Inflation Expectations and Labor Supply: Evidence From an Experimental Study*

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Abstract

How individual labor supply responds to changes in (expected) inflation? To establish the link empirically, we run an experiment in an online labor market, Amazon Mechanical Turk. First, we use randomized information treatments to generate exogenous variation in subjective expectations about price inflation, wage inflation, and unemployment rate. Second, we investigate how these changes in expectations affect MTurk workers' reservation wages and the desired employment duration. We find that the resulting increase in wage inflation expectation significantly increases reservation wages. Higher expected price inflation rates, on the other hand, decrease reservation wages. Higher unemployment expectation increases the desired duration of employment and decreases reservation wages. These results suggest that wage-price spiral risks appear limited despite the high current price inflation rates.

Keywords: survey data, inflation expectations, labor supply, randomized control trial
JEL Codes: D84, E83, J22

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> *"Inflation has just about everyone's attention right now, which highlights a particular risk today: The longer the current bout of high inflation continues, the greater the chance that expectations of higher inflation will become entrenched. ... History shows that the employment costs of bringing down inflation are likely to increase with delay, as high inflation becomes more entrenched in wage and price setting."*
>
> — Jerome Powell, at the *Jackson Hole Symposium* on August 26th, 2022.

1 Introduction

How do workers change their labor supply decisions in response to changes in expected inflation? The answer to this question is important in order to understand whether and to what extent changes in expected inflation play a role in explaining fluctuations in labor supply over the business cycle. This question is particularly relevant today when many countries experience elevated inflation rates despite the central bank's efforts to curb inflation. In June 2022, the U.S. inflation rate hit its highest level since 1982 at 9.1%. According to the Federal Reserve Bank of New York's Survey of Consumer Expectations, inflation expectations were also running high at 6.8% in June 2022. If wages are, in turn, responsive to the revision of inflation expectations, resulting wage increases could cause prices to rise further. Such dynamics can launch a wage-price spiral, thus making it very difficult for a central bank to control inflation.

Although wage-price inflation is much discussed, as can be seen from the quote above, there has been no direct causal evidence of the relationship between (expected) inflation and labor supply. To test this relationship empirically, one needs information on subjective expectations about the economy and labor supply preferences. Furthermore, while such information can be obtained from observational data, variations in subjective expectations about future economic variables are unlikely to be exogenous. In a similar spirit, individuals' observed labor supply decisions could reflect many unobserved factors researchers cannot directly control for.

We overcome these problems by designing and running an experiment in an online labor market Amazon Mechanical Turk (MTurk, hereafter) in April-July 2022. Specifically, we hire workers to perform a series of forecasting tasks during which we vary their expectations via *randomized* information provision. This allows us to generate exogenous variation in subjective expectations about the economy and thereby identify causal effects on worker's behavior (see Haaland, Roth, and Wohlfart, 2023). Specifically, we examine how the resulting revision of expectations affects labor supply measured by reservation wages and desired employment duration. The main advantage of conducting the experiment in MTurk is that, in addition to asking *hypothetical* questions about labor supply, we can credibly offer workers employment on the terms provided by respondents by following up with them based on their answers. Therefore, we can capture the *actual* labor supply response in the online labor market.

The experiment shows that information treatments affect participants' expectations about price inflation, wage inflation, and unemployment rates. Participants meaningfully updated their sub-

jective forecasts based on the provided information. When respondents received one relevant signal, they updated their expectations across all variables jointly. For example, respondents updated their wage inflation expectations and unemployment expectations when provided with the current CPI inflation rate. Similarly, they updated their price inflation and unemployment rate expectations when they received information about hourly earnings inflation rates. This suggests that researchers need to control for all observed expectations *jointly* to avoid potential omitted-variable biases when examining how *one* macroeconomic expectation affects households' behaviors. We also find that information treatments affect beliefs across all three waves.

The variation in expectations due to a randomized information treatment allows us to analyze the causal relationship between inflation expectations and labor supply in a cross-section of respondents. We elicit labor supply preferences by asking about desired pay and duration of employment for working on a similar task with us. We find that in response to exogenous variation in macroeconomic expectations, MTurk workers adjust their labor supply preferences, in particular, reservation wages. Specifically, when they update their hourly earnings inflation expectations upwards, they increase their reservation wages. In contrast, when workers adjust their price inflation expectations upwards, they rather *decrease* their reservation wages. We associate this decrease in reservation wages with the stagflationary view of U.S. households from our first stage results about the information treatment effects. When provided with the current CPI inflation rate, which tends to be higher than their expectation, respondents further increase their unemployment expectations. That is, households associate higher inflation with a bad economic outlook consistent with Kamdar (2018) and Binder (2020). This induces them to reduce the smallest reward necessary for accepting a job offer. We do not find a consistent effect of unemployment expectations on reservation wages. Similarly, given that most respondents expressed interest in working with us for as many months as possible, we have little variation in the desired duration of employment and cannot detect a statistically significant effect on this outcome.

Overall, our results suggest that, contrary to policymakers' concerns, the risk of the wage-price spiral in the U.S. is limited. Even though current high inflation could raise price and wage inflation expectations, this would likely increase unemployment expectations at the same time. While higher wage inflation expectation raises reservation wages, higher price inflation expectations tend to decrease reservation wages at the same time, partially offsetting the initial shock. This suggests that wage-price spirals do not seem to be very likely.

To our knowledge, this is the first study to empirically examine the *direct* causal relationship between inflation expectations and labor supply. More broadly, our paper contributes to a growing literature about the information effect of macroeconomic expectations (see, for example, Coibion, Gorodnichenko, and Weber, 2022; Coibion et al., 2019; Binder, 2020; Cavallo, Cruces, and Perez-Truglia, 2017; Coibion et al., 2021, 2022; Hajdini et al., 2022a; Weber et al., 2023) and the effects of macroeconomic expectations on behavior (see, for example, Armona, Fuster, and Zafar, 2019; Armantier et al., 2016; Bottan and Perez-Truglia, 2020; Coibion, Gorodnichenko, and Weber, 2022; Coibion et al., 2019; Hajdini et al., 2022b; Belot, Kircher, and Muller, 2022). These studies have

shown that randomized information treatment can successfully generate exogenous variation in households' inflation expectations. A distinguishing feature of our experiments compared to these studies is that we implemented them in a high inflation period when workers have more incentives to be informed about inflation (even so, we find clear treatment effects of information provision on inflation expectations). By building on this rapidly growing literature, we provide novel evidence on the effect of expected inflation on labor supply decisions.

We also contribute to the literature studying wage-price inflation spirals and the role of expectations in generating these spirals. In short, labor market developments depend on how workers form their expectations and adjust their labor supply accordingly. Previous empirical studies have relied on observational data across different countries (see, for example, Kandil, 2003; Boissay et al., 2022). However, because of the inherent endogeneity of subjective expectations, the available evidence is not identified cleanly. We use a randomized control trial to generate exogenous variation in subjective expectations and hence our results provide direct causal evidence.

Clearly, understanding how households adjust their labor supply to expected inflation is important for policy discussions and communications. For example, many central banks have made enormous efforts to control inflation expectations. Our results could provide evidence of the direct effects such policies might have on labor supply. Our study is particularly relevant today. With elevated inflationary pressures, workers are more likely to pay attention to changes in inflation and adjust their behavior accordingly. In this regard, our results could help design employment policy by providing useful guidance on likely changes in labor supply in this high-inflation environment.

The remainder of the paper is organized as follows. Section 2 describes survey and experimental design. Section 3 presents the treatment effects of information provision on subjective expectations. Section 4 then examines how changes in expectations affect labor supply preferences. Section 5 discusses the robustness of results to alternative specifications. Lastly, section 6 concludes.

2 Survey and Experimental Design

This section describes the survey and experimental design we use to elicit the effect of inflation expectations on labor supply and provides descriptive statistics of participants. Our study design follows recommendations in Haaland, Roth, and Wohlfart (2023).

2.1 Survey Design

We implemented our survey via Amazon Mechanical Turk (MTurk). Amazon MTurk is a crowdsourcing website for hiring remotely-located crowd workers to perform on-demand tasks, called HITs (Human Intelligence Tasks), in exchange for monetary rewards. We posted our HITs on MTurk in April and May 2022 for the first wave of our survey. We informed participants that the purpose of the HIT was to train a machine learning forecasting algorithm in order to motivate them to carefully answer forecasting questions and avoid the experimenter demand effects. For

the quality of data, we allowed participation only for those age 18 or older who had completed at least 1,000 HITS on MTurk and had approval rates of at least 75%.[1] Because our information treatment is for the U.S. economic variables, we restrict our sample to residents of the U.S. (*i.e.* those registered at MTurk in the U.S. and having a U.S. location.) No additional demographic criteria were applied for sample selection to make the sample as representative as possible. A total of 10,758 MTurk workers (MTurkers, hereafter) attempted to participate in our survey. Among them, 5,487 MTurkers completed the first wave of our survey.[2]

Our survey consists of six blocks. Figure 1 summarizes our survey flow. The survey begins with a screening task and a numerical competence check. They are followed by the main part of the survey which allows us to compare the initial forecasts and labor supply preferences with their revised version. The revision of expectations and labor supply preferences is prompted by the randomized information provision in the "Main task". In the "Main Task", a key element of our experimental design, we provide random sub-groups of respondents with different information about price and wage inflation rates and unemployment which allows us to generate exogenous variation in expectations and thereby to identify the causal effect of expectations revision on labor supply. At the end of the survey, respondents are asked to provide some basic demographic information as well as additional information about their employment offline and online. The specific questions asked are available in Appendix H.

Screening Task. Our survey starts with a screening task. The screening task is of a similar format to the main task related to the information treatment. It tests participants' ability to transcribe information from a screenshot accurately. If participants answered the screening task incorrectly, they are prompted to the end of the survey. If the answer is correct, they are prompted to participate in the rest of the survey. We include the screening task to make sure that only those who thoughtfully provide their best answers participate in our survey. Among 10,758 MTurkers who attempted to participate in our survey, 7,457 of them passed the screening task. Among them, 5,487 completed the first wave of the survey. Because most of the attrition happened early in the survey, due to inaccurate answers to screening tasks or reluctance to complete numerical competence checks, attrition is not systemically correlated with the information treatment.

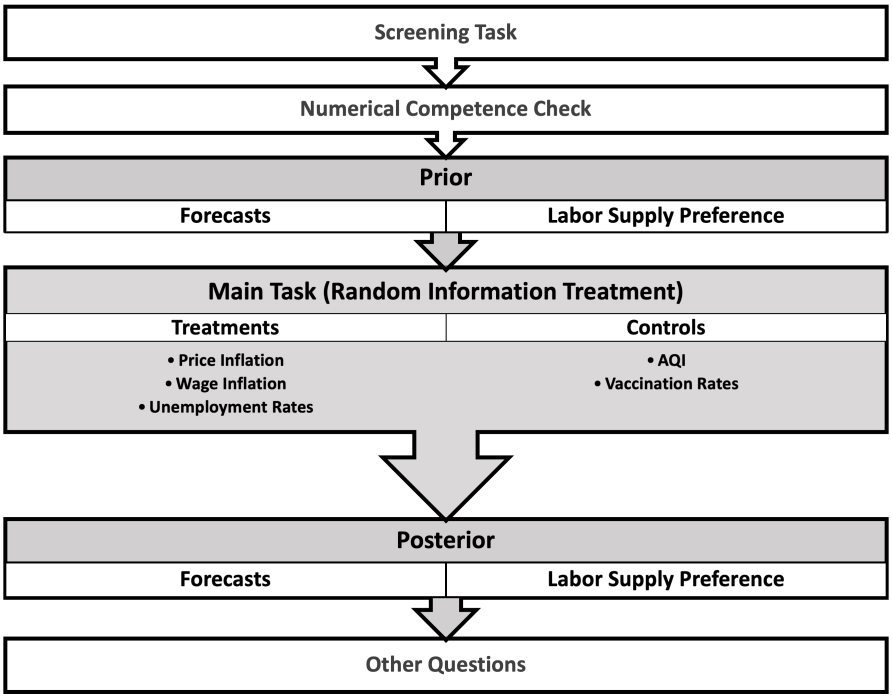
Numerical Competence Check. Upon successful completion of the screening task, participants are prompted to solve a few mathematical problems that evaluate their numerical competence. These questions are designed to check respondents' ability to convert pay per 10 minutes to hourly pay and evaluate percentage change based on absolute change. Although respondents answered these questions incorrectly, they were still able to proceed and complete our survey. Because we

[1] Requesters who post HITs approve MTurkers' HIT submissions based on their answers. If their answers meet certain criteria set by each requester, they approve HITs. Once their HITs are approved, MTurkers receive posted rewards. Otherwise, they will not receive any rewards.

