)	(0.06)	(0.04)	(0.05)	(0.43)	(0.34)	(0.20)
U	65.83	31.86	2.32	41.91	33.24	24.85	23.92	-1.39	-22.53
	(4.96)	(4.82)	(0.94)	(0.69)	(0.67)	(0.61)	(5.01)	(4.86)	(1.11)
N	10.75	13.71	75.54	10.61	3.23	86.16	0.14	10.48	-10.62
	(2.12)	(2.20)	(3.25)	(0.17)	(0.10)	(0.19)	(2.13)	(2.20)	(3.26)
2017									
E	96.41	2.25	1.34	95.25	1.48	3.27	1.16	0.78	-1.93
	(0.40)	(0.22)	(0.29)	(0.06)	(0.03)	(0.05)	(0.40)	(0.22)	(0.30)
U	67.61	27.36	5.04	44.68	30.36	24.96	22.92	-3.00	-19.93
	(4.63)	(3.76)	(2.14)	(0.75)	(0.71)	(0.66)	(4.69)	(3.82)	(2.23)
N	14.31	16.23	69.47	11.08	2.71	86.21	3.22	13.52	-16.74
	(1.75)	(2.78)	(3.70)	(0.18)	(0.09)	(0.20)	(1.75)	(2.78)	(3.71)
2018									
E	96.27	2.39	1.34	95.46	1.31	3.23	0.82	1.08	-1.89
	(0.40)	(0.27)	(0.21)	(0.06)	(0.03)	(0.05)	(0.40)	(0.27)	(0.22)
U	63.83	27.18	9.00	44.25	29.83	25.92	19.58	-2.65	-16.92
	(5.98)	(3.85)	(3.46)	(0.80)	(0.74)	(0.71)	(6.03)	(3.92)	(3.53)
N	10.67	9.59	79.74	10.85	2.49	86.65	-0.19	7.10	-6.91
	(1.98)	(1.22)	(2.66)	(0.18)	(0.09)	(0.20)	(1.99)	(1.23)	(2.67)
2019									
E	96.82	1.94	1.23	94.96	1.68	3.36	1.87	0.26	-2.13
	(0.31)	(0.18)	(0.19)	(0.07)	(0.04)	(0.06)	(0.31)	(0.18)	(0.20)
U	61.88	25.73	12.39	45.12	28.45	26.43	16.76	-2.72	-14.03
	(6.15)	(4.48)	(5.80)	(0.93)	(0.86)	(0.83)	(6.22)	(4.56)	(5.86)
N	11.01	15.81	73.19	10.96	2.67	86.38	0.05	13.14	-13.19
	(1.67)	(2.83)	(3.43)	(0.21)	(0.11)	(0.23)	(1.68)	(2.83)	(3.44)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses.

Table 24: 4-Months subjective and actual transition probabilities (by year)

Household income

	Subjective E	Subjective U	Subjective N	Actual E	Actual U	Actual N	Subjective - Actual E	Subjective - Actual U	Subjective - Actual N
				Less than $30,000					
E	90.84	5.43	3.73	91.22	3.22	5.56	-0.39	2.22	-1.83
	(0.74)	(0.48)	(0.42)	(0.10)	(0.06)	(0.08)	(0.75)	(0.48)	(0.43)
U	62.13	30.72	7.15	37.56	33.95	28.50	24.58	-3.23	-21.35
	(3.23)	(2.65)	(1.86)	(0.48)	(0.47)	(0.44)	(3.27)	(2.69)	(1.92)
N	10.50	17.47	72.03	8.91	3.42	87.66	1.58	14.05	-15.63
	(1.27)	(1.61)	(2.14)	(0.11)	(0.07)	(0.13)	(1.27)	(1.61)	(2.14)
				$30,000 - $49,000					
E	96.73	2.27	1.00	94.02	1.99	3.99	2.71	0.28	-2.99
	(0.29)	(0.22)	(0.16)	(0.07)	(0.04)	(0.06)	(0.30)	(0.23)	(0.17)
U	57.33	36.01	6.66	42.59	32.40	25.01	14.74	3.60	-18.35
	(5.32)	(4.18)	(2.35)	(0.70)	(0.67)	(0.61)	(5.37)	(4.23)	(2.43)
N	13.46	14.64	71.89	10.78	2.87	86.34	2.68	11.77	-14.45
	(2.19)	(2.97)	(3.98)	(0.17)	(0.09)	(0.19)	(2.20)	(2.98)	(3.98)
				$50,000 - $99,000					
E	97.30	1.82	0.88	95.64	1.36	3.00	1.66	0.46	-2.12
	(0.21)	(0.14)	(0.14)	(0.04)	(0.02)	(0.03)	(0.21)	(0.14)	(0.14)
U	64.91	30.09	5.00	47.63	29.49	22.88	17.27	0.60	-17.88
	(3.54)	(2.67)	(2.30)	(0.63)	(0.59)	(0.54)	(3.60)	(2.74)	(2.37)
N	9.76	10.17	80.07	12.54	2.85	84.62	-2.77	7.32	-4.55
	(1.19)	(1.66)	(2.24)	(0.16)	(0.08)	(0.18)	(1.20)	(1.67)	(2.24)
				More than $100,000					
E	97.15	1.82	1.03	96.80	0.88	2.32	0.35	0.94	-1.29
	(0.22)	(0.12)	(0.17)	(0.04)	(0.02)	(0.03)	(0.23)	(0.12)	(0.17)
U	59.50	35.09	5.41	47.64	31.65	20.71	11.86	3.43	-15.30
	(5.39)	(4.91)	(1.89)	(0.84)	(0.79)	(0.69)	(5.45)	(4.97)	(2.01)
N	8.90	7.87	83.23	12.02	2.24	85.74	-3.11	5.63	-2.52
	(1.38)	(1.15)	(2.14)	(0.19)	(0.09)	(0.21)	(1.40)	(1.15)	(2.15)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. Household income: total annual pre-tax income of all household members (older than 15 years), from all sources including employment, business, farm or rent, pensions, financial assets, government transfers and benefits.

