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

Almut Balleer, Georg Duernecker, Susanne Forstner, Johannes Goensch

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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 low-skilled individuals tend to be strongly over-optimistic about their labor market prospects, whereas high-skilled individuals have rather precise beliefs. In the context of a quantitative heterogeneous agents life cycle model we show that the optimistic bias has a 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, consumption, asset accumulation, wealth inequality
JEL classification: E21, D84

Balleer: RWI Essen and TU Dortmund, IIES at Stockholm University and CEPR, RWI Hohenzollernstrasse 1-3, D-45128 Essen, Germany, almut.balleer@rwi-essen.de. Duernecker: Goethe-University Frankfurt and CEPR, Theodor-W.-Adorno-Platz 4, D-60323 Frankfurt/Main, Germany, duernecker@econ.uni-frankfurt.de. Forstner: Institute for Advanced Studies Vienna, Josefstaedter Strasse 39, A-1080 Vienna, Austria, forstner@ihs.ac.at. Goensch: Goethe-University Frankfurt, Theodor-W.-Adorno-Platz 4, D-60323 Frankfurt/Main, Germany, Goensch@econ.uni-frankfurt.de. For helpful comments and suggestions, we would like to thank the seminar audiences at the Universities of Amsterdam, Frankfurt, Mannheim, Rotterdam, Vienna, and Zurich, Bocconi University, the Banco Central de Chile, Tinbergen Institute Rotterdam, VfS Makroausschuss, and conference participants at the 28^{th} CEPR European Summer Symposium in International Macroeconomics, Barcelona Summer Forum, BdF-CEPR-PSE Paris Conference on the Macroeconomics of Expectations, 2021-Workshop on Dynamic Macroeconomics in Vigo, 2021-Annual Meeting of the Austrian Economic Association, 11^{th} ifo Conference on Macroeconomics and Survey Data, and 2021-ifo-Research Days. All errors are our own. Susanne Forstner gratefully acknowledges financial support by the Austrian National Bank under grant no. 18302. This manuscript was previously circulated under the title "Actual and Perceived Labor Market Risk".

"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 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 (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. 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 18.2 percentage points, while employed workers underestimate the likelihood of leaving the labor force by 2.0 percentage points. Individuals who are not in the labor force overestimate the probability of entering the labor force by 10.1 percentage points.

Furthermore, we document the heterogeneity in the optimistic bias in expectations across different demographic groups. In this context, we find a strongly negative relation between education and the size of the bias. Accordingly, the optimistic bias is largest for low-skilled individuals (those with a high-school degree or less), while high-skilled individuals (those with a college degree and higher) – who are still over-optimistic – have more accurate beliefs. For example, low-skilled job seekers overestimate the probability to be employed in fours months by 22.8 percentage points, whereas this number is 8.9 percentage points for high-skilled job seekers. Similarly, low-skilled inactive individuals overestimate the likelihood of entering the labor force by 12.4 percentage points, where it is 6.3 percentage points for the high-skilled.

In the second part of the paper, we perform a quantitative analysis. The purpose of this analysis is to explore the extent to which the empirically observed bias in workers' labor market expectations affects individuals' life cycle consumption, income and asset holdings and thereby shapes the aggregate wealth distribution.[1] As part of this analysis, we also 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 allocation and it discourages individual asset accumulation. This effect is quantitatively sizable, particularly for the low-skilled who are highly optimistic. For example, the savings rate for these individuals is, on average, 8.6 percentage points lower in the economy with biased expectations. In contrast, for high-skilled individuals the savings rate is essentially the same as in the economy with full-information. As a result, the low-skilled accumulate less wealth over the life cycle and enter retirement with approximately 50% 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 5.3% (in terms of equivalent variation in expected lifetime consumption). Naturally, these effects are less pronounced for high-skilled individuals who have a much smaller optimistic bias than the low-skilled. As a result, the heterogeneity in the optimistic bias across individuals has a substantial effect on

[1] In related work, we use a general equilibrium labor market matching models to study the implications of biased labor market expectations on individual and aggregate labor market outcomes (see Balleer et al. 2023a and Balleer et al. 2023b).

wealth inequality. Without the bias in expectations the wealth Gini coefficient would be 8 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.[2]

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 segmenta-

[2]We present a complementary theoretical analysis in Appendix M where we use a tractable two-period model to explore in closed form how the bias in expectations distorts the inter-temporal consumption decision of households. 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.

tion and lower wages for low-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 comprehensive representation 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 life-cycle 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.[3] 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 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 distri-

[3]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 loses relevance.

bution 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 and expectation biases in the U.S. In Sections 3 and 4 we set up and calibrate the model and perform the quantitative analysis. Section 5 discusses extension of the model and robustness of the results. Section 6 concludes. An Appendix contains additional material.

2 Facts about biased labor market expectations

2.1 Aggregate

We use data from the Federal Reserve Bank of New York's *Survey of Consumer Expectations* to measure the subjective probabilities of U.S. individuals to experience a change in their labor market state.[4] 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. The SCE has several components. We make use of the data provided by the 07/2014-07/2021 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 unemployment and non-participation used in the literature, active job search is the key characteristic that distinguishes unemployed individuals from non-participants. Hence, we classify [4] as 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 assigned to the three states adds up to 1. We exclude the few observations (34) for which the sum is not equal to one.

[4] See SCE (2023) for details on data availability and background materials, and Armantier et al. (2016) for an introduction to the SCE.

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 15,332 observations. See Table 18 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.[5] The results are in Table 1 in the columns labelled "Subjective".[6] 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 2.6%, and not in the labor force with 1.3% in four months after the interview.

We now compare these subjective transition probabilities to the actual probabilities. To this end, we use observations from the Current Population Survey (CPS) on individual labor market transitions to compute the implied actual labor market transition probabilities.[7] 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. For details, see Appendix A.2. 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 also use the sample weights provided by the CPS to aggregate the individual observations from the SCE. The details of these calculations can be found in Appendix A.2.[8]

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

[6]Throughout the paper, the transition probabilities may not add to one due to rounding.

[7]The CPS data were extracted from the IPUMS data repository; see Flood et al. (2023).

[8]In Table 20 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.

	Subjective			Actual			Subjective - Actual		
	E	U	N	E	U	N	E	U	N
E	96.1 (0.15)	2.6 (0.10)	1.3 (0.09)	94.9 (0.03)	1.8 (0.02)	3.3 (0.02)	1.2 (0.15)	0.7 (0.10)	-2.0 (0.09)
U	61.9 (1.96)	31.2 (1.56)	6.9 (1.02)	43.7 (0.27)	32.5 (0.26)	23.8 (0.24)	18.2 (1.98)	-1.4 (1.58)	-16.9 (1.05)
N	10.9 (0.77)	13.6 (0.86)	75.5 (1.28)	11.1 (0.07)	3.4 (0.04)	85.6 (0.08)	-0.2 (0.77)	10.3 (0.86)	-10.1 (1.28)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-07/2021. Source: SCE and CPS. Standard errors in parentheses. E: Employment, U: Unemployment, N: Not in the labor force. Example: "row U/column E" 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 these 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 94.9%. The standard errors around the two probabilities are very small; hence, the difference of 1.2 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 2.0 percentage points. Also this difference is highly significant. Another important finding is that unemployed individuals vastly over-estimate their re-employment prospects.[9] Job seekers expect to be employed in four months with a probability of 61.9%. This is 18.2 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 16.9 percentage points. Furthermore, our results show that individuals who are not in the labor force, generally over-estimate the probability of entering the labor force by 10.1 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, $E \to N$, $U \to N$) and they overestimate the likelihood of moving to good states ($U \to E$, $N \to \neg N$).[10]

[9] 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.

[10] The only exception from this pattern is the transition from employment to unemployment, about which workers are pessimistic. In Balleer et al. (2023a) we use data from the German Socio-Economic Panel to document

At this point it is important to notice that 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.[11] Table 21 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.

Moreover, an often-raised concern regarding survey data on subjective expectations is related to the reliability of such data due to respondents' limited ability to deal with probabilities. If the reported probabilities were systematically biased in a certain way, e.g. if subjective probabilities are generally over-estimated, then it would still be valid to compare the relative bias across groups. However, 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.[12] 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 22. 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 more precise labor market expectations.

2.2 Heterogeneity

In the next step, we explore whether there is noteworthy heterogeneity in the population in terms of the sign and the magnitude of the expectation bias. 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 24 - 29 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. We explore this relationship in more detail in Section

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.

[11] Notice that the number of transitions observed in the SCE (7,748) is also significantly below the number of observations from which we compute the subjective transition probabilities (15,332). This is because the calculation of the actual probabilities requires us to observe individuals in two consecutive waves of the labor market module.

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

2.3 below.

	EE	EU	EN	UE	UU	UN	NE	NU	NN
All	1.2 (0.15)	0.7 (0.10)	-2.0 (0.09)	18.2 (1.98)	-1.4 (1.58)	-16.9 (1.05)	-0.2 (0.77)	10.3 (0.86)	-10.1 (1.28)
High school or less	2.4 (0.41)	0.3 (0.26)	-2.7 (0.23)	22.8 (3.86)	-4.9 (2.92)	-17.9 (2.06)	1.6 (1.38)	10.8 (1.55)	-12.4 (2.32)
Some college	1.2 (0.23)	0.6 (0.14)	-1.8 (0.16)	19.6 (2.46)	-1.0 (2.19)	-18.6 (1.25)	-1.1 (0.83)	10.2 (0.98)	-9.2 (1.41)
College and higher	0.4 (0.12)	1.2 (0.08)	-1.5 (0.07)	8.9 (2.13)	4.3 (2.02)	-13.2 (1.03)	-2.9 (1.04)	9.2 (0.99)	-6.3 (1.55)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-07/2021. 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 (by education)

Interestingly, we find a systematic relationship between education and the level of workers' over-optimism. More concretely, we consider three education groups: low-skilled, medium-skilled and high-skilled individuals. We define low-skilled individuals as those who have a high school degree or less education, medium-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 actual and subjective probabilities are shown in Table 24 in Appendix D. The results in Table 2 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.[13] This pattern applies to almost every labor market transition and it is particularly pronounced for unemployed workers and non-participants. For example, low-skilled job seekers overestimate the probability to be employed in four months by 22.8 percentage points. In contrast, for the high-skilled the difference between the subjective and the actual reemployment probability is less than half of that and equal to 8.9 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 this probability by 12.4 percentage points, whereas the number for the high-skilled is only half of that and equal to 6.3 percentage points. Lastly, among employed workers, the low-skilled overestimate the probability of being employed four months later by 2.4 percentage points, whereas for the high-skilled the subjective reemployment

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

probability is only slightly above the actual probability.[14]

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 multinomial probit model, $P(Y_i|x_i) = \Phi(x_i'\beta)$, in order to predict the probability of individual i to experience a given labor market transition, Y_i, conditional on the observable variables x_i and the individual's current labor market state. The set of possible transitions depends on individual i's labor market state and includes $Y_i \in \{EE, EU, EN\}$ for employed individuals, $Y_i \in \{UE, UU, UN\}$ for unemployed individuals, $Y_i \in \{NE, NU, NN\}$ for individuals out of the labor force. The characteristics we include in x_i control for age, gender, race, income, and year fixed effects. Moreover, we include in x_i a set of dummy variables to represent the education groups as above. We use data from the CPS on actual individual labor market transitions to estimate β. The estimates are used to compute for each individual observed in the SCE the predicted actual labor market transition probabilities. That is, we evaluate the estimated model using the individual's characteristics and obtain the predicted transition probabilities as the fitted values from the probit model. Next, we subtract the predicted actual probabilities from the individual's reported subjective transition probabilities 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_i. The vector x_i contains the same control variables as in the multinominal probit estimation. In Table 3 we report the implied expectation bias by education group. The bias is computed as the marginal effect for each education group.

	EE	EU	EN	UE	UU	UN	NE	NU	NN
High school or less	3.0	0.1	-3.1	24.8	-5.0	-19.9	1.8	10.3	-12.1
	(0.36)	(0.23)	(0.20)	(3.32)	(2.51)	(1.65)	(1.31)	(1.46)	(2.15)
Some college	1.4	0.5	-1.9	20.2	-0.5	-19.7	-0.6	10.0	-9.5
	(0.22)	(0.14)	(0.15)	(2.28)	(2.01)	(1.17)	(0.81)	(0.95)	(1.36)
College and higher	0.1	1.4	-1.5	10.8	4.5	-15.3	-2.0	10.9	-8.9
	(0.14)	(0.10)	(0.08)	(2.22)	(2.03)	(1.04)	(1.21)	(1.20)	(1.80)

Table 3: Conditional expectation bias (by education)

Clearly, the results would be identical to those in Table 2 when we included as control variables only the education dummies. Hence, any difference to the previous results are due to compositional differences in age, race, income or year across education groups. Most importantly, the expectation biases we obtain after controlling for worker observables are very similar to those in

[14] 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 27 for the results.

Table 2. These results continue to hold when we also control for job tenure, as well as duration of unemployment and non-participation, as shown in Table 32.[15]

2.3 Learning

In the next step, 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 38% of individuals in our sample more than two interviews in which respondents report their transition expectations. Given the limited information available, we refrain from analyzing the updating of expectations at the individual level. An alternative approach to address learning involves utilizing 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, unemployment duration or age. A decline in the (absolute value of the) bias with increasing duration or age may be interpreted as learning. We proceed along these lines and, as a first step, we 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 duration.

E_{dur}	EE	EU	EN	U_{dur}	UE	UU	UN	N_{dur}	NE	NU	NN
< 3 m	7.6	-2.1	-5.5	0-3 m	15.3	-0.4	-14.9	0-12 m	-12.3	11.4	0.8
	(0.86)	(0.61)	(0.48)		(3.07)	(2.05)	(2.03)		(2.44)	(2.01)	(3.21)
3-6 m	5.9	-2.0	-4.0	4-6 m	23.0	-2.7	-20.3	>12 m	6.1	12.5	-18.6
	(0.62)	(0.57)	(0.18)		(5.77)	(3.86)	(3.09)		(1.42)	(1.55)	(2.19)
6-12 m	4.0	-1.9	-2.1	7-12 m	38.2	-13.3	-24.9				
	(0.49)	(0.29)	(0.34)		(4.86)	(4.36)	(1.79)				
1-5 y	3.2	-1.3	-1.9	>12 m	34.3	-1.7	-32.6				
	(0.18)	(0.11)	(0.11)		(5.21)	(3.29)	(2.77)				
>5 y	1.1	0.0	-1.1								
	(0.14)	(0.09)	(0.09)								

E_{dur}: Tenure in 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), to become unemployed (EU), or to leave the labor force (EN)

[15] This extension of the model to include labor market durations addresses the concern that the education gradient in the bias may be due to the fact that workers with different skill levels have systematically different durations in the labor market, and that duration itself affects the magnitude of the bias. For instance, suppose that low-skilled workers are more likely to experience long-term unemployment. Then, even if the bias was unrelated to skill, the duration dependence would imply a higher measured bias among low-skilled workers.

decreases (in absolute value) with job tenure. As is well known, job stability increases with job tenure. Hence, the EE outcome becomes more likely, and EU and EN transitions are less likely to occur as tenure increases. This pattern suggests that workers' subjective job separation hazard is relatively stable over time, or at least it decreases at a slower rate than the actual separation hazard. For unemployed workers, the expectation bias to become employed (UE) and to leave the labor force (UN) increase with unemployment duration. 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 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 findings for individuals who are out of the labor force are generally ambiguous. While the beliefs about finding employment (NE) become more precise with increasing duration of non-employment, the beliefs about remaining out of the labor force (NN) become less accurate.

