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Subjective Unemployment Expectations and (Self-)Insurance.

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Abstract

We study subjective unemployment expectations and their influence on economic behavior. We utilize a longitudinal data set combining survey elicited subjective unemployment expectations with administrative data on income, savings, and unemployment insurance. Our findings indicate that subjective expectations hold valuable predictive information about subsequent unemployment experiences. We find that individuals tend to overestimate their risk of unemployment. Moreover, higher unemployment expectations leads to a greater likelihood of enrolling in unemployment insurance and accumulation of liquid savings.

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1 Introduction

Individual expectations are fundamental in models of choice under uncertainty. For example, when individuals make decisions about work, spending, saving and insurance, they need to form beliefs about their future earnings and, in particular, the risks that earnings can deviate from what they expected. A key component of earnings risk relates to unemployment (Guvenen et al., 2021). Expectations about earnings risk play a crucial role in shaping economic behavior, influencing decisions such as reducing spending, increasing savings, and joining unemployment insurance (UI) funds to prepare for potential income loss.[1] Such risk is in essence subjective.

Without data on subjective expectations, we can only speculate about how people perceive the risk of future unemployment and how expectations determine the choices that they make. Previous studies using subjective data on job-loss risk have shown that private knowledge about future job-loss impact willingness to pay for unemployment insurance (Hendren, 2017), and that it can affect consumption and saving choices (Stephens, 2004; Lusardi, 1998). However, the evidence about how subjective measures of unemployment risk predict actual choices is extremely sparse. This is due to the lack of longitudinal data with information about subjective unemployment expectations, subsequent realizations and relevant outcomes.

In this paper, we examine how subjective expectations about own unemployment affect decisions about unemployment insurance, both formal, in the form of unemployment insurance, and informal, in the form of liquid savings. We consider these two margins of adjustment because UI and liquid savings are the two key insurance channels at play when people become unemployed Andersen et al. (2023). We do this using a longitudinal data

[1]In this paper, we consider subjective expectations about unemployment in a short term horizon. There is a wider literature that considers other labor market related risks (see Mueller and Spinnewijn (2022) for an overview) and long-term earnings risk related to choice of education (see Giustinelli (2022) for an overview).

set with subjective unemployment expectations. The data is based on a sequence of surveys conducted annually from 2010 to 2016, and it includes over 11,500 respondents, out of which 7,300 participated several years in a row. We combine the subjective unemployment expectations with administrative data for the respondents. The administrative data contains third-party reported information about realized unemployment, income, savings and UI fund membership, both before, during and after the surveys were conducted. Importantly, the panel structure of the data allows us to evaluate the predictive power of the expectations and follow the outcomes over time at the individual level.

Our study begins by highlighting three empirical findings that shed light on the relationship between unemployment expectations and actual unemployment experiences. First, subjective unemployment expectations contain valuable information, as they are predictive of subsequent unemployment outcomes. Second, many people adjust their unemployment expectations. Around half of the respondents change their unemployment expectations between surveys, and many do so even if they are not affected by unemployment. Third, we reject that individuals have rational expectations. Rather, we observe a systematic bias in subjective unemployment expectations, with most individuals overestimating the risk of unemployment. We find that the unemployment probability is 0.3 pct. points higher for individuals who report a 1 pct. point higher probability of experiencing unemployment in the coming year. This indicates that individuals have a pessimistic outlook on unemployment prospects relative to realized outcomes. Building on the work of Mueller and Spinnewijn (2022), we group individuals by gender, age, education, income and unemployment history and calculate group unemployment probabilities. We then define prediction errors as the difference between the individual's subjective unemployment expectations and the unemployment probabilities for the group which the individual belongs to. We show that prediction errors are positively auto correlated, indicating that individuals tend to persistently overestimate their probability of unemployment.

We then turn to show how subjective unemployment expectations and prediction errors shape the choice of formal unemployment insurance and informal insurance, i.e., the accumulation of liquid savings. UI fund enrollment is heavily subsidized in Denmark. As a result, more than 80 pct. of workers are enrolled and there is little turnover. Nevertheless, we find that higher unemployment expectations are correlated with higher probabilities of enrolling in a UI fund. For a 10 pct. points increase in unemployment expectations, we find an increase in the probability of being a member of a UI fund of 0.3 pct. points. Further, there is a negative effect for individuals who overestimated their unemployment probability. Thus, while few respondents enter or leave a UI fund during the period in which the survey ran, for those who do, unemployment expectations appear to matter for their UI membership.

We also examine whether unemployment expectations influence savings. With the substantial enrollment rate in UI and the fact that UI benefits are limited in their coverage, liquid savings serve as a self-insurance resource that is complementary to formal UI. In fact, we observe a robust inverse correlation between the UI replacement rate and liquid savings. We also show that there is a positive effect of subjective unemployment expectations on liquid savings, and that this effect is only significant for individuals who are unlikely to be liquidity constrained. Additionally, we follow Lusardi (1998) and define a measure of income risk which depends on unemployment expectations. We find that an increase in income risk, driven by subjective unemployment expectations, leads to increased liquid savings. Moving from the 25th percentile to the 75 percentile in the distribution of income risk is associated with an increase in liquid savings rate of 2.36 pct. points. This finding is consistent with the idea that liquid savings is influenced by a precautionary motive. We further find positive, and significant effects of income expectations and income shocks on the liquid savings rate. Overall, our analyses show that subjective unemployment expectations hold information that is valuable for describing people's insurance choices, i.e., UI fund membership and self-insurance through the accumulation of liquid savings. As expectations vary across people, this can help explain why people, who otherwise appear observationally similar, make different economic decisions.

Our paper contributes to a growing literature studying subjective expectations. We add to the branch of the literature which considers the power of expectations in predicting future outcomes as lead by Manski (2004). Consistent with Stephens (2004), Campbell et al. (2007) and Hendren (2017), we show that subjective unemployment expectations are predictive of actual future unemployment. However, while this indicates that the expectations contain relevant information about future unemployment shocks, we also show that the expectations are biased, and individuals tend to overestimate their probability of becoming unemployed. This too confirms the findings of previous papers, e.g. Balleer et al. (2023) and Dickerson and Green (2012). We contribute to this literature by showing that individuals persistently overestimate their unemployment probability.

We further add to the literature which considers how expectations affect economic behavior and decision making. Carroll et al. (2003) develop a model in which precautionary savings is positively correlated with job loss risk, and empirically find this to be the case for moderate and high level income households. Similarly, Lusardi (1998) finds that individuals who face higher income risk as a result of unemployment risk accumulate more wealth. We show, among other things, that an increase in income risk induced by an increase in the unemployment risk leads to increased liquid savings, in line with a precautionary savings motive. We also add to the literature studying selection into UI insurance. Landais et al. (2021) use Swedish population-wide administrative data and quasi-experimental designs to show that individuals who opt into UI membership have a higher unemployment risk than individuals who do not. Using subjective unemployment expectations data, Hendren (2017) provides evidence that individuals have private information about their unemployment risk which causes the market for private UI to be too adversely selected to be profitable. We provide first evidence that subjective unemployment expectations predict enrollment into UI fund membership. Additionally, we find that individuals who are already members of a UI fund are more likely to opt out when their realized unemployment risk is smaller than they expected. Both pieces of evidence are consistent with adverse selection into UI fund membership.

The remainder of this paper is organized as follows: Section 2 presents the survey and administrative data used in our analysis. Section 3 characterizes unemployment expectations and highlights their informational value. In Section 4, we define prediction errors and demonstrate persistent overestimation of unemployment probabilities. Section 5 examines the influence of unemployment expectations on UI membership and savings. Finally, Section 6 concludes the paper.

2 Data

The data used for our analyses is constructed by combining survey data and administrative data. The survey data provides us with information on subjective expectations about unemployment and the administrative data provides us with third-party reported information on unemployment spells, income, UI fund membership, liquid wealth and a rich set of background characteristics for each respondent. The data is combined at the individual level, using the Central Person Registry number, a number which uniquely identifies all individuals in the Danish population.

2.1 Survey Data

Information on subjective expectations is collected through a custom, longitudinal survey. The surveys were conducted by the survey agency Epinion A/S, who was commissioned to conduct the surveys by telephone at the beginning of each year in 2010 to 2016. Invitations to participate in the survey were sent to a random sample of Danes who are likely attached to the labour market. Specifically, the target population consists of all people who had accumulated funds in a compulsory labour market pension fund. This included anyone with earned income during 1998-2003. In practice, this covers the entire Danish work force during these years, totally around 2.9 million workers.[2] In the subsequent survey rounds

[2]The details of this are explained in Kreiner et al. (2019) who study the effect of paying out these funds as part of a stimulus policy implemented in 2009

(2011-2016), respondents consisted of individuals who had participated in the survey in the previous year and new, randomly selected individuals, creating a pool of both newcomers and repeat respondents with a re-interview rate of approximately 75 pct. Each interview covered close to 40 questions and lasted 10 to 12 minutes. The questions covered a range of topics, including expectations about unemployment.