Table 25: 4-Months subjective and actual transition probabilities (by income)

E Average marginal effect of education on expectation bias

As described in the main text, the average expectation biases reported in Table 2 might be blurred by compositional differences across education groups. To combat this concern, we compute the average marginal effects of education on the biases for all transitions. Table 26 reports the estimated effects for the transitions out of employment, Table 27 for transitions out of unemployment and Table 28 for transitions out of non-participation. In addition to the results from Table 3, these tables also report the effects for different sets of control variables. To obtain these results we perform the following steps: First, we chose a set of control variables (x) always containing education and the intercept. Second, in CPS, we fit the Probit model

$$P(Y_i = 1|x_i) = \Phi(x_i'\beta)$$

for each 3 and 9 month transition rate. In this step we use the CPS sample weights WTFINL. Third, we use the estimated coefficients of the previous 18 regressions to generate fitted values for 3 and 9 months transition rates for each individual in the SCE. We interpolate linearly to obtain predicted 4 months transition rates for the relevant flows for each individual. Fourth, we subtract the predicted transition rates from the stated subjective expectations to obtain individual-level biases. Fifth, we perform a linear regression analogously to step 2, with weights from the SCE re-weighted to match the CPS targets as described in the baseline exercise. This regression is of the form

$$z_{iY} = x_i'\gamma_Y$$

, where Y is one of the 9 biases (regarding the different flows), and x contains the identical variables as in step 2. Finally, we compute the average marginal effect and the associated standard errors by evaluating the estimated equation at the means of all variables and by using the delta method.

	Mean	Regressions					
		EE					
High school or less	1.82	1.82	1.86	1.87	2.11	2.09	2.35
	(0.45)	(0.45)	(0.45)	(0.45)	(0.45)	(0.44)	(0.42)
Some college	0.85	0.85	0.86	0.83	0.83	0.83	1.04
	(0.26)	(0.25)	(0.25)	(0.25)	(0.25)	(0.25)	(0.25)
College and higher	0.27	0.27	0.26	0.24	0.21	0.16	0.21
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.17)
		EU					
High school or less	0.71	0.71	0.68	0.69	0.69	0.69	0.45
	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)	(0.27)
Some college	0.77	0.77	0.76	0.78	0.77	0.77	0.64
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.14)
College and higher	1.22	1.22	1.23	1.24	1.24	1.27	1.40
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.12)
		EN					
High school or less	-2.53	-2.53	-2.54	-2.56	-2.79	-2.77	-2.79
	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.25)	(0.26)
Some college	-1.62	-1.62	-1.62	-1.61	-1.60	-1.59	-1.68
	(0.19)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)
College and higher	-1.49	-1.49	-1.49	-1.48	-1.46	-1.43	-1.61
	(0.09)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.10)
Additional control variables							
Year			x	x	x	x	x
Age				x	x	x	x
Gender					x	x	x
Race						x	x
Income							x
N	10550	10550	10550	10550	10549	10549	10509
		0.00	0.00	0.01	0.01	0.01	0.02
R^2		0.00	0.00	0.00	0.00	0.01	0.01
		0.00	0.00	0.01	0.02	0.02	0.03

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. Average marginal effect of education on the bias for transitions out of employment. Actual transition rates are estimated in CPS and used to generate fitted values in the SCE sample.

Table 26: Average marginal effect of education on 4-months bias for employed

	Mean	Regressions					
		UE					
High school or less	21.72 (4.26)	21.72 (4.24)	21.96 (4.13)	21.80 (3.83)	22.63 (3.75)	23.18 (3.46)	23.70 (3.42)
Some college	21.41 (2.78)	21.41 (2.72)	20.91 (2.72)	21.06 (2.68)	21.58 (2.74)	21.35 (2.69)	22.32 (2.70)
College and higher	10.56 (2.67)	10.56 (2.60)	11.11 (2.62)	11.62 (2.65)	11.63 (2.65)	10.70 (2.77)	13.00 (2.78)
		UU					
High school or less	-2.82 (3.27)	-2.82 (3.25)	-2.76 (3.08)	-2.49 (2.79)	-1.62 (2.79)	-1.79 (2.74)	-2.43 (2.72)
Some college	0.13 (2.56)	0.13 (2.50)	0.34 (2.57)	0.17 (2.48)	0.58 (2.50)	0.70 (2.47)	0.09 (2.45)
College and higher	4.79 (2.52)	4.79 (2.45)	4.21 (2.46)	3.56 (2.48)	3.98 (2.48)	4.33 (2.53)	4.01 (2.60)
		UN					
High school or less	-18.90 (2.44)	-18.90 (2.41)	-19.20 (2.26)	-19.34 (2.14)	-21.19 (2.05)	-21.57 (1.82)	-21.51 (1.81)
Some college	-21.54 (1.15)	-21.54 (1.03)	-21.24 (1.09)	-21.21 (1.09)	-22.16 (1.14)	-22.06 (1.15)	-22.38 (1.17)
College and higher	-15.35 (1.01)	-15.35 (0.87)	-15.33 (0.90)	-15.17 (0.96)	-15.61 (0.97)	-15.13 (1.01)	-16.99 (0.99)
Additional control variables							
Year			x	x	x	x	x
Age				x	x	x	x
Gender					x	x	x
Race						x	x
Income							x
N	364	364	364	364	364	364	364
		0.02	0.03	0.08	0.08	0.09	0.10
R^2		0.01	0.02	0.09	0.10	0.10	0.11
		0.02	0.05	0.10	0.10	0.13	0.15

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. Average marginal effect of education on the bias for transitions out of unemployment. Actual transition rates are estimated in CPS and used to generate fitted values in the SCE sample.