In the next step, we consider individuals' age as the relevant time dimension and we explore whether individuals form more accurate beliefs as they grow older. For this purpose, we consider different age groups and compute the conditional expectation bias for each skill/age cell. Concretely, we use two age groups with ages 25-39 and 40-60 years.[16] The results are shown in Table 5.

	Age	EE	EU	EN	UE	UU	UN	NE	NU	NN
High school or less	25-39	4.2	-0.3	-3.8	33.7	-12.7	-21.0	1.7	11.9	-13.5
		(0.54)	(0.38)	(0.28)	(4.40)	(3.18)	(2.42)	(3.04)	(3.15)	(4.54)
	40-60	2.1	0.4	-2.5	15.9	2.7	-18.6	1.9	9.4	-11.3
		(0.50)	(0.31)	(0.30)	(5.06)	(4.02)	(2.29)	(1.39)	(1.37)	(2.29)
Some college	25-39	1.5	0.3	-1.8	22.8	-3.5	-19.4	-2.3	10.7	-8.3
		(0.40)	(0.24)	(0.28)	(3.56)	(3.00)	(2.11)	(1.43)	(1.73)	(2.49)
	40-60	1.4	0.6	-2.0	17.8	2.4	-20.2	0.3	9.6	-9.9
		(0.24)	(0.16)	(0.16)	(2.89)	(2.75)	(0.95)	(1.01)	(1.14)	(1.62)
College and higher	25-39	0.2	1.4	-1.6	13.7	-0.1	-13.6	-3.8	8.6	-4.8
		(0.18)	(0.13)	(0.11)	(3.22)	(2.90)	(1.78)	(2.07)	(1.58)	(2.73)
	40-60	0.1	1.4	-1.5	7.5	9.4	-16.9	-0.7	12.7	-12.1
		(0.18)	(0.13)	(0.11)	(3.04)	(2.76)	(1.09)	(1.30)	(1.54)	(2.19)

Table 5: Conditional expectation bias (by education and age)

Three important observations emerge from this analysis. First, the expectation bias tends to decrease (in absolute value) with age across different skill groups, with the most significant decline observed among low-skilled workers. For instance, the job finding bias of low-skilled unemployed workers decreases substantially from 33.7% to 15.9%. For high-skilled workers, the UE-bias declines from 13.7% to 7.5%. As a caveat, it should be noted that the standard errors for this and several other transitions are sizable and often render the decline in the bias insignificant,

[16] The limited sample size of our data does not allow to consider finer age groups which would lead to large standard errors for many transitions. Table 33 presents results for alternative age groups (25-34 and 35-60 years as well as 25-44 and 45-60 years).

in particular for individuals not in the labor force. The second important observation is that although the optimistic bias diminishes with age, it does not vanish or even turn into a significant pessimistic bias.[17] Lastly, the table shows that the negative relationship between the bias and skill continues to hold for each age group. Accordingly, young high-skilled workers hold more accurate beliefs than young low-skilled workers, and the same applies to prime age workers. Taken together, our results suggest that individuals form increasingly precise beliefs over the life cycle and that this learning occurs in a similar way across skill groups. Looking ahead, in the baseline version of our quantitative model studied in Section 5, we consider differences in the bias across skill groups. In a robustness check, we also incorporate differences in the bias across age groups.

2.4 Bias and macroeconomic conditions

In the next step of the empirical analysis, we address the important question of whether the optimistic bias of U.S.-workers is a stable phenomenon or whether it varies over time and changes with macroeconomic conditions. As a first check, we calculate the actual and the subjective transition probabilities for each year separately from 2014-2021. The results in Tables 27-28 show that the transition probabilities vary somewhat year-by-year but there is no systematic trend in the bias over time.

In the next step, we explore the extent to which the expectation bias changes with macroeconomic conditions. To this end, we consider the following two approaches. In the first approach, we split the sample into three time periods and we calculate the expectation bias separately for each period. The first time period covers the long expansionary period from the start of the SCE in 07/2014 until 11/2019. This is the last wave with questions about labor market expectations before the onset of the recession. The second time period covers the recession which according to the NBER lasted from 02-04/2020. The SCE has only one survey wave (03/2020) conducted during this period. The third time period covers the subsequent recovery, starting with the wave in 07/2020 and ending with the most recent survey wave.

The top part of Table 6 reveals the interesting finding that the optimistic bias was present in all three periods, but was particularly pronounced during the recession period. For example, during the recession, employed workers overestimated the probability of remaining employed by almost 6 percentage points, while in non-recession periods the bias was about 1 percentage point. We also find that workers underestimated the likelihood of unemployment during the recession. The opposite was the case during non-recessionary periods. Moreover, our results suggest that unemployed workers were more optimistic about finding a job during the recession than before and after. Note that in this analysis we account for potential composition effects by controlling for worker observables. The standard errors for the recession period are often large, but our results suggest that workers are even more optimistic in bad times. The same holds

[17] We document a similar finding in Balleer et al. (2023a) using German survey data: The estimated bias in individual job finding and job separation expectations decreases with age, but to a relatively small extent.

when we consider each skill group separately – see Table 34 in the Appendix.

	EE	EU	EN	UE	UU	UN	NE	NU	NN
Expansion	1.2	0.9	-2.0	20.0	0.1	-20.1	0.6	11.3	-11.9
	(0.16)	(0.10)	(0.09)	(2.02)	(1.66)	(1.01)	(0.83)	(0.95)	(1.31)
Recession	5.9	-2.6	-3.3	34.5	-16.3	-18.2	-0.4	7.4	-7.0
	(0.57)	(0.46)	(0.26)	(8.64)	(5.34)	(5.00)	(2.47)	(2.82)	(4.77)
Recovery	0.9	1.2	-2.0	20.1	-2.7	-17.4	-0.4	7.6	-7.2
	(0.33)	(0.19)	(0.23)	(3.72)	(2.98)	(1.56)	(1.88)	(1.91)	(3.28)
$u_t > \bar{u}$	1.0	1.1	-2.2	15.6	0.9	-16.5	1.0	13.7	-14.6
	(0.25)	(0.17)	(0.14)	(3.11)	(2.47)	(1.54)	(1.52)	(1.57)	(2.37)
$u_t < \bar{u}$	1.6	0.4	-2.1	22.9	-2.5	-20.5	0.0	8.2	-8.1
	(0.22)	(0.13)	(0.14)	(2.45)	(1.97)	(1.13)	(0.96)	(1.05)	(1.57)

Expansion: Survey waves 07/2014–11/2019, Recession: Wave 03/2020, Recovery: Waves 07/2020–07/2021, $u_t < \bar{u}$ ($u_t > \bar{u}$): Sample of respondents who reside in a state where the unemployment rate is below (above) trend.

Table 6: Conditional expectation bias and macroeconomic conditions

In the second approach, we exploit variation in state unemployment rates to investigate whether the bias varies at the state level with macroeconomic conditions. Specifically, we compute for each U.S. state and each month during the sample period, the deviation of the state's monthly unemployment rate from the state's trend unemployment rate.[18] Then we divide all state–month observations into two groups based on whether a state's unemployment rate in a given month is above trend or below trend. Lastly, we calculate the expectation bias for respondents who, in the month of the interview, reside in an "above-trend" state, denoted by $u_t > \bar{u}$, or in a "below-trend" state, denoted by $u_t < \bar{u}$. The results are in the lower part of Table 6. In Table 35 we show the results for each skill group. Unlike before, we find no evidence of a larger optimistic bias during downturns. If anything, the bias tends to be smaller during periods of high unemployment. But, as before, the standard errors around the estimates are often sizable. As a modification of this approach, we also use the variation in unemployment rates across states and compute the expectation bias in states with monthly unemployment rates above (below) the U.S. aggregate unemployment rate. Also for this approach, there is no clear-cut pattern, as shown in Table 36. If anything, employed workers tend to have a larger optimistic bias in states with above-average unemployment rates.

Taken together, the evidence based on this analysis is inconclusive whether workers' expectation bias varies with the business cycle. However, this topic should be considered for future research. Be that as it may, our findings suggest that the optimistic bias is a robust phenomenon that persists even during periods of adverse macroeconomic conditions.[19]

[18] We obtain the trend unemployment rate by HP-filtering the state's monthly unemployment rate.

[19] In a separate exercise, we use data on labor market expectations from the U.S. Survey of Economic Expec-

2.5 Bunching and rounding of responses

As is well documented in studies measuring expectations, individuals tend to round their responses. The SCE is no exception. For instance, of the 45,984 responses in our sample to the three labor market questions analyzed above, 24,657 responses indicated a value of "0% probability", 1,125 responses indicated a value of "10% probability", 740 responses indicated a value of "50% probability", 864 responses indicated a value of "90% probability", and 10,628 responses indicated a value of "100% probability". Our analysis in the previous sections takes the survey responses at face value and thereby ignores the possibility that responses may bunch at certain values or be rounded to the nearest decile. While this approach aligns with the common practice in much of survey analysis, we want to evaluate the potential importance of bunching or rounding for our empirical results. Clearly, we have no knowledge of the extent or reasons for rounding performed by the respondents in the SCE. Hence, in order to shed some light on this issue we implement two approaches based on strategies outlined in Manski and Molinari (2010) and Dominitz and Manski (2011). The first strategy uses responses to other probability questions in the survey to identify and remove respondents who habitually answer 0, 50, or 100. The second strategy defines and uses intervals of probabilities rather than exact responses. We describe both approaches in detail in Section E in the Appendix. The results are presented in Tables 30 and 31. We find in this robustness check that rounding has only a minor effect on the results and, most importantly, it does not affect the two main aspects of our empirical findings that U.S. workers have an optimistic bias and that the bias is more pronounced for low-skilled workers.

3 Model

Motivated by our empirical findings, we perform in the next step a quantitative analysis to explore the effects of workers' optimistic bias on life cycle asset accumulation and consumption, as well as individuals' welfare and aggregate wealth inequality.[20] 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, Mitman, and Perri (2016); henceforth KMP. In a nutshell, the agents in our model economy have a life cycle including working-age and retirement, they have different levels of human capital, and face 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

tations (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 and Dominitz and Manski (2004) for a description of the SEE data. Consistent with the findings of this section, we find that workers' over-optimism has been present consistently throughout during the entire time period covered by the SEE.

[20] We conduct a complementary theoretical analysis in Appendix M where we use a stylized two-period model to study theoretically how the expectation bias shapes individuals' choices and thereby affects aggregate wealth inequality. The main insights of this theoretical analysis can be useful for interpreting of the results of the quantitative analysis.

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 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.[21] The invariant distribution of workers with human capital h across labor market states s 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 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 flexible 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. In a robustness check in Section 5.7 consider a two-state version of the labor market.

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. $\pi(z'|z)$ is the conditional probability that a worker will transit from state z today to state z' tomorrow. The invariant distribution of z is $\Pi(z)$. Given the focus of our analysis, it is useful to incorporate productivity risk into the model. This will enable us to obtain a more realistic representation of individual labor income processes and thereby capture the actual degree of labor market risk that individuals face. Moreover, as is well known, 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 $\alpha \in [0, 1]$ and K denotes aggregate capital. N denotes total labor in efficiency units which is computed as the sum over all employed workers' effective labor supply

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

[21] In the model, all transitions out of employment are unexpected and involuntary. However, in the data, some job separations may be expected and voluntary. Clearly, the type of separation may be relevant for the agents' precautionary savings motive. Using data from the SCE's core survey and the CPS we find suggestive evidence that involuntary separations are much more likely to occur ($\sim$ 6 times more likely) than voluntary separations. At the same time, workers expect the opposite, i.e. that if a separation does occur, it is more likely to be voluntary. We believe that this discrepancy may actually reinforce workers' optimistic bias. However, because of data availability we do not pursue this avenue further.

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 $\Pi(z)$ is the fraction of workers with idiosyncratic productivity z. Factor markets are competitive

Optimization problem of a retired individual

Retirees earn income on their asset holdings and they collect social security payments. 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.

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

where w is the wage per efficiency unit of labor. Pension benefits depend on the individual's human capital but not on her actual history of past contributions.[22] 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

$$W^R(a, h) = \max_{a'} \left\{ u(c) + \nu \beta W^R(a', h) \right\} \tag{1}$$

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 do not leave any bequests; therefore, the value 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:

$$\begin{aligned} W^W(a, h, s, z) = \max_{a'} \Big\{ u(c) \quad & + \beta\theta \sum_{s'} \sum_{z'} \widehat{p}_h(s'|s) \pi(z'|z) W^W(a', h, s', z') \\ & + \beta(1 - \theta) W^R(a', h) \Big\} \end{aligned} \tag{2}$$

subject to

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

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

With probability $1-\theta$, working age individuals retire and obtain the value of retirement, W^R, next period. An individual's labor productivity, z, can change between periods as captured by the transition probability $\pi(z'|z)$. Moreover, an individual expects to move from its current labor market state s to state s' with the subjective probability $\widehat{p}_h(s'|s)$. Crucially, we allow $\widehat{p}_h(s'|s)$, to differ from the actual probability, $p_h(s'|s)$. 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. We assume $\widehat{p}_h$ to be constant over time. In an extension of the baseline model studied in Section 5.5, we allow individuals' labor market expectations to vary with age.

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.[23] 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.

The timing of events at birth is as follows. A newborn individual first draws its initial labor productivity level z according to $\Pi(z)$ and human capital level h according to $P(h)$, and conditional on the realization of h, she draws the labor market state s according to $P_h(s)$.

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. 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. See Appendix G for the government budget constraints.

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

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 $a \in A$. See Appendix G for the definition of the recursive competitive equilibrium.

4 Quantitative analysis

4.1 Calibration

We calibrate the model economy to quarterly U.S. data. All calibrated values are reported in Table 7. 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 a high school degree or less education, medium-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 2014-2021 American Community Survey (ACS) and we restrict the sample to individuals aged between 25-60 years.[24]

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 0.9887. 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 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 2015-2021 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

[24]The ACS data were extracted from the IPUMS USA data repository; see Ruggles et al. (2024).

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.[25]

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 $\pi(z'|z)$. 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 assume that individual labor earnings follow a continuous stochastic process with a transitory and a persistent component:

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

ϕ governs the persistence of the process, and ϵ_t and η_t are the innovations of the persistent and the transitory shocks, respectively, with variances σ^2_ϵ and σ^2_η. We take the values of these parameters from KMP who use data on individual labor earnings from the Panel Study of Income Dynamics (PSID) to estimate the income process above.[26] The parameter estimates reported in Table 7 are at an annual frequency. We convert these values to quarterly frequency using the procedure suggested in KMP. The quarterly values are then used to approximate the continuous stochastic process for z with a discrete Markov chain as described in Appendix J. 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 per efficiency unit 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.[27] 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.[28] We compare model outcomes with the data counterparts to assess the

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

[26] We also estimated the income process separately for each education group and find that the parameters are are very similar. Thus, we chose to use only one set of parameters.