Respondents were asked about their unemployment expectations using a probabilistic question, inspired by Manski (2004). This has the advantage of being comparable across respondents, as the information content is less ambiguous than asking respondents to choose the most probable outcome (Potter et al., 2017). This question was asked early in the interview, immediately following questions on the respondent's financial circumstances. Specifically, respondents were asked:

How do you assess the probability that you will experience a period without a job during the coming year? I would like you to state a number between 0 and 100, in which 0 means that you believe that, with certainty, the event will not occur and 100 means that you believe, with certainty, that the event definitely will occur.

We denote individual i's expectations about own unemployment in year t, reported at the beginning of year t, by $E_{i,t-1}[U_{i,t}]$.

2.2 Administrative Data

We use administrative data from various sources compiled by Statistics Denmark and made available for research. We draw primarily on the population register and from the income-tax register which includes annual information for all survey respondents. From the administrative data, we obtain demographic characteristics and longitudinal information about UI fund membership, liquid savings and income. Liquid savings, which we denote $S_{i,t}$, includes cash in deposit accounts and is third party reported from from financial institutions to the Danish Tax Agency. Income is also third-party reported by employers directly to the tax agency. We define income, $Y_{i,t}$, as labor earnings, income from self-employment and unemployment benefits, before taxes are deducted and excluding contributions to employer administered pension accounts. The administrative data, including the data from the income-tax register, is known to be of high quality (Kleven et al., 2011) and have been used extensively in previous studies of savings behavior, see, for example, Leth-Petersen (2010), Kreiner et al. (2019) and Andersen and Leth-Petersen (2021).

The administrative data further contains third-party reported information recorded at a monthly frequency on both earnings and transfer payments, such as unemployment insurance benefit payments. We use this information to construct a measure of unemployment. We identify an individual as being unemployed in a period of time if, during that period, the individual did not received any income from an employer, but did receive unemployment insurance transfers. Constructing the unemployment measure this way allows us to identify how long a given unemployment spell lasts. Based on this information we construct an indicator for having experienced unemployment during a year which is what we asked respondents about in the survey.

2.3 Final Dataset

Combining the survey data with administrative data at the individual level, we are able to compare survey measures of expectations with third-party reported information about the corresponding realizations. The administrative data used in this paper is recorded at the end of the year and the survey was conducted at the beginning of the year, i.e. immediately after the administrative data is recorded. The close synchronization means that observed outcomes from the previous year have been realized shortly before the survey was conducted.

The panel format of our data is critical (Mueller and Spinnewijn, 2022; Mueller et al., 2021), as it allows us to follow the evolution of expectations and outcomes over time at the individual level. This, in combination with the fact that we have both subjectively reported expectations and third-party reported outcomes for all our respondents allows us to evaluate the predictive power of the expectations and measure potential biases herein.

Since we know the identity of all individuals who were invited to participate in the survey, we are able to characterize survey participants and non-participants in terms of the information that we see in the administrative data. Survey respondents include all individuals who reported their unemployment expectations, as this is the main question of interest in the survey. Our survey sample consists of 11,511 respondents. 4,205 respondents, equal to 37 pct., only participate once, while 7,306 respondents participate several times, cf. table 1.

Table 1: Observations by Times of Participation

	2010	2011	2012	2013	2014	2015	2016	Total
1	1616	463	384	290	283	326	843	4205
2	777	232	165	162	177	611	0	2124
3	566	186	97	133	418	0	0	1400
4	428	127	83	416	0	0	0	1054
5	378	120	285	0	0	0	0	783
6	370	405	0	0	0	0	0	775
7	1170	0	0	0	0	0	0	1170
Total	5305	1533	1014	1001	878	937	843	11,511

The tables shows the number of times the survey respondents participated in the survey, by first year of participation. Rows refer to times of participation and columns refer to year of first participation.

Table 2 presents a comparison between the survey respondents and non-respondents. Survey respondents are between the ages 24 and 71, with an average age of 51, a little younger than non-respondents. Respondents are 3 pct. points more likely to be male and

15 pct. points more likely to be married than the general population. Respondents have higher education and slightly higher income than non-respondents. Lastly, respondents experience less unemployment and are more likely to be members of a UI fund. On average, respondents are unemployed 6 days a year, while non-respondents are unemployed for 7 days a year. 73 pct. of the respondents have unemployment insurance, which is 12 pct. points more than non-respondents. Despite the statistical significant differences between respondents and non-respondents, the differences are economically small, and overall, the two groups are quite similar.

Table 2: Survey Respondents vs. Non-Respondents

	Sample = 0	Std. Dev.	Sample = 1	Std. Dev.	Difference	t-test
Males	0.45	0.50	0.48	0.50	-0.03	-5.93
Age	51.48	12.15	51.19	10.85	0.30	2.16
Married	0.49	0.50	0.64	0.48	-0.15	-27.38
Unemployed	0.05	0.23	0.05	0.21	0.01	3.16
Days of Unemployment	7.00	36.54	5.72	32.56	1.28	3.09
UI Membership	0.61	0.49	0.73	0.44	-0.12	-22.60
Self-Employed	0.10	0.30	0.15	0.35	-0.05	-12.28
Elementary School	0.22	0.42	0.13	0.34	0.09	19.89
High School/Vocational	0.45	0.50	0.42	0.49	0.03	5.07
Short Education	0.05	0.22	0.06	0.23	-0.01	-2.77
Middle Education	0.17	0.38	0.24	0.43	-0.07	-14.48
Long Education	0.09	0.29	0.15	0.35	-0.05	-14.09
Avg. Income, 2007-2009 (DKK)	284,920.14	217,150.25	339,275.54	221,538.25	-54,355.40	-21.69
Liquid Savings (DKK)	163,295.49	975,551.48	176,692.89	342,267.96	-13,397.40	-1.42
Observations	23,219		11,511			

The table shows average characteristics in 2016 for survey participants and non-participants. Males, Married, Unemployed, UI Membership, Self-Employed and all education groups are dummy variables.

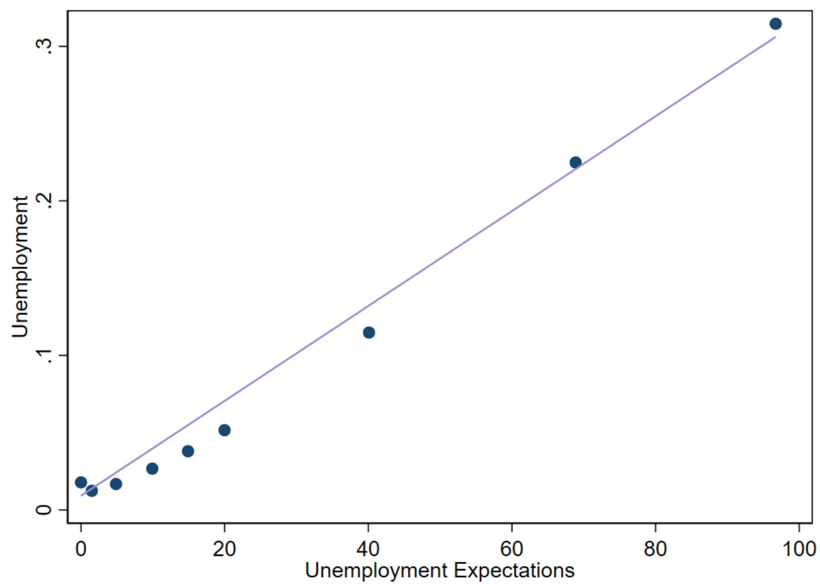
3 Facts about Unemployment Expectations

Data with longitudinal information about unemployment beliefs and unemployment realizations are rare. We start out by showing some empirical facts about unemployment expectations and how they relate to actual unemployment in our data. We highlight three findings. First, subjective unemployment expectations are predictive of subsequent unemployment experiences. Second, many people change their unemployment expectations. Third, subjective unemployment expectations are not rational. Instead, they are biased, with most individuals overestimating the risk of unemployment.

We first show that there is valuable information in subjective unemployment expectations. That is, our subjective unemployment expectations, $E_{i,t-1}[U_{i,t}]$, are predictive of subsequent unemployment experiences, $U_{i,t}$. This is important, as it means that individuals have relevant knowledge about potential unemployment shocks in the future (Manski, 2004; Campbell et al., 2007; Conlon et al., 2018; Mueller and Spinnewijn, 2022). Here, we exploit the panel structure of our dataset, which allows us to follow the same individuals over time, and the fact that we have both elicited subjective expectations and third-party reported information on outcomes. Figure 1 illustrates the unconditional association between $\mathbb{I}(U_{it} > 0)$ and $E_{i,t-1}[U_{i,t}]$, i.e., how expectations about unemployment in period t predicts actual unemployment in period t. The figure shows a very clear and practically linear relationship between the expectations and subsequent realization. That is, higher subjective unemployment expectations are correlated with a higher probability of subsequently experiencing unemployment. This indicates that respondents' unemployment expectations hold information about the actual probability of unemployment.