[2] Attrition from the attempt to the completion is not systemically correlated with the treatment arms (see Appendix Table A.1 and A.2 for details).

provided the information treatments (price and hourly wage) in change *rates* and pay respondents per 10 minutes of work, we include these questions to learn how many respondents are comfortable with interpreting such information. In our sample, about 87% of the participants answered at least two questions correctly. About 75% of the participants answered all three questions correctly.

Figure 1: Survey flow



Prior. This block consists of questions about forecasts and labor supply preferences. Before providing participants with any additional information about macroeconomic variables, we asked for their subjective forecasts for the following variables: price inflation rates, hourly earnings inflation rates, unemployment rates, air quality index in Seattle, and COVID-19 vaccination rates. These variables are associated with our randomized information treatment. In addition to this, we elicited on what terms (desired duration and reservation rewards) respondents were willing to accept and complete follow-up HITs. First, we asked what was the smallest reward for a respondent to be willing to accept a similar HIT taking *10 minutes* of their time *per month* using the following question:

> "*Suppose after completing a HIT on MTurk you are offered to participate in a follow-up task that asks you to do a 10-minute HIT two times – in May and June 2022. What is the smallest reward for 20 minutes of your work that you would accept? (in USD)*"

We then asked for how many months a respondent would be interested in accepting a similar HIT using the following question:

> "*Suppose you could choose for how many months to work on a monthly hit paying (*a respondent's own answer for the reservation wage question*) USD for 10 minutes of work. For*

how many months would you prefer to work?"

Main Task. In this block, we randomly assign MTurkers into one of the five groups: three treatment groups and two control groups. Each group is provided with different information treatment in the form of a text transcription task. Specifically, respondents are asked to transcribe information from the screenshot into a table. The information refers to official information about either macroeconomic variables of interest (price inflation, hourly earnings inflation, and unemployment rate – treatment groups) or variables unrelated to a macroeconomic situation (air quality index in Seattle and Covid-19 vaccination rates – control groups). Our identification strategy exploits exogenous variation in macroeconomic expectations for respondents in the treatment groups, i.e., provided with pertinent information, relative to those in the control groups. The examples of screenshots are available in Appendix G. For instance, participants assigned to a price inflation group were prompted to a screenshot of the BLS report about Consumer Price Index (CPI) inflation (Appendix Figure G.1). They were asked to transcribe the data about the CPI 1-month percentage change and 12-month percentage change. Similarly, participants assigned to a wage inflation group were prompted to transcribe the average hourly earnings in the private sector in the U.S. from a BLS news release (see Appendix Figure G.2). To ensure that participants paid attention to the information treatment, they were informed that if they recorded the information from the screenshot incorrectly, they would not be paid for the entire HIT. We also added attention-check questions to verify the recall rate after completion of the transcription task. About 75% of the participants in the price and wage inflation treatment groups correctly recalled the information they transcribed.

Posterior. After the information treatment, we elicited respondents' subjective expectations about the economy (price and hourly earnings inflation rates and unemployment) and other variables in the control group (air quality in Seattle and Covid-19 vaccination rates) again. We used similar but different wording to avoid asking exactly the same questions. We then asked about their desired duration of employment and reservation wages again. Specifically, we used the following questions similar to those in the prior block:

> "*Suppose in the future we offered you to perform a* similar *task you did today taking about 10 minutes of your time once a month. I.e. you would record the information from the same website and provide your prediction based on it. How many months would you be interested in working?"*
>
> "*In the previous question, you answered that you are willing to work on a similar 10-min task for (*a respondent's own answer to the previous question*) months, which corresponds to (*10$\times$a respondent's own answer to the previous question*) min of your time. What is the* ***lowest*** *total reward that you would accept to work? (in USD)"*

Other Questions. In this block, we asked about respondents' characteristics such as gender, age, education level, employment status, household income, marital status, number of children, etc. Furthermore, we asked some hypothetical labor supply questions for their day jobs in *offline* labor markets. Answers to these questions complement our main analysis of labor supply preferences in the online labor market.

2.2 Follow-up Surveys

At the beginning of the survey, respondents were informed that our HIT is designed to train a machine-learning algorithm for forecasting. This description signals to participants that answers to forecasting questions are very important for the project's success, but it is different than the "true" purpose of the survey, which is to examine how the revision of people's subjective expectations affects their labor supply decisions. We chose not to fully disclose the purpose of our study for the following reasons. First, the full disclosure of the survey's purpose could bias respondents' responses about labor supply decisions. Second, we wanted MTurkers to understand that our project is an ongoing project that takes a few months with follow-up HITs. Because MTurk is an *actual* labor market, we expected them to believe that we would follow up with them based on their answers for the desired terms (rewards and duration), thereby providing us with their best answers. This would allow us to learn about their labor supply preferences without asking *hypothetical* questions.

Based on their answers in the first wave, we followed up with respondents interested in participating in the follow-up HITs. If participants answered that they would be willing to participate in the follow-up HITs, we offered them an opportunity to work with us in the following month at the rate they asked for. Among 4,611 participants in wave 1, net of duplicates, we followed up with 2,763 participants: those in the two treatment groups (CPI and hourly earnings group) and those in the AQI control group. Among them, about 1,450 (about 52%) participated in the second and/or third waves, and 937 of them participated in all three waves.[3]

2.3 Descriptive Statistics

Table 1 provides descriptive statistics about respondents. In terms of gender, race, and age, our sample is representative of the U.S. population. The average age is about 40 years old, about half of them are female, and 80% of them are white. But our respondents are more educated compared to the U.S. population, as other MTurkers are.[4] About 74% of them have a 4-year college degree or more. About 82% of them are either employed full-time or employed part-time. In other words, most of them have day jobs and not many of them use MTurk as their major income source. Nonetheless, they spend on average 20 hours per week working on MTurk. Their households

[3] Appendix Table A.3 summarizes attrition from participation in the follow-up waves of the survey.

[4] Our survey has numerical competency check questions. It is more likely that those who are more comfortable with numbers tend to complete our surveys.

spend $704 for food and $290 for gas per week. The median household income bin is $50,000 - 59,999 per year.

The average expected price inflation rate is 6.2% and the median expected inflation rate is 5%. According to the Michigan survey of consumer sentiments, the median one-year ahead inflation expectation was 5.4% in April 2022 and 5.3% in May 2022. The median expected inflation rate from the New York Fed's survey of consumer expectations is 6.3% in April and 6.6% in May. The average and median from our survey are close to these numbers but are lower than the actual inflation rate of around 8% in April and May 2022. The average expected wage inflation rate is 7.22%, which is higher than the actual wage inflation rate of around 5% in April and May 2022. But the median expected wage inflation rate is 4%, which is lower than the actual wage inflation rate. The average expected unemployment rate is 7.2% which is more than double the actual unemployment rate of around 3.5% in April and May 2022.[5] The average desired duration of employment on a monthly HIT like ours is 3.76 months, and the average reservation wage is about $1 per 10 minutes of work. Descriptive statistics about respondents in the second and the third waves are similar to Table 1 (see Appendix Table A.4)

Table 1: Descriptive statistics (late April-May, 2022)

	Mean	Percentiles			Std. Dev.
		p25	p50	p75	
age	40.33	31.00	38.00	48.00	12.20
female	0.49	0.00	0.00	1.00	0.50
white	0.80	0.00	1.00	1.00	0.40
with college degree	0.74	0.00	1.00	1.00	0.44
employed	0.82	0.00	1.00	1.00	0.38
full-time employed	0.68	0.00	1.00	1.00	0.47
number of children	0.97	0.00	1.00	2.00	1.10
monthly spending on food	$704.40	$150.00	$300.00	$600.00	$2591.86
monthly spending on gas	$289.68	$40.00	$100.00	$200.00	$1756.90
$\mathbb{E}_t^{\texttt{prior}}[\pi_{t+12}]$	6.12	1.00	5.00	10.00	8.12
$\mathbb{E}_t^{\texttt{prior}}[\pi^w_{t+12}]$	7.22	1.00	4.00	10.00	11.31
$\mathbb{E}_t^{\texttt{prior}}[u_{t+12}]$	7.24	4.46	6.45	9.20	3.80
$\Delta^{\texttt{post-prior}}\mathbb{E}_t[\pi_{t+12}]$	0.53	-1.80	0.00	3.00	7.58
$\Delta^{\texttt{post-prior}}\mathbb{E}_t[\pi^w_{t+12}]$	-0.92	-3.00	0.00	2.00	11.60
$\Delta^{\texttt{post-prior}}\mathbb{E}_t[u_{t+12}]$	0.89	-1.18	0	1.96	5.01
$\mathbb{E}_t^{\texttt{prior}}[\texttt{duration}_{t+1}]$	3.76	2.00	5.00	5.00	1.53
$\mathbb{E}_t^{\texttt{prior}}[\texttt{reservation wages}_{t+1}]$	1.00	0.50	1.00	1.25	0.54
Observations	4,614				

[5]When we asked about their expected unemployment rates, we gave information about the lowest and highest unemployment rates between 2019 and 2021.

3 Effects of Information Provision on Subjective Expectations

This section studies the treatment effect of the information provision. Before and after the information treatment, respondents were asked about their subjective expectations about macroeconomic and other variables. Based on this information, we study if respondents update their expectations when they receive a relevant signal relative to an irrelevant one. We are interested in whether there are systematic differences in the revision of expectations across treatment groups relative to the control groups. Since respondents were randomly allocated into treatment vs. control groups, the differential revision patterns must be caused by the information signal they received. To illustrate the expectations revision, we first analyze binned scatter plots of respondents' posterior price inflation expectations and their revisions against the differences between their priors and signals received, and then perform regression analysis.

3.1 Graphical Representation

Each panel of Figure 2 summarizes the revision of expectations about one macroeconomic variable due to information treatment. Panel A presents the results for price inflation expectations for respondents in the treatment group who received information about the CPI inflation rate and respondents in the control group who received information about the air quality index and Covid-19 vaccination rate. If respondents in the treatment group did not pay attention to the information about inflation they received, they should behave in a similar way as the control group that received information largely irrelevant to macroeconomic conditions. The revision of price inflation expectations in the control group can be attributed to a change in wording in prior and posterior questions. The difference between revision patterns in the control and treatment groups denoted by black and blue lines respectively illustrates the effect of the information treatment.