[27] See PSID (2024) for details on data availability and background materials

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

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	0.9887			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	0.021			CPS
Labor productivity process					
Persistence	ϕ	0.9695			KMP
Variance of persistent component	σ_η^2	0.0384			KMP
Variance of transitory component	σ_ϵ^2	0.0522			KMP
Human capital specific parameters		L	M	H	
Probability of being born with h	P_h	0.36	0.30	0.34	ACS
Deterministic productivity level	h	1.00	1.29	1.76	PSID

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

Table 7: Calibrated parameter values

empirical fit of the model. Our calibration implies an equilibrium quarterly net interest rate of $r-\delta = 0.99\%$, as well as unit wage equal to $w = 2.38$. The tax rates that balance the government budget constraints are equal to $\tau = 2.6\%$ and $\tau_{ss} = 19.8\%$. Moreover, we obtain a quarterly capital to output ratio of $K/Y = 10.3$ and an investment to output ratio of $I/Y = 0.26$. These values are in line with those typically applied in the RBC literature. For example, Cooley and Prescott (1995) obtain values of $K/Y = 9.76$ and $I/Y = 0.252$.

The model perfectly matches the observed average employment-to-population ratio as well as the unemployment rate for each education group. This comes by construction because we use the observed labor market transition probabilities, $p_h(s'|s)$ in our calibration. Table 8 shows that the wealth distribution implied by the model matches very well the high degree of wealth inequality in the U.S. economy.[29] 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

[29]The empirical wealth distribution is computed from the 1999-2021 waves of the PSID. Household wealth is defined as the value of farms and businesses, checking and saving accounts, stocks, bonds, real estate, vehicles, and individual retirement accounts, net of liabilities including debt on real estate, farms, businesses, student loans, medical debt, credit card debt, legal debt, and other debt.

0.72 is very close to that of the U.S. economy of 0.78. Table 8 also reports the Gini coefficient computed from the sample of households with non-negative net worth. This measure provides a more appropriate comparison, because the baseline model does not permit households to borrow. 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 8.

	Wealth share			s/y
	Data		Model	Model
	All	nw≥0		
Q1	-1.4	0.3	0.3	5.5
Q2	1.6	2.6	2.0	9.1
Q3	6.3	7.2	5.9	14.3
Q4	15.8	16.0	16.8	21.8
Q5	77.6	73.9	75.1	34.9
90-95	14.9	14.4	17.4	
95-99	23.0	21.7	24.9	
Top 1%	23.4	21.8	13.1	
Gini	0.78	0.74	0.72	

Wealth share: Share of each quintile, or percentile in total wealth. All: All households. nw≥0: Households with non-negative net worth. s/y: Average savings rate, in %

Table 8: Wealth inequality – Model and data

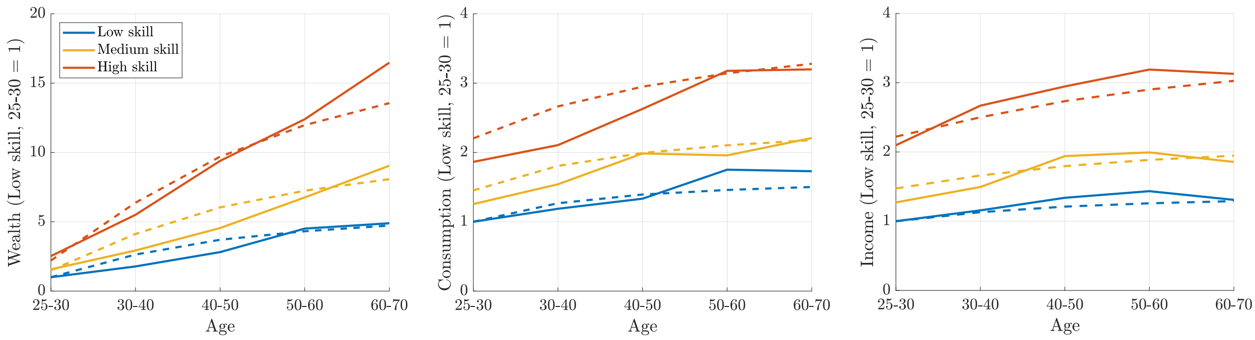
Table 9 shows that the model matches remarkably well the observed distribution of wealth for each education group. In the model, education groups differ in terms of the deterministic component of labor productivity h, as well as actual and subjective labor market transition rates $p_h, \widehat{p}_h$. These features matter for individual asset accumulation. The first row of the table 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). The good fit of the model in terms of wealth holdings is by no means mechanical because we did not target any data moments related to aggregate wealth inequality or asset holdings by education group. 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

	Data			Model		
	L	M	H	L	M	H
Share in wealth, total	0.19	0.17	0.64	0.19	0.28	0.53
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	0.70	0.15	0.27	0.59

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

Table 9: Share of wealth by education group – Model and data

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: Life cycle path of income, wealth and consumption;
Model (dashed) and Data (solid)

Due to the optimistic bias in labor market expectations, individuals in the model systematically over-predict their future labor income. For example, job seekers expect to become employed and earn labor income with a higher probability than the actual probability. Since, labor earnings are typically higher than unemployment benefits, the job seekers in the model over-predict future income. As a consequence of higher expected income, individuals in the model also over-predict future consumption. Table 10 shows that, on average, individuals' expected future income is 2.1% higher than their actual future income. The larger optimistic bias of the low-skilled is reflected by their higher forecast error with respect to labor income and consumption.

	All	L	M	H
$\widehat{E}(y') - E(y')$	2.1%	2.9%	1.9%	1.3%
$\widehat{E}(c') - E(c')$	0.7%	1.1%	0.6%	0.3%

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

Table 10: Bias in expected income and consumption (model)

It is of interest to explore the extent to which these model predictions hold in the data. The exact empirical counterparts of the model outcomes are not available in the SCE. Therefore, we resort to data outcomes which are arguably closely related. This allows us to gauge the empirical validity of the model predictions – at least qualitatively. Concretely, we use information from the SCE on individual's expected growth of earnings, household income and consumption expenditures. Moreover, we use information from the SCE on individuals' expected inflation to obtain the growth rate of real variables.[30] The results of these calculations are in Table 11 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.

Clearly, there are conceptual differences between the measures of labor income and consumption expenditures in the model and the data reported in the table. For example, in the 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 the data these variables are measured at the household level. These conceptual differences should be kept in mind when comparing the model outcomes with the data.

[30] See Appendix K for details of the calculation of expected and actual growth of income, earnings, and expenditures.

	All	L	M	H	E	(U,N)
Earnings (real, 4-months growth, in %)						
Actual	0.67	0.36	0.70	0.90		
Expected	1.45	1.62	1.14	1.52		
Income (real, annual growth, in %)						
Actual	1.15	0.03	1.35	2.05	1.36	-0.81
Expected	1.86	1.85	1.62	2.06	2.01	1.71
Expenditures (real, annual growth, in %)						
Actual	0.05	-0.10	-0.36	0.40	0.13	-0.65
Expected	0.59	0.29	0.65	0.88	0.71	0.47

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

Table 11: Bias in expected earnings, income and expenditures (data)

For all three variables displayed in Table 11 we find a substantial positive expectation bias. That is, individuals' expected annual 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: 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 1.85%, whereas realized growth is only 0.03%. This difference amounts to a substantial positive expectation bias of 1.82 percentage points. Instead for middle- and high-skilled individuals, the difference between expected and actual income growth is substantially smaller and equal to 0.27 and 0.01 percentage points, respectively. 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 over-estimate 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 conduct the experiment in which we remove the bias entirely and assume that all individuals know the correct labor market transition probabilities. This is achieved by setting $\widehat{p}_h(s'|s) =$

$p_h(s'|s)$ for every h. All other model parameters are the same as before.

By labor market state			By skill		
	Baseline	$\widehat{p} = p$		Baseline	$\widehat{p} = p$
E	37.4	40.3	L	27.9	36.5
U	19.8	28.8	M	31.0	34.6
N	-57.1	-47.2	H	33.0	32.9

L: Low-skill, M: Medium-skill, H: High-skill. E: Employed. U: Unemployed. N: Not in labor force. $\widehat{p} = p$: Individuals have rational expectations. Savings rate in %.

Table 12: Saving rate with and without expectation bias

Without the optimistic bias, agents save more than in the baseline case, as shown in Table 12. The left panel of the table shows average savings rates conditional on labor market status. Employed workers and job seekers save more in the counterfactual economy than in the baseline. In addition, agents deplete their wealth less quickly when they are out of the labor force because they expect to remain in this state longer than in the baseline case.

The right panel of Table 12 reports the savings rate by skill level. The large optimistic bias of the low-skilled implies that these individuals experience the largest adjustment in their expectations. As a result, they increase their saving rates more than the other skill groups. Consequently, asset holdings increase for all education groups, but the increase is more pronounced for the low-skilled. This is shown in Table 13 which reports the percentage change in life cycle asset holdings compared to the baseline economy. For instance, low-skilled individuals between ages 30-40 experience an increase in asset holdings, on average, of 51%, while the high-skilled experience an increase of 14%.

Age		[25-30)	[30-40)	[40-50)	[50-60)	At retirement
	L	47%	51%	51%	50%	51%
Δ Assets	M	33%	29%	24%	20%	20%
	H	23%	14%	7%	1%	1%

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

Table 13: 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 9), the relatively larger increase of their asset holdings in the counterfactual economy implies that wealth is distributed more equally and aggregate wealth inequality is lower than in the baseline economy.[31] The Gini coefficient of wealth in the counterfactual economy, without

[31] More asset accumulation implies a higher equilibrium capital stock in the counterfactual economy. The K/Y ratio increases from 10.3 in the baseline to 11.0. Since aggregate labor is unchanged, the equilibrium quarterly net interest rate drops from $r - \delta = 0.99\%$ to 0.78% and the unit wage rises from $w = 2.38$ to 2.46. The change in the factor prices adds to the decline in aggregate inequality. Labor earnings are the primary source of income

the expectation bias, is 0.64. This is 8 percentage points lower than in the baseline economy, as shown in Table 14. This result has two important implications. First, it suggests that a substantial part of wealth inequality in the U.S. is a result of individuals having optimistically biased labor market expectations. Second, the expectation bias is a key feature in the model that allows to match the observed wealth inequality in the data. In contrast, the version of the model with rational expectations fails to generate the high wealth concentration at the top.[32]

The magnitude of the effect of worker's optimism on wealth inequality is comparable to, or even larger, than the contribution of other important drivers of wealth inequality explored in the literature. These drivers include, for example, the intergenerational transmission of physical and human capital (De Nardi 2004), heterogeneity in personal discount factors (Hendricks 2007), imperfect access to insurance markets (Mengus and Pancrazi 2020), or capital income taxes in the presence of idiosyncratic returns on wealth (Benhabib et al. 2011). Each of these mechanisms have been shown to contribute significantly to wealth inequality and to raise the corresponding Gini by 3-10 percentage points.[33]

	Data	Baseline	$\widehat{p} = p$
Q1	0.3	0.3	0.9
Q2	2.6	2.0	3.9
Q3	7.2	5.9	8.9
Q4	16.0	16.8	19.4
Q5	73.9	75.1	66.9
90-95	14.4	17.4	15.8
95-99	21.7	24.9	21.2
Top 1%	21.8	13.1	10.7
Gini	0.74	0.72	0.64

Table 14: Wealth inequality with and without expectation bias

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 lose from the lower interest rate.

[32] 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.

[33] Larger effects (ranging up to 20 percentage points) have been found for mechanisms relying on the interaction between entrepreneurship, bequests and financial frictions – as emphasized, for example, by Quadrini (2000) and Cagetti and De Nardi (2006). Several other important mechanisms have been proposed in the literature to account for the observed high rates of wealth concentration in the data. These mechanisms emphasize the role of medical expenditure shocks in old age (De Nardi et al. 2010, Ameriks et al. 2020), very large but transient income shocks (Castaneda et al. 2003), financial literacy (Lusardi et al. 2017, or heterogeneity in rates of return Cao and Luo 2017. See De Nardi and Fella (2017), and Benhabib and Bisin (2018) for recent surveys of this literature.

4.4 Welfare

In this section, we evaluate the welfare effects of biased subjective expectations. In the first step, we address the question whether the optimists in our baseline economy would be better off being realists. To this end, we compute the equivalent variation in expected lifetime consumption that would make a new born agent in the baseline economy as well off as in the counterfactual economy without the bias. Concretely, we compute the value of ϕ that satisfies

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

In this context, it is important to notice that the welfare calculations are conducted from the viewpoint of a social planner. That is, we calculate the expected value E_0 using the actual labor market transition probabilities $p_h(s'|s)$ and not the subjective probabilities $\widehat{p}_h(s'|s)$. The first row in Table 15 shows that $\phi > 0$ for all education groups. That is, agents attain a higher level of welfare in the counterfactual economy. On average, the welfare gain is equal to 3.9%. The intuition for this result can be best understood through the lens of the stylized two-period model presented in Appendix M. There we show that, 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 5.3% for low-skill individuals who experience the largest adjustment in their savings behavior.

In terms of magnitude, this effect is sizable compared to the welfare effects associated with important distortions and policies studied in the literature. This includes for example, the welfare costs of business cycles (Storesletten et al. 2001), the gains from social security (İmrohoroğlu et al. 1995 and Krueger and Kubler 2006) and from unemployment insurance (Hansen and İmrohoroğlu 1992), or the welfare costs of borrowing constraints restricting entrepreneurship (Buera 2009) and childhood human capital investment (Caucutt and Lochner 2020). The welfare effects of these mechanisms have been shown to range from 0.7%-6%.

Instead of a social planner, we could ask the agent in our model economy to report the value of ϕ that makes her indifferent between the baseline and the counterfactual economy. In this case, the expected value in the expression above is computed using the individual's subjective labor market probabilities $\widehat{p}_h(s'|s)$. Not unexpectedly, in this scenario we find that $\phi < 0$ for all agents, as shown in the second row of Table 15. The result is intuitive: The optimistic individuals in the baseline find the counterfactual economy very unattractive since there they face higher probabilities to move into bad labor market states.

In our model economy assets serve as a means of self insurance against adverse shocks. Our

	All	ϕ_L	ϕ_M	ϕ_H
E_0	0.039	0.053	0.035	0.026
$\widehat{E}_0$	-0.194	-0.279	-0.181	-0.105

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 15: Consumption equivalent variation

previous findings imply that in the absence of the optimistic bias individuals have higher buffer stock savings. This should generally lead to better self-insurance than in the baseline economy. To quantify the degree of consumption smoothing in the model, we estimate the following equation on simulated data on individual income and consumption

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

Δc_{it} is the log-difference of individual i's consumption between two periods 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 16.