Figure 2a shows the distribution of subjective unemployment expectations. We see that while approximately half of all elicited expectations are 0 pct., there is still large variation in expectations. With mass points at 0, 10, 50 and 100, there is indication of rounding of responses. The mass points at 0 and 100 seemingly indicate that respondents are certain that they will not become unemployed, or certain that they will become unemployed

Figure 1: Actual Unemployment vs. Unemployment Expectations



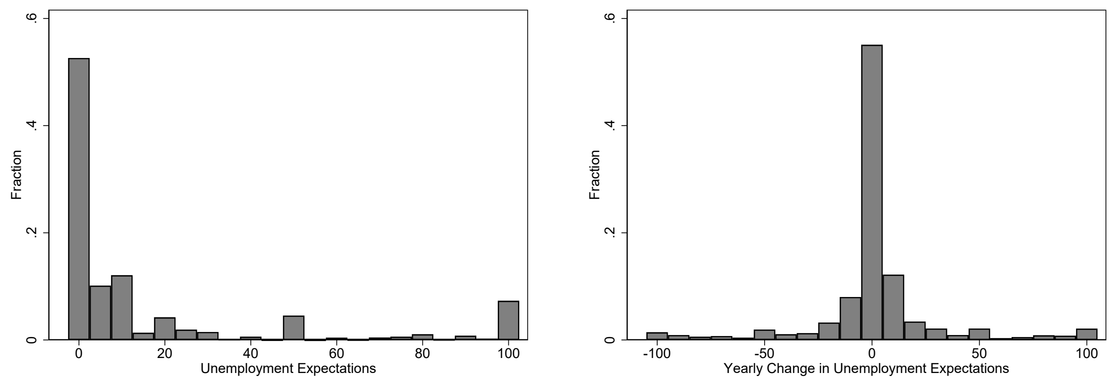
This figure shows a binned scatterplot of the correlation between actual unemployment ($\mathbb{I}[U_{it} > 0]$) and unemployment expectations ($E_{t-1}[U_t]$).

respectively. These patterns of rounding and mass points are common in responses to probabilistic questions (Bruine de Bruin et al., 2022). However, we note that there are also many reported probabilities in the middle of the scale.

Figure 2b shows the distribution of within-individual yearly changes in subjective unemployment expectations, i.e. $E_{i,t}[U_{i,t+1}] - E_{i,t-1}[U_{i,t}]$. The mass point at 0 indicates that close to 50 pct. of the respondents do not change their expectations from year to year. However, the remaining 50 pct. of respondents do change their expectations, and while most of these changes lie in the range of ±20 pct. points, 3 pct. of the observations reflect within-individual yearly changes of ±100 pct. points. Figure 2b informs us that subjective unemployment expectations are far from constant at the individual level. Rather, a significant fraction of individuals appear to change their expectations from year to year, and this is also the case even for individuals who are never actually affected by unemployment during the period in which we observed them.

Figure 2: Distribution of Subjective Unemployment Expectations

(a) Unemployment Expectations (b) Change in Unemp. Expectations



The figures show the distribution of subjective unemployment expectations and within-individual yearly changes in subjective unemployment expectations, respectively.

While Figure 1 shows us that subjective unemployment expectations hold valuable information about subsequent unemployment experience, it also highlights the fact that subjective unemployment expectations are biased. In particular, individuals tend to overestimate the probability of experiencing unemployment in the following year. Table 3 underlines this point. The tables presents the estimation results of the regression given by equation (1).

$$\mathbb{I}[U_{i,t} > 0] = \beta_0 + \beta_1 E_{i,t-1}[U_{i,t}] + \beta_2 X_{i,t} + \varepsilon_{i,t} \tag{1}$$

Here, $\mathbb{I}[U_{i,t} > 0]$ is a dummy for individual i being unemployed in year t, $E_{i,t-1}[U_{i,t}]$ is subjective unemployment expectations about unemployment in year t and $X_{i,t}$ is a vector of observable characteristics, including gender, four age groups, four education groups, an indicator for having above median income, and an indicator for being unemployed in year $t-1$. Column 1 in table 3 corresponds to figure 1. It informs us that the unconditional correlation between subjective unemployment expectations and subsequent realized unemployment is 0.0031. This means that on average, the unemployment probability is

0.3 pct. points higher for individuals who report a 1 pct. point higher probability of experiencing unemployment in the coming year. This correlation only decreases slightly when we include a the observable characteristics, but remains positive and highly significant. This illustrates that while subjective unemployment expectations contain relevant information about unemployment probabilities, on average, individuals are not perfectly able to foresee their own unemployment probabilities. If that was the case, the estimate of β_1 would have been 0.01, and the unemployment probability would have been 1 pct. points higher for individuals who report a 1 pct. point higher probability of experiencing unemployment. As β_1 is estimated to be significantly below 0.01, this suggests that individuals are pessimistic about the probability that they will experience unemployment, that is, they overestimate this probability of unemployment. This is in line with previous literature considering subjective expectations about the probability of experiencing job-loss (Hendren, 2017; Stephens, 2004).

We perform a test of rational expectations. The theory of rational expectations states that expectations do not systematically differ from subsequent outcomes. As our outcome is binary, we can test whether this is the case, simply by testing whether the average outcome, equals the average expectation, $\mathbb{E}[\mathbb{I}[U_{i,t} > 0]] = \mathbb{E}[E_{i,t-1}[U_{i,t}]]$ (D'Haultfoeuille et al., 2021). Under the null of rational expectations, the two means would not be significantly different from one another. We perform a paired t-test of the null that $\mathbb{E}[\mathbb{I}[U_{i,t} > 0]] = \mathbb{E}[E_{i,t-1}[U_{i,t}]]$. The result is shown in the first row of table 4. The results show that the means of $E_{i,t-1}[U_{i,t}]$ and $\mathbb{I}[U_{i,t} > 0]$ are significantly different. That is, we reject the null that individuals have rational expectations. In the remaining rows of table 4, we perform the same test for different subgroups of our sample. For all groups, we reject the null of rational expectations. This is in line with results in table 3. If individuals have rational expectations, the estimate of β_1 should be 0.01 and the estimate of β_0 should be 0. The regression results suggest that individuals do not have rational expectations, even when we control for age, sex, education, income and unemployment history. The fact that our respondents do not exhibit rational expectations is in line with previous

Table 3: Unemployment, $\mathbb{I}[U_{i,t} > 0]$

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
Unemployment Expectations, $E_{i,t-1}(U_{i,t})$	0.00326***	0.00287***	0.00259***	0.00234***
	(0.000224)	(0.000185)	(0.000153)	(0.000135)
Unemployed in $t-1$			0.260***	0.245***
			(0.0235)	(0.0215)
Age 35-44		-0.0188		-0.0135
		(0.0158)		(0.0107)
Age 45-54		-0.0216		-0.0137
		(0.0162)		(0.0106)
Age 55-65		-0.0368**		-0.0239**
		(0.0155)		(0.0101)
Male		0.00781		0.00588
		(0.00827)		(0.00483)
High School and Vocational		0.00696		0.00657
		(0.0145)		(0.00700)
Short and Middle Higher Education		0.00184		0.00304
		(0.0126)		(0.00641)
Long Higher Education		0.0162		0.0131
		(0.0145)		(0.00940)
Income Above Median		-0.0708***		-0.0516***
		(0.0104)		(0.00624)
Constant	0.00846**	0.0784***	0.00217	0.0505***
	(0.00345)	(0.0177)	(0.00254)	(0.0110)
Observations	31,164	31,164	31,164	31,164
R-Squared	0.157	0.174	0.222	0.231

Clustered standard errors by the stratified groups described in section 4 in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All variables, except for unemployment expectations are dummies.

literature (Mueller and Spinnewijn, 2022; Balleer et al., 2021). However, other papers find substantial heterogeneity in the accuracy of expectations. D'Haultfoeuille et al. (2021) find that while their full sample do not have rational earnings expectations, they cannot reject that some subgroups, including males and college-educated individuals, may have rational earnings expectations. Similarly, Giustinelli and Shapiro (2023) find heterogeneity in rationality in subjective expectations about health-contingent working probabilities by age. The fact that we find no evidence of such heterogeneity, is likely due to the difference in outcomes.

4 Prediction Errors

The fact that individuals have biased expectations gives rise to prediction errors. As individuals are not able to perfectly foresee unemployment, there is a discrepancy between their unemployment expectations and their subsequent unemployment outcomes. In this section, we calculate individual prediction errors based on group unemployment probabilities. We use these prediction errors to show that individuals persistently overestimate the probability of unemployment.