The left graph of panel A shows that respondents who have received the relevant information about the current CPI inflation rate exhibit a much flatter slope compared to those in the control group who have received irrelevant information. This suggests that, in line with Bayesian updating, those in the treatment group place much smaller weights on their priors.[6] The right graph shows that individuals whose prior inflation expectations closely align with the signal revise expectations very little both in the control and treatment groups. However, when the signal significantly deviates from the prior, respondents in the treatment group revise expectations sig-

[6] To illustrate belief updating, consider a worker with a prior expectation of macroeconomic variable of interest $\mathbb{E}^{\text{prior}}[Z_{t+12}]$ who receives a relevant *Signal*. Under Bayesian learning, workers' posterior expectation should be a weighted average of a prior and a signal:

$$\mathbb{E}^{\text{post}}[Z_{t+12}] = (1-\alpha)\mathbb{E}^{\text{prior}}[Z_{t+12}] + \alpha\ Signal$$

and revision of expectations should be a similar function of a prior and a signal:

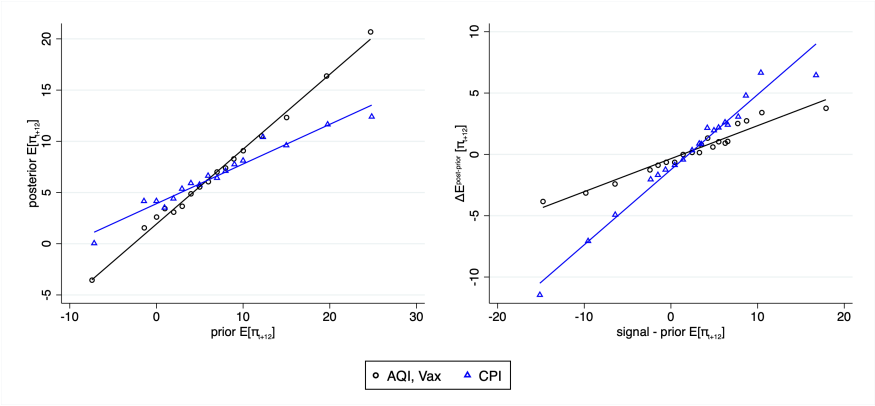
$$\Delta\mathbb{E}^{\text{post-prior}}[Z_{t+12}] = \alpha\left(\ Signal - \ \mathbb{E}^{\text{prior}}[Z_{t+12}]\right)$$

The graphical and regression specifications in the text estimate weight parameter α from the equations above.

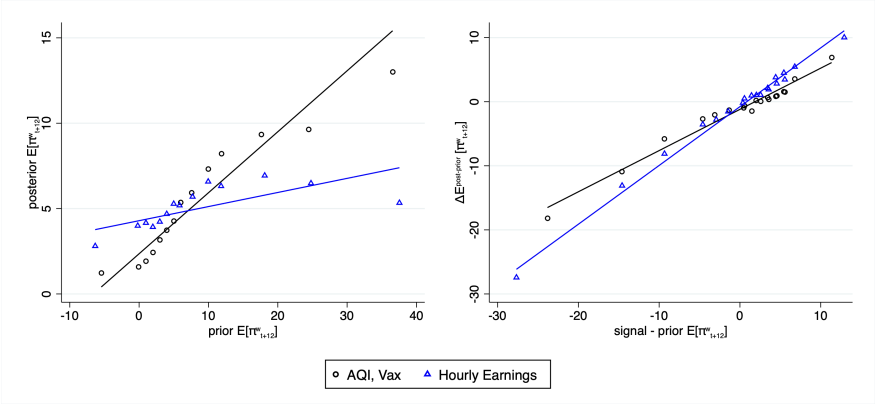
nificantly more in line with the signal.

Figure 2: Effects of information treatments on macroeconomic expectations

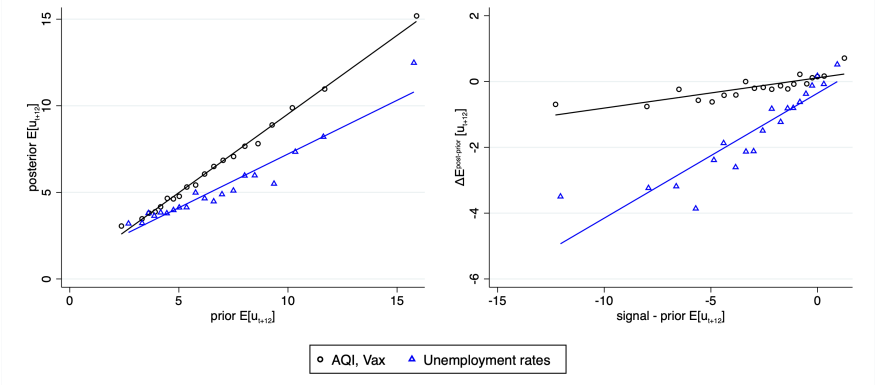
A. CPI information treatment and price inflation expectations



B. Hourly earnings treatment and earnings growth expectations



C. Unemployment rate treatment and unemployment expectations



Notes: This figure draws binned scatter plots of the highly numerate respondents' posterior expectations over the next 12 months (the left panel, on y-axis) and their revision of forecasts against the difference between their priors and signals received (the right panel) to illustrate the effect of the most relevant information provision from the first wave of the survey. Huber-robust weights are applied. Highly numerate respondents are those who answered all numerical competence check questions correctly. Additional results for revision of expectations in response to various signals are reported in Appendix B.1.

As depicted by the difference in slopes of black and blue lines, respondents in the control group revised their expectations less than those in the treatment group given their prior inflation expectations. Taking into account that those in the treatment group were provided with a signal about an annual CPI inflation rate of 7.9%, the graph shows that respondents revised their expectations toward the signal by placing a higher weight on the signal and decreasing weight on the prior. Panels B and C of Figure 2 depict posterior or revisions of earnings growth expectations and unemployment expectations in response to signals about past earnings growth and the unemployment rate forecast. Similar to the results in Panel A, respondents who received relevant information placed a lower weight on their priors and a higher weight on the signal than those in the control group.

Since many macroeconomic phenomena are interrelated, revisions of macroeconomic expectations about one variable may be responsive to signals about other macroeconomic variables. To examine whether this is the cause in our experiment, we analyze how respondents revise their expectations about a variable Z (e.g., price inflation expectations) when they receive a signal about another variable (e.g., wage growth rate or unemployment rate). Appendix Figure B.1 indicates that a signal about hourly earnings growth results in a similar revision of price inflation expectations as a signal about the CPI inflation rate. The effect of a signal about the unemployment rate is qualitatively similar, although smaller in magnitude. Similar to price inflation expectations, hourly earnings growth expectations react to signals about several variables (Appendix Figure B.2). At the same time, unemployment rate expectations are largely unresponsive to signals about price and wage inflation.

3.2 Regression Analysis

To study the effect of information treatments on expectations revision more formally, we analyze the effect of information treatments illustrated in Figure 2 by estimating the following regression equation:

$$\begin{aligned}\mathbb{E}_{it}^{\text{post}}[Z_{t+12}] = \alpha_0 + \alpha_1 \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}] + \alpha_2 \texttt{treat}_i^Z \\ + \alpha_3 \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}] \times \texttt{treat}_i^Z + \varepsilon_i \end{aligned} \tag{1}$$

for $Z = \{\pi, \pi^w, u\}$. Here, $\mathbb{E}_{it}^{\text{prior}}[Z_{t+12}]$ is a prior expectation of variable Z over the next 12 months, $\mathbb{E}_{it}^{\text{post}}[Z_{t+12}]$ is a posterior expectation after the information provision, and $\texttt{treat}_i^Z$ is a treatment dummy denoting if a respondent i is in the treatment group that received a signal about variable Z. In other words, to study information treatment effects, we regress posterior forecasts following the information treatment on prior expectations, treatment dummy, the interaction between a treatment dummy and prior expectation, and a set of control variables. Following Coibion et al. (2019), Coibion, Gorodnichenko, and Weber (2022), Hajdini et al. (2022b) and others, we use Huber-Robust regressions to control for outliers. The results are summarized in Table 2.

Columns 1-4 of Table 2 show the effect of information treatment about the CPI inflation rate

on the revision of inflation expectations. First, when provided with information about the current CPI inflation rates, respondents, on average, revise their posterior expected price inflation rates upward by 1.55-2.01 percentage points. In addition, their implied weight on prior price inflation expectations falls from 0.62-0.76 by 0.30-0.33 points. The results in columns 5-8 show that statistics about hourly earnings have a statistically significant effect on wage inflation expectations. Respondents, on average, revise their posterior expectations upward by 1.19-1.92 percentage points as well as reduce weight on prior wage inflation expectations from 0.21-0.37 by 0.15-0.30 points. Finally, according to columns 9-12, when workers receive information about the unemployment rate forecast, they tend to update their unemployment rate expectations upward. In addition, they reduced the weight they put on prior from 0.88-0.92 by about 0.19-0.33 points. These results support the conclusion that information treatments induce respondents to revise their expectations as intended.

Table 2: Effects of information treatments on the revision of price inflation, wage inflation, and unemployment expectations

Dependent variable:	Price inflation ($Z = \pi$)				Wage inflation ($Z = \pi^w$)				Unemployment rate ($Z = u$)			
$\mathbb{E}_{it}^{\texttt{post}}[Z_{t+12}]$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
`treat_cpi`	1.97***	1.58***	1.55***	2.01***								
	(0.23)	(0.24)	(0.25)	(0.24)								
`treat_wage`					1.29***	1.19***	1.96***	1.91***				
					(0.19)	(0.19)	(0.21)	(0.19)				
`treat_unemp`									0.05	0.23	0.85***	0.53**
									(0.23)	(0.23)	(0.23)	(0.22)
`treat_cpi` $\times$ $\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.32***	-0.29***	-0.30***	-0.33***								
	(0.02)	(0.02)	(0.02)	(0.02)								
`treat_wage` $\times$ $\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$					-0.16***	-0.15***	-0.30***	-0.26***				
					(0.01)	(0.02)	(0.02)	(0.02)				
`treat_unemp` $\times$ $\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$									-0.19***	-0.22***	-0.33***	-0.29***
									(0.03)	(0.03)	(0.03)	(0.03)
$\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	0.62***	0.63***	0.72***	0.76***	0.22***	0.21***	0.37***	0.34***	0.88***	0.89***	0.92***	0.92***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Sample	All	All	Numerate	Consistent	All	All	Numerate	Consistent	All	All	Numerate	Consistent
N	2860	2794	2060	2050	2881	2810	2052	2141	2445	2382	1772	1844
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Notes: This table presents the Huber-Robust regression output from equation (2). For each outcome variable specified in the header, the first column reports results without controls, the second column adds control variables, the third column restricts the sample to highly numerate respondents only (who answered all the numerical competence questions correctly), and the fourth column restricts the sample to consistent respondents only (For reservation wage questions, respondents were initially asked to provide their answers within specified ranges and then provide detailed numerical values. Consistent respondents are those who provided answers that matched these two questions). Control variables are female, age, age^2, white, whether cohabiting or not, whether having a child or not, full-time employed or not, logarithmic monthly spending on food, hours working at MTurk, whether having a college degree or not, frequency of checking news, and income). The control group refers to those who have received irrelevant information such as the air quality index in Seattle or Covid-19 vaccination rates.

Specification (1) implies that respondents revise expectations about a specific variable only if they receive a signal about this variable. However, given one signal, respondents may revise multiple expectations simultaneously (see Appendix B.1). If this is the case, results in Table 2 suffer from an omitted variable bias. To avoid the bias, and allow for the possibility that multi-

ple information treatments affect expectations for multiple variables, we extend equation (1) by including indicator variables for multiple information treatments and their interactions with the prior expectation of the variable of interest for $Z = \{\pi, \pi^w, u\}$.

$$\begin{aligned}\mathbb{E}_{it}^{\text{post}}[Z_{t+12}] =& \beta_0 + \beta_1 \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}] \quad + \sum_{k\in\{\pi,\pi^w,u\}} \beta_{2,k}\texttt{treat}_i^k \\ &+ \sum_{k\in\{\pi,\pi^w,u\}} \beta_{3,k}\left(\texttt{treat}_i^k \times \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}]\right) + \mathbf{X}_i'\gamma + \varepsilon_i \end{aligned} \tag{2}$$

The estimation results for equation (2) are reported in Table 3. Columns 1-4 show the effect of information treatments on the revision of price inflation expectations. When provided with information about the current CPI inflation rates, respondents revised their posterior expected price inflation rates upward by 1.59-2.02 percentage points, about the same amount as in Table 2. When respondents received information about the current hourly earnings inflation rate, they also increased their expected *price* inflation rate on average by 1.04-1.62 percentage points. Similarly, respondents in the treatment group placed significantly smaller weights on their priors than those in the control group, both when provided information about the CPI inflation rate and about other macroeconomic variables (the negative and statistically significant coefficient on $\texttt{treat} \times \mathbb{E}_{it}^{\texttt{prior}}[\pi_{t+12}]$). In other words, respondents in the treatment group update their expectations when provided with *any* relevant signal. This is consistent with earlier works on the effects of information treatment on inflation expectations (see, for example, Coibion et al., 2019; Coibion, Gorodnichenko, and Weber, 2022; Binder, 2020; Cavallo, Cruces, and Perez-Truglia, 2017; Hajdini et al., 2022b). It also shows that respondents updated their subjective expectations about future price inflation not only in response to the signal about current inflation rates but also in response to other relevant information such as hourly earnings inflation rates and unemployment rates. But they are more responsive to the direct signals about the current CPI inflation rate and/or hourly earnings wage inflation, rather than to signals about unemployment rates.