	Baseline			$\widehat{p} = p$		
	L	M	H	L	M	H
b	0.116	0.091	0.065	0.068	0.065	0.059

Table 16: 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, low-skilled individuals are more exposed to income fluctuations and thus achieve a lower degree of consumption smoothing. 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.

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 17. 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.

5.1 Actuals from SCE

In the baseline, 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 21). Given these differences, we assess whether the choice of the SCE instead of the CPS for computing the actual probabilities matters quantitatively through the lens of our model. Reassuringly, we find that the properties of the equilibrium are very similar to the ones of the baseline case, as shown in the column labelled "SCE" in Table 17. Moreover, when eliminating the expectation bias we obtain very similar results as in the baseline case. We conclude from this analysis 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.

5.2 Risk aversion

In the baseline calibration, we set the coefficient of relative risk aversion $\sigma = 1$. Naturally, in the context of our model, agents' attitude towards risk 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. A higher risk aversion leads to more asset accumulation in the model, as shown in the column labelled "σ=2" in Table 17. Interestingly, in this case, the elimination of the expectation bias leads to a larger adjustment in individual savings than in the baseline and to a larger reduction in aggregate wealth inequality. Also the implied welfare effect is higher because individuals are able to sustain a higher level of consumption over the life cycle.

5.3 Endogenous labor supply

Next, we extend the baseline economy to include an endogenous labor supply choice. The purpose of this extension is twofold. First, we want to study the quantitative effects of the observed expectation bias 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,

	Baseline		SCE		$\sigma = 2$		Labor		Bias only for			Age		$\underline{a} < 0$	
	w	w/o	w	w/o	w	w/o	w	w/o	E	U	N	w	w/o	w	w/o
	Panel (a): Wealth quintiles														
$Q1$	0.3	0.9	0.3	0.7	0.6	1.4	0.3	0.9	0.6	0.8	0.7	0.3	0.9	-1.4	-0.3
$Q2$	2.0	3.9	2.0	3.4	3.0	4.9	1.9	3.6	2.9	3.6	3.4	1.9	3.8	0.6	2.8
$Q3$	5.9	8.9	6.1	8.5	7.4	10.2	5.6	8.5	7.5	8.4	8.2	5.8	8.6	5.0	8.1
$Q4$	16.8	19.4	17.1	19.7	17.9	20.3	16.5	18.9	18.2	19.0	18.8	16.2	19.0	16.9	19.5
$Q5$	75.1	66.9	74.6	67.7	71.1	63.3	75.8	68.1	70.7	68.3	68.9	75.8	67.7	78.9	69.9
	Panel (b): Gini coefficient														
	0.72	0.64	0.72	0.65	0.68	0.60	0.72	0.65	0.68	0.65	0.66	0.73	0.65	0.77	0.68
	Panel (c): Savings rate, in %														
L	27.9	36.5	27.0	37.2	28.9	39.2	29.8	36.1	32.5	35.0	33.0	28.8	37.0	26.4	35.7
M	31.0	34.6	31.9	35.8	31.6	37.2	32.1	34.7	32.9	33.6	34.0	30.9	35.2	30.8	34.5
H	33.0	32.9	32.9	29.8	33.2	35.1	33.6	33.4	32.3	33.0	33.8	32.6	33.2	33.5	33.2
	Panel (d): Consumption smoothing														
b_{all}	0.10	0.07	0.06	0.06	0.09	0.06	0.07	0.05	0.09	0.07	0.06	0.10	0.07	0.08	0.06
	Panel (e): Welfare, in %×100														
ϕ_L	5.3		5.3		12.4		5.2		3.6	4.9	4.5	5.8		6.3	
ϕ_M	3.5		3.0		9.5		3.3		2.1	3.0	3.1	3.7		3.8	
ϕ_H	2.6		1.4		7.5		2.4		1.2	2.2	2.3	2.9		2.7	

"SCE": Actual and subjective transition probabilities computed from SCE; "$\sigma = 2$": Coefficient of relative risk aversion = 2.0; "Labor": Model 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; "Age": Model with young and prime-age workers; "$\underline{a} < 0$": Model with borrowing. "w" ("w/o"): Subjective expectations in the model are with (without) bias; "L, M, H": Low-, middle-, high-skilled. Panel (c): Average savings rate of working-age individuals. Panel (d): Coefficient estimate of b from $\Delta c_{it} = a + b \cdot \Delta y_{it} + e_{it}$. Panel (e): Consumption equivalent variation.

Table 17: Robustness analysis

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.1 for model details and the calibration. The optimistic bias induces individuals to work less hours. This is because optimistic workers 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 hold little assets and thus, they react more strongly and increase their hours by more than the high-skilled when the bias is removed. As can be seen in the column labelled "Labor" in Table 17, the results of the baseline economy in terms of asset accumulation and aggregate wealth inequality are robust to the inclusion of an endogenous labor supply choice.

5.4 Bias only for E, U, or N

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. To this end, we re-run the quantitative analysis but allow only a given labor market group to have biased expectations. The two other groups are assumed to have the correct expectations.[34] In the column labelled "Bias for E, U, or N" in Table 17 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 group is quantitatively important.

5.5 Age groups

As another extension we partition the work-life of individuals into two age intervals – young and prime-age. New working-age individuals enter the economy as young. Every period, young individuals reach prime-age with a constant probability. The transition from prime-age into retirement is stochastic as in the baseline model. Moreover, we allow the subjective and the actual labor market transition probabilities for each skill group to differ between both ages as is documented in Section 2.3. By analyzing the extended model, we aim to assess how much the fact that workers' expectation bias tends to diminish with age matters quantitatively for the properties of the model. See Appendix L.2 for a description of the extended model and calibration details. The results are documented in the columns labelled "Age" in Table 17. The age-dependence of the bias has only a minor effect on the results. Moreover, the removal of the bias leads to a similar adjustment in the extended economy than in the baseline model. The reason for these small effects relates to the fact that while the bias tends to diminish with age it does not disappear but remains sizable for prime-age individuals of every skill group. The large optimistic bias among young workers induces them to save less than in the baseline. For example, the average savings rate among young low-skilled workers is lower by 1.5 percentage points. Prime-age workers have a stronger incentive to accumulate assets than the young. This is because their bias is smaller and retirement is more imminent than for the young. As a result, the life cycle path of asset accumulation is steeper in the extended model. However, over the life cycle, the average savings rate for each skill group is comparable to that in the baseline model. Thus, aggregate wealth inequality is hardly affected by the age-dependent expectation bias.

5.6 Borrowing

In the baseline model, we follow Krueger et al. (2016) – and much of the related literature – and impose a zero-borrowing limit by setting $\underline{a} \geq 0$. In the data, however, a substantial fraction of the U.S. population holds negative net worth. Moreover, in the presence of biased expectations, the zero-borrowing limit in the model may be more restrictive than under rational expectations.

[34] 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.

Optimistic workers accumulate fewer precautionary savings in the first place and, thus, after a negative productivity or employment shock, they are more likely to be borrowing constrained. In order to assess the quantitative importance of the zero-borrowing limit, we now extend the baseline model by allowing individuals to raise debt. We implement this extension in two ways: First, we relax the borrowing constraint in our baseline economy by allowing $\underline{a} < 0$. Second, we allow individuals in the model to borrow by introducing mortgage debt and housing capital.

When relaxing the borrowing constraint, we calibrate $\underline{a}$ so that the model matches the share of -1.4% of aggregate wealth held by the poorest 20% of the U.S. population (see Table 8). The calibrated value of $\underline{a} = -4.2$ implies a maximum debt level of about 1/3 of average annual after-tax labor earnings. The quantitative properties of the re-calibrated model are presented in Table 17 in the columns labeled "$\underline{a} < 0$". Relaxing the borrowing constraint primarily affects the low-skilled. These workers generally hold fewer precautionary savings and, thus, they are more likely to be constrained in the baseline model. In the alternative calibration, they occasionally raise debt in response to negative shocks. Hence, on average, their savings rate is 1.5 percentage points below the value in the baseline. As a result, the distribution of wealth in the economy becomes more unequal. The Gini coefficient increases to 0.77 which is very close to the Gini coefficient in the data of 0.78. At the same time, the removal of the expectation bias has a more pronounced effect on wealth inequality and welfare than in the baseline. This effect is related to the curvature of the utility function. With concave utility, the effect of the bias on individual savings depends on the level of individual asset holdings. In the extended model, the low-skilled hold fewer assets, on average, than in the baseline and, thus, they increase their savings by more when the bias is removed. This leads to a substantial increase in the share of asset holdings among individuals in the first two wealth quintiles. As a result, the Gini coefficient drops by 9 percentage point to a value of 0.68. Through larger asset holdings, the low-skilled can better self-insurance against income fluctuations. This is reflected by larger welfare gains for the low-skilled than in the baseline.

In the second case, we relax the zero-borrowing limit by introducing mortgage debt and housing capital. This extension is motivated by the fact that housing wealth accounts for a substantial part of wealth of poorer households and this housing wealth is usually acquired through mortgage debt. We borrow the features of the housing sector from the model in Jeske, Krueger, and Mitman (2013) where households derive utility from housing services and can invest in one-period bonds, physical capital, and houses. See Section L.3 in the Appendix for the details of the model and the calibration. As in Jeske et al. (2013), the model requires a very high risk aversion of $\sigma = 7.5$ to generate a realistic median leverage ratio. With high risk aversion, the precautionary savings motive is very dominant and, thus, agents in the model save substantially more than in the baseline model - see the results in Table 37. This applies particularly to low-skilled individuals and, thus, the distribution of wealth in the model is substantially less skewed than in the data and in our baseline model. For example, the Gini coefficient is only 0.53 compared to 0.72 in baseline and the poorest 40% of the population hold a significant amount of wealth. Due to the strength of the precautionary savings motive, individuals' savings react very sensitively to changes in the expectation bias. When turning off the bias, all individuals save more - also the high-skilled. This is different in the baseline model, where primarily the low- and medium-skilled workers accumulate more assets but the savings behavior of the high-skilled barely changes. For this reason, wealth inequality in the extended model decreases but by less than in the baseline.

5.7 Collapse U and N

In our analysis, we consider three labor market states: employment, unemployment and non-participation. In the model, the distinction between unemployment and non-participation is clear cut. However, in the data the boundary between these two labor market states may be considered blurry. Like the unemployed, the non-participants search for employment, even though passively, and are often available for work in principle. This is reflected by large numbers of non-participants entering employment directly without experiencing a spell of unemployment. We address this issue in a robustness check by collapsing unemployment and non-participation into one state of non-employment (nE). The resulting two-state representation of the labor market (with the states E and nE) can be implemented in the quantitative analysis in a straightforward way. See Appendix L.4 for details of the calibration. Table 37 (columns "U&N") presents the quantitative results indicating that low-skilled workers have higher savings rates than in the baseline model. This is because in the two-state model, the average duration of non-employment spells is somewhat higher than in the baseline. This increases the need for self-insurance, especially for the low-skilled. As a result, there is less wealth inequality. Since, the savings motive for the low-skilled is stronger than in the baseline economy, the removal of the expectation bias has a more moderate effect on savings than in the baseline. The implied decrease in the wealth Gini of 4 percentage points is still substantial but less than the decrease of 8 percentage points in the baseline.

5.8 Monthly frequency

In the baseline, we calibrate the model to quarterly data. Due to this choice of frequency, the model cannot account for short-term transitions of workers between labor market states. These transitions are, however, not uncommon in the U.S. labor market. In the model, the choice of frequency may affect the savings behavior of workers because it determines the minimum duration of labor market states. For example, unemployed workers can expect to find a job after a minimum of three months in the quarterly model, but already after a minimum of one month in the monthly model. To test the sensitivity of our results to the choice of the model period, we calibrate the model to a monthly frequency. See Appendix L.5 for calibration details. The results of this calibration are almost identical to the baseline findings as can be seen in Table 37. In the monthly model, individuals experience more frequent transitions out of employment, which per se would lead to higher precautionary savings. However, this effect is offset by the fact that the average duration of non-employment spells is shorter than in the quarterly model. As a result, individuals' savings behavior is largely unaffected by the change in the model frequency.

6 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 (e.g. finding a job or remaining employed) and they underestimate the probability of transiting into a bad state (e.g. job separation or 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 more precise beliefs.

We explore the quantitative implications of biased labor market expectations on individual choices and aggregate outcomes in the context of a calibrated life cycle model with heterogenous individuals, idiosyncratic labor market risk and incomplete insurance markets. 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 aggregate wealth inequality.

Our results have important implications for economic policy. Generally, in the presence of optimistically 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 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 July 2021, 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 18 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 July 2021. The last two columns of Table 18 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	3825	49.47	7484	48.64	2239187	49.11
Women	3923	50.53	7848	51.36	2412481	50.89
25–29	976	12.06	1974	12.65	624372	14.99
30–39	2161	26.74	4313	26.85	1328182	28.74
40–49	2224	29.15	4368	29.04	1279999	27.23
50–54	1163	15.74	2317	15.58	695650	14.38
55–59	1226	16.31	2363	15.88	723465	14.66
≤HS	747	31.65	1540	32.20	1670995	36.17
C	2338	29.33	4735	29.98	1262748	26.59
≥Bachelor	4665	39.03	9053	37.81	1717925	37.25
White	6386	81.45	12606	81.46	3717800	76.53
Non-white	1364	18.55	2729	18.54	933868	23.47
Single	2606	33.57	5165	33.62	1871030	41.21
Married	5144	66.43	10170	66.38	2780638	58.79
<30,000	1092	21.05	2160	20.68	874819	18.83
30,000–49,000	1172	16.30	2361	16.83	792592	17.16
50,000–99,000	2845	32.40	5542	32.21	1551909	32.83
≥100,000	2625	30.25	5238	30.28	1432348	31.18
E	6641	81.96	13124	81.98	3592887	76.96
U	250	3.36	520	3.74	152635	3.52
N	859	14.68	1691	14.28	906146	19.52

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-07/2021. Obs: Number of observations. %-share: Population shares in sample.

Table 18: 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 18 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 19 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 19 – 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	2.77	8.47	1.91	4.19	9.35	6.12
25–29	C	3.11	3.51	2.63	4.21	5.61	3.62
25–29	≥Bachelor	7.78	2.62	1.75	5.87	4.70	3.10
30–39	≤HS	7.22	12.61	8.17	8.54	13.64	12.12
30–39	C	7.32	8.51	5.77	7.59	8.73	6.37
30–39	≥Bachelor	13.81	7.07	4.01	12.97	7.37	7.05
40–49	≤HS	8.96	8.48	14.61	9.03	11.76	12.56
40–49	C	9.06	10.29	7.96	7.38	6.81	6.12
40–49	≥Bachelor	11.66	7.30	3.42	12.17	7.06	6.23
50–54	≤HS	5.32	3.84	8.64	5.02	5.82	8.69
50–54	C	5.21	6.86	6.43	3.96	3.57	3.99
50–54	≥Bachelor	4.81	4.28	2.14	5.78	3.73	3.21
55–59	≤HS	4.44	6.18	16.98	4.75	4.97	11.20
55–59	C	4.39	5.36	11.13	3.65	3.43	5.44
55–59	≥Bachelor	4.13	4.62	4.46	4.89	3.46	4.18
Total		100	100	100	100	100	100

Sample: Individuals with age 25-60 years, non-school or -college. Period: 07/2014-07/2021.