In line with Mueller and Spinnewijn (2022), we construct prediction errors by comparing the subjective unemployment expectations to the unemployment realizations for groups of individuals. We construct the groups for our whole sample, consisting of both respondents and invited, non-responding individuals. The groups are formed by stratifying the data by gender, age, education, income and unemployment history. This yields a total of 128 unique groups and an average of 1,544 observations per group.[3]

[3]In appendix A we show the correlation between unemployment expectations and realized unemployment for each of the observables we use to stratify the data. In accordance with the test results in table 4, we see very little heterogeneity in the bias of the unemployment expectations. However, there appears to be some variation by education and income, with the bias decreasing with higher levels of education and increasing with income.

Table 4: Test of Rational Expectations

	$\mathbb{E}[\mathbb{I}[U_{i,t} > 0]]$	$\mathbb{E}[E_{i,t-1}[U_{i,t}]]$	Difference	Std. Dev.	t-test	Number of Obs.
All	0.17	0.06	0.11	0.00	63.58	32,702
Males	0.17	0.06	0.11	0.00	45.26	16,286
Females	0.16	0.06	0.10	0.00	44.75	16,416
Age 25-34	0.23	0.11	0.12	0.01	20.70	4,102
Age 35-44	0.16	0.06	0.10	0.00	31.35	8,008
Age 45-54	0.15	0.06	0.09	0.00	35.20	10,305
Age 55-65	0.15	0.05	0.11	0.00	33.65	9,145
Elementary School	0.22	0.08	0.14	0.01	23.11	3,804
High School/Vocational	0.17	0.07	0.10	0.00	39.28	13,241
Short/Middle Education	0.15	0.05	0.10	0.00	36.96	10,426
Long Education	0.15	0.06	0.09	0.00	25.19	5,007
Low Income	0.32	0.15	0.17	0.00	39.38	9,728
High Income	0.10	0.02	0.08	0.00	54.69	22,974
Not Unemployed in $t-1$	0.14	0.04	0.11	0.00	65.70	30,325
Unemployed in $t-1$	0.50	0.39	0.11	0.01	9.40	2,105

The table shows results from paired t-tests of $\mathbb{E}[\mathbb{I}[U_{i,t} > 0]] = \mathbb{E}[E_{i,t-1}[U_{i,t}]]$. The null hypothesis is that $\mathbb{E}[\mathbb{I}[U_{i,t} > 0]] = \mathbb{E}[E_{i,t-1}[U_{i,t}]]$, while the alternative hypothesis is that $\mathbb{E}[\mathbb{I}[U_{i,t} > 0]] \neq \mathbb{E}[E_{i,t-1}[U_{i,t}]]$.

We calculate the probability of unemployment, $\hat{Pr}(U_{s,t} = 1)$, for each group s, as the share of the group that experience unemployment in year t. Based on this group specific unemployment probability, we calculate each individual's prediction error, $\theta_{i,t}$ as,

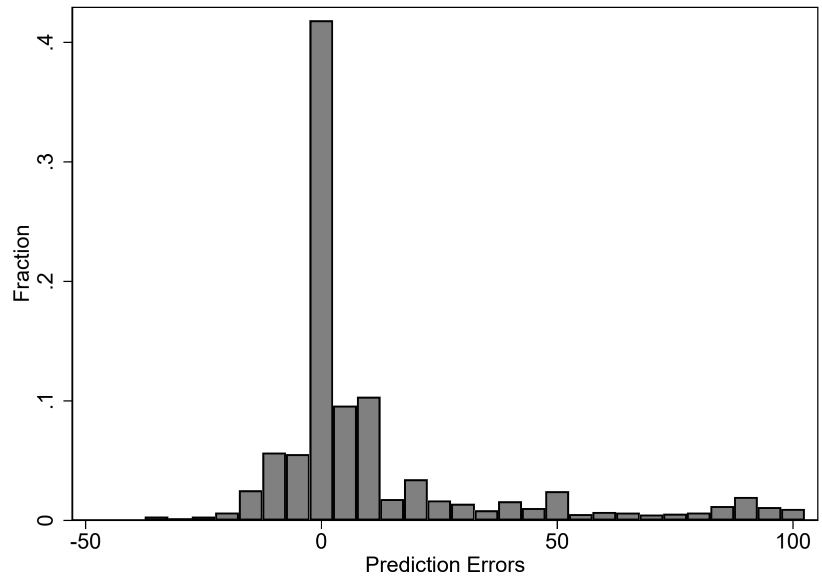
$$\theta_{i,t} = E_{i,t-1}[U_{i,t}] - \hat{Pr}(U_{s,t} = 1) \cdot 100 \tag{2}$$

Equation (2) yields a measure of the prediction error, confined to the interval [-100,100]. A positive value of $\theta_{i,t}$ means that the individual overestimated the probability of unemployment, relative to the realized unemployment probabilities for the group that the individual belongs to. Conversely, a negative value of $\theta_{i,t}$ means that the individual underestimated the probability of unemployment, relative to the realized unemployment probabilities for the group that the individual belongs to.

Figure 3 shows the distribution of the prediction errors. It shows that the majority of respondents have positive prediction errors, meaning that they overestimated the probability of becoming unemployed, relative to their group. Further, 41 pct. of the prediction errors are in the range $[-2.5, 2.5[$. Thus, a large share of respondents' unemployment expectations are very accurate. However, we also see a share of individuals with very large prediction errors. Especially large positive prediction errors, stemming from individuals who report high subjective unemployment expectations, but whose group's actual unemployment probability is relatively low. In contrast, fewer individuals have large negative prediction errors, with most negative prediction errors being numerically smaller than -10. That is, while prediction errors go in both directions, individuals most commonly overestimate the probability of unemployment.

The prediction errors, $\theta_{i,t}$, are positively correlated with their previous values, $\theta_{i,t-1}$. An AR(1) regression of the prediction errors yields an estimated autocorrelation of 0.28. That is, individuals do not tend to alternate between over- and underestimating their unemployment probability. Rather, their biases, if any, tend to persistently go in one direction. Coupled with the distribution shown in Figure 3, this indicates that many individuals persistently overestimate their unemployment probability, leading to reiterated

Figure 3: Distribution of Prediction Errors, $\theta_{i,t}$



This figure shows the distribution of the prediction errors, $\theta_{i,t}$ given by equation (2).

positive prediction errors.

5 Insurance Behavior

Ultimately, the interest in expectations stems from the fact that economic models stipulate that expectations are important determinants of choice when individuals make choice under uncertainty. It is therefore important to understand whether this also holds true empirically. In this section, we investigate whether and how unemployment expectations and unemployment prediction errors are empirically relevant for explaining UI fund enrollment and saving behavior, two leading outcomes for which unemployment risk should be relevant.

Unemployment Insurance

Unemployment insurance (UI) is often provided, or at least subsidized, by governments because of concerns that adverse selection will not make it possible to sustain a private market for insurance against unemployment. Adverse selection refers to the case where people join UI funds only when they face a large risk of actually becoming unemployed based on subjective knowledge about their unemployment risk. Strategic enrollment can happen when the individual has advance knowledge about his/her unemployment risk. However, adverse selection can also show up when individuals who are already enrolled learn that their unemployment risk is smaller than they thought and opt out of unemployment insurance. This is directly testable using our data since we observe subjective unemployment expectations, how expectations turn out to deviate from realizations, and UI fund membership.

Denmark has a voluntary UI scheme where workers have the option to enroll in a UI fund. Upon 12 months of membership, UI benefits can be claimed when unemployed. UI benefits replace up to 90 pct. of the income in the previous job but benefits are capped at 18,113 DKK[4] per month (2016 level) which roughly compares to the level of income earned in a full-time job for an unskilled worker paid the minimum wage rate. For people who are not members of a UI fund, it is possible to qualify for cash benefits. At 11,554 DKK per month, cash benefits provide a significantly lower level of payments. Rates are lower for people aged less than 30, but are higher for parents. Cash benefits are means tested at a very low threshold (10,000 DKK) which, in practice, only allows people to hold a minimal transaction balance, and thus few people in Denmark actually qualify to receive cash benefits. UI fund membership costs between 450-500 DKK per month. UI funds are heavily subsidized by the government, and UI benefits are therefore generous compared to the cost of membership. As a result, the majority of workers are members of a UI fund. On average, throughout the survey period 2010-2016, 78% of respondents were members

[4] 1 DKK $\approx$ 0.15 USD.

of a UI fund, and among wage earners it is 84%.[5]

We examine how UI fund membership is related to expected unemployment and prediction errors. Specifically, we consider the equation (3),

$$\begin{aligned} UI_{i,t} = \alpha_0 + \alpha_1 E_{i,t-1}[U_{i,t}] + \alpha_2\theta_{i,t} + \alpha_3\mathbb{I}[\theta_{i,t} \geq 0] + \alpha_4(\theta_{i,t} \times \mathbb{I}[\theta_{i,t} \geq 0]) \\ + \alpha_5 X_{i,t} + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{3}$$

where $UI_{i,t}$ is an indicator of UI membership for individual i in year t. Everything else follows the notation from above. The covariate vector, $X_{i,t}$ includes age, education, occupation, municipality and year dummies as well as a continuous measure of labor experience. We allow for a discontinuation at $\theta_{i,t} = 0$, as eligibility for UI benefits requires a minimum of one year membership prior to the unemployment shock. Individuals with positive prediction errors, i.e. individuals who learn that they overestimated the probability of unemployment, may opt out of the UI fund. However, individuals whose prediction errors are negative, i.e. they underestimated the probability of unemployment, do not necessarily have an incentive to opt in, as they may not become eligible to receive UI benefits, before they expect to become unemployed.