We observe similar patterns for hourly earnings inflation expectations from columns 5-8 of Table 3. First, respondents, on average, increased their expected wage inflation rates when provided with either the current CPI inflation rate or the hourly earnings inflation rate. When given the information about the current hourly earnings inflation rate, they increased their expectations about hourly earnings inflation rates by 1.15-1.92 percentage points. When provided with information about the current CPI inflation rates, they increase their expected hourly earnings inflation rates by 0.66-1.18 percentage points. Second, respondents in the treatment groups placed significantly smaller weights on their priors than respondents in the control group. The implied weight on the prior expectations falls from 0.21-0.36 by 0.16-0.29 for respondents who received information about hourly earnings growth. Similar to price inflation expectations, respondents react not only to the most relevant information, signal about hourly earnings inflation, but also to CPI inflation rates and unemployment rates. This suggests that when receiving information about the current CPI inflation rates, respondents update not only their expectations about price inflation rates but

also other macroeconomic expectations. Just like in the case of the CPI inflation expectations, they are more responsive to the signal about price or hourly earnings inflation than the signal about unemployment rates.

Table 3: Effects of information treatments on the revision of price inflation, wage inflation, and unemployment expectations (multiple treatments)

Dependent variable:	Price inflation ($Z = \pi$)				Wage inflation ($Z = \pi^w$)				Unemployment rate ($Z = u$)			
$\mathbb{E}_{it}^{\texttt{post}}[Z_{t+12}]$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
`treat_cpi`	2.02***	1.60***	1.59***	2.02***	0.89***	0.66***	1.18***	1.04***	-0.11	-0.20	-0.17	-0.33
	(0.23)	(0.23)	(0.25)	(0.24)	(0.20)	(0.21)	(0.23)	(0.21)	(0.22)	(0.23)	(0.21)	(0.21)
`treat_wage`	1.21***	1.04***	1.35***	1.62***	1.28***	1.15***	1.88***	1.92***	-0.12	-0.18	0.03	-0.06
	(0.22)	(0.22)	(0.24)	(0.22)	(0.20)	(0.20)	(0.22)	(0.20)	(0.22)	(0.23)	(0.23)	(0.21)
`treat_unemp`	-0.25	-0.18	-0.26	0.00	-0.34	-0.27	0.38	0.27	-0.19	-0.12	0.61**	0.40*
	(0.27)	(0.27)	(0.29)	(0.27)	(0.23)	(0.24)	(0.26)	(0.23)	(0.26)	(0.27)	(0.25)	(0.24)
`treat_cpi` $\times \mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.33***	-0.29***	-0.30***	-0.33***	-0.15***	-0.15***	-0.28***	-0.25***	0.09***	0.09***	0.07***	0.09***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
`treat_wage` $\times \mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.26***	-0.25***	-0.31***	-0.29***	-0.16***	-0.15***	-0.29***	-0.26***	0.04	0.05	-0.01	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
`treat_unemp` $\times \mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.08***	-0.07**	-0.04	-0.11***	-0.07***	-0.07***	-0.21***	-0.17***	-0.14***	-0.15***	-0.28***	-0.26***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
$\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	0.63***	0.63***	0.72***	0.76***	0.23***	0.21***	0.36***	0.34***	0.87***	0.88***	0.92***	0.91***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Sample	All	All	Numerate	Consistent	All	All	Numerate	Consistent	All	All	Numerate	Consistent
N	4611	4511	3315	3371	4614	4514	3316	3373	4614	4514	3316	3373
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Notes: This table presents the Huber-Robust regression output from equation (2). For each outcome variable specified in the header, the first column reports results without controls, the second column adds control variables, the third column restricts the sample to highly numerate respondents only (who answered all the numerical competence questions correctly), and the fourth column restricts the sample to consistent respondents only (For reservation wage questions, respondents were initially asked to provide their answers within specified ranges and then provide detailed numerical values. Consistent respondents are those who provided answers that matched these two questions). Control variables are female, age, age^2, white, whether cohabiting or not, whether having a child or not, full-time employed or not, logarithmic monthly spending on food, hours working at MTurk, whether having a college degree or not, frequency of checking news, and income). The control group refers to those who have received irrelevant information such as the air quality index in Seattle or Covid-19 vaccination rates.

In contrast to previous results, columns 9-12 of Table 3 show that respondents' expectations about unemployment rates mostly respond to the signal about unemployment rates. When provided with information about the current unemployment rates, respondents significantly revised their unemployment rate expectations toward the signal. The implied weight on the prior expectations falls from 0.87-0.92 by 0.14-0.28.

When provided with the signal about high current price inflation rates, respondents further corroborated their prior unemployment rate expectations. Interestingly, the positive coefficient on $\texttt{treat\_cpi} \times \mathbb{E}_{it}^{\texttt{prior}}[u_{t+12}]$ in Table 3 shows that people put even *higher* weights on their priors when they received signals about price inflation rates. This is consistent with a stagflationary view of inflation (see, for example, Kamdar, 2018; Binder, 2020). That is, they tend to think that when inflation rates are higher, unemployment rates tend to increase as well.

While information treatments induce respondents to revise macroeconomic expectations in the short run, these effects persist over a longer horizon (see Table C.1 in Appendix C.1). Specif-

ically, we find that when respondents update their expectations, they still place some weight on the relevant information that they received one or two months ago. The implied weights on the information received in the past are, however, smaller than weights on information received contemporaneously from Table 3. This is consistent with standard Bayesian learning. As time passes, the information gets more dated, so respondents put less weight on the information that they received a month or two months ago. The fact that respondents in the treatment groups have learned about either the current CPI inflation rates or hourly earnings inflation rates by participating in the first wave of the survey could weaken the information treatment effect from the subsequent follow-up surveys. Although we find statistically significant information treatment effects across all three waves, the magnitude of the effect decreases in the third wave (see Table C.2 in Appendix C.2). This is consistent with "learning-through-survey" effects documented by Binder and Kim (2020).

To recap, this section studies the effect of information treatment on subjective inflation and unemployment expectations. We find that, on average, respondents increase their posterior price or wage inflation expectations when they are provided with either the current CPI inflation rate or the hourly earnings inflation rate. Interestingly, they update their posterior price (wage) inflation rate upwards even when they receive information about the current hourly earnings (CPI) inflation rates. Moreover, individuals in the treatment groups place significantly smaller weights on their priors than those in the control group. Price inflation expectations respond to both signals about price and hourly earnings inflation. The same is true for hourly earnings inflation expectations. Unemployment rate treatment has larger effects on hourly earnings inflation expectations than on price inflation expectations. Unemployment expectations respond mostly to the signal about current unemployment rates. When provided with information about current high CPI inflation rates, respondents tend to revise their expectations about unemployment rates in the next 12 months *upwards*.

Overall, our results show that when provided with *one* relevant signal, respondents update their expectations about *all* variables altogether. This suggests that when examining the effect of macroeconomic expectations on households' behaviors, we need to control for *all* observed expectations to avoid potential omitted variable biases. For this reason, when we examine how expectations affect labor supply preferences, we include posterior price, wage inflation, and unemployment expectations at the same time.

4 Effects of Subjective Expectations on Labor Supply

In this section, we examine the *causal* relationship between macroeconomic expectations and labor supply. As we discussed above, subjective expectations about future economic variables are unlikely exogenous. Many unobserved factors affect both expectations and individuals' labor supply decisions. To overcome these issues, we use an instrumental variable approach. In light of the discussion in Section 3, we use information treatments and the interactions of information treatments

with priors as instruments to identify exogenous variations in expectations and study the causal link between expectations and labor supply decisions.

As we have examined in Section 3, when provided with *one* of the relevant pieces of information about the economy, respondents update their expectations about *all* relevant variables together. For example, when respondents received information about CPI inflation rates, they updated their expectations about price inflation rates, wage inflation, and unemployment rates. For this reason, we estimate the regression model with all the measured expectations (price, wage, and unemployment rates) as endogenous variables in the second-stage equation:

$$\begin{aligned} Y_{it}^{\texttt{post}} = \beta_0 + \beta_1 \mathbb{E}_{it}^{\text{post}}[\pi_{t+12}] + \beta_2 \mathbb{E}_{it}^{\text{post}}[\pi_{t+12}^{w}] + \beta_3 \mathbb{E}_{it}^{\text{post}}[u_{t+12}] \\ + \gamma_0 Y_{it}^{\texttt{prior}} + \gamma_1 \mathbb{E}_{it}^{\text{prior}}[\pi_{t+12}] + \gamma_2 \mathbb{E}_{it}^{\text{prior}}[\pi_{t+12}^{w}] + \gamma_3 \mathbb{E}_{it}^{\text{prior}}[u_{t+12}] + \mathbf{X}_{it}'\delta + \eta_i \end{aligned} \tag{3}$$

where $Y_{it} = \{\texttt{dur}_{it}^{\texttt{post}}, \overline{\texttt{rw}}_{it,t+\texttt{dur}_t}^{\texttt{post}}\}$ are the desired duration of employment on our MTurk project (in months) and reservation wage per 10-minute monthly task.

Because of the endogeneity inherent in posterior macroeconomic expectation variables in equation (3), we instrument them with information treatment dummies and their interactions with prior expectations. The first stage can be concisely summarized with equation (2). To be more specific, our instrument set includes the information treatment dummies, the interaction of prior price inflation expectations with the CPI treatment dummy and hourly earnings treatment dummies, the interaction of prior hourly earnings inflation expectations with the CPI treatment dummy and hourly earnings treatment dummy, and the interaction of prior unemployment expectations with unemployment treatment.[7] The parameters of our interest are β_1-β_3's.

4.1 Effects on MTurk Reservation Wages

This section focuses on the effect of macroeconomic expectations on reservation wages in the online labor market. Table 4 reports the effect of posterior macroeconomic expectations on the reservation wages per 10 minutes of respondents' time. The data is obtained from an answer to questions we asked before and after the information treatment about the smallest reward that respondents would be willing to accept to complete a similar task in the future.

The results in Table 4 show that respondents raise reservation wages in response to the increase in expected wage inflation rates, after controlling for expected price inflation rates and expected unemployment rates. A one percentage point increase in the expected wage inflation rate is associated with a 0.82-2.38 cent increase in their reservation wages per ten minutes. This corresponds to about 1 to 2 *percent* increase given the average/median reward per 10 minutes of $1. On the other hand, higher expected price inflation rates tend to rather *decrease* reservation wages, controlling for expected wage inflation rates and expected unemployment rates in specifications with

[7] In other words, we instrument $\mathbb{E}_{it}^{\text{post}}[Z_{t+12}]$ for $Z \in \{\pi, \pi^2, u\}$ with the following set of IVs: $\texttt{treat\_cpi}_{it}$, $\texttt{treat\_wage}_{it}$, $\texttt{treat\_unemp}_{it}$, $(\texttt{treat\_cpi}_{it} \times \mathbb{E}_{it}^{\texttt{prior}}[\pi_{t+12}])$, $(\texttt{treat\_cpi}_{it} \times \mathbb{E}_{it}^{\texttt{prior}}[\pi_{t+12}^{w}])$, $(\texttt{treat\_wage}_{it} \times \mathbb{E}_{it}^{\texttt{prior}}[\pi_{t+12}^{w}])$, $(\texttt{treat\_wage}_{it} \times \mathbb{E}_{it}^{\texttt{prior}}[\pi_{t+12}])$, and $(\texttt{treat\_unemp}_{it} \times \mathbb{E}_{it}^{\texttt{prior}}[u_{t+12}])$.

highly numerate respondents and respondents who provided consistent answers to reservation wage questions.[8] A 1 percentage point increase in the expected price inflation rate is associated with up to 1.62 cent *decrease* (1.6%) in nominal reservation wages on average.