Table 19: Sample composition conditional on labor market state

The standard errors for the subjective transition probabilities – reported in the tables throughout the paper – 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): CPS-weights								
	Subjective			Actual			Subjective − Actual		
	E	U	N	E	U	N	E	U	N
E	96.1	2.6	1.3	94.9	1.8	3.3	1.2	0.7	-2.0
	(0.15)	(0.10)	(0.09)	(0.03)	(0.02)	(0.02)	(0.15)	(0.10)	(0.09)
U	61.9	31.2	6.9	43.7	32.5	23.8	18.2	-1.4	-16.9
	(1.96)	(1.56)	(1.02)	(0.27)	(0.26)	(0.24)	(1.98)	(1.58)	(1.05)
N	10.9	13.6	75.5	11.1	3.4	85.6	-0.2	10.3	-10.1
	(0.77)	(0.86)	(1.28)	(0.07)	(0.04)	(0.08)	(0.77)	(0.86)	(1.28)
	Panel (b): Survey-specific weights								
	Subjective			Actual			Subjective − Actual		
	E	U	N	E	U	N	E	U	N
E	96.2	2.5	1.3	94.9	1.8	3.3	1.3	0.7	-2.0
	(0.14)	(0.09)	(0.08)	(0.03)	(0.02)	(0.02)	(0.14)	(0.09)	(0.08)
U	61.1	32.5	6.4	43.7	32.5	23.8	17.4	0.0	-17.4
	(1.79)	(1.52)	(0.90)	(0.27)	(0.26)	(0.24)	(1.81)	(1.54)	(0.93)
N	10.3	12.9	76.7	11.1	3.4	85.6	-0.8	9.5	-8.9
	(0.70)	(0.73)	(1.13)	(0.07)	(0.04)	(0.08)	(0.70)	(0.73)	(1.13)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-07/2021. 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 20: 4-Months subjective and actual transition probabilities (with survey-specific weights)

Panel (a): Actual transition probabilities calculated from CPS									
	Subjective			Actual			Subjective − Actual		
	E	U	N	E	U	N	E	U	N
E	96.1	2.6	1.3	94.9	1.8	3.3	1.2	0.7	-2.0
	(0.15)	(0.10)	(0.09)	(0.03)	(0.02)	(0.02)	(0.15)	(0.10)	(0.09)
U	61.9	31.2	6.9	43.7	32.5	23.8	18.2	-1.4	-16.9
	(1.96)	(1.56)	(1.02)	(0.27)	(0.26)	(0.24)	(1.98)	(1.58)	(1.05)
N	10.9	13.6	75.5	11.1	3.4	85.6	-0.2	10.3	-10.1
	(0.77)	(0.86)	(1.28)	(0.07)	(0.04)	(0.08)	(0.77)	(0.86)	(1.28)
Panel (b): Actual transition probabilities calculated from SCE									
	Subjective			Actual (SCE)			Subjective − Actual		
	E	U	N	E	U	N	E	U	N
E	96.3	2.5	1.2	96.8	2.0	1.2	-0.6	0.5	0.0
	(0.19)	(0.12)	(0.11)	(0.32)	(0.24)	(0.22)	(0.37)	(0.27)	(0.25)
U	57.6	35.8	6.7	38.8	44.6	16.7	18.8	-8.8	-10.0
	(2.62)	(2.31)	(1.06)	(3.87)	(4.10)	(3.46)	(4.67)	(4.70)	(3.62)
N	10.6	12.8	76.6	7.0	2.7	90.3	3.6	10.1	-13.7
	(0.97)	(1.02)	(1.62)	(1.16)	(0.70)	(1.33)	(1.51)	(1.24)	(2.09)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-07/2021. Source: SCE and CPS. Standard errors in parentheses.

Table 21: 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, 90% 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 57% 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 22 shows the results.

	Subjective			Actual (CPS)			Subjective − Actual		
	E	U	N	E	U	N	E	U	N
Actual probabilities calculated from CPS									
Panel (a): Wrong answer to at least one control question									
E	94.8	3.2	2.0	94.9	1.8	3.3	-0.1	1.4	-1.3
	(0.32)	(0.20)	(0.17)	(0.03)	(0.02)	(0.02)	(0.32)	(0.20)	(0.18)
U	61.6	30.0	8.5	43.7	32.5	23.8	17.9	-2.6	-15.3
	(2.87)	(2.18)	(1.52)	(0.27)	(0.26)	(0.24)	(2.88)	(2.20)	(1.54)
N	10.6	14.1	75.3	11.1	3.4	85.6	-0.5	10.8	-10.3
	(1.05)	(1.26)	(1.81)	(0.07)	(0.04)	(0.08)	(1.06)	(1.26)	(1.81)
Panel (b): All control questions answered correctly									
E	97.0	2.2	0.9	94.9	1.8	3.3	2.1	0.3	-2.4
	(0.13)	(0.09)	(0.08)	(0.03)	(0.02)	(0.02)	(0.13)	(0.09)	(0.08)
U	62.5	33.1	4.4	43.7	32.5	23.8	18.8	0.6	-19.4
	(2.12)	(1.96)	(0.86)	(0.27)	(0.26)	(0.24)	(2.14)	(1.98)	(0.89)
N	11.3	12.9	75.8	11.1	3.4	85.6	0.2	9.6	-9.8
	(1.12)	(1.08)	(1.78)	(0.07)	(0.04)	(0.08)	(1.12)	(1.08)	(1.78)
Actual probabilities calculated from SCE									
	Subjective			Actual (SCE)			Subjective − Actual		
	E	U	N	E	U	N	E	U	N
Panel (c): Wrong answer to at least one control question									
E	94.8	3.1	2.1	95.1	3.0	1.9	-0.3	0.1	0.2
	(0.43)	(0.26)	(0.25)	(0.69)	(0.54)	(0.45)	(0.81)	(0.60)	(0.52)
U	56.0	36.2	7.8	34.0	48.2	17.8	22.0	-12.0	-10.0
	(3.91)	(3.41)	(1.52)	(5.17)	(5.71)	(4.63)	(6.49)	(6.66)	(4.87)
N	10.7	14.1	75.1	8.0	3.4	88.6	2.8	10.7	-13.5
	(1.31)	(1.53)	(2.27)	(1.81)	(1.17)	(2.09)	(2.24)	(1.93)	(3.09)
Panel (d): All control questions answered correctly									
E	97.1	2.1	0.8	97.8	1.3	0.9	-0.7	0.8	-0.1
	(0.15)	(0.10)	(0.09)	(0.32)	(0.23)	(0.23)	(0.35)	(0.25)	(0.25)
U	60.1	35.2	4.8	46.4	38.7	14.8	13.6	-3.6	-10.1
	(2.73)	(2.48)	(1.21)	(5.49)	(5.21)	(5.13)	(6.13)	(5.77)	(5.27)
N	10.3	11.0	78.7	5.8	1.8	92.4	4.6	9.2	-13.7
	(1.46)	(1.22)	(2.27)	(1.23)	(0.52)	(1.33)	(1.91)	(1.32)	(2.63)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-07/2021. Source: SCE and CPS. Standard errors in parentheses.

Table 22: 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 23 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)	$x = 1$	30.0	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	14.0	13.7	13.0	12.9	13.5	18.8

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

Table 23: 12-Months subjective and actual probability of job loss

D Expectation bias for different demographic groups

	Subjective			Actual			Subjective − Actual		
	E	U	N	E	U	N	E	U	N
High school or less									
E	95.31 (0.40)	2.90 (0.26)	1.79 (0.22)	92.96 (0.05)	2.55 (0.03)	4.49 (0.04)	2.36 (0.41)	0.35 (0.26)	-2.70 (0.23)
U	64.01 (3.84)	26.91 (2.89)	9.08 (2.03)	41.23 (0.40)	31.80 (0.38)	26.97 (0.36)	22.78 (3.86)	-4.89 (2.92)	-17.89 (2.06)
N	11.03 (1.37)	13.95 (1.55)	75.02 (2.32)	9.45 (0.09)	3.15 (0.06)	87.41 (0.11)	1.58 (1.38)	10.81 (1.55)	-12.39 (2.32)
Some college									
E	95.94 (0.22)	2.49 (0.14)	1.57 (0.15)	94.71 (0.05)	1.92 (0.03)	3.38 (0.04)	1.23 (0.23)	0.58 (0.14)	-1.81 (0.16)
U	63.14 (2.41)	32.12 (2.13)	4.75 (1.17)	43.52 (0.52)	33.16 (0.49)	23.33 (0.44)	19.62 (2.46)	-1.04 (2.19)	-18.58 (1.25)
N	10.45 (0.82)	14.04 (0.98)	75.51 (1.40)	11.51 (0.14)	3.80 (0.09)	84.69 (0.16)	-1.06 (0.83)	10.24 (0.98)	-9.18 (1.41)
College or higher									
E	96.84 (0.11)	2.36 (0.08)	0.80 (0.07)	96.48 (0.03)	1.21 (0.02)	2.32 (0.03)	0.36 (0.12)	1.15 (0.08)	-1.52 (0.07)
U	56.98 (2.06)	37.49 (1.95)	5.53 (0.94)	48.08 (0.54)	33.15 (0.52)	18.77 (0.43)	8.90 (2.13)	4.34 (2.02)	-13.24 (1.03)
N	11.17 (1.03)	12.51 (0.98)	76.32 (1.54)	14.08 (0.16)	3.33 (0.09)	82.59 (0.18)	-2.91 (1.04)	9.18 (0.99)	-6.27 (1.55)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-07/2021. Source: SCE and CPS. Standard errors in parentheses.

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

	Subjective			Actual			Subjective − Actual		
	E	U	N	E	U	N	E	U	N
Men									
E	96.28	2.49	1.23	95.75	1.84	2.41	0.53	0.65	-1.18
	(0.19)	(0.12)	(0.12)	(0.03)	(0.02)	(0.02)	(0.20)	(0.12)	(0.12)
U	64.63	31.94	3.43	45.01	34.92	20.07	19.62	-2.98	-16.64
	(2.87)	(2.71)	(0.85)	(0.39)	(0.37)	(0.31)	(2.90)	(2.74)	(0.91)
N	12.73	15.17	72.10	13.20	4.46	82.34	-0.47	10.71	-10.24
	(1.59)	(1.53)	(2.45)	(0.14)	(0.09)	(0.16)	(1.60)	(1.53)	(2.45)
Women									
E	95.95	2.64	1.41	93.92	1.80	4.28	2.03	0.84	-2.87
	(0.23)	(0.15)	(0.13)	(0.04)	(0.02)	(0.03)	(0.23)	(0.16)	(0.13)
U	60.17	30.65	9.17	42.23	29.94	27.83	17.94	0.71	-18.65
	(2.58)	(1.88)	(1.51)	(0.39)	(0.37)	(0.35)	(2.61)	(1.91)	(1.55)
N	10.18	13.01	76.80	10.12	2.85	87.03	0.07	10.16	-10.23
	(0.85)	(1.03)	(1.49)	(0.08)	(0.05)	(0.09)	(0.86)	(1.03)	(1.49)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-07/2021. Source: SCE and CPS. Standard errors in parentheses.

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

	Subjective E	Subjective U	Subjective N	Actual E	Actual U	Actual N	Subjective - Actual E	Subjective - Actual U	Subjective - Actual N
25 − 29									
E	95.77	2.83	1.40	93.50	2.34	4.16	2.26	0.49	-2.76
	(0.42)	(0.29)	(0.22)	(0.08)	(0.05)	(0.06)	(0.43)	(0.30)	(0.23)
U	69.94	22.26	7.80	43.58	31.38	25.04	26.36	-9.12	-17.24
	(4.53)	(3.00)	(2.54)	(0.66)	(0.62)	(0.57)	(4.57)	(3.07)	(2.60)
N	9.03	15.20	75.77	16.36	5.74	77.89	-7.33	9.46	-2.12
	(1.84)	(3.43)	(4.51)	(0.25)	(0.16)	(0.28)	(1.86)	(3.43)	(4.52)
30 − 39									
E	96.10	2.58	1.32	94.90	1.91	3.20	1.21	0.68	-1.88
	(0.27)	(0.17)	(0.16)	(0.05)	(0.03)	(0.04)	(0.27)	(0.18)	(0.16)
U	67.46	26.13	6.41	44.98	31.93	23.09	22.48	-5.80	-16.68
	(3.07)	(2.48)	(2.16)	(0.51)	(0.48)	(0.43)	(3.11)	(2.52)	(2.20)
N	14.40	14.18	71.42	13.05	3.94	83.01	1.36	10.24	-11.59
	(2.08)	(2.01)	(3.06)	(0.15)	(0.09)	(0.17)	(2.08)	(2.01)	(3.06)
40 − 49									
E	96.33	2.62	1.05	95.52	1.67	2.81	0.81	0.95	-1.75
	(0.27)	(0.17)	(0.15)	(0.04)	(0.03)	(0.03)	(0.28)	(0.17)	(0.16)
U	54.99	36.53	8.48	44.65	32.14	23.21	10.34	4.39	-14.73
	(3.80)	(2.83)	(2.01)	(0.53)	(0.51)	(0.45)	(3.84)	(2.87)	(2.07)
N	13.20	16.47	70.34	11.16	3.15	85.69	2.04	13.32	-15.35
	(1.40)	(1.37)	(2.26)	(0.14)	(0.08)	(0.16)	(1.41)	(1.38)	(2.26)
50 − 54									
E	96.59	2.19	1.22	95.37	1.57	3.06	1.22	0.61	-1.83
	(0.29)	(0.18)	(0.18)	(0.06)	(0.04)	(0.05)	(0.30)	(0.18)	(0.19)
U	59.14	34.69	6.17	41.86	34.97	23.17	17.28	-0.28	-17.00
	(5.97)	(4.70)	(2.11)	(0.72)	(0.71)	(0.62)	(6.01)	(4.75)	(2.20)
N	8.53	13.39	78.09	8.90	2.59	88.50	-0.38	10.79	-10.42
	(1.50)	(2.04)	(2.97)	(0.16)	(0.09)	(0.18)	(1.51)	(2.04)	(2.97)
55 − 59									
E	95.55	2.55	1.90	94.46	1.68	3.86	1.08	0.87	-1.95
	(0.50)	(0.33)	(0.32)	(0.07)	(0.04)	(0.06)	(0.50)	(0.33)	(0.32)
U	52.75	42.99	4.26	40.23	34.24	25.53	12.52	8.75	-21.27
	(4.93)	(4.95)	(1.21)	(0.76)	(0.74)	(0.68)	(4.99)	(5.00)	(1.39)
N	6.89	8.77	84.33	6.79	1.93	91.28	0.10	6.85	-6.94
	(1.07)	(1.07)	(1.63)	(0.12)	(0.07)	(0.14)	(1.08)	(1.07)	(1.64)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-07/2021. Source: SCE and CPS. Standard errors in parentheses.