Table 27: Average marginal effect of education on 4-months bias for unemployed

	Mean	Regressions					
		NE					
High school or less	1.33	1.33	1.25	1.46	1.71	1.67	1.25
	(1.40)	(1.39)	(1.37)	(1.37)	(1.38)	(1.37)	(1.28)
Some college	-0.28	-0.28	-0.29	-0.05	-0.05	-0.04	0.29
	(0.92)	(0.90)	(0.90)	(0.90)	(0.91)	(0.90)	(0.92)
College and higher	-2.81	-2.81	-2.62	-2.58	-2.71	-2.48	-0.81
	(1.15)	(1.13)	(1.14)	(1.15)	(1.15)	(1.15)	(1.28)
		NU					
High school or less	12.44	12.44	12.40	12.64	12.78	12.65	11.90
	(1.88)	(1.88)	(1.83)	(1.77)	(1.77)	(1.64)	(1.63)
Some college	10.44	10.44	10.52	10.54	10.52	10.51	10.11
	(1.01)	(1.01)	(1.01)	(0.99)	(1.00)	(0.97)	(0.97)
College and higher	9.39	9.39	9.48	9.17	9.15	9.66	11.69
	(1.07)	(1.07)	(1.08)	(1.09)	(1.09)	(1.10)	(1.37)
		NN					
High school or less	-13.77	-13.77	-13.65	-14.10	-14.48	-14.31	-13.12
	(2.51)	(2.51)	(2.42)	(2.37)	(2.37)	(2.22)	(2.15)
Some college	-10.16	-10.16	-10.23	-10.49	-10.45	-10.44	-10.40
	(1.48)	(1.47)	(1.47)	(1.45)	(1.46)	(1.40)	(1.43)
College and higher	-6.59	-6.59	-6.86	-6.59	-6.42	-7.18	-10.86
	(1.70)	(1.69)	(1.71)	(1.71)	(1.71)	(1.72)	(1.96)
Additional control variables							
Year			x	x	x	x	x
Age				x	x	x	x
Gender					x	x	x
Race						x	x
Income							x
N	1474	1474	1474	1474	1474	1474	1468
		0.01	0.01	0.02	0.02	0.03	0.04
R^2		0.00	0.01	0.03	0.04	0.10	0.11
		0.01	0.02	0.03	0.03	0.08	0.10

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. Average marginal effect of education on the bias for transitions out of nonparticipation. Actual transition rates are estimated in CPS and used to generate fitted values in the SCE sample.

Table 28: Average marginal effect of education on 4-months bias for out-of-labor force

F Average marginal effect of time in labor market state on expectation bias

This section repeats the exercise outlined in Section E. Therefore, we focus here on the definition of the variables in CPS and SCE. To compute job tenure in CPS, we use the Job Tenure & Occupational Mobility Supplement as well as the monthly datasets. Since the supplement is only available in January every second year, we use January 2014, 2016, and 2018 as the main sample. From the tenure supplement we use the information on the "length of time worked at current job in years" (JTYEARS) as well as the weights (JTSUPPWT). We group tenure into 5 different bins and check if the reported job tenure aligns with the reported employment status of the preceding months. If the respondent reported to be unemployed or out of the labor force in the preceding two months, the tenure is set to the lowest duration bin. For all other bins, if the reported employment status contradicts the tenure information (i.e, if the respondent stated to be not employed during that time) it is discarded. In SCE we rely on the question L1 of the Labor Market Module, which asks about the month and year when the respondent started working at the main/current job. We apply the same grouping and correction using the reported employment status as with the CPS data.

For unemployed individuals, we use the variable DURUNEMP from the regular monthly CPS datasets. This variable indicates the "continuous weeks unemployed". Since this variable is available each month, we use our baseline CPS dataset and the corresponding basic individual weight WTFINL. We convert weeks into months by multiplying with 4.345. Analogously, we consider question Q16 from the SCE core survey asking about the unemployment duration in months. In both cases, we check if the reported unemployment duration is consistent with the reported employment status from the preceding interviews. If not, we discard the observation. Additionally, we group the duration into 4 categories.

For out-of-the-labor force individuals, we use yet another CPS sample. This time we rely on the weights and four variables from the Annual Social and Economic Supplement (ASEC) between 2014 and 2019. This supplement is conduced every March for the outgoing rotation groups, i.e., for respondents in their 4th or 8th interview. We use the variables WNLWNILF ("When last worked for pay (NILF last week)"), WKSWORK1 ("Weeks worked last year"), WKSUNEM1 ("Weeks unemployed last year"), and NWLOOKWK ("Weeks looked for work last year (didn't work)"). We divide individuals into two groups based on non-participation durations being shorter or longer than one year. For 3 month transition rates, we consider the transitions from interview 5 to 8, such that respondents are part of the ASEC sample at the time of the 8th interview. We define the two groups as follows: The duration at the time of the 5th interview is shorter than one year, if the respondent reported to be employed or unemployed in any interview in the preceding 12 months or if the person reported to have worked last year or looked any number of weeks for a job, both at the time of the 8th interview. If these three conditions are all not met, the duration is set to be longer than one year. For the 9 month transition rate, we consider the change in the labor market state from interview 4 to 5. For this case, we define