Table 4: Effects of expectations on reservation wages

	Reservation Wages (in cents)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	-0.70	0.24	-1.23**	-0.61	-1.50**	-1.07*
	(0.66)	(0.63)	(0.59)	(0.59)	(0.68)	(0.62)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	2.03***	2.28***	1.03***	0.66*	0.80*	1.06*
	(0.66)	(0.66)	(0.36)	(0.38)	(0.44)	(0.56)
$\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	-1.41	0.19	0.06	-1.45**	0.25	0.11
	(0.91)	(0.95)	(0.80)	(0.63)	(0.64)	(0.62)
N	3,499	3,442	2,409	2,341	2,417	2,348
Sample	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	12.99	13.45	15.21	13.84	14.16	15.93
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	18.30	17.69	40.09	31.70	41.91	29.79
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	27.34	20.55	31.51	40.72	37.14	36.81

Notes: This table presents the regression output to estimate the effects of expectations on reservation wages in the online labor market according to equation (3). We instrument the posterior expectations with the treatment dummies of CPI inflation rates, hourly earnings inflation rates, and unemployment rates, the interactions of prior price inflation expectations with the CPI inflation treatment dummies and with the hourly earnings inflation treatment dummies, the interactions of prior wage inflation expectations with the CPI inflation treatment dummies and with the hourly earnings treatment dummies, and the interaction of unemployment treatment dummies with prior expected unemployment rates. Highly numerate respondents are those who answered all the numerical competence check questions correctly. For reservation wage questions, respondents were initially asked to provide their answers within specified ranges and then provide detailed numerical values. Consistent respondents are those who provided answers that matched between these two questions. Kleibergen and Paap (2006) rk Wald F-statistics for weak identification tests are reported. We use the geometric average of the weights generated from the Huber-robust regressions for each variable of interest in the first stage to control for outliers of the variables regarding expectations. To control for outliers in the second stage, we use a jackknife approach. See Appendix F for details about the treatment of outliers.

We interpret the qualitatively different responses of workers to wage and price inflation as evidence that households have a stagflationary view of inflation, i.e., they interpret inflation as a bad signal about the economy. Therefore, rather than demanding that employers compensate them for the decline in purchasing power of their earnings, they are willing to accept lower pay to secure employment. Importantly, due to the countervailing effect of inflation expectations on reservation wages, such behavior is unlikely to result in a wage-price spiral.

[8] Highly numerate respondents are those who answered all the numerical competence check questions correctly. For reservation wage questions, respondents were initially asked to provide their answers within specified ranges and then provide detailed numerical values. We refer to respondents as consistent if they provided answers that matched these two questions.

4.2 Effects on Desired Duration of Employment on MTurk

This section focuses on the effect of macroeconomic expectations on the desired duration of employment on a specific MTurk project. Table 5 shows the regression results from equation (3) for the desired duration of employment on our MTurk project which takes about 10 minutes.

Table 5 shows that, in contrast to reservation wages, macroeconomic expectations do not exert a significant influence on the desired duration of employment. The dependent variable here is whether respondents wish to extend their intended duration of employment with us.[9] We construct this variable from respondents' answers to the question, "For how many months would you be willing to accept a similar follow-up HIT taking 10 minutes of your time," both before and after the information treatment. This suggests that while their overall labor supply may change, their desired duration of employment *with us* could remain unaffected.[10] To address this question, we supplement the evidence about labor supply preferences on MTurk analyzed Table 5 with additional evidence about the offline labor market preferences elicited by the respondents at the end of the survey (see Appendix Section E).

[9] Our results are robust to the use of the alternative dependent variable, the desired duration of employment *in months*. See Appendix **??**.

[10] See Section 5.2 for the effects of broad regime changes.

Table 5: Effects of expectations on desired duration of employment

	$\mathbb{1}_{\texttt{increase the desired duration of employment}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	0.000	0.001	0.005	0.003	0.008	0.006
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	0.001	-0.001	-0.003	-0.005	-0.003	-0.003
	(0.007)	(0.007)	(0.003)	(0.004)	(0.003)	(0.005)
$\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	-0.015	-0.018	-0.013	-0.012	-0.007	-0.007
	(0.010)	(0.011)	(0.009)	(0.009)	(0.008)	(0.007)
N	3,498	3,440	2,408	2,340	2,417	2,347
Sample	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	12.97	13.48	15.21	13.92	14.14	15.93
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	18.06	17.54	39.80	31.45	41.74	29.50
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	27.20	20.64	31.24	40.77	37.38	36.90

Notes: This table presents the regression output to estimate the effects of expectations on the desired duration of employment on our MTurk HIT according to equation (3). We instrument the posterior expectations with the treatment dummies of CPI inflation rates, hourly earnings inflation rates, and unemployment rates, the interactions of prior price inflation expectations with the CPI inflation treatment dummies and with the hourly earnings inflation treatment dummies, the interactions of prior wage inflation expectations with the CPI inflation treatment dummies and with the hourly earnings treatment dummies, and the interaction of unemployment treatment dummies with prior expected unemployment rates. Highly numerate respondents are those who answered all the numerical competence check questions correctly. For reservation wage questions, respondents were initially asked to provide their answers within specified ranges and then provide detailed numerical values. Consistent respondents are those who provided answers that matched between these two questions. Kleibergen and Paap (2006) rk Wald F-statistics for weak identification tests are reported. We use the geometric average of the weights generated from the Huber-robust regressions for each variable of interest in the first stage to control for outliers of the variables regarding expectations.

5 Robustness to Alternative Specifications

This section discusses the robustness of the previously discussed results to alternative specifications. The main focus of the section is the analysis of the effect of information treatments through the framework of broad regime changes following Andrade, Gautier, and Mengus (2021) who provide evidence that what matters for households' decision-making is not the precise change in expectations but the broad regime changes. Additionally, we provide evidence about the robustness of the main results to alternative assumptions.

5.1 Information Treatment Effect on Broad Regime Changes in Expectations

Broad regime changes in expectations are indicator variables for the fact that respondents substantially switch their forecasts in response to information treatment (e.g., before treatment, respondents thought the overall price level would decrease and after treatment, they thought it would increase).

To evaluate the effect of information treatment on regime changes we estimate the following

regression:[11]

$$\texttt{Regime Change}_i^Z = \beta_0 + \sum_{k\in\{\pi,\pi^w,u\}} \beta_{1,k}\texttt{treat}_i^k + \beta_2 \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}] + \varepsilon_i, \;\; Z \in \{\pi, \pi^w, u\}, \tag{4}$$

where $\texttt{Regime Change}_i^Z$ denotes if a respondent i revises her *qualitative* assessment about variable Z *upwards*. For instance, if respondent i thinks that the overall price level will stay the same over the next 12 months, before the treatment, and changes this assessment so that she now thinks the overall price level will increase, after the treatment, then $\texttt{Regime Change}_i^{\pi}$ takes on the value of one. Similarly, if another respondent thinks that the overall price level will decrease over a year, before the treatment, but changes this assessment to "stay the same," or "increase," after the treatment, then $\texttt{Regime Change}_i^{\pi}$ is equal to one. It will take on the value of zero otherwise. We define $\texttt{Regime Change}_i^{\pi^w}$ similarly. Meanwhile, because unemployment rate expectations are elicited differently, we define $\texttt{Regime Change}_i^{u}$ as equal to one as long as respondents raise their unemployment expectations after the treatment and zero otherwise.

Table 6 shows the results. They paint the same picture as Table 3. First, columns 1-4 in table 6 show that when respondents receive either information about current CPI inflation rates or current hourly earnings inflation rates, they adjust their price inflation expectations upwards. Relative to those in the control group who received information about the air quality index in Seattle or COVID-19 vaccination rates, those in the CPI inflation treatment group are more likely to move to the higher CPI inflation rates regime by 3-6 percentage points. When respondents receive information about hourly earnings inflation rates, they are more likely to change their price inflation expectation regimes upward by 3-5 percentage points.

Similarly, columns 5-8 of Table 6 show that respondents adjust their expected hourly earnings inflation rates upwards when they receive the relevant information. Relative to those in the control group, those in the CPI treatment group have a higher probability of moving to a higher hourly earnings inflation regime by 3-4 percentage points. When they receive information about current hourly earnings inflation rates, they are more likely to move to a higher hourly earnings inflation regime by 5-11 percentage points relative to those in the control group.

[11] Appendix B.2 discusses results for an alternative specification that includes interactions of treatment dummies with prior expectations. They are qualitatively similar to the baseline results reported here.

Table 6: **(NEW)** Information treatment effects on broad regime changes in forecast revisions

Dependent variable:	Price inflation ($Z = \pi$)				Wage inflation ($Z = \pi^w$)				Unemployment rate ($Z = u$)			
$\texttt{Regime Change}_i^Z$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
treat_cpi	0.06***	0.03**	0.03*	0.04**	0.04**	0.03*	0.03	0.03	0.06***	0.04**	0.03	0.03
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
treat_wage	0.05***	0.03*	0.03**	0.05***	0.09***	0.08***	0.11***	0.11***	0.01	-0.01	-0.06**	-0.04*
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
treat_unemp	-0.03	-0.01	0.01	-0.02	-0.04**	-0.04**	-0.02	-0.03	-0.19***	-0.18***	-0.19***	-0.22***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Sample	All	All	Numerate	Consistent	All	All	Numerate	Consistent	All	All	Numerate	Consistent
N	4535	4457	3228	3281	4462	4363	3176	3214	4282	4212	3022	3076
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Notes: This table presents the Huber-Robust regression output from equation (4) for respondents in all control and treatment groups. The outcome variable is an indicator that respondents revised expectations of the variable in the column header upward. For each outcome variable, the first column reports results without controls, the second column adds control variables, the third column restricts the sample to highly numerate respondents only (who answered all the numerical competence questions correctly), and the fourth column restricts the sample to consistent respondents only (For reservation wage questions, respondents were initially asked to provide their answers within specified ranges and then provide detailed numerical values. Consistent respondents are those who provided answers that matched these two questions). Control variables are female, age, age^2, white, whether cohabiting or not, whether having a child or not, full-time employed or not, logarithmic monthly spending on food, hours working at MTurk, whether having a college degree or not, frequency of checking news, and income). The control group refers to those who have received irrelevant information such as the air quality index in Seattle or Covid-19 vaccination rates. Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Lastly, columns 9-12 of Table 6 show that relative to those in the control group, those in the unemployment treatment group are *less* likely to move to higher unemployment rate regimes by 18-22 percentage points. In contrast, when they receive information about current CPI inflation rates, they tend to move to a higher unemployment rate regime. Compared to those in the control group, those in the CPI inflation treatment group tend to be more likely to move to a higher unemployment rate regime by 3-6 percentage points. This is consistent with the result in Table 3 in Section 3 pointing to the stagflationary view of U.S. households.