The regression estimates are presented in table 5. We first consider the OLS regression with no controls in column (1). When we do not control for covariates, neither subjective unemployment expectations nor the negative prediction errors appear to be correlated with UI membership. However, positive prediction errors are generally associated with a higher level of UI membership, cf. the positive estimate of α_3, but with a tendency for UI membership to decline as prediction errors grow, cf. the negative estimate of α_4. Overall, according to the estimates, the propensity to have joined a UI fund is higher for people with positive prediction errors in the range in which most prediction errors are observed. Given that prediction errors tend to be positive, this is consistent with the idea that people tend to insure more than what the objective risk would imply.

[5] Note, that the membership rate among respondents reported in 2 is for 2016, where the membership rate in the survey sample was the lowest.

In column (2) we control for a number of covariates. When including controls, we also find a positive and significant correlation between unemployment expectations and private UI, indicating that a 1 pct. point increase in expected unemployment probability is correlated with a 0.12 pct. point increase the probability of having private UI. Thus, individuals who believe it more probable that they will experience unemployment are more likely to have insurance against an unemployment shock.

In columns (3) and (4), we include individual fixed effects to restrict our analysis to within-individual variation in expectations and prediction errors. In column (4), where we also include controls, we see that a 1 pct. point increase in subjective unemployment expectations leads to a 0.03 pct. point increase in private UI uptake. Further, we find an effect of having a positive prediction error. In particular, a 1 pct. point increase for individuals with positive prediction errors, leads to a 0.06 pct. point decrease in private UI uptake. That is, individuals who overestimate their group specific unemployment probability opt out of private UI. We find no significant effect of changes in negative prediction errors.

The estimates presented in table 5 may appear small in magnitude. This owes to the fact that there is generally little variation in UI membership in Denmark. That is, most workers are members of a UI fund and hence the pool of people who could enroll is relatively small. However, despite this fact, we do find highly significant effects of subjective unemployment expectations on UI membership, and that individuals enroll/opt out in a way that is consistent with adverse selection based on the privately held information about unemployment risk.

Our study is, to the best of our knowledge, the first to document how subjective expectations concerning future unemployment and prediction errors predict of actual selection into UI fund membership. Our results speak to those of Hendren (2017) and Landais et al. (2021), who both study adverse selection in the UI market. Landais et al. (2021) use population-wide administrative data for UI fund membership in Sweden and exploit various quasi-experimental empirical strategies and different sources of variation to show that workers who face higher (ex ante) unemployment risk select into UI fund membership. Hendren (2017) shows that workers have advance information about future unemployment and that this is critical for assessing their willingness to pay for UI such that a private market for UI would be too adversely selected to deliver a positive profit.

Table 5: Unemployment Insurance ($UI_{i,t}$)

	(1)	(2)	(3)	(4)
	OLS	OLS	FE	FE
Unemployment Expectations, $E_{i,t-1}[U_{i,t}]$	0.000590	0.00115***	0.000344	0.000271*
	(0.000492)	(0.000318)	(0.000214)	(0.000145)
Prediction Errors, θ_{it}	0.00115	-0.000633	0.000642**	0.000340
	(0.000844)	(0.000514)	(0.000270)	(0.000226)
Positive Prediction Errors, $\mathbb{I}[\theta_{i,t} \geq 0]$	0.0880***	0.0517***	0.0107***	0.00280
	(0.0108)	(0.00818)	(0.00332)	(0.00293)
$\theta_{i,t} \times \mathbb{I}[\theta_{i,t} \geq 0]$	-0.00381***	-0.000987*	-0.00137***	-0.000567**
	(0.000833)	(0.000524)	(0.000384)	(0.000240)
Constant	0.844***	0.588***	0.868***	1.029***
	(0.0157)	(0.0927)	(0.00231)	(0.113)
Observations	31,392	29,410	27,486	25,938
R-squared	0.018	0.122	0.871	0.917
Individual FE			X	X
Controls		X		X

Clustered standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by stratified groups described in section 4, yielding 128 clusters. Controls include age, education, industry, municipality and year FE as well as experience.

5.1 Saving

In addition to purchasing private unemployment insurance, individuals may self-insure using liquid assets, as formal unemployment insurance only partially insures against income loss. A typical interpretation of the life-cycle consumption-savings framework with incomplete markets, see e.g., Browning and Lusardi (1996)[6], is that individuals smooth marginal utility of consumption across time given the available information at the beginning of the planning horizon and their expectations about the development of income over the planning horizon. Within this framework, expected income growth should lead to savings adjustments in order to reduce consumption fluctuations. Deviations from the consumption plan are driven by unanticipated innovations to income. For example, a transitory income shock could be fully absorbed by adjustments in savings. Finally, when there is a precautionary savings motive, an increase in income risk could generate increased saving. These predictions are based on a version of the standard model where agents are not liquidity constrained. When agents have limited access to credit markets they tend to run down their liquid assets. As a result, they are unable to smooth marginal utility of consumption, i.e., adjustments are concentrated on consumption. In this section we investigate whether the evidence is consistent with these basic predictions.

We first consider the reduced form effect of subjective unemployment expectations on liquid savings relative to the average income in 2007-2009, $S_{i,t}/\bar{Y}_{i,2007-2009}$, as described by equation (4). As individuals' ability to adjust their saving to changes in their expected income depend on their liquidity, we split the sample by liquidity. Following Zeldes (1989) and Leth-Petersen (2010) we assume that people are likely to be liquidity constrained if they hold deposits amounting to less than two months of disposable income in period

[6] The basic theory behind the incomplete markets models is developed by Bewley (1977), Huggett (1993), and Aiyagari (1994)

$t-1$[7].

$$S_{i,t}/\bar{Y}_{i,2007-2009} = \eta_0 + \eta_1 E_{i,t-1}[U_{i,t}] + \eta_2 X_{i,t} + \mu_i + \varepsilon_{i,t} \tag{4}$$

where $\bar{Y}_{i,2007-2009} = 1/3 \sum_{t=2007}^{2009} Y_{i,t}$ is the average income for individual i in the years 2007-2009.

The regression results are shown in table 6. It is immediately evident that subjective unemployment expectations are positively correlated with the saving rate for individuals who are unlikely to be liquidity constrained. That is, individuals with a higher subjective probability of unemployment, also hold more liquid savings, relative to their average income. In columns (1)-(3) we present the results for liquidity constrained individuals. We see no effect for these individuals. For individuals who are not liquidity constrained, the response is significant even when we control for individual fixed effects and for a number of observables, as seen in column (6). Here we see that a 10 pct. point increase in unemployment expectations lead to an increase in the liquid savings to average income of 0.06 pct. points. Thus, individuals who are arguably better able to adjust their saving, do in fact increase their liquid saving more in response to an increase in expected probability of unemployment.

Subjective unemployment expectations should affect saving through expected income growth. However, the subjective unemployment expectations captures aspects of both the mean and variance of the expected income growth. In order to distinguish between the two, we follow Lusardi (1998) and impose structure in order to link subjective unemployment expectations to expected income,

$$E_{i,t-1}[Y_{i,t}] = p_{i,t} \cdot rr_{i,t} \cdot Y_{i,t-1} + (1-p_{i,t}) \cdot Y_{i,t-1} \tag{5}$$

where $p_{i,t} = E_{i,t-1}[U_{i,t}]/100$ is individual i's subjective probability of becoming unemployed in year t and $Y_{i,t-1}$ is individual i's income measured by the end of year $t-1$. $rr_{i,t}$ is the

[7]Changing the definition of liquidity constrained to having less than one month's disposable income worth of liquid savings has no sizable effect on our results.