a duration of less than one year, if the respondent was employed or unemployed in any of the first three interviews, reported to have worked in the previous 12 months (WNLWNILF), or the sum of WKSWORK1, WKSUNEM1, and NWLOOKWK is larger than 8.428. Since the ASEC questions ask about the preceding calendar year, this condition guarantees that the respondent has at least worked or search 1 day in the past 12 months at the time of the interview. Again, we set the duration to "longer than one year", if all these conditions are not met. We use ASECWT to weight the observations. Luckily, we can directly use question L7 of the Labor Market Module asking about the month and year when the respondent started working at the last job. Again, we assign observations to the shorter duration if the implied duration is below one year or if the respondent stated to be employed or unemployed in any of the preceding interviews. If the implied duration is longer than one year and the respondent always reported to be out of the labor force, it is assigned to be in the second group.
Finally, note that we re-weight the SCE weights targeting the age education shares by employment status of the corresponding CPS sample.

G Additional Learning Results

To check the robustness of our learning results, we consider an additional set of questions that allows us to relate the duration of the current individual labor market state to the perceived and actual transitions. This exercise is inspired by (and partly replicates) Table 2 of Mueller et al. (2019). Table 29 focuses on employed workers: in their first interview employed workers are asked about their job tenure (Q37). Every month, and therefore also in their first interview, questions Q13new and Q14new ask about the subjective probability that the respondent looses or voluntarily leaves the main/current job during the next 12 months. To compare theses expectations to actual outcomes, we restrict the sample to only those individuals which are in the sample for all the next 11 months. This allows us to compute the share of workers who are at some point within the next 11 months unemployed, not in the labor force, or work for a different employer. While this does not match the horizon of the expectation question, it provides a reference point. Regarding the perceived job-loss probability as the closed match to the EU transitions of Table 4, we confirm that subjective expectations get more precise as tenure increases.

Turning to unemployed workers, Table 30 reports the average perceived and actual job-finding probability by unemployment duration. This table is directly comparable to Table 2 of Mueller et al. (2019) but features a larger sample size and therefore displays slightly different values. Exploiting that unemployed workers are asked about their unemployment duration (Q18New) as well as their perceived job-finding rate for a 3 month horizon, we mirror the previous exercise: we restrict the sample to all currently unemployed workers reporting the duration and which are in the sample the following three months. This allows us to compute the actual job finding probability by computing the share of workers which report to be employed at least once during these interviews. Except for the long-term unemployed, we find little adjustment in the perceived job-finding rate, while the actual job-finding rate drops substantially. This implies a larger bias for longer unemployment duration and is therefore in line with the results for UE from Table 4.

Finally, we consider workers currently being out of the labor-force. We apply the same procedure as for the unemployed: Question Q19 asks about the non-employment duration and Q21new about the probability of starting to look for a job in the next three months. We restrict the sample analogously to before and compute the share of respondents who are employed or unemployed at least once in the following three interviews. Sadly, the sample size is not sufficiently large to obtain any meaningful results. If any, we find that the actual as well as the perceived probability of starting to search for a job declines in the non-employment duration.

Tenure	Perceived Job-Loss Probability	Perceived Job-Quit Probability	Actual Job-Separation Probability	Sample Size
Full sample	15.25 (0.66)	22.43 (0.82)	13.09 (1.10)	1946
< 1 month	33.85 (9.66)	27.30 (10.03)	49.96 (11.41)	34
$1-6$ months	18.91 (4.26)	24.99 (4.27)	30.61 (7.56)	93
$6-12$ months	18.44 (2.22)	34.37 (3.67)	20.63 (4.30)	116
$1-5$ years	16.37 (0.98)	28.21 (1.49)	12.63 (1.63)	656
> 5 years	13.28 (0.88)	17.19 (0.94)	9.71 (1.41)	1047

Sample: Employed individuals with age 25-60 years, non-school or -college which reported job tenure and are in the sample for all 12 interviews; Period: 01/2013-12/2019. Source: SCE. Standard errors in parentheses. Subjective expectations about job loss and quit in the next 12 months and actual separations within the following 11 months in % by job tenure.

Table 29: Average perceived and actual job separation probabilities by job tenure

Unemployment Duration	Perceived Job-Finding Probability	Actual Job-Finding Probability	Sample Size
Full sample	50.54 (1.95)	38.89 (3.06)	1318
$0-3$ months	64.25 (3.37)	61.34 (4.92)	362
$4-6$ months	54.40 (3.51)	44.79 (6.50)	191
$7-12$ months	56.25 (3.79)	38.52 (5.62)	217
≥ 13 months	38.96 (2.67)	23.68 (3.65)	548

Sample: Unemployed individuals with age 25-60 years, non-school or -college which reported unemployment duration and are in the sample for the following 3 interviews; Period: 01/2013-12/2019. Source: SCE. Standard errors in parentheses. Subjective expectations about job finding in the next 3 months and actual job finding rates within the following 3 months in % by unemployment duration.

Table 30: Average perceived and actual job finding probability by unemployment duration

Non-employment Duration	Perceived Job-Search Probability	Actual Job-Search Probability	Sample Size
Full sample	30.72 (3.44)	29.35 (4.30)	323
$0-3$ months	68.75 (5.03)	41.89 (13.09)	34
$4-6$ months	48.87 (10.40)	45.61 (19.25)	20
$7-12$ months	44.40 (6.85)	51.04 (13.73)	39
≥ 13 months	22.79 (3.17)	23.70 (4.61)	230

Sample: Out-of-labor force individuals with age 25-60 years, non-school or -college which reported non-employment duration and are in the sample for the following 3 interviews; Period: 01/2013-12/2019. Source: SCE. Standard errors in parentheses. Subjective expectations about starting to search for a job in the next 3 months and actual job search rates within the following 3 months in % by non-employment duration.