5.2 Effect of Broad Regime Changes in Expectations on Labor Supply

Next, we discuss how broad regime changes affect online labor supply. We estimate regressions similar to equation (3) but now with dummy variables, $\texttt{Regime Change}^Z$ with $Z \in \{\pi, \pi^w, u\}$, denoting the broad regime changes before and after the information treatment, rather than the precise rate changes:

$$Y_{it}^{\texttt{post}} = \beta_0 + \beta_1 \texttt{Regime Change}_i^{\pi} + \beta_2 \texttt{Regime Change}_i^{\pi^w} + \beta_3 \texttt{Regime Change}_i^{u} + \gamma_0 Y_{it}^{\texttt{prior}} + \mathbf{X}_{it}'\delta + \varepsilon_i, \tag{5}$$

where $Y_{it} = \{\texttt{dur}_{it}^{\texttt{post}}, \overline{\texttt{rw}}_{it,t+\texttt{dur}_t}^{\texttt{post}}\}$ are changes in the desired duration of employment on our MTurk project (in month) and reservation wage per 10-minute monthly task. $\texttt{Regime Change}_i^Z$ is an in-

dicator variable denoting if respondent i revises her *qualitative* assessment about a variable Z *upwards* defined in the same way as in Section 5.1. The first stage for this specification is summarized in Appendix B.2. The results reported in Table 7 are qualitatively similar to the baseline results in Section 4.

Table 7: Effects of regime changes in expectations on MTurk labor supply

	Reservation Wages (in cents)						$\mathbb{1}_{\texttt{increase the desired duration of employment}}$					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\texttt{Regime}^{\pi}$	-11.03***	-3.06	-14.26***	-2.07	-13.45***	-7.99	0.00	0.02	0.01	0.02	0.04*	0.04
	(3.79)	(3.88)	(4.67)	(5.06)	(4.80)	(4.90)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$\texttt{Regime}^{\pi^w}$	9.81***	10.18***	9.13**	6.35*	7.37**	6.45*	-0.01	-0.01	-0.01	-0.02	0.01	0.00
	(3.47)	(3.33)	(3.55)	(3.48)	(3.66)	(3.76)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$\texttt{Regime}^{u}$	-6.05	3.89	1.22	9.39	6.18	7.08	0.05	0.11**	-0.02	-0.02	0.06**	0.05*
	(6.21)	(7.02)	(5.23)	(5.88)	(5.29)	(5.71)	(0.04)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)
N	3,624	3,575	2,510	2,456	2,518	2,461	3,716	3,662	2,604	2,534	2,612	2,543
Sample	All	All	Numerate	Numerate	Consistent	Consistent	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
F-stat for $\texttt{Regime}^{\pi}$	55.59	40.86	26.38	20.76	24.25	23.06	37.17	29.51	17.77	17.18	19.13	18.55
F-stat for $\texttt{Regime}^{\pi^w}$	53.20	52.95	34.90	35.22	31.71	28.62	58.83	61.12	40.29	38.31	35.95	33.91
F-stat for $\texttt{Regime}^{u}$	20.97	15.31	38.34	26.94	30.19	23.16	17.95	14.72	26.88	21.47	22.84	23.46

Notes: This table presents the regression output to estimate the effects of broad regime changes in expectations on MTurk labor supply for equation (5). We instrument the regime changes in expectations with the treatment dummies of CPI inflation rates, hourly earnings inflation rates, and unemployment rates, the interactions of prior price inflation expectations with the CPI inflation treatment dummies and with the hourly earnings inflation treatment dummies, the interactions of prior wage inflation expectations with the CPI inflation treatment dummies and with the hourly earnings treatment dummies, and the interaction of unemployment treatment dummies with prior expected unemployment rates. Highly numerate respondents are those who answered all the numerical competence check questions correctly. For reservation wage questions, respondents were initially asked to provide their answers within specified ranges and then provide detailed numerical values. Consistent respondents are those who provided answers that matched between these two questions. Heteroskedasticity-robust-standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Kleibergen and Paap (2006) rk Wald F-statistics for weak identification tests are reported. We use the geometric average of the weights generated from the Huber-robust regressions for each variable of interest in the first stage to control for outliers of the variables regarding expectations. To control for outliers in the second stage for reservation wages, we use a jackknife approach. See Appendix F for details about the treatment of outliers.

Columns 1-4 of Table 7 report the results for the desired duration of employment. Consistent with the previous results, broad changes in inflation or unemployment expectation regimes do not significantly affect the desired duration of employment.

Columns 5-8 in Table 7 report the results for MTurk reservation wages. They are qualitatively similar to those in Table 4, but some coefficients are not statistically significant given that there is less variation in endogenous variables. As respondents revise their broad regime about hourly earnings inflation expectation upwards, they increase their reservation wages. The upward revision of price inflation expectations, however, is associated with the decrease in reservation wages.

5.3 Additional Robustness Checks

This section provides evidence about the robustness of the results to adjustment of p-values for multiple hypothesis testing, alternative instrument sets, and dependent variables.

Adjustment of $p-$values for Multiple Hypothesis Testing. To address the concern that having three endogenous variables in our preferred specification biases standard errors and, thus, invalidates hypothesis testing, in this section we discuss the results with adjusted p-values. When estimating equation (3), we are interested in six parameter values. The regression coefficients on the forecast revisions in price and wage inflation rates, and unemployment rates with two dependent variables: the desired duration of employment and the reservation wages. To minimize the likelihood of false rejections with multiple hypothesis testing, we use Westfall-Young step-down adjusted p-values using `wyoung` command in STATA. This procedure controls the familywise error rate (FWER) and allows for dependence amongst p-values. The results with adjusted p-values are reported in Appendix D.1. They are similar to the main results about the effect of expectations on labor supply both in terms of continuous expectations revisions and discrete regime changes.

Alternative Instruments. The main specifications considered in Sections 4 and 5.2 instruments three endogenous expectations variables with a set of information treatment dummies, the interaction of prior price inflation expectations with the CPI treatment dummy and hourly earnings treatment dummies, the interaction of prior hourly earnings inflation expectations with the CPI treatment dummy and hourly earnings treatment dummy, and the interaction of prior unemployment expectations with unemployment treatment. Alternatively, we could include additional interaction terms with the unemployment treatment dummy as well as prior and posterior unemployment expectations. The results reported in Appendix D.2 for the alternative set of instruments are similar to the baseline IV results. However, a baseline specification is preferred because it produces a stronger first stage by excluding weaker instruments.

6 Discussion and Conclusions

We study how changes in macroeconomic expectations affect labor supply preferences by conducting an experiment in an online labor market. To this end, we generate exogenous variation in subjective expectations about price inflation, wage inflation, and unemployment rates by randomizing information treatments. We then use the resulting exogenous variation in expectations to study how it affects MTurk workers' reservation wages and the desired employment duration. Our results provide the first direct causal evidence about the effect of inflation expectations on labor supply and suggest that the risks of wage-price spirals are limited in the current high inflation setting.

First, we show that respondents significantly revise their macroeconomic expectations when provided with relevant information. Importantly, in response to a signal about one variable (e.g., unemployment rate) respondents revise multiple expectations *jointly*. When workers revise unemployment or wage growth expectations, they tend to revise price inflation expectations in the same direction. While inflation expectations are the most responsive to signals about other variables, unemployment expectations are mostly responsive to signals about unemployment. Wage inflation expectations tend to comove with price inflation expectations.

Next, exploiting the resulting variation in macroeconomic expectations, we document several results about the effect of expectations on labor supply. First, we document that higher wage inflation expectations increase reservation wages. Second, higher price inflation expectations appear to *decrease* reservation wages whereas higher unemployment expectations do not significantly affect reservation wages. Third, we find that the desired duration of employment on our MTurk project does not significantly respond to changes in macroeconomic expectations.

The result that wage and price inflation expectations affect reservation wages in opposite directions has important implications for understanding how households interpret inflation. This interpretation matters for the likelihood of wage-price spirals. The fact that reservation wages are increasing in wage growth expectations is not surprising. However, the fact that workers are willing to accept work at lower pay due to an increase in inflation expectations, rather than demanding additional compensation to restore the purchasing power of their income, is surprising. This result implies that the response of labor supply to inflation mitigates the threat of wage-price spirals. From the perspective of a search-theoretic model (e.g., Rogerson, Shimer, and Wright, 2005), the observed response to inflation expectations shock is consistent with households interpreting an increase in price inflation expectations as a signal about the deterioration of outside options, which induces them to reduce reservation wages and duration for job search/unemployment. The response to an increase in wage inflation expectations is similar to the reaction to an increase in outside options.

There is additional evidence that points to the fact that households interpret an inflation increase as a cautionary sign. When analyzing the revision of expectations in response to a randomized information provision, we find that households associate higher inflation rates with higher unemployment rates. Respondents tend to increase their expected unemployment rates when provided with the current inflation rates. This is consistent with the evidence in the literature that U.S. households tend to exhibit the stagflationary view (see Kamdar, 2018; Binder, 2020). This result suggests that the first chain of wage-price spirals could be partially muted with higher expected unemployment rates.

Our results are based on the experiments conducted in an online labor market, Amazon MTurk, which has distinctive features compared to offline labor markets. Online labor markets, in particular, feature much greater flexibility. It is much easier for workers to adjust their labor supply in online labor markets than in offline labor markets. Because MTurk workers are much more flexible, they represent those who are on the margin of adjustment and about whom policymakers care the most. Moreover, because in the follow-up surveys, we offer workers employment on the terms provided by them, we were able to capture the "actual" labor supply preferences as opposed to hypothetical preferences based on hypothetical questions only. At the same time, however, because of the distinctive features of online labor markets, offline labor supply responses could be different from our results to some extent. Due to the inflexibility, we might not be able to observe responses to the same degree. Because most workers use offline labor markets as their primary income source, their labor supply responses could be much larger. How much offline responses

are different from online responses is left for our future work.

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Appendix

A Descriptive Statistics

A.1 Attrition

When we launched our first wave of the survey, 10,758 MTurk workers attempted to participate in our survey. Among then 5,487 MTurkers completed the first wave of the survey. We examine if the attrition is systematically correlated with treatment arms. Table A.1 shows that the attrition rates are not different across treatment arms.

Table A.1: Attrition rates by treatment arms ($N = 10,758$)

CPI	Wage	Unemp	AQI	Vax
0.50	0.50	0.48	0.49	0.48

To further examine if the attrition is systematically different across treatment arms, we regress the indicator variable denoting the attrition on treatment arm dummies. Table A.2 further illustrates that attrition is not systematically related to the treatment arms.

Table A.2: Regression of attrition rates on treatment arms

`treat_cpi`	`treat_unemp`	`treat_vax`	`treat_wave`	Constant
0.007	-0.011	-0.011	0.013	0.489***
(0.015)	(0.016)	(0.015)	(0.014)	(0.010)

Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3 below summarizes the attrition from participating in the follow-up surveys. It shows that attrition was the highest in the control group that received the information about the air quality index in Seattle. The attrition rates between the two treatment groups are similar. This likely happened because workers might have found the information about the air quality in Seattle less interesting than the one about CPI or hourly earnings inflation rates. Another reason might be that air quality transcription task asked workers to record four numbers rather than three as is the case for the treatment groups (CPI and Wage groups). We also find that, overall, older workers and those without children are more likely to participate in the follow-up waves. Other than this, there are no systematic differences for other demographic characteristics.

Table A.3: Attrition rates from participating in the follow-up waves

Wave 1 $\rightarrow$ Wave2			Wave 1 $\rightarrow$ Wave 3			All three waves		
CPI	Wage	AQI	CPI	Wage	AQI	CPI	Wage	AQI
0.45	0.43	0.50	0.49	0.47	0.55	0.67	0.64	0.75

A.2 Descriptive statistics (follow-up surveys)

Table A.4 below provides descriptive statistics about respondents who participated in the second and third waves. Table A.4 shows that they are similar to those from the first wave of the survey in Section 2.3.