Table 6: Liquid Savings to Average Income, $S_{i,t}/\bar{Y}_{2007-2009}$

	Liquidity Constrained			Not Liquidity Constrained		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	FE	OLS	OLS	FE
$E_{i,t-1}(U_{i,t})$	9.55e-05	-4.11e-05	6.24e-05	0.00146***	0.000563*	0.000569**
	(6.93e-05)	(4.96e-05)	(5.66e-05)	(0.000341)	(0.000327)	(0.000262)
Constant	0.0762***	0.0433**	-0.0192	0.808***	1.043***	-0.144
	(0.00847)	(0.0179)	(0.0314)	(0.0302)	(0.373)	(0.341)
Observations	13,620	12,960	10,487	17,410	16,401	13,740
R-squared	0.001	0.053	0.862	0.007	0.060	0.822
Individual FE			X			X
Controls		X	X		X	X

Clustered standard errors by stratified groups in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Controls include age, education, occupation, municipality and year FE as well as experience and replacement rates. Liquidity constrained is defined as having less than two months' disposable income worth of liquid savings. $S_{i,t}/\bar{Y}_{2007-2009}$ and $E_{i,t-1}(U_{i,t})$ are winsorized at the 1st and 99th percentiles.

replacement rate, i.e. the share of the individual's labor income that the individual can expect to receive in unemployment benefits in case of unemployment. The replacement rate is individual and time specific as it depends on whether the individual is member of a UI fund, on the individual's income and wealth and on a number of other individual specific characteristics such as household composition, past employment conditions and health status[8].

With this definition of expected income, the variance of expected income becomes,

$$V[Y_{i,t}] = (1 - rr_{i,t})^2 \times E_{i,t-1}[U_{i,t}] \times (1 - E_{i,t-1}[U_{i,t}])Y_{i,t-1}^2 \tag{6}$$

It follows from equation (6) that the variance of the expected income increases with unemployment uncertainty. Individuals who see employment and unemployment as equally possible, i.e. their expected probability of unemployment, $E_{i,t-1}[U_{i,t}]$ is close to 50 pct., have higher income uncertainty than individuals who know with near certainty that they will either be employed or unemployed in the following year, i.e. their expected probability of unemployment, $E_{i,t-1}[U_{i,t}]$, is close to either 0 pct. or 100 pct. Similarly, a lower replacement rate, $rr_{i,t}$, results in a higher income variance, as the income decrease from an unemployment shock, becomes larger when the replacement rate is low.

To account for the fact that subjective unemployment expectations affect both the mean and the variance of expected income, we define income risk as,

$$SD_{i,t}^Y = \sqrt{(1 - rr_{i,t})^2 \times E_{i,t-1}[U_{i,t}] \times (1 - E_{i,t-1}[U_{i,t}])Y_{i,t-1}^2} \tag{7}$$

We examine how income expectations and income risk[9] affect saving, by estimating

[8] In appendix B we show the distribution of replacement rates among respondents.

[9] According to equation 7 three things may result in a computed income SD value of 0. We do the following to account for this these. First, individuals may have an income SD of zero if they report a probability of unemployment of either 0 pct. or 100 pct. We account for this by censoring $E_{i,t}[U_{i,t+1}]$ at $(0.01; 0.99)$. This yields a relatively small, but non-zero income SD, reflecting that even though a respondent is very certain about future unemployment, they may still incur a small amount of income uncertainty. Second, individuals with zero income in year $t-1$ will have an income SD of 0. In such cases we use the individual's income in year $t-2$ or $t-3$. If an individual has zero income both year

the following regression,

$$S_{i,t}/\bar{Y}_{i,2007-2009} = \beta_0 + \beta_1 E_{i,t-1}[Y_{i,t}] + \beta_2 \theta^Y_{i,t} + \beta_3 SD^Y_{i,t} + \beta_4 rr_{i,t} + \beta_5 X_{i,t} + \mu_i + \varepsilon_{i,t} \quad (8)$$

where $E_{i,t-1}[Y_{i,t}]$ and $SD^Y_{i,t}$ are defined by equations (5) and (6), respectively. $X_{i,t}$ is a vector of control variables including age, education, occupation, municipality and year dummies as well as a a continuous measure of labor experience. μ_i is an individual level fixed effect, and $\varepsilon_{i,t}$ is a random error term. We define income prediction errors as $\theta^Y_{i,t} = Y_{i,t} - E_{i,t-1}[Y_{i,t}]$. This means that a positive income prediction error occurs when the individual underestimated their income, and thus receives a higher income than expected.

The results are presented in table 7. We consider first the liquidity constrained sample, which is shown in columns (1)-(3). As expected, we see little saving response among liquidity constrained individuals. We initially see a negative correlation between income expectations and liquid savings to average income and this correlation is significant only at a ten pct. significance level, when we control for observables and year fixed effects as in column (2). However, when we further include individual fixed effects, the estimate becomes positive and the significance level increases. We find that a 1000 DKK increase in income expectations for liquidity constrained individuals leads to an increase in the liquid savings to average income of 0.0008 pct. points. While the estimate is statistically significant at a five pct. significance level, it is small in magnitude and arguably economically insignificant. We find no significant response of income prediction errors, meaning that any positive income shock is used for consumption among individuals who are liquidity constrained. Finally, we do find a small, positive effect of income uncertainty. In accordance with the basic predictions, the estimate is positive, meaning that individuals who are have a higher income than they expected, increase their liquid savings. However, the estimate is small in magnitude, and only significant at a 10 pct. significance level.

In columns 4-6 we turn to the sample that consists of individuals who are unlikely to be affected by liquidity constraints. For all specifications we find that both income

$t-1$, $t-2$ and $t-3$, we let $Y_{i,t} = 0$, which results in an income SD of zero.

expectations, income prediction errors, and income risk have positive, significant effects on liquid savings relative to average income. Focusing on the regression in which we control for individual fixed effects and only rely on within-individual variation, cf. column 6, we find that an increase in income expectations of 1000 DKK leads to an increase in liquid savings to average income of 0.05 pct. points. Similarly, an increase in income prediction errors of 1000 DKK leads to an increase in the liquid savings rate of 0.04 pct. points. We further find that an increase in income risk leads to an increase in liquid savings.[10] Moving from the 25th percentile to the 75 percentile in the distribution of income risk is associated with an increase in liquid savings to average income of 2.36 pct. points.

Finally, we find that a change in the individual's replacement rate from 0 to 1, reduces liquid savings to average income with 17.9 pct. points. This robust inverse correlation between the UI replacement rate and liquid saving reflects the fact that the vast majority are enrolled in UI and that benefits are capped at a level corresponding to the level of earnings in a full-time job at the minimum wage. In other words, formal UI has limited coverage, and the coverage declines in the level of earnings. Consequently, for most people liquid savings serve as a self-insurance resource that is complementary to formal UI.

These findings are broadly consistent with the predictions of the basic life cycle framework outlined above and shows that the individuals in our survey who are unlikely liquidity constrained adjust their liquid savings to accommodate changes in unemployment related income risk.

[10]Expected income and income risk, SD_{it} are functions of unemployment risk, $p_{i,t}$, the replacement rate, $rr_{i,t}$ and the the earnings level, $Y_{i,t-1}$. To make sure that the findings are not driven by within-individual variation in $rr_{i,t}$ and $Y_{i,t-1}$ rather than within-individual variation in $p_{i,t}$, we have run regressions where $rr_{i,t}$ and $Y_{i,t-1}$ are held fixed at their within-individual average levels. This did not change the results.

Table 7: Liquid Savings to Average Income, $S_{i,t}/\bar{Y}_{i,2007-2009}$

	Liquidity Constrained			Not Liquidity Constrained		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	FE	OLS	OLS	FE
Income Expectations, $E_{i,t-1}(Y_{i,t})$	-0.000129**	-7.23e-05*	8.33e-05**	-0.000229**	-0.000200**	0.000460***
	(5.69e-05)	(4.33e-05)	(4.13e-05)	(0.000115)	(9.21e-05)	(0.000155)
Income Prediction Errors, $\theta^Y_{i,t}$	-0.000132	-7.44e-05	3.96e-05	0.000379**	0.000227*	0.000363***
	(8.93e-05)	(7.38e-05)	(4.83e-05)	(0.000177)	(0.000136)	(0.000128)
Income Risk $SD^Y_{i,t}$	0.000125	7.17e-05	6.92e-05*	-0.000322	-5.57e-05	0.000582**
	(8.23e-05)	(6.94e-05)	(4.10e-05)	(0.000319)	(0.000281)	(0.000249)
Replacement Rate, $rr_{i,t}$	-0.0507**	-0.0192*	-0.0138	-0.308***	-0.187***	-0.179***
	(0.0215)	(0.0111)	(0.0125)	(0.0482)	(0.0627)	(0.0675)
Constant	0.141***	0.0591***	-0.0458	0.928***	1.084***	-0.257
	(0.0349)	(0.0221)	(0.0402)	(0.0579)	(0.372)	(0.340)
Observations	13,620	12,960	10,487	17,410	16,401	13,740
R-squared	0.008	0.056	0.863	0.011	0.063	0.823
Individual FE			X			X
Controls		X	X		X	X

Clustered standard errors by the stratified groups described in section 4 in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Controls include age, education, occupation, municipality and year FE as well as experience. Liquidity constrained is defined as having less than two months' disposable income worth of liquid savings. $S_{i,t}/\bar{Y}_{2007-2009}$, $E_{i,t-1}(U_{i,t})$, $\theta^Y_{i,t}$ and $SD^Y_{i,t}$ are winsorized at the 1st and 99th percentiles. $E_{i,t-1}(U_{i,t})$, $\theta^Y_{i,t}$ and $SD^Y_{i,t}$ measured in 1000 DKK.