Table 31: Average perceived and actual job finding probability by unemployment duration

Age	EE	EU	EN	UE	UU	UN	NE	NU	NN
25-29	2.25	0.45	-2.70	24.04	-5.21	-18.94	-4.87	16.51	-11.55
	(0.44)	(0.28)	(0.24)	(4.62)	(3.43)	(2.67)	(1.91)	(4.36)	(4.78)
30-39	1.21	0.79	-1.99	27.14	-6.77	-20.35	2.13	12.93	-15.06
	(0.28)	(0.19)	(0.17)	(3.72)	(2.94)	(2.30)	(2.54)	(2.24)	(3.41)
40-49	0.72	1.13	-1.85	13.14	3.97	-17.30	1.99	12.83	-14.81
	(0.31)	(0.20)	(0.16)	(3.53)	(2.69)	(1.91)	(1.48)	(1.47)	(2.34)
50-54	1.25	0.74	-1.98	26.24	-2.37	-23.92	-0.18	11.45	-11.27
	(0.33)	(0.20)	(0.21)	(6.14)	(5.41)	(1.36)	(1.48)	(2.38)	(2.90)
55-60	0.72	1.10	-1.81	11.20	14.53	-25.99	0.48	6.55	-7.01
	(0.53)	(0.33)	(0.39)	(4.46)	(4.39)	(1.42)	(1.06)	(1.08)	(1.65)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. E: employment, U: unemployment, N: not in the labor force. XY: Transition from current labor market state X to future state Y. Example: "UE" represents the bias in unemployed workers' expectation to be employed in four months.

Table 32: Conditional expectation bias, by age

H Input to calibration

H.1 CPS Welfare Benefits

We use data from the 2015–2019 waves of the March supplement of the CPS. In this supplement, individuals report their income from various sources during the preceding 12 months. Aggregate welfare income is computed as total annual income reported by welfare recipients. It includes 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. The sample of welfare recipients includes non-retired individuals (aged 25-60 years) who did not work nor searched for a job in the preceding 12 months and who did not received wage, or business income, or income related to retirement. Aggregate annual labor earnings are computed from the sample of individuals who worked full-time, and were formally employed for the whole year, and who did not received any income from self-employment or retirement. We define total labor earnings as wage and salary income. Average welfare (labor) income is computed as aggregate welfare (labor) income divided by the number of welfare recipients (workers).

H.2 Conversion from 4-months to 3-months frequency

We implement the following approach to convert the 4-months subjective transition probabilities into 3-months transition probabilities. Let by p_h^{4m} denote the 4-months transition probability matrix for skill group h. The matrix has dimension 3×3. We assume that labor market transitions follow a Markov Chain with monthly transition probabilities. Thus, the four months transition matrix, p_h^{4m}, is identical to the (unobserved) 1-month transition matrix multiplied four times with itself. Let by p_h^{1m} denote the 1-month transition matrix. We obtain p_h^{1m} by solving the following 9-dimensional system of equations:

$$vec\left[\left(p_h^{1m}\right)^4 - p_h^{4m}\right] = 0$$

where *"vec"* vectorizes the 3x3 array inside the square brackets. Lastly, we obtain the 3-months transition probabilities as $(p_h^{1m})^3$. The values of the 3-months subjective and actual transition probabilities are given by:

$$\widehat{p}_{h_L} = \begin{pmatrix} 96.16 & 2.43 & 1.41 \\ 52.83 & 38.71 & 8.46 \\ 6.58 & 13.69 & 79.73 \end{pmatrix} \quad \widehat{p}_{h_M} = \begin{pmatrix} 96.69 & 2.01 & 1.31 \\ 54.29 & 42.70 & 3.00 \\ 6.98 & 12.20 & 80.83 \end{pmatrix} \quad \widehat{p}_{h_H} = \begin{pmatrix} 97.51 & 1.85 & 0.64 \\ 49.03 & 47.40 & 3.57 \\ 7.52 & 10.63 & 81.86 \end{pmatrix}$$

$$p_{h_L} = \begin{pmatrix} 93.83 & 2.02 & 4.15 \\ 37.58 & 33.66 & 28.76 \\ 8.39 & 2.82 & 88.79 \end{pmatrix} \quad p_{h_M} = \begin{pmatrix} 95.40 & 1.50 & 3.10 \\ 39.91 & 34.60 & 25.50 \\ 10.01 & 3.42 & 86.57 \end{pmatrix} \quad p_{h_H} = \begin{pmatrix} 96.89 & 0.90 & 2.21 \\ 45.40 & 35.14 & 19.46 \\ 12.78 & 2.82 & 84.40 \end{pmatrix}$$

H.3 PSID: Estimation of labor productivity process

To estimate the parameters of the stochastic labor productivity process, we use annual data from PSID for the time period 1968-1997. Our sample consists of household heads. We only include individuals who belong to the SRC-sample. We drop observations where (i) the household head is younger than 25 years and older than 60 years, (ii) there is no information on education, (ii) annual hours are below 520 hours (10h/week), or above 5110 hours (14h/day), (iv) reported labor earnings are zero, (v) the household head is female, (vi) hourly labor earnings are below $\underline{w}$ and above $\bar{w}$, where $\underline{w}$ =2 and $\bar{w}$ =400 in 1993, as in Guvenen (2009), and in the other years $\underline{w}$ and $\bar{w}$ grow at the same rate as nominal wages according to the Federal Reserve Bank of St. Louis' FRED database. Lastly, we deflate nominal hourly wages by using the series of the "Consumer Price Index for All Urban Consumers" from the FRED database. Hourly wages are computed as annual labor income (variable code "V3863" in year 1975) divided by annual hours worked ("V3823").