Table A.4: Descriptive Statistics (Wave 2&3)

Wave 2 (June 2022)	Mean	Percentiles			Std. Dev.
		p25	p50	p75	
age	40.38	31.00	39.00	49.00	12.17
female	0.47	0.00	0.00	1.00	0.50
white	0.80	0.00	1.00	1.00	0.40
with college degree	0.75	1.00	1.00	1.00	0.43
employed	0.82	1.00	1.00	1.00	0.38
full-time employed	0.69	0.00	1.00	1.00	0.46
number of children	0.85	0.00	1.00	2.00	1.01
monthly spending on food	$593.70	$175.00	$350.00	$600.00	2214.87
monthly spending on gas	$392.66	$50.00	$100.00	$200.00	7649.37
$\mathbb{E}_t^{\texttt{prior}}[\pi_{t+12}]$	5.57	1.00	5.00	10.00	8.10
$\mathbb{E}_t^{\texttt{prior}}[\pi^w_{t+12}]$	5.78	1.00	3.00	8.00	9.93
$\mathbb{E}_t^{\texttt{prior}}[u_{t+12}]$	7.05	4.30	6.30	9.00	3.57
$\mathbb{E}_t^{\texttt{prior}}[\texttt{duration}_{t+1}]$	3.87	3.00	5.00	5.00	1.49
$\mathbb{E}_t^{\texttt{prior}}[\texttt{reservation wages}_{t+1}]$	0.94	0.50	0.92	1.17	0.54
Observations	1,540				

Wave 2 (June 2022)	Mean	Percentiles			Std. Dev.
		p25	p50	p75	
age	40.79	31.00	39.00	49.00	12.22
female	0.49	0.00	0.00	1.00	0.50
white	0.81	0.00	1.00	1.00	0.39
with college degree	0.74	1.00	1.00	1.00	0.44
employed	0.82	1.00	1.00	1.00	0.38
full-time employed	0.67	0.00	1.00	1.00	0.47
number of children	0.89	0.00	1.00	2.00	1.10
monthly spending on food	$519.16	$150.00	$350.00	$560.00	1165.40
monthly spending on gas	$205.74	$50.00	$120.00	$225.00	361.07
$\mathbb{E}_t^{\texttt{prior}}[\pi_{t+12}]$	4.85	1.00	4.00	9.00	7.78
$\mathbb{E}_t^{\texttt{prior}}[\pi^w_{t+12}]$	5.32	1.00	3.00	6.00	9.43
$\mathbb{E}_t^{\texttt{prior}}[u_{t+12}]$	6.96	4.23	6.20	8.90	3.47
$\mathbb{E}_t^{\texttt{prior}}[\texttt{duration}_{t+1}]$	3.97	3.00	5.00	5.00	1.44
$\mathbb{E}_t^{\texttt{prior}}[\texttt{reservation wages}_{t+1}]$	0.98	0.50	1.00	1.25	0.54
Observations	1,472				

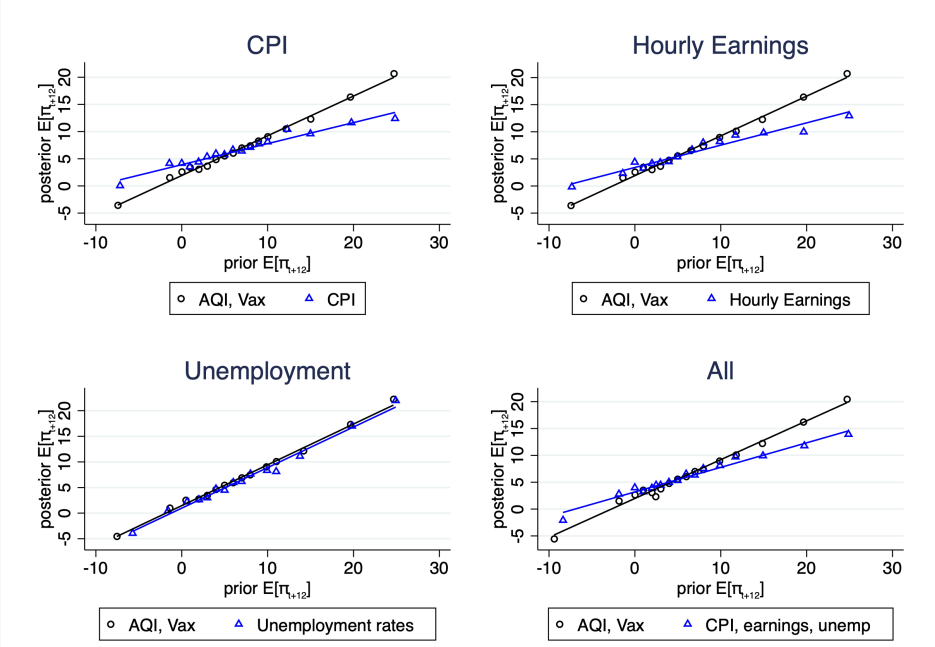
B Effects of Information Treatment on Subjective Expectations

This section supplements Section 3. First, we present binned scatter plots of respondents' posterior expectations after the information provision against their priors by each treatment (CPI inflation, hourly earnings inflation, unemployment, and all three pooled together). Second, we provide regression results from alternative specifications to study information treatment effects.

B.1 Graphical Illustration of Information Treatment Effects

This section presents binned scatter plots of respondents' posterior expectations against their priors by each treatment (CPI inflation, hourly earnings inflation, unemployment, and all three pooled together). Consistent with discussion in Section 3, Figure B.1 shows that respondents in the treatment group put smaller weights on their prior when they received the relevant signals, whether it is information about price inflation or other macroeconomic variables. Treatment groups exhibit much flatter slopes in all cases. Respondents adjust their weights towards the signal the most when they have received the information about the CPI inflation.

Figure B.1: Effects of information treatment on price inflation expectations

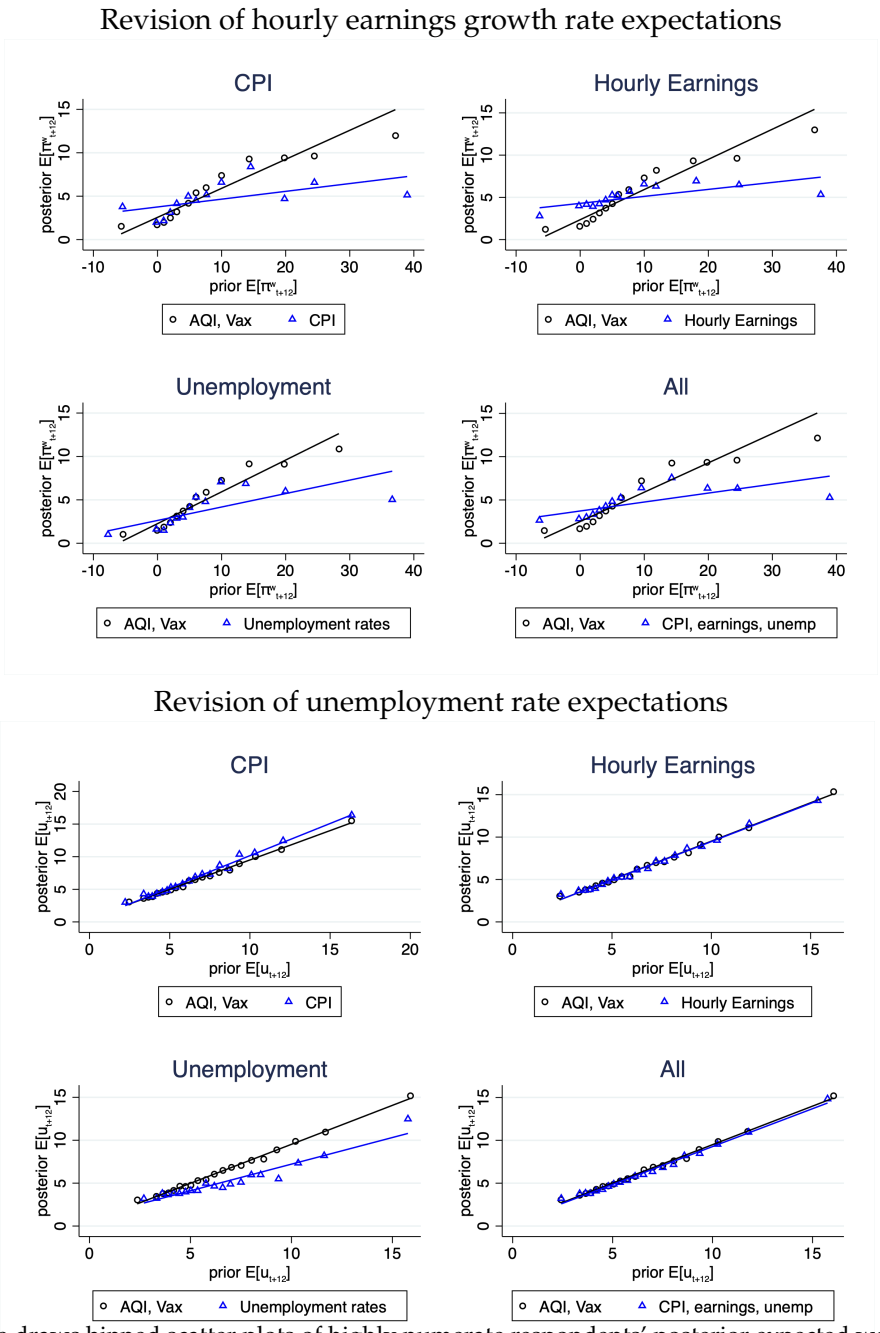


Notes: This figure draws binned scatter plots of highly numerate respondents' posterior expected price inflation rates over the next 12 months (on y-axis) against their priors (on $x-$axis) from the first wave of the survey. Huber-robust weights are applied. Blue triangles are for those who have received the relevant information treatment and black circles are for those who have received irrelevant information about the air quality index (AQI) in Seattle or Covid-19 vaccination rates (Vax). Panels 1-4 refer respectively to CPI inflation treatment, hourly earnings treatment, unemployment rate, and all treatments pooled together.

Figure B.2 paints the same picture. The slopes are much flatter for those in the treatment groups, suggesting that respondents in the treatment group update their expectations about either hourly earnings inflation or unemployment rates after receiving the relevant signals. While hourly earnings inflation expectations are more responsive to the signals about price and hourly earnings inflation, the unemployment rate responds mostly to the signal about unemployment rates. The

above figures illustrate the effect of information provision on subjective expectations (price and wage inflation rates and unemployment rates).

Figure B.2: Effects of information treatment on hourly earnings and unemployment rates expectations



Notes: This figure draws binned scatter plots of highly numerate respondents' posterior expected wage inflation rates (upper panel) and unemployment rates (lower panel) over the next 12 months (on y-axis) against their priors (on $x-$axis) from the first wave of the survey. Huber-robust weights are applied. Blue triangles are for those who have received the relevant information treatment and black circles are for those who have received irrelevant information about the air quality index (AQI) in Seattle or Covid-19 vaccination rates (Vax). Panels 1-4 refer respectively to CPI inflation treatment, hourly earnings treatment, unemployment rate, and all treatments pooled together.

B.2 Information Treatment Effects on Broad Regime Changes in Expectations

This section summarizes information treatment effects on broad regime changes in expectations to supplement discussion in Section 5.1. We extend the specification estimated there by introducing interaction terms of regime change indicators with prior expectations:

$$\begin{aligned}\texttt{Regime Change}_i^Z =& \beta_0 + \beta_1 \mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}] + \sum_{k\in\{\pi,\pi^w,u\}} \beta_{2,k}\texttt{treat}_i^k \\ &+ \sum_{k\in\{\pi,\pi^w,u\}} \beta_{3,k}\left(\texttt{treat}_i^k \times \mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]\right) + \varepsilon_i, \;\; Z \in \{\pi, \pi^w, u\},\end{aligned} \tag{B.1}$$

where $\texttt{Regime Change}_i^Z$ denotes if a respondent i revises her *qualitative* assessment about variable Z *upwards*. For instance, if a respondent i thinks that the overall price level will stay the same over the next 12 months, before the treatment, and changes this assessment so that she now thinks the overall price level will increase, after the treatment, then $\texttt{Regime Change}_i^{\pi}$ takes on the value of one. Similarly, if another respondent thinks that the overall price level will decrease over a year, before the treatment, but changes this assessment to "stay the same," or "increase," after the treatment, then $\texttt{Regime Change}_i^{\pi}$ equals to one. It will take on the value of zero otherwise. We define $\texttt{Regime Change}_i^{\pi^w}$ similarly. Meanwhile, because unemployment rates are defined differently, we define $\texttt{Regime Change}_i^{u}$ equals to one as long as respondents raise their unemployment expectations after the treatment and zero otherwise.