Table 26: 4-Months subjective and actual transition probabilities (by age)

	Subjective			Actual			Subjective − Actual		
	E	U	N	E	U	N	E	U	N
2014									
E	95.31	3.24	1.45	95.22	1.68	3.11	0.09	1.57	-1.66
	(0.48)	(0.34)	(0.23)	(0.08)	(0.05)	(0.06)	(0.48)	(0.34)	(0.24)
U	55.97	38.24	5.79	39.26	35.59	25.14	16.70	2.65	-19.35
	(5.52)	(4.42)	(1.64)	(0.81)	(0.81)	(0.73)	(5.58)	(4.49)	(1.79)
N	6.94	14.35	78.71	10.28	3.59	86.12	-3.35	10.76	-7.41
	(1.44)	(2.51)	(3.24)	(0.22)	(0.14)	(0.25)	(1.45)	(2.51)	(3.25)
2015									
E	95.88	2.50	1.62	95.12	1.64	3.24	0.76	0.86	-1.62
	(0.45)	(0.25)	(0.27)	(0.06)	(0.04)	(0.05)	(0.46)	(0.25)	(0.28)
U	54.69	39.08	6.23	40.70	34.51	24.79	13.99	4.57	-18.56
	(5.01)	(4.19)	(2.45)	(0.67)	(0.66)	(0.59)	(5.06)	(4.24)	(2.52)
N	9.78	15.75	74.47	10.69	3.41	85.90	-0.91	12.34	-11.43
	(2.61)	(2.64)	(3.46)	(0.17)	(0.10)	(0.20)	(2.62)	(2.64)	(3.47)
2016									
E	96.07	2.84	1.09	95.20	1.59	3.21	0.87	1.25	-2.13
	(0.43)	(0.35)	(0.19)	(0.06)	(0.04)	(0.05)	(0.43)	(0.35)	(0.19)
U	65.75	32.09	2.16	42.13	33.14	24.74	23.62	-1.04	-22.58
	(5.06)	(4.91)	(0.84)	(0.70)	(0.68)	(0.61)	(5.11)	(4.96)	(1.04)
N	11.19	14.59	74.22	10.86	3.30	85.84	0.33	11.29	-11.62
	(2.24)	(2.33)	(3.42)	(0.18)	(0.10)	(0.20)	(2.24)	(2.34)	(3.43)
2017									
E	96.40	2.25	1.35	95.30	1.49	3.22	1.11	0.76	-1.87
	(0.43)	(0.24)	(0.31)	(0.06)	(0.04)	(0.05)	(0.43)	(0.24)	(0.31)
U	65.45	28.90	5.65	44.83	30.40	24.77	20.62	-1.50	-19.12
	(4.72)	(3.77)	(2.43)	(0.76)	(0.71)	(0.66)	(4.78)	(3.84)	(2.52)
N	14.98	16.84	68.18	11.28	2.78	85.94	3.70	14.06	-17.76
	(1.88)	(2.66)	(3.63)	(0.19)	(0.10)	(0.20)	(1.89)	(2.66)	(3.64)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-07/2021. Source: SCE and CPS. Standard errors in parentheses.

Table 27: 4-Months subjective and actual transition probabilities (by year)

	Subjective			Actual			Subjective − Actual		
	E	U	N	E	U	N	E	U	N
2018									
E	96.31	2.33	1.36	95.48	1.32	3.19	0.82	1.01	-1.83
	(0.42)	(0.27)	(0.22)	(0.06)	(0.03)	(0.05)	(0.42)	(0.27)	(0.23)
U	64.21	25.99	9.80	44.31	29.78	25.92	19.90	-3.78	-16.11
	(6.07)	(3.66)	(3.71)	(0.81)	(0.75)	(0.72)	(6.13)	(3.73)	(3.78)
N	11.33	10.03	78.64	11.03	2.56	86.40	0.30	7.47	-7.77
	(2.11)	(1.30)	(2.84)	(0.19)	(0.10)	(0.21)	(2.12)	(1.31)	(2.85)
2019									
E	96.84	1.95	1.20	94.88	1.77	3.35	1.96	0.18	-2.15
	(0.32)	(0.19)	(0.19)	(0.07)	(0.04)	(0.05)	(0.33)	(0.19)	(0.20)
U	63.52	23.09	13.39	44.53	28.97	26.49	18.99	-5.88	-13.11
	(6.73)	(4.48)	(6.08)	(0.87)	(0.81)	(0.78)	(6.78)	(4.55)	(6.13)
N	11.89	15.37	72.74	11.18	2.76	86.06	0.71	12.61	-13.32
	(1.90)	(2.69)	(3.43)	(0.20)	(0.11)	(0.22)	(1.92)	(2.69)	(3.43)
2020									
E	95.55	3.47	0.98	92.87	3.55	3.58	2.68	-0.08	-2.60
	(0.34)	(0.26)	(0.18)	(0.09)	(0.07)	(0.06)	(0.36)	(0.27)	(0.19)
U	59.80	30.72	9.49	47.26	33.18	19.56	12.53	-2.46	-10.07
	(5.06)	(3.83)	(2.40)	(0.68)	(0.64)	(0.54)	(5.11)	(3.89)	(2.46)
N	7.56	11.50	80.94	11.42	4.67	83.91	-3.87	6.83	-2.97
	(1.74)	(2.04)	(3.53)	(0.22)	(0.16)	(0.26)	(1.76)	(2.05)	(3.54)
2021									
E	96.31	2.08	1.60	95.24	1.39	3.37	1.07	0.69	-1.76
	(0.50)	(0.25)	(0.35)	(0.09)	(0.05)	(0.08)	(0.51)	(0.25)	(0.36)
U	70.62	26.33	3.05	43.13	33.63	23.24	27.49	-7.30	-20.19
	(4.25)	(3.76)	(1.12)	(0.91)	(0.88)	(0.79)	(4.35)	(3.87)	(1.38)
N	12.62	9.53	77.86	12.01	4.22	83.78	0.61	5.31	-5.92
	(3.30)	(2.19)	(4.65)	(0.28)	(0.18)	(0.32)	(3.32)	(2.20)	(4.66)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-07/2021. Source: SCE and CPS. Standard errors in parentheses.

Table 28: 4-Months subjective and actual transition probabilities (by year)

	Subjective			Actual			Subjective − Actual		
	E	U	N	E	U	N	E	U	N
				Less than $30,000					
E	90.43	5.68	3.89	90.53	3.65	5.82	-0.10	2.03	-1.93
	(0.72)	(0.47)	(0.41)	(0.10)	(0.06)	(0.08)	(0.73)	(0.47)	(0.41)
U	62.04	30.52	7.44	38.09	34.46	27.45	23.95	-3.94	-20.00
	(2.92)	(2.39)	(1.63)	(0.43)	(0.43)	(0.40)	(2.95)	(2.43)	(1.68)
N	10.36	16.70	72.94	9.27	3.72	87.02	1.09	12.99	-14.08
	(1.18)	(1.38)	(2.04)	(0.11)	(0.07)	(0.13)	(1.19)	(1.39)	(2.04)
				$30,000 − $49,000					
E	96.17	2.55	1.28	93.53	2.32	4.15	2.63	0.23	-2.87
	(0.31)	(0.21)	(0.20)	(0.07)	(0.04)	(0.06)	(0.32)	(0.21)	(0.21)
U	60.22	33.65	6.12	43.76	32.57	23.67	16.46	1.09	-17.55
	(4.74)	(3.58)	(2.02)	(0.61)	(0.59)	(0.52)	(4.78)	(3.63)	(2.09)
N	12.18	11.60	76.22	11.20	3.35	85.45	0.98	8.25	-9.23
	(2.09)	(2.28)	(3.30)	(0.16)	(0.10)	(0.19)	(2.10)	(2.28)	(3.31)
				$50,000 − $99,000					
E	97.17	1.98	0.85	95.25	1.67	3.07	1.91	0.31	-2.22
	(0.18)	(0.13)	(0.12)	(0.04)	(0.02)	(0.03)	(0.19)	(0.13)	(0.12)
U	61.63	31.66	6.71	48.23	30.58	21.18	13.40	1.07	-14.47
	(3.34)	(2.44)	(2.06)	(0.55)	(0.51)	(0.45)	(3.38)	(2.49)	(2.11)
N	11.74	10.88	77.38	12.85	3.36	83.79	-1.11	7.51	-6.41
	(1.44)	(1.51)	(2.40)	(0.15)	(0.09)	(0.17)	(1.45)	(1.51)	(2.40)
				More than $100,000					
E	97.42	1.84	0.74	96.60	1.13	2.27	0.82	0.72	-1.53
	(0.15)	(0.10)	(0.09)	(0.03)	(0.02)	(0.03)	(0.16)	(0.10)	(0.10)
U	66.06	27.51	6.42	48.92	31.26	19.82	17.14	-3.74	-13.40
	(4.57)	(3.91)	(1.83)	(0.70)	(0.65)	(0.57)	(4.62)	(3.97)	(1.92)
N	9.92	9.31	80.78	12.13	2.61	85.26	-2.21	6.69	-4.48
	(1.45)	(1.25)	(2.16)	(0.17)	(0.09)	(0.19)	(1.46)	(1.25)	(2.17)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-07/2021. 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 29: 4-Months subjective and actual transition probabilities (by household income)

E Bunching and rounding

The first approach aims to identify individuals who habitually respond to expectation questions by only using probabilities of 0%, 50%, or 100%, for example, due to naïveté, ambiguity or pure ignorance. Such responses are supposedly uninformative, hence we want to remove them from the sample. In doing so, we follow Manski and Molinari (2010) who suggest to analyze response patterns of individuals across questions in order to identify specific types of respondents. Accordingly, we consider the responses to five additional expectation questions - three from the *Core survey* and two from the *Labor Market Survey*. These questions include: *"What do you think is the percent chance that 12 months from now: ... (1) the unemployment rate in the U.S. will be higher than it is now? (2) the average interest rate on saving accounts will be higher than it is now? (3) stock prices in the U.S. stock market will be higher than they are now? Thinking about work in general and not just your present job (if you currently work), what do you think is the percent chance that you will be working full-time after you reach: ...(4) age 62? (5) age 67?"* We classify the responses of survey participants as non-informative if they respond to all of these questions (as well as the three main questions used in our baseline analysis) by using only the values 0%, 50%, or 100%. This applies to a small but non-negligible number of 254 observations. After dropping these observations, we perform the multinomial probit regression and find that the results for the bias are very similar to the baseline results (see Table 30).

	EE	EU	EN	UE	UU	UN	NE	NU	NN
High school or less	2.86	0.12	-2.98	24.87	-4.82	-20.05	2.04	10.07	-12.11
	(0.37)	(0.24)	(0.21)	(3.32)	(2.51)	(1.66)	(1.31)	(1.44)	(2.11)
Some college	1.47	0.41	-1.88	19.78	0.12	-19.90	-0.10	10.31	-10.22
	(0.22)	(0.13)	(0.15)	(2.30)	(2.02)	(1.18)	(0.84)	(0.98)	(1.39)
College and higher	0.14	1.41	-1.55	11.10	4.26	-15.37	-1.70	11.02	-9.32
	(0.14)	(0.10)	(0.08)	(2.26)	(2.06)	(1.06)	(1.23)	(1.21)	(1.83)

Table 30: Conditional expectation bias (drop 0, 50,100 rounders)

The second approach is based on the study of Dominitz and Manski (2011) who note that *"The pervasiveness of rounding suggests that we should interpret [the survey response] as providing an interval rather than point measure of [a person's] subjective probability, the interval depending on the response given"*.[35] We follow their strategy and define for each reported subjective transition probability an interval that the person's response represents. Clearly, the extent of rounding performed by the respondent is unknown. However, Dominitz and Manski (2011) emphasize that individuals tend to provide rather precise responses at the extremes (close to 0% and 100%) and otherwise tend to round their responses to the nearest 5 or 10, with more pronounced rounding around 50%. Based on this notion, they further assume that *"persons reporting a value [] that ends in a 0 other than 50 are rounding no more than to the nearest 10, those reporting a value ending in a 5 are rounding to no more than the nearest 5, and those reporting other values are rounding to no more than the nearest 1"*.[36] These considerations give

[35]See Dominitz and Manski (2011) p. 365.
[36]See Dominitz and Manski (2011) p. 365.

rise to the following set of intervals, where r represents a given survey response: $r = 0 \Rightarrow [0, 5]$, $r = 50 \Rightarrow [40, 60]$, $r = 100 \Rightarrow [95, 100]$, r end in a 0, but $r \neq 0, 50, 100 \Rightarrow [r-5, r+5]$, r end in a 5 $\Rightarrow [r-3, r+3]$, otherwise: $\Rightarrow [r-1, r+1]$.

We use these intervals and the predicted actual transition probability for each individual to re-compute the expectation bias. Specifically, if the predicted actual transition probability for a given respondent is inside the interval that is defined by the respondent's reported subjective probability, then we assign a value of zero for the bias. Any value within the interval can correspond to the person's true subjective probability, thus, we cannot exclude the possibility that the bias is actually equal to zero. If instead the predicted actual value is outside the interval, then we compute the bias as the difference between the prediction and the mid point of the interval. After these calculations, we run the probit regression and find that the results for the bias are very similar to the baseline results (see Table 31).