In the first step of the estimation procedure, we compute residual wages by filtering out the effect of observables. More concretely, we regress *log*-hourly wages on age dummies (25-30, 30-40, 40-50, 50-60), education dummies (high school or less, some college, college degree and higher), interaction of age and education dummies and year dummies. Then, we recover the wage residuals - which are equal to labor productivity in the model. The underlying empirical process for residual wages is assumed to be

$$\begin{aligned} w_t &= z_t + \epsilon_t \\ & \quad z_t = \rho z_{t-1} + \eta_t \end{aligned}$$

where $E(\epsilon_t) = E(\eta_t) = 0$, $Var(\epsilon_t) = \sigma^2_\epsilon$, $Var(\eta_t) = \sigma^2_\eta$. The identification of the parameters $\rho, \sigma^2_\epsilon, \sigma^2_\eta$ is based on the variance-(auto)covariance matrix of the wage process. The variance is defined as $\sigma_{tt} \equiv Cov(w_t, w_t) = E(w_t w_t) - E(w_t)E(w_t)$ and it is equal to

$$\sigma_{tt} = \frac{1}{1-\rho^2}\sigma^2_\eta + \sigma^2_\epsilon$$

The auto-covariance is defined as $\sigma_{t,t+j} \equiv Cov(w_t, w_{t+j}) = E(w_t w_{t+j}) - E(w_t)E(w_{t+j})$, where $j > 0$, and it is given by:

$$\sigma_{t,t+j} = \frac{\rho^j}{1-\rho^2}\sigma^2_\eta$$

$\sigma_{t,t}$ and $\sigma_{t,t+j}$ are independent of time t (because of time-invariant variances), thus, we write:

$$\sigma = \frac{1}{1-\rho^2}\sigma^2_\eta + \sigma^2_\epsilon \qquad \sigma_j = \frac{\rho^j}{1-\rho^2}\sigma^2_\eta$$

where j denotes the lag. The parameters of the stochastic process: $\rho, \sigma^2_\epsilon, \sigma^2_\eta$ are identified as follows: Take σ_j and σ_{j+1}, where $j > 0$. The ratio between the two is given by

$$\frac{\sigma_{j+1}}{\sigma_j} = \frac{\frac{\rho^{j+1}}{1-\rho^2}\sigma_\eta^2}{\frac{\rho^j}{1-\rho^2}\sigma_\eta^2} = \frac{\rho^{j+1}}{\rho^j} = \rho$$

and it identifies ρ. Given ρ, any σ_j:

$$\sigma_j = \frac{\rho^j}{1-\rho^2}\sigma_\eta^2$$

identifies σ_η^2. Lastly, given ρ and σ_η^2, the expression for σ:

$$\sigma = \frac{1}{1-\rho^2}\sigma_\eta^2 + \sigma_\epsilon^2$$

identifies σ_ϵ^2. The estimation strategy is based on minimizing the distance between the (empirical) covariance matrix of income residuals and the (theoretical) counterpart implied by the income process. Let $\hat{y}_{it}$ denote the income residual, obtained from regressing the period-t wage of individual i on observables (see above). Define $\hat{y}_i \equiv \left(\hat{y}_{i1}, \hat{y}_{i2}, ..., \hat{y}_{iT}\right)$ and compute

$$\hat{y}_i'\hat{y}_i = \begin{pmatrix} \hat{y}_{i1}^2 & \hat{y}_{i1}\hat{y}_{i2} & ... & \hat{y}_{i1}\hat{y}_{iT} \\ \hat{y}_{i2}\hat{y}_{i1} & \hat{y}_{i2}^2 & ... & \hat{y}_{i2}\hat{y}_{iT} \\ ... & ... & ... & \\ \hat{y}_{iT}\hat{y}_{i1} & \hat{y}_{iT}\hat{y}_{i2} & ... & \hat{y}_{iT}^2 \end{pmatrix}$$

Build average across individuals (taking into account that the panel may be unbalanced; that is, the number of individuals that contribute to the moments may differ across moments)

$$\hat{y}'\hat{y} = \begin{pmatrix} \hat{y}_1^2 & \hat{y}_1\hat{y}_2 & ... & \hat{y}_1\hat{y}_T \\ \hat{y}_2\hat{y}_1 & \hat{y}_2^2 & ... & \hat{y}_2\hat{y}_T \\ ... & ... & ... & \\ \hat{y}_T\hat{y}_1 & \hat{y}_T\hat{y}_2 & ... & \hat{y}_T^2 \end{pmatrix} = \begin{pmatrix} \sum_i \hat{y}_{i1}^2/N_{11} & \sum_i \hat{y}_{i1}\hat{y}_{i2}/N_{12} & ... & \sum_i \hat{y}_{i1}\hat{y}_{iT}/N_{1T} \\ \sum_i \hat{y}_{i2}\hat{y}_{i1}/N_{21} & \sum_i \hat{y}_{i2}^2/N_{22} & ... & \sum_i \hat{y}_{i2}\hat{y}_{iT}/N_{2T} \\ ... & ... & ... & \\ \sum_i \hat{y}_{iT}\hat{y}_{i1}/N_{T1} & \sum_i \hat{y}_{iT}\hat{y}_{i2}/N_{T2} & ... & \sum_i \hat{y}_{iT}^2/N_{TT} \end{pmatrix}$$

where $\hat{y}_\tau^2$ is the sample variance of period τ; $\hat{y}_\tau\hat{y}_{\tau+s}$ is the s-order sample covariance between observations of periods τ and $\tau+s$; and $N_{\tau\tau+s}$ is the number of individuals contributing to the estimation of the s-order covariance between periods τ and $\tau+s$.