6 Conclusion

Subjective beliefs about income risk play a key role in theories of individual behavior such as how much to save or whether to insure against earnings losses stemming from unemployment. In this paper, we have study subjective expectations about own unemployment and how these expectations affect insurance against unemployment. The analysis is based on a data set with longitudinal information about individual unemployment expectations, elicited through a survey collected annually in 2010-2016. The survey data are linked with third-party reported register data on labor market realizations, such that we are able to examine whether subjective unemployment expectations carry relevant information about subsequent unemployment shocks and whether expectations affect economic behavior.

We find that subjective unemployment expectations are predictive of subsequent unemployment experiences. However, many individuals tend to persistently overestimate the probability that they will experience unemployment. We show that subjective unemployment expectations drive the uptake of unemployment insurance. We find that a higher (ex ante) perceived risk of becoming unemployed leads some people to opt into private unemployment insurance, and that some, who had overestimated the risk of unemployment, tend to opt out of UI insurance. This pattern is consistent with adverse selection into UI insurance. Given that people, on average, overestimate their unemployment risk, this could potentially have induced some to insure more than they would have done had their unemployment expectations not been overly pessimistic and in this way lessened the extent of adverse selection. Further, we find that people tend to increase liquid savings when their subjectively assessed risk of unemployment increases. We also find evidence that income risk related to the risk of becoming unemployed drive liquid savings. This latter finding is consistent with the idea that liquid savings is influenced by a precautionary motive.

Our findings have several implications. First, they document a role for both formal unemployment insurance as well as self-insurance through the accumulation of liquid savings. More generally, our analyses show that subjective unemployment expectations hold information that is valuable for describing people's real-life choices of UI membership and liquid savings. We document that there is a lot of heterogeneity in people's unemployment expectations that cannot be explained by observable characteristics. In this way, subjective expectations contribute to explaining why people, who appear observationally similar, make different economic decisions.

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Online Appendix

to

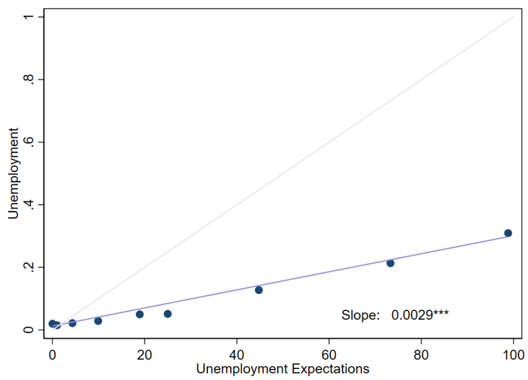
Subjective Unemployment Expectations

Ida Maria Hartman Søren Leth-Petersen

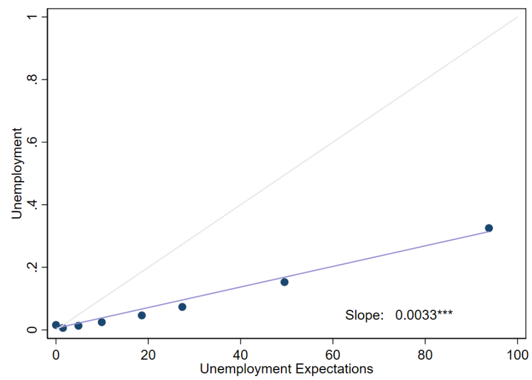
A Heterogeneity in Predicted and Realized Unemployment

Figure A1: Unemployment vs. Unemployment Expectations (by Gender)

(a) Females



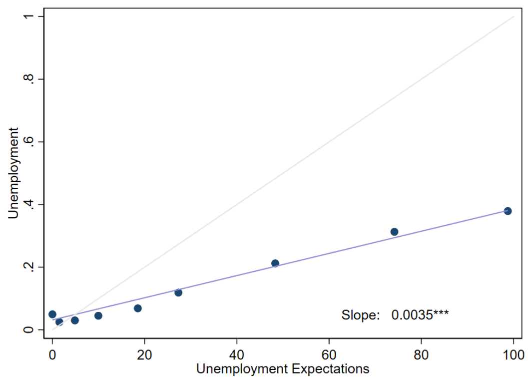
(b) Males



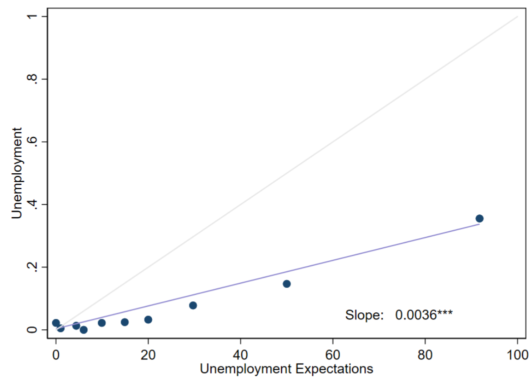
These figures show a binned scatterplot of the correlation between realized unemployment and unemployment expectations for females (Panel a) and males (Panel b). The y-axis shows unemployment, $\mathbb{I}[U_{i,t}]$, measured by a dummy equal to 1 if the individual is unemployed in year t. The x-axis shows unemployment expectations, $E_{i,t-1}[U_{i,t}]$, about unemployment in year t. The linear fit is depicted by the solid, purple line, and the 45-degree line is depicted by the solid, grey line.

Figure A2: Unemployment vs. Unemployment Expectations (by Age)

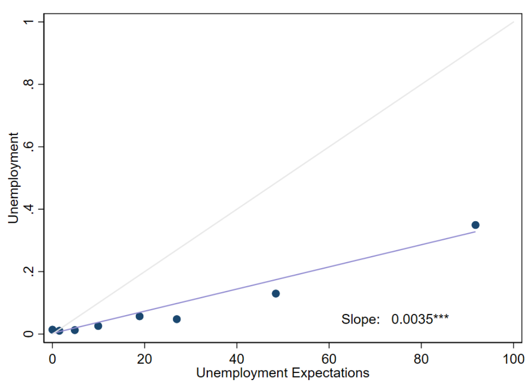
(a) Age 25-34



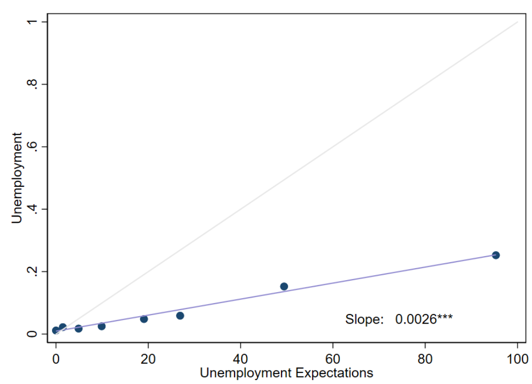
(b) Age 35-44



(c) Age 45-54



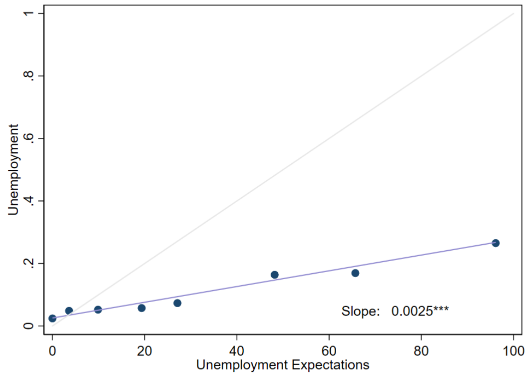
(d) Age 55-65



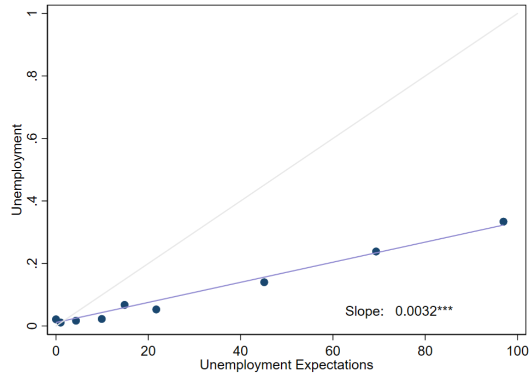
These figures show a binned scatterplot of the correlation between realized unemployment and unemployment expectations for age groups 25-34 (Panel a), 35-44 (Panel b), 45-54 (Panel c) and 55-65 (Panel d). The y-axis shows unemployment, $\mathbb{I}[U_{i,t}]$, measured by a dummy equal to 1 if the individual is unemployed in year t. The x-axis shows unemployment expectations, $E_{i,t-1}[U_{i,t}]$, about unemployment in year t. The linear fit is depicted by the solid, purple line, and the 45-degree line is depicted by the solid, grey line.