	EE	EU	EN	UE	UU	UN	NE	NU	NN
High school or less	0.69	1.71	-0.45	23.65	-4.28	-18.50	3.56	11.80	-13.38
	(0.33)	(0.21)	(0.19)	(3.30)	(2.42)	(1.54)	(1.25)	(1.39)	(2.06)
Some college	-0.73	1.77	0.51	19.03	0.02	-17.76	1.10	11.57	-10.50
	(0.21)	(0.13)	(0.14)	(2.24)	(1.94)	(1.11)	(0.77)	(0.91)	(1.30)
College and higher	-1.76	2.32	0.50	10.14	4.61	-13.45	-0.45	12.35	-9.93
	(0.13)	(0.10)	(0.08)	(2.19)	(1.98)	(0.98)	(1.16)	(1.15)	(1.74)

Table 31: Conditional expectation bias (with intervals)

F Additional tables

	EE	EU	EN	UE	UU	UN	NE	NU	NN
High school or less	5.01	-2.46	-2.56	25.27	-5.19	-20.08	-1.58	12.85	-11.27
	(0.32)	(0.21)	(0.19)	(3.47)	(2.37)	(2.05)	(1.93)	(1.79)	(2.66)
Some college	3.73	-1.67	-2.06	17.27	1.03	-18.29	-1.83	10.75	-8.92
	(0.18)	(0.11)	(0.12)	(2.81)	(2.33)	(1.60)	(1.35)	(1.36)	(1.96)
College and higher	1.03	0.39	-1.42	10.76	4.60	-15.36	-4.72	9.59	-4.87
	(0.12)	(0.09)	(0.06)	(2.92)	(2.49)	(1.41)	(2.00)	(1.71)	(2.69)

Table 32: Conditional expectation bias (controlling for labor market duration)

	EE	EU	EN	UE	UU	UN	NE	NU	NN
High school or less (25-34)	5.4	-0.8	-4.6	30.8	-11.6	-19.2	3.6	14.5	-18.1
	(0.66)	(0.47)	(0.31)	(5.62)	(3.74)	(3.49)	(4.49)	(4.65)	(6.77)
High school or less (35-60)	2.1	0.4	-2.5	21.2	-1.0	-20.3	1.6	9.3	-10.9
	(0.44)	(0.29)	(0.26)	(4.49)	(3.49)	(1.93)	(1.32)	(1.39)	(2.15)
Some college (25-34)	2.0	0.0	-2.0	23.3	-6.2	-17.1	-2.6	12.9	-10.3
	(0.52)	(0.31)	(0.37)	(4.60)	(3.64)	(3.09)	(1.69)	(2.14)	(3.01)
Some college (35-60)	1.2	0.6	-1.9	18.8	2.2	-21.0	-0.1	8.7	-8.5
	(0.23)	(0.15)	(0.15)	(2.63)	(2.45)	(0.79)	(0.96)	(1.03)	(1.51)
College and higher (25-34)	0.3	1.3	-1.6	12.2	1.0	-13.2	-6.0	8.7	-2.8
	(0.22)	(0.16)	(0.14)	(3.94)	(3.68)	(2.08)	(2.47)	(1.89)	(3.23)
College and higher (35-60)	0.0	1.5	-1.5	10.0	6.3	-16.3	-0.4	12.0	-11.7
	(0.16)	(0.12)	(0.09)	(2.70)	(2.41)	(1.15)	(1.25)	(1.38)	(2.02)
High school or less (25-44)	3.6	-0.2	-3.4	32.4	-11.7	-20.7	2.6	12.0	-14.6
	(0.46)	(0.31)	(0.26)	(4.07)	(3.07)	(2.08)	(2.49)	(2.54)	(3.75)
High school or less (45-60)	2.1	0.5	-2.6	14.7	3.9	-18.6	1.4	8.9	-10.2
	(0.58)	(0.37)	(0.34)	(5.84)	(4.65)	(2.58)	(1.46)	(1.50)	(2.44)
Some college (25-44)	1.5	0.4	-1.9	22.9	-2.7	-20.2	-1.5	10.5	-9.0
	(0.31)	(0.19)	(0.21)	(3.04)	(2.64)	(1.73)	(1.27)	(1.47)	(2.11)
Some college (45-60)	1.4	0.5	-1.9	16.1	2.9	-19.0	-0.1	9.3	-9.1
	(0.30)	(0.19)	(0.21)	(3.38)	(3.18)	(1.11)	(0.99)	(1.20)	(1.69)
College and higher (25-44)	0.2	1.4	-1.6	13.6	0.4	-14.1	-2.6	10.7	-8.1
	(0.16)	(0.12)	(0.09)	(2.92)	(2.62)	(1.53)	(1.90)	(1.69)	(2.65)
College and higher (45-60)	0.1	1.4	-1.4	7.2	9.8	-17.0	-1.0	11.4	-10.4
	(0.21)	(0.15)	(0.13)	(3.28)	(3.00)	(1.23)	(1.32)	(1.48)	(2.20)

Table 33: Conditional expectation bias (by education and age)

		EE	EU	EN	UE	UU	UN	NE	NU	NN
High school or less	Expansion	2.6	0.4	-3.0	22.9	-2.1	-20.8	1.8	11.7	-13.5
		(0.40)	(0.27)	(0.22)	(3.75)	(3.01)	(1.97)	(1.42)	(1.75)	(2.36)
	Recession	10.8	-5.2	-5.6	41.2	-18.5	-22.6	0.6	3.3	-3.9
		(1.63)	(1.39)	(0.60)	(14.40)	(7.75)	(7.29)	(4.59)	(4.18)	(8.45)
	Recovery	2.6	0.0	-2.6	36.6	-13.7	-23.0	3.0	6.3	-9.2
		(1.05)	(0.48)	(0.77)	(8.54)	(6.83)	(2.20)	(3.51)	(3.25)	(5.93)
Some college	Expansion	1.1	0.6	-1.7	23.9	-1.4	-22.5	0.2	10.3	-10.5
		(0.25)	(0.15)	(0.18)	(2.76)	(2.43)	(1.14)	(1.0)	(1.04)	(1.53)
	Recession	6.2	-3.5	-2.7	19.8	-9.1	-10.7	-2.8	6.6	-3.7
		(1.01)	(0.66)	(0.54)	(6.08)	(8.81)	(7.81)	(2.01)	(3.27)	(4.29)
	Recovery	1.3	1.3	-2.7	16.9	0.6	-17.5	-2.6	10.3	-7.7
		(0.46)	(0.41)	(0.17)	(4.72)	(3.79)	(2.91)	(1.85)	(2.62)	(3.57)
College	Expansion	0.1	1.4	-1.6	11.3	5.4	-16.7	-1.6	11.4	-9.8
		(0.15)	(0.11)	(0.09)	(2.67)	(2.49)	(1.00)	(1.40)	(1.34)	(2.03)
	Recession	2.8	-0.7	-2.1	33.6	-19.1	-14.5	-0.3	15.3	-15.0
		(0.54)	(0.46)	(0.31)	(11.01)	(8.60)	(9.06)	(3.91)	(5.25)	(7.03)
	Recovery	-0.6	1.9	-1.3	5.2	5.5	-10.7	-5.2	7.4	-2.2
		(0.28)	(0.20)	(0.19)	(3.76)	(3.33)	(1.92)	(2.01)	(1.90)	(3.08)

Table 34: Conditional expectation bias during expansion, recession and recovery

	EE	EU	EN	UE	UU	UN	NE	NU	NN
High school or less ($u_t > \bar{u}$)	2.8	0.5	-3.2	20.1	-3.4	-16.7	4.2	14.7	-18.9
	(0.56)	(0.39)	(0.30)	(5.93)	(4.75)	(2.49)	(2.45)	(2.46)	(3.78)
High school or less ($u_t < \bar{u}$)	3.1	-0.2	-2.9	28.3	-6.0	-22.3	0.0	7.1	-7.1
	(0.53)	(0.31)	(0.33)	(4.23)	(3.21)	(2.06)	(1.54)	(1.87)	(2.66)
Some college ($u_t > \bar{u}$)	1.0	1.0	-2.0	17.1	0.7	-17.8	-1.0	11.6	-10.6
	(0.40)	(0.28)	(0.23)	(3.79)	(3.14)	(2.01)	(1.47)	(1.77)	(2.44)
Some college ($u_t < \bar{u}$)	1.8	0.1	-1.9	22.3	-0.9	-21.4	0.0	9.1	-9.2
	(0.28)	(0.16)	(0.20)	(3.06)	(2.78)	(1.57)	(1.13)	(1.33)	(1.93)
College and higher ($u_t > \bar{u}$)	-0.3	1.8	-1.5	6.2	8.0	-14.2	-4.5	13.4	-8.9
	(0.23)	(0.16)	(0.14)	(3.70)	(3.12)	(1.80)	(1.53)	(1.91)	(2.68)
College and higher ($u_t < \bar{u}$)	0.4	1.1	-1.5	14.1	1.9	-16.1	-0.4	9.3	-9.0
	(0.20)	(0.14)	(0.12)	(3.15)	(2.88)	(1.50)	(1.67)	(1.43)	(2.23)

$u_t < \bar{u}$ ($u_t > \bar{u}$): Sample of respondents who reside in a state where the unemployment rate is below (above) trend.

Table 35: Conditional expectation bias and state-unemployment rate (within states)

	EE	EU	EN	UE	UU	UN	NE	NU	NN
All ($u_t > \bar{u}$)	1.7	0.6	-2.3	18.7	-1.3	-17.4	0.7	10.3	-11.0
	(0.20)	(0.13)	(0.11)	(2.32)	(1.76)	(1.27)	(1.13)	(1.08)	(1.66)
All ($u_t < \bar{u}$)	1.0	0.8	-1.8	20.3	-0.7	-19.6	-0.1	10.1	-9.9
	(0.22)	(0.14)	(0.15)	(2.58)	(2.28)	(1.05)	(0.92)	(1.29)	(1.77)
High school or less ($u_t > \bar{u}$)	3.4	0.0	-3.4	21.3	-4.7	-16.6	3.7	9.5	-13.2
	(0.52)	(0.36)	(0.25)	(4.30)	(3.13)	(2.46)	(2.06)	(1.83)	(2.88)
High school or less ($u_t < \bar{u}$)	2.2	0.3	-2.4	28.7	-3.7	-25.0	-0.6	10.8	-10.2
	(0.59)	(0.36)	(0.40)	(5.19)	(4.57)	(1.64)	(1.51)	(2.41)	(3.24)
Some college ($u_t > \bar{u}$)	2.0	0.2	-2.1	23.7	-3.1	-20.6	-1.5	9.4	-7.9
	(0.30)	(0.16)	(0.22)	(3.01)	(2.72)	(1.21)	(1.02)	(1.19)	(1.72)
Some college ($u_t < \bar{u}$)	0.9	0.7	-1.7	17.1	1.3	-18.3	1.1	10.6	-11.7
	(0.33)	(0.22)	(0.21)	(3.74)	(3.16)	(2.18)	(1.43)	(1.62)	(2.31)
College and higher ($u_t > \bar{u}$)	0.2	1.3	-1.6	9.8	6.1	-15.9	-3.4	13.3	-9.9
	(0.19)	(0.13)	(0.12)	(2.96)	(2.76)	(1.34)	(1.43)	(1.79)	(2.49)
College and higher ($u_t < \bar{u}$)	0.2	1.3	-1.5	11.4	2.3	-13.7	-0.6	8.2	-7.5
	(0.18)	(0.13)	(0.11)	(3.36)	(2.98)	(1.71)	(1.79)	(1.29)	(2.35)

$u_t < \bar{u}$ ($u_t > \bar{u}$): Sample of respondents who reside in a state where the unemployment rate is below (above) the aggregate unemployment rate

Table 36: Conditional expectation bias and state-unemployment rate (across states)

G Additional model features

G.1 Government

Government budget balance requires the following condition to hold:

$$\tau \sum_h \sum_z P_h \Pi_h(z) \left[P_h(e) wzh + P_h(u) b(z,h) \right] = \underbrace{\sum_h \sum_z P_h P_h(u) \Pi_h(z) b(z,h)}_{\text{Unemployment benefits}} + \underbrace{\sum_h \sum_z P_h P_h(n) \Pi(z) T}_{\text{Welfare benefits}} \tag{3}$$

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

$$\tau = \frac{\sum_h \sum_z P_h \Pi(z) \Big(P_h(u) \rho_u z h + P_h(n) \rho_n \bar{z} \bar{h} \Big)}{\sum_h \sum_z P_h \Pi(z) z h \Big(P_h(e) + P_h(u) \rho_u \Big)},$$

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

The budget constraint of the social security program is:

$$\Pi_R \sum_h P_h b_{ss}(h) = \tau_{ss} \Pi_W \sum_h P_h P_h(e) wh \sum_z \Pi(z) z \tag{4}$$

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

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

G.2 Recursive competitive equilibrium

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 (1) and (2) and* (c, a') *are the optimal policy functions for consumption and next period's assets.*
- *the factor prices satisfy the firm's optimality conditions*
- *the government budget constraints in (3) and (4) are satisfied*
- *markets clear*

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

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

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.

H Input to calibration

H.1 CPS Welfare Benefits

We use data from the 2015–2021 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:

$$\widehat{p}_{h_L} = \begin{pmatrix} 96.17 & 2.47 & 1.36 \\ 55.47 & 36.51 & 8.02 \\ 7.08 & 12.57 & 80.35 \end{pmatrix} \quad \widehat{p}_{h_M} = \begin{pmatrix} 96.70 & 2.09 & 1.21 \\ 53.81 & 42.14 & 4.05 \\ 6.71 & 12.41 & 80.88 \end{pmatrix} \quad \widehat{p}_{h_H} = \begin{pmatrix} 97.43 & 1.96 & 0.60 \\ 47.77 & 47.48 & 4.75 \\ 7.61 & 10.86 & 81.53 \end{pmatrix}$$

$$p_{h_L} = \begin{pmatrix} 93.26 & 2.47 & 4.27 \\ 39.26 & 33.60 & 27.14 \\ 8.65 & 3.15 & 88.21 \end{pmatrix} \quad p_{h_M} = \begin{pmatrix} 94.99 & 1.84 & 3.17 \\ 41.16 & 35.34 & 23.50 \\ 10.40 & 3.84 & 85.76 \end{pmatrix} \quad p_{h_H} = \begin{pmatrix} 96.65 & 1.14 & 2.20 \\ 45.28 & 35.84 & 18.87 \\ 12.96 & 3.35 & 83.69 \end{pmatrix}$$

I PSID: Life cycle 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 (Tauchen 1986) with three grid points and the Rouwenhorst-method (Kopecky and Suen 2010) 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 extend 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 $64, 000 \times 64, 000$ 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.[37] 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

[37] See FRED (2024) for data availability.

individuals as those with 0-12 grades of school completed, medium-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 Robustness analysis

L.1 Model with endogenous labor supply

In Section 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:

$$\begin{aligned} W_W(a, h, s, z) = \max\nolimits_{c,a',l} u(c, 1-l) \quad &+\beta\theta \textstyle\sum_{s'} \sum_{z'} \widehat{p}_h(s'|s)\pi_h(z'|z)W_W(a', h, s', z') \\ &+\beta(1-\theta)W_R(a', h) \end{aligned} \tag{5}$$

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:

$$\tau \int wzhl(a,h,z)1_{s=e} + b(h,z)1_{s=u} d\Phi(a,h,z,s) = \underbrace{\int b(h,z)1_{s=u} d\Phi(a,h,z,s)}_{\text{Unemployment benefits}} + \underbrace{\int T1_{s=n} d\Phi(a,h,z,s)}_{\text{Welfare benefits}} \tag{6}$$

$$\int b_{ss}(h)1_{s=r} d\Phi(a,h,z,s) = \tau_{ss} \int wzhl(a,h,z)1_{s=e} d\Phi(a,h,z,s) \tag{7}$$

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.

L.2 Model with young and prime-age workers

In Section 5, we extend the baseline model by splitting the work life of individuals into two age intervals: Young and prime-age. Each period, young individuals reach prime age with probability $1 - \theta_1 = 0.0146$ and prime-age individuals retire with probability $1 - \theta_2 = 0.0109$. As in the baseline model, individuals can expect 40 years of work life. The aging probabilities, (θ_1, θ_2), are chosen so that the length of each age interval as a proportion of total work life is the same as in the empirical analysis in Section 2.3. In the extended model, we allow the subjective and actual transition probabilities for every skill group (low-, medium-, and high-skill) to vary with age. We compute these probabilities from SCE and CPS data as described in Section 2.3. In the calibration of the quantitative model, we use the following quarterly values.