Since, $\hat{y}_\tau\hat{y}_{\tau'} = \hat{y}_{\tau'}\hat{y}_\tau$, the effective number of moments is less than $T \times T$ but equal to the $\frac{T(T+1)}{2}$ elements of the upper-triangular matrix. Hence, the data moments m^d are given by the following vector of dimension $\frac{T(T+1)}{2} \times 1$

$$m^d = \begin{pmatrix} \hat{y}_1^2 \\ \hat{y}_1\hat{y}_2 \\ ... \\ \hat{y}_1\hat{y}_T \\ \hat{y}_2^2 \\ \hat{y}_2\hat{y}_3 \\ ... \\ \hat{y}_2\hat{y}_T \\ ... \\ \hat{y}_T^2 \end{pmatrix}$$

Let $\Theta = \left(\rho, \sigma_\eta^2, \sigma_\epsilon^2\right)$ be the parameters of the stochastic process and $m(\Theta)$ be the vector of model moments:

$$m(\Theta) = \begin{pmatrix} \sigma^2 \\ \sigma_1 \\ ... \\ \sigma_{T-1} \\ \sigma^2 \\ \sigma_1 \\ ... \\ \sigma_{T-1} \\ ... \\ \sigma^2 \end{pmatrix}$$

The model parameters, Θ are recovered by minimizing a squared distance function $\Big[m(\Theta) - m^d\Big]' \times\ W\ \times \Big[m(\Theta) - m^d\Big]$ where W is the weighting matrix with dimension $\frac{T(T+1)}{2} \times \frac{T(T+1)}{2}$. We follow Kaplan (2012) and use as weighting matrix a diagonal matrix with elements $n^{-1/2}$, where n is the number of observations used to construct the sample moment. In the estimation, we use a maximum number of 25 lags. We estimate the parameters of the stochastic process for the entire sample and separately for each skill group. Standard errors are obtain by bootstrap with 250 replications. The estimated parameters are reported in Table 33.

	ρ	σ^2_η	σ^2_ϵ
All	0.9653 (0.0040)	0.0138 (0.0018)	0.0739 (0.0041)
Low skill	0.9677 (0.0043)	0.0126 (0.0019)	0.0640 (0.0048)
Middle skill	0.9614 (0.0073)	0.0135 (0.0029)	0.0767 (0.0066)
High skill	0.9661 (0.0084)	0.0147 (0.0040)	0.0847 (0.0088)

Table 33: Estimated coefficients

I PSID: Lifecycle path of income, consumption and wealth

We follow KMP and construct the measures of income, consumption and wealth as follows. Pre-tax income 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%.

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)

All observations are aggregated using sample weights.

J Computational algorithm

The numerical computation of the general equilibrium involves the following sequence of steps:

1. Specify a grid for individual assets, a.
2. Discretize the idiosyncratic productivity shocks as described below.
3. Use the labor market transition probabilities to compute the total labor supply in efficiency units and the mass of agents in each labor market state. Use these quantities to compute the budget-balancing tax rates.

4. Guess the equilibrium interest rate r.
5. Use the first-order conditions of the firm to compute the equilibrium wage w.
6. Use the endogenous grid point method to solve the optimization problem of working-age individuals and retirees.
7. Use the eigenvector method to solve for the cross-sectional distribution Φ.
8. Compute the implied equilibrium aggregate capital stock and the interest rate r'.
9. If r' is sufficiently close to r, stop. Otherwise, update r using the bisection algorithm and continue with step 5.

We use the Tauchen-method with three grid points and the Rouwenhorst-method with 7 grid points to discretize, respectively, the transitory component and the permanent component of the stochastic productivity process. 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. In the endogenous grid point method, we use a grid for assets with 301 exponentially spaced points to cover the range $[0, 10, 000]$. When computing the stationary distribution Φ, we interpolate the policy functions linearly on a finer grid of 1,000 points. In the last step of the iteration, we 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.

K Growth of earnings, household income and household consumption

K.1 Actual growth

For the calculations, we use observations on household heads (aged 25-60 years) taken from the SRC sample of the 2013-2019 waves of the PSID. Our measure of consumption expenditures comprises of the annual household expenditures on all expenditure categories reported in the PSID. This includes expenditures on food (variable code in the 2019-wave: ER77513), housing (ER77520), transportation (ER77539), education (ER77562), child care (ER77564), health care (ER77566), clothing (ER77581), vacation trips (ER77583), and recreation (ER77585). Total household income (ER77448) includes the annual taxable income, transfers and social security receipts of all family members. Earnings (ER77315) consist of the head's annual wage and salary income, as well as bonuses, overtime payments, tips, commissions and other labor income (but not farm income and the labor portion of business income). We follow Guvenen (2009) and exclude observations of earnings for which the reported annual hours (ER77255) are below 520 (10h/week), or above 5110 (14h/day), and the implied hourly wage is below half of the federal minimum wage rate of 7.25$.

All nominal variables are deflated by the CPI (CPIAUCSL) taken from the FRED database of the Federal Reserve Bank of St. Louis. Household income and expenditures are converted into per-capita terms by applying a standard equivalence scale. According to this scale, the total effective number of household members is given by the weighted sum of adult household members and children, where the first household member aged 14 years and over is assigned a weight of 1, each additional household member aged 14 years and over is assigned a weight 0.5, and each child who is under 14 years old is assigned a weight of 0.3. As before, we define low-skilled individuals as those with 0-12 grades of school completed, middle-skilled as those with at least a high-shool degree but no college degree, and high-skilled as those with at least a college degree.