Figure A3: Unemployment vs. Unemployment Expectations (by Education)

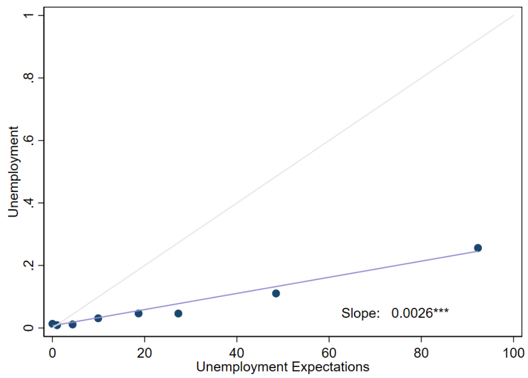
(a) Elementary School



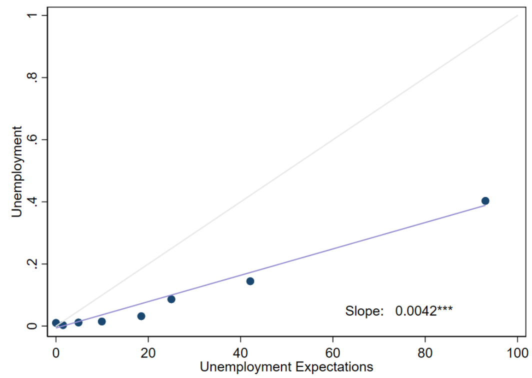
(b) High School and Vocational Training



(c) Short and Middle Higher Education



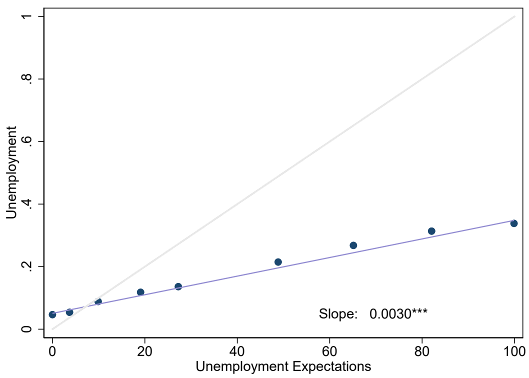
(d) Long Higher Education



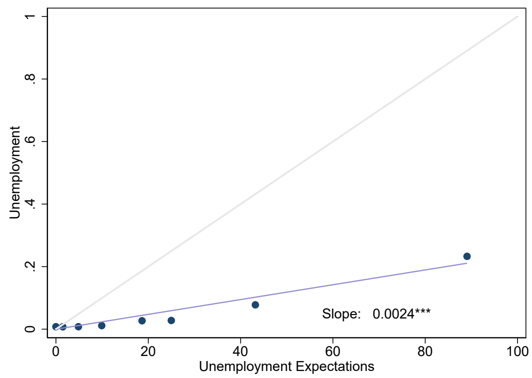
These figures show a binned scatterplot of the correlation between realized unemployment and unemployment expectations for education groups elementary school (Panel a), high school and vocational training (Panel b), short and middle higher education (Panel c) and long higher education (Panel d). The y-axis shows unemployment, $\mathbb{I}[U_{i,t}]$, measured by a dummy equal to 1 if the individual is unemployed in year t. The x-axis shows unemployment expectations, $E_{i,t-1}[U_{i,t}]$, about unemployment in year t. The linear fit is depicted by the solid, purple line, and the 45-degree line is depicted by the solid, grey line.

Figure A4: Unemployment vs. Unemployment Expectations (by Income)

(a) Below Median Income



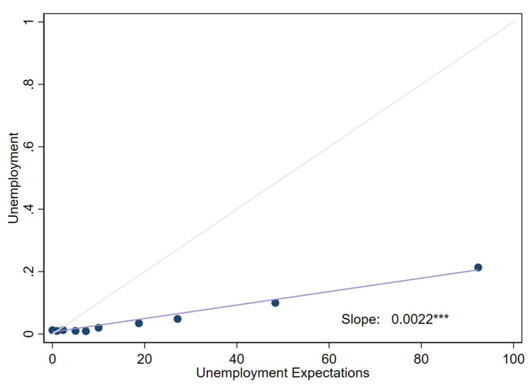
(b) Above Median Income



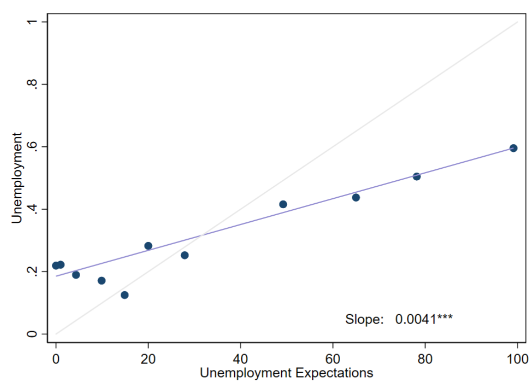
These figures show a binned scatterplot of the correlation between realized unemployment and unemployment expectations for individuals with below median income (Panel a) and individuals with above median (Panel b). The median income is determined within respondents in each year. The y-axis shows unemployment, $\mathbb{I}[U_{i,t}]$, measured by a dummy equal to 1 if the individual is unemployed in year t. The x-axis shows unemployment expectations, $E_{i,t-1}[U_{i,t}]$, about unemployment in year t. The linear fit is depicted by the solid, purple line, and the 45-degree line is depicted by the solid, grey line.

Figure A5: Unemployment vs. Unemployment Expectations (by Unemployment History)

(a) Not Unemployed in $t-1$



(b) Unemployed in $t-1$

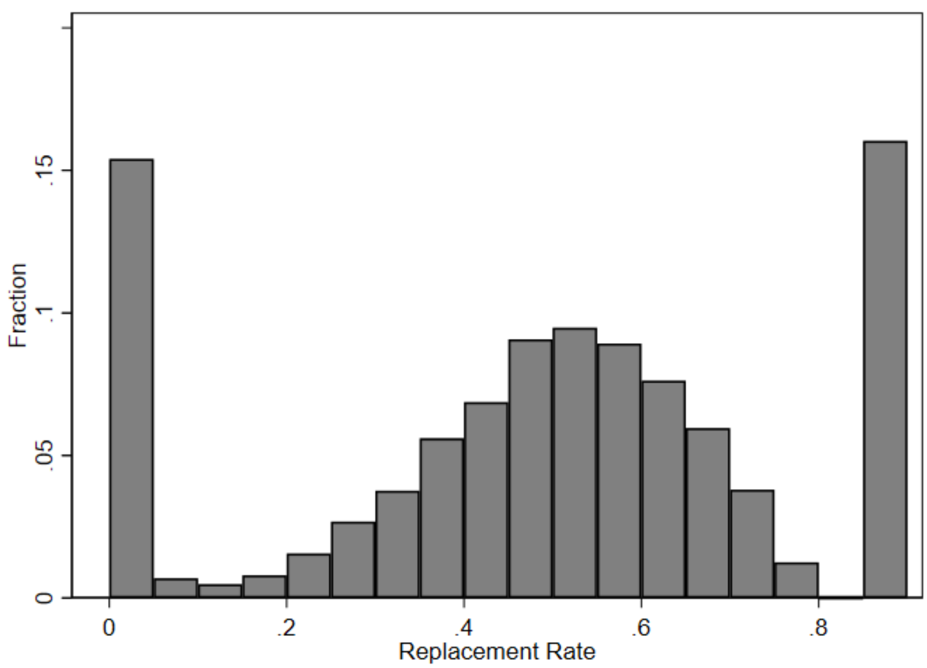


These figures show a binned scatterplot of the correlation between realized unemployment and unemployment expectations for individuals who did not experience unemployment in year $t-1$ (Panel a) and individuals who did experience unemployment in year $t-1$ (Panel b). The y-axis shows unemployment, $\mathbb{I}[U_{i,t}]$, measured by a dummy equal to 1 if the individual is unemployed in year t. The x-axis shows unemployment expectations, $E_{i,t-1}[U_{i,t}]$, about unemployment in year t. The linear fit is depicted by the solid, purple line, and the 45-degree line is depicted by the solid, grey line.

B Unemployment Insurance

Figure A6 shows the distribution of replacement rates among respondents. There are two mass points, one at the replacement rate 0 and one at the replacement rate 0.9. The first mass point is caused by the fact that individuals who are not members of a UI fund and who have a savings amounting to more than 10,000 DKK (1,500 USD) are ineligible for both UI and cash benefits, giving them a replacement rate of 0. The second mass point is caused by individuals who are members of a UI fund, with a low enough income to receive the highest possible replacement rate, which is 0.9. Individuals in between the two mass points are either members of a UI fund, but have an income which is so high that their replacement rate becomes smaller than 0.9, or they are not members of a UI fund, but have savings amounting to less than 10,000 DKK, making them eligible for cash benefits.

Figure A6: Distribution of Replacement Rates



The graph shows the distribution in replacement rates among survey respondents. Replacement rates depend on respondents' wealth, income and UI membership.