Young:

$$\widehat{p}_{h_L} = \begin{pmatrix} 96.08 & 2.73 & 1.19 \\ 64.87 & 27.10 & 8.03 \\ 8.42 & 15.84 & 75.74 \end{pmatrix} \quad \widehat{p}_{h_M} = \begin{pmatrix} 96.14 & 2.30 & 1.56 \\ 57.30 & 38.10 & 4.60 \\ 7.56 & 13.79 & 78.65 \end{pmatrix} \quad \widehat{p}_{h_H} = \begin{pmatrix} 97.45 & 1.98 & 0.57 \\ 53.66 & 41.49 & 4.85 \\ 7.73 & 8.53 & 83.74 \end{pmatrix}$$

$$p_{h_L} = \begin{pmatrix} 92.29 & 3.03 & 4.68 \\ 38.82 & 33.58 & 27.60 \\ 11.21 & 4.57 & 84.22 \end{pmatrix} \quad p_{h_M} = \begin{pmatrix} 94.33 & 2.10 & 3.57 \\ 42.71 & 34.01 & 23.28 \\ 13.46 & 5.13 & 81.40 \end{pmatrix} \quad p_{h_H} = \begin{pmatrix} 96.56 & 1.17 & 2.27 \\ 48.90 & 33.17 & 17.93 \\ 15.38 & 4.09 & 80.53 \end{pmatrix}$$

Prime-age:

$$\widehat{p}_{h_L} = \begin{pmatrix} 96.23 & 2.30 & 1.47 \\ 46.71 & 45.16 & 8.13 \\ 6.32 & 10.79 & 82.89 \end{pmatrix} \quad \widehat{p}_{h_M} = \begin{pmatrix} 97.14 & 1.93 & 0.93 \\ 50.34 & 46.17 & 3.49 \\ 6.19 & 11.51 & 82.30 \end{pmatrix} \quad \widehat{p}_{h_H} = \begin{pmatrix} 97.42 & 1.95 & 0.63 \\ 42.97 & 52.36 & 4.67 \\ 7.57 & 12.55 & 79.88 \end{pmatrix}$$

$$p_{h_L} = \begin{pmatrix} 93.93 & 2.08 & 3.99 \\ 39.73 & 33.62 & 26.65 \\ 7.18 & 2.33 & 90.49 \end{pmatrix} \quad p_{h_M} = \begin{pmatrix} 95.51 & 1.63 & 2.86 \\ 39.53 & 36.74 & 23.74 \\ 8.39 & 2.99 & 88.62 \end{pmatrix} \quad p_{h_H} = \begin{pmatrix} 96.73 & 1.12 & 2.15 \\ 42.13 & 38.18 & 19.69 \\ 11.13 & 2.79 & 86.08 \end{pmatrix}$$

In the extended model, we allow the deterministic part of labor productivity, h, for each skill group to vary with age. Specifically, we use the same data as in the baseline calibration to obtain the values of h. While in the baseline we computed h for each skill group, we now compute it for each skill/age group. We obtain the following values:

$$h(row = skill, column = age) = \begin{pmatrix} 1.0000 & 1.1137 \\ 1.2174 & 1.5253 \\ 1.6052 & 2.1716 \end{pmatrix}$$

All other parameter values can be taken directly from Table 7. In the extended model, total labor in efficiency units, N, is computed as the sum of all (young and prime-age) employed workers' effective labor supply. $\frac{\theta_1}{\theta_1+\theta_2}$ and $\frac{\theta_2}{\theta_1+\theta_2}$ denote the share of young and prime-age individuals in the workforce, respectively. The remainder of the model is as in the baseline.

L.3 Model with housing capital and mortgages

The baseline model is extended to allow for housing wealth and mortgage borrowing. We build on the housing model in Jeske, Krueger, and Mitman (2013) (henceforth JKM). In this model, households derive utility from nondurable consumption c and housing services x. Following JKM, we assume that individuals' preferences are given by

$$U(c, x) = \frac{(c^{\alpha_c} x^{1-\alpha_c})^{1-\sigma} - 1}{1 - \sigma}$$

with $0 < \alpha_c < 1$ and $\sigma > 0$. Individuals can invest in three types of assets, one-period bonds b', physical assets a', and perfectly divisible houses g'. Houses can be rented out and provide housing services. Moreover, houses are subject to idiosyncratic depreciation shocks denoted by δ_g. The distribution of depreciation shocks is a (truncated) generalized Pareto distribution with pdf

$$f_g(\delta_g) = \frac{1}{\sigma_{\delta_g}} \left(1 + \frac{\kappa(\delta_g - \underline{\delta}_g)}{\sigma_{\delta_g}}\right)^{-\frac{1}{\kappa}-1}$$

with $\delta_g \in [\underline{\delta}_g, 1]$ and $\underline{\delta}_g \leq 0$. F_g denotes the cdf of the distribution. Individuals can borrow against their housing wealth by taking on one-period mortgage debt m'. They can default on their mortgages in which case they lose their housing wealth (but keep the physical assets and bonds). In this setting, individuals' default decision depends only on the leverage ratio $\frac{m'}{g'}$. Specifically, an individual prefers to default iff $\delta_g > \delta_g^*(m', g') = 1 - \frac{m'}{g'}$.

A retired individual with physical assets a, housing wealth g, mortgages m, bonds b, human capital h, and idiosyncratic depreciation δ_g solves the following optimization problem:

$$W^R(a, g, m, b, \delta_g, h) = \max_{c,x,b',m',g',a'} \left\{ U(c, x) + \nu\beta \int_{\underline{\delta}_g}^{1} W^R(a', g', m', b', \delta_g', h) dF_g(\delta_g') \right\} \quad (8)$$

subject to

$$c+a'+xP_x+b'P_b+g'P_g-m'P_m(g',m') = (1+r-\delta)\frac{a}{\nu}+\frac{b}{\nu}+\max\{0,P_g(1-\delta_g)g-m\}\frac{1}{\nu}+g'P_x+b_{ss}(h)$$

where (P_b, P_x, P_g, P_m) denote the prices of bonds, housing services, houses, and mortgages. Houses can be rented out immediately after purchase, thus, g' generates rental income equal to $g'P_x$. While in the baseline model, we assumed that (physical) assets of the deceased individuals are redistributed among the retired survivors, we extend this assumption for tractability to include bonds, houses, and mortgage debt.

A working-age individual with physical assets a, houses g, mortgages m, bonds b, human capital h, labor market state s, productivity z, and idiosyncratic depreciation δ_g solves the following optimization problem:

$$\begin{aligned} W^W(a,g,m,b,\delta_g,h,s,z) = \max_{c,x,b',m',g',a'} & \Bigg\{ U(c,x) + \beta(1-\theta)\int_{\underline{\delta}_g}^{1} W^R(a',g',m',b',\delta_g',h)dF_g(\delta_g') \\ & + \beta\theta \sum_{s'}\sum_{z'} \hat{p}_h(s'|s)\pi_h(z'|z)\int_{\underline{\delta}_g}^{1} W^W(a',g',m',b',\delta_g',h,s',z')dF_g(\delta_g') \Bigg\} \end{aligned} \tag{9}$$

subject to

$$c+a'+xP_x+b'P_b+g'P_g-m'P_m(g',m') = (1+r-\delta)\frac{a}{\nu}+\frac{b}{\nu}+\max\{0,P_g(1-\delta_g)g-m\}\frac{1}{\nu}+g'P_x+y$$

There is a perfectly competitive construction sector in which a representative firm produces houses using the linear production technology $I = C_g$. I denotes new houses and C_g is the cost (in units of the final good). The problem of the firm is

$$\max_I P_g I - I \tag{10}$$

which implies an equilibrium price of houses equal to $P_g = 1$

There is a perfectly competitive banking sector in which banks issue bonds to finance mortgages. Banks compete on a loan-by-loan basis which implies that the price of a mortgage of size m' which is collateralized by housing capital equal to g' is given by

$$P_m(g',m') = \frac{P_b}{(1+r_w)}\left(F_g\left(\delta_g^*(m',g')\right) + \gamma\frac{g'}{m'}\int_{\delta_g^*(m',g')}^{1}(1-\delta')dF_g(\delta')\right) \tag{11}$$

where r_w is the percentage real resource cost of issuing mortgages to the bank, and $0 < \gamma \leq 1$ captures the fact that the bank only recovers a fraction of the value from the collateral when foreclosing.

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 $h \in \{h_L, h_M, h_H\}$, physical assets a, houses g, mortgages m, bonds b, and depreciation shock δ_g. In equilibrium, the rental market for housing services has to clear which implies that $\int g' d\Phi = \int x d\Phi$. Bond market clearing implies that $P_b \int b' d\Phi = (1 + r_w) \int P_m(g', m') m' d\Phi$. Goods market clearing implies that

$$K^\alpha L^{1-\alpha} = \int c d\Phi + I + \delta K + r_w \int P_m(g', m') m' d\Phi$$

where gross investment in the housing stock is given by

$$I = \int g' d\Phi + \int \left[\int_{\underline{\delta}_g}^{\delta_g^*(m',g')} g'(1 - \delta_g') dF_g(\delta_g') - \gamma \int_{\delta_g^*(m',g')}^{1} g'(1 - \delta_g') dF_g(\delta_g') \right] d\Phi$$

The remaining features of the model are as in the baseline.

Next, we describe the calibration of the extended model. The parameters for the life cycle (θ, ν), final goods production (δ, α), government policy $(\rho_{ss}, \rho_u, \rho_n)$, human capital (P_h, h), idiosyncratic productivity process $(\phi, \sigma_\eta^2, \sigma_\epsilon^2)$, actual transition probabilities $p_h(s'|s)$, and perceived transition probabilities $\widehat{p}_h(s'|s)$ are calibrated as in the baseline; see Table 7 for the parameter values. We take from JKM the values of the parameters related to the housing features in the model. This includes the parameters for the foreclosure technology ($\gamma = 0.78$), non-durable consumption ($\alpha_c = 0.8590$), mortgage administration fee ($r_w = 0.001$), as well as the parameters associated with the distribution of house price shocks ($\kappa = 0.7302, \sigma_{\delta_g} = 0.0078, \underline{\delta_g} = -0.0077$). Lastly, we calibrate the coefficient of relative risk aversion, σ, to match the median leverage ratio.

L.4 Collapse U and N

When calibrating this version of the model, we can take most of the parameter values directly from Table 7. Only two sets of parameters have to be adjusted. The first set of parameters includes the labor market transition probability matrices $(p_h(s'|s), \widehat{p_h}(s'|s))$ which govern the transition between the two labor market states employment (E) and non-employment (nE). For each given skill group h, the 2×2 transition matrix (actual and subjective) can be computed directly from the 3×3 matrix used in the baseline, where the EE probability is as before and the new EnE probability is equal to 1–Pr(EE). Moreover, the nEE probability is computed as the population-weighted average of the UE and NE probabilities. This procedure yields the following transition matrices.

$$\widehat{p}_{h_L} = \begin{pmatrix} 96.35 & 3.65 \\ 17.79 & 82.21 \end{pmatrix} \quad \widehat{p}_{h_M} = \begin{pmatrix} 96.84 & 3.16 \\ 17.31 & 82.69 \end{pmatrix} \quad \widehat{p}_{h_H} = \begin{pmatrix} 97.54 & 2.46 \\ 19.73 & 80.27 \end{pmatrix}$$

$$p_{h_L} = \begin{pmatrix} 93.26 & 6.74 \\ 13.11 & 86.89 \end{pmatrix} \quad p_{h_M} = \begin{pmatrix} 94.99 & 5.01 \\ 15.68 & 84.32 \end{pmatrix} \quad p_{h_H} = \begin{pmatrix} 96.65 & 3.35 \\ 18.43 & 81.57 \end{pmatrix}$$

The second set of parameters to adjust are the policy parameters. In the baseline, we assume that unemployed workers receive a fraction ρ_u of their potential wage and inactive individuals receive a fraction ρ_n of the economy-wide average wage. In this version of the model with one state of non-employment, we assume that non-employed workers receive benefits which are equal to a fraction ρ_{un} of their potential wage. We compute the replacement rate ρ_{un} as the weighted average of ρ_U and ρ_n, where the weights are population shares of unemployed and inactive individuals. This procedure yields a value for ρ_{un} of 0.08.

L.5 Monthly frequency

Several parameter values depend on the model frequency. Hence, we adjust them, when we calibrate the model to a monthly frequency. This includes the labor market transition probabilities $(p_h(s'|s), \hat{p_h}(s'|s))$ which are transformed to monthly values as described in Appendix H.2. The monthly probability of retiring is set to $1 - \theta = 0.0021$ so that individuals expect 40 years of work life as in the baseline calibration. The monthly probability of dying is set to $1 - \nu = 0.0056$ so that retirees expect to spend 15 years in retirement. The value of the monthly depreciation rate is equal to 0.84% which implies a 2.5% quarterly depreciation rate. As in the baseline, the personal discount factor is calibrated so that the model generates a 4% annual net return. This implies a value of $\beta = 0.9962$. Lastly, the parameters of the stochastic labor productivity process are transformed to a monthly frequency following the procedure as described in KMP:

$$\phi = \widehat{\phi}^{\frac{1}{12}} \qquad \sigma_\epsilon^2 = \widehat{\sigma_\epsilon^2} \qquad \frac{\sigma_\eta^2}{1-\phi^2} = \frac{\widehat{\sigma_\eta^2}}{1-\widehat{\phi}^2}$$

where the "hat" denotes annual values as shown in Table 7. All other parameters are invariant to the model frequency.

M Stylized 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

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

	Baseline		Housing		U&N		Monthly	
	w	w/o	w	w/o	w	w/o	w	w/o
Panel (a): Wealth quintiles								
$Q1$	0.3	0.9	2.1	2.5	0.6	1.0	0.3	1.0
$Q2$	2.0	3.9	6.6	7.6	2.6	3.6	2.0	3.9
$Q3$	5.9	8.9	12.3	13.5	6.8	8.2	5.9	8.9
$Q4$	16.8	19.4	21.9	22.6	17.4	18.8	16.7	19.4
$Q5$	75.1	66.9	57.1	53.9	72.7	68.4	75.1	66.8
Panel (b): Gini coefficient								
	0.72	0.64	0.53	0.50	0.69	0.65	0.72	0.64
Panel (c): Savings rate, in %								
L	27.9	36.5	33.4	42.6	28.7	34.7	27.9	36.6
M	31.0	34.6	35.1	42.0	31.8	33.3	31.0	34.7
H	33.0	32.9	36.5	41.7	32.8	32.0	33.1	33.0
Panel (d): Consumption smoothing								
b_{all}	0.10	0.07	0.07	0.05	0.08	0.07	0.01	0.01
Panel (e): Welfare, in %×100								
ϕ_L	5.3		11.9		2.1		5.4	
ϕ_M	3.5		11.9		1.2		3.5	
ϕ_H	2.6		11.9		1.1		2.6	

"Housing": Baseline model extended by housing wealth and mortgage debt. "U&N": Unemployment and non-participation combined in one state. "Monthly": Monthly frequency. "w" ("w/o"): Subjective expectations in the model are with (without) bias; "L","M","H": Low-, middle-, high-skilled. Panel (c): Average savings rate of working-age individuals. Panel (d): Coefficient estimate of b from $\Delta c_{it} = a + b \cdot \Delta y_{it} + e_{it}$. Panel (e): Consumption equivalent variation.

Table 37: Robustness analysis - additional results

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 affects 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.