To correct for outliers, we trim the data by excluding observations for which the level (growth rate) of earnings, income, or expenditures is above the 90^{th} (95^{th}) percentile and below the 10^{th} (5^{th}) percentile of the distribution of the respective variable. Moreover, we exclude observations with negative reported income, earnings or expenditures. We convert the 2-year growth rate of earnings, income and expenditures into annual growth (for income and expenditures) using the formula $(1+g_{2y})^{\frac{1}{2}}-1$, and into 4-months growth (for earnings) using $(1+g_{2y})^{\frac{1}{6}}-1$.

Lastly, we use sample weights to compute average growth rates.

K.2 Expected growth

To compute the expected growth rates in the SCE, we use our baseline sample but do not impose that the expectations regarding labor market transitions are reported. This allows us to also include the answer to the monthly core survey at times where the Labor Market Module is not available. Additionally, in the baseline sample we rely on the Labor Market Module to assign non-employed workers to U or N. Hence, we collapse all non-employed workers (but with non-missing information) into a single group. Every month, individuals are asked about their expected annual earnings growth conditional that they keep their current job (Q23v2part2), about their expected annual growth of household income (Q25v2part2), and about their expected annual growth of household consumption expenditure (Q26v2part2). To compute the expected 4 months growth rate regarding annual earnings, we use question L3 (OO2e2) asking currently employed respondents about their current (expected annual earnings in 4 months). Contrary to the questions before, the latter two are part of the Labor Market Module.
All these nominal growth rates are deflated using the reported inflation expectations (Q9): To do so, we follow Armantier et al. (2016) and use the provided estimated mean based on the assigned probabilities to each bin of potential future inflation rates. For the 4 month growth rate, we compute the implied 4 month expected inflation rate using the previous formula. Then, we compute the median inflation rate for each considered group and for each variable separately to account for the fact that not all respondents see or answer all questions.
We further restrict the sample and exclude employed respondents earnings less than 15,080 USD. Additionally, to be able to deflate all expected growth rates, we require individuals to state their expected inflation rate. Finally, to account for outliers, we consider only those observations which fall into the 10^{th} (5^{th}) and 90^{th} (95^{th}) percentile for each variable, conditional on having answered it.
Lastly, we then estimate the means and medians of the deflated variables. In this step, as well

as when we compute the median inflation expectation, we use sample weights. Similar to our baseline procedure, we re-weight the weights supplied by the SCE to match the share of each age and education cell in each labor market state of the corresponding sample from which the actual growth rates are computed.

L Model with endogenous labor supply

In Section 4.5, we extend the baseline model by introducing an endogenous labor supply choice of employed individuals. This modification affects the following parts of the baseline model.

Preferences and assets:
We assume that each period individuals have one unit of disposable time, which they can allocate to working and leisure. Preferences are described by a CRRA utility function over current consumption and leisure:

$$u(c, \bar{l} - l) = \frac{c^{1-\sigma_c} - 1}{1 - \sigma_c} + A\frac{(1-l)^{1-\sigma_l} - 1}{1 - \sigma_l}$$

where $1 - l$ is leisure, and $\sigma_c, \sigma_l > 0$, $A > 0$.

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, labor l, and next period's assets to solve:

$$\begin{aligned} W_W(a, h, s, z) = \max\nolimits_{c,a',l} u(c, 1 - l) \quad & + \beta\theta \textstyle\sum_{s'} \sum_{z'} \widehat{p}_h(s'|s)\pi_h(z'|z) W_W(a', h, s', z') \\ & + \beta(1 - \theta) W_R(a', h) \end{aligned} \tag{6}$$

subject to

$$c + a' = (1 + r - \delta)a + y(a, h, s, z) \qquad \text{and} \qquad a' \geq \underline{a} \qquad \text{and} \qquad 0 \leq l \leq 1$$

Let by $l(a, h, z)$ denote the optimal policy function for labor. Earnings, y, depend on the individual's labor market state:

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

When employed, a worker with human capital h and productivity z earns $z \cdot h \cdot w \cdot l$, where w is the wage per efficiency unit of labor and $z \cdot h \cdot l$ is the worker's labor supply in efficiency units. Unemployed workers receive benefits $b(h, z)$, which are a constant fraction ρ^u of the individual's potential wage earnings, that is given by $b(h, z) = \rho^u z \cdot h \cdot w \cdot \bar{l}$, where $\bar{l}(h, z)$ is the average labor supply by individuals with (h, z). 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. Average labor earnings are computed as $\frac{\int wzhl(a,h,z)1_{s=e}d\Phi(a,h,z,s)}{\int 1_{s=e}d\Phi(a,h,z,s)}$, which is the wage per efficiency unit of labor times the efficiency labor per employed worker.

Budget constraints of the government and the social security program:

$$\tau \int wzhl(a,h,z)1_{s=e} + b(h,z)1_{s=u}d\Phi(a,h,z,s) = \underbrace{\int b(h,z)1_{s=u}d\Phi(a,h,z,s)}_{\text{Unemployment benefits}} + \underbrace{\int T1_{s=n}d\Phi(a,h,z,s)}_{\text{Welfare benefits}} \tag{7}$$

$$\int b_{ss}(h)1_{s=r}d\Phi(a,h,z,s) = \tau_{ss}\int wzhl(a,h,z)1_{s=e}d\Phi(a,h,z,s) \tag{8}$$

In the calibration, we follow Marcet et al. (2007) and set $A = 2$ and $\sigma_c = \sigma_l = 1$. All other parameters and stochastic processes are as in the baseline model.