Table B.1 shows the results. They are in line with the results in Table 6 and broadly consistent with the results for actual revisions in Table 3. First, columns 1-4 show the results for broad regime changes in forecast revisions on price inflation expectations. They show that when respondents are provided with either the current CPI inflation rate or the current hourly earnings inflation rates, they are more likely to revise their price inflation expectations upwards, on average. As expected, they are less likely to do so, if their prior expectations are already high. Columns 5-8 show the results for broad regime changes in forecast revisions on wage inflation expectations. Again, they show broadly consistent results with Table 3. When they are provided with either the current CPI inflation rates or hourly earnings inflation rates, they are more likely to revise wage inflation expectations upwards. As is the case for the price inflation expectations, they are less likely to do so if their prior wage inflation expectations are high from the beginning. Lastly, columns 9-12 show the results from the unemployment rate expectations. They show that those in the treatment group are *less* likely to revise their unemployment expectations upwards when provided with the current unemployment rates. Consistent with the results in Table 3, they are mostly responsive to the current unemployment rate information. Moreover, the higher their prior expected unemployment rate is, the smaller the likelihood of revising their expected unemployment rate upward. Interestingly, but consistent with the results in Table 3, the higher their prior expected unemployment rate is, the higher the likelihood of moving to higher unemployment rate regimes when provided with the current CPI inflation rates. This again reflects the stagflationary view of the U.S. households.

Table B.1: Information treatment effects on broad regime changes in forecast revisions

Dependent variable:	Price inflation ($Z = \pi$)				Wage inflation ($Z = \pi^w$)				Unemployment rate ($Z = u$)			
$\texttt{Regime Change}_{it}^{Z}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
treat_cpi	0.089***	0.079***	0.052**	0.070***	0.014	0.008	0.002	0.001	-0.023	-0.046	-0.055	-0.106**
	(0.019)	(0.022)	(0.022)	(0.022)	(0.020)	(0.024)	(0.024)	(0.024)	(0.043)	(0.051)	(0.052)	(0.052)
treat_wage	0.074***	0.080***	0.071***	0.092***	0.109***	0.128***	0.131***	0.125***	-0.021	-0.018	-0.024	-0.037
	(0.018)	(0.021)	(0.021)	(0.020)	(0.019)	(0.023)	(0.023)	(0.023)	(0.043)	(0.052)	(0.053)	(0.051)
treat_unemp	-0.026	-0.004	0.013	-0.012	-0.051**	-0.038	-0.035	-0.035	-0.211***	-0.079	-0.041	-0.200***
	(0.022)	(0.025)	(0.024)	(0.024)	(0.023)	(0.026)	(0.027)	(0.027)	(0.050)	(0.061)	(0.061)	(0.059)
treat_cpi $\times$ $\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.005***	-0.004**	-0.004**	-0.005**	0.003**	0.004*	0.003	0.004**	0.012**	0.014**	0.013*	0.019***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.007)	(0.007)	(0.007)
treat_wage $\times$ $\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.005**	-0.006**	-0.006***	-0.008***	-0.004**	-0.003	-0.003	-0.003	0.004	-0.004	-0.005	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.007)	(0.007)	(0.007)
treat_unemp $\times$ $\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	0.000	-0.001	-0.001	-0.001	0.001	0.002	0.003	0.001	0.003	-0.019**	-0.023***	-0.004
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.007)	(0.008)	(0.009)	(0.008)
$\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.021***	-0.018***	-0.018***	-0.017***	-0.019***	-0.021***	-0.021***	-0.020***	-0.014***	-0.008**	-0.006	-0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)	(0.004)	(0.004)
Sample	All	All	Numerate	Consistent	All	All	Numerate	Consistent	All	All	Numerate	Consistent
N	4535	3301	3237	3281	4462	3276	3175	3214	4282	3106	3013	3076
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Notes: This table presents the Huber-Robust regression output from equation (2) for respondents in all control and treatment groups where the outcome variable is an indicator that respondents revised expectations of the variable in column header upward. For each outcome variable, the first column reports results without controls, the second column adds control variables, the third column restricts the sample to highly numerate respondents only (who answered all the numerical competence questions correctly), and the fourth column restricts the sample to consistent respondents only (For reservation wage questions, respondents were initially asked to provide their answers within specified ranges and then provide detailed numerical values. Consistent respondents are those who provided answers that matched these two questions). Control variables are female, age, age^2, white, whether cohabiting or not, whether having a child or not, full-time employed or not, logarithmic monthly spending on food, hours working at MTurk, whether having a college degree or not, frequency of checking news, and income). The control group refers to those who have received irrelevant information such as the air quality index in Seattle or Covid-19 vaccination rates. Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Learning Effects

This section explores the learning effects of information provision. First, we study the long-run effects of information provision. In specific, we examine if the information treatment effects persist in the subsequent follow-up surveys. Second, we study the learning through survey effects by comparing the treatment effects across the three waves.

C.1 Bayesian Learning Effects

In this section, we examine if the information treatment effects are persistent over the next few months. To that end, we run the following regression:

$$\begin{aligned}\mathbb{E}^{\text{prior}j}_{it+j}[Z_{t+12}] =& \beta_0 + \beta_1 \mathbb{E}^{\text{prior1}}_{it}[Z_{t+12}] \quad + \sum_{k\in\{\pi,\pi^w,u\}} \beta_{2,k}\texttt{treat}^k_i \\ &+ \sum_{k\in\{\pi,\pi^w,u\}} \beta_{3,k}\left(\texttt{treat}^k_i \times \mathbb{E}^{\text{prior}}_{it}[Z_{t+12}]\right) + \mathbf{X}_i'\gamma + \varepsilon_i,\ j=\{1,2\} \end{aligned} \tag{C.1}$$

for $Z = \{\pi, \pi^w, u\}$. This is similar to the specification in the main text, equation (2), but the dependent variable is now the revisions in *prior* expectations from the first wave to the subsequent follow-up waves.

Table C.1 shows the results. From $\hat{\beta}_{3,k}$'s, it is clear that the information treatment effects persist over, at least, two more months. When respondents update their expectations, they still place some weight on the relevant information they received one or two months ago. The implied weights on the new information are, however, smaller than those from Table 3. This is consistent with standard Bayesian learning. As time passes, the information gets more dated and so respondents put less weight on the information that they received a month or two months ago.

Table C.1: Effects of information treatments on price inflation, wage inflation, and unemployment expectations (Wave 2-3)

	Price inflation ($Z = \pi$)				Wage inflation ($Z = \pi^w$)				Unemployment rate ($Z = u$)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Part 1: Dependent variable: $\mathbb{E}_{it}^{\texttt{prior2}}[Z_{t+12}]$												
`treat_cpi`	0.01	-0.03	0.23	0.05	0.38	0.20	0.22	0.36	-0.42	-0.24	-0.32	-0.35
	(0.56)	(0.56)	(0.65)	(0.60)	(0.36)	(0.39)	(0.47)	(0.42)	(0.40)	(0.41)	(0.47)	(0.43)
`treat_wage`	0.51	0.55	0.76	0.78	-0.19	-0.36	-0.66	-0.37	-0.10	0.00	0.16	-0.05
	(0.55)	(0.55)	(0.63)	(0.58)	(0.35)	(0.38)	(0.45)	(0.40)	(0.41)	(0.42)	(0.49)	(0.44)
`treat_cpi` $\times$ $\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.05	-0.05	-0.07	-0.05	-0.06**	-0.04	0.01	-0.04	-0.00	-0.03	-0.02	-0.00
	(0.06)	(0.06)	(0.07)	(0.06)	(0.03)	(0.03)	(0.04)	(0.03)	(0.05)	(0.05)	(0.06)	(0.05)
`treat_wage` $\times$ $\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.18***	-0.19***	-0.19***	-0.22***	-0.03	0.01	-0.08**	0.05	-0.01	-0.03	-0.08	-0.01
	(0.05)	(0.05)	(0.06)	(0.06)	(0.03)	(0.03)	(0.04)	(0.03)	(0.05)	(0.05)	(0.06)	(0.06)
$\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	0.52***	0.53***	0.59***	0.59***	0.12***	0.11***	0.08***	0.13***	0.49***	0.45***	0.50***	0.47***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.04)	(0.05)	(0.04)
Sample	All	All	Numerate	Consistent	All	All	Numerate	Consistent	All	All	Numerate	Consistent
N	1365	1340	1031	1170	1365	1340	1031	1170	1365	1340	1031	1170
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Part 2: Dependent variable: $\mathbb{E}_{it}^{\texttt{prior3}}[Z_{t+12}]$												
`treat_cpi`	0.70	0.57	0.18	0.05	0.31	0.08	0.39	0.36	-0.10	-0.15	-0.76*	-0.35
	(0.53)	(0.54)	(0.60)	(0.60)	(0.32)	(0.32)	(0.34)	(0.42)	(0.41)	(0.42)	(0.46)	(0.43)
`treat_wage`	0.47	0.39	0.60	0.78	0.10	0.01	0.48	-0.37	-1.18***	-1.04**	-1.24***	-0.05
	(0.50)	(0.52)	(0.56)	(0.58)	(0.31)	(0.31)	(0.33)	(0.40)	(0.42)	(0.43)	(0.46)	(0.44)
`treat_cpi` $\times$ $\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.11**	-0.11**	0.01	-0.05	-0.10***	-0.08***	-0.10***	-0.04	0.02	0.04	0.13**	-0.00
	(0.05)	(0.05)	(0.06)	(0.06)	(0.02)	(0.02)	(0.03)	(0.03)	(0.05)	(0.05)	(0.06)	(0.05)
`treat_wage` $\times$ $\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.17***	-0.18***	-0.16***	-0.22***	-0.07***	-0.05**	-0.10***	-0.05	0.20***	0.18***	0.20***	-0.01
	(0.05)	(0.05)	(0.05)	(0.06)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.06)	(0.06)
$\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	0.43***	0.43***	0.45***	0.59***	0.15***	0.13***	0.16***	0.13***	0.35***	0.32***	0.35***	0.47***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)
Sample	All	All	Numerate	Consistent	All	All	Numerate	Consistent	All	All	Numerate	Consistent
N	1444	1416	1140	1170	1444	1416	1140	1170	1444	1416	1140	1170
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes

This table presents the Huber-Robust regression output from equation (C.1) for $j = 1, 2$. For each outcome variable specified in the header, the first column reports results without controls, the second column adds control variables, the third column restricts the sample to highly numerate respondents only (who answered all the numerical competence questions correctly), and the fourth column restricts the sample to consistent respondents only (For reservation wage questions, respondents were initially asked to provide their answers within specified ranges and then provide detailed numerical values. Consistent respondents are those who provided answers that matched these two questions). Control variables are female, age, age^2, white, whether cohabiting or not, whether having a child or not, full-time employed or not, logarithmic monthly spending on food, hours working at MTurk, whether having a college degree or not, frequency of checking news, and income). The control group refers to those who have received irrelevant information such as the air quality index in Seattle or Covid-19 vaccination rates. Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.2 Learning Through Survey Effects

This section examines the treatment effects of information provision on expectations in the follow-up waves. Because respondents in the treatment groups have learned about either current CPI inflation rates or current hourly earnings inflation rates by participating in the first wave of the survey, the information treatment effect from subsequent follow-up surveys might be weaker. We explore the possibility of having this "learning-through-survey" effect in this section.

To that end, we run the following regression:

$$\begin{aligned}\mathbb{E}_{it}^{\text{post}}[Z_{t+12}] =& \beta_0 + \mathbb{1}_{\texttt{wave1}} \times \left(\beta_1^{\texttt{wave1}} \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}] + \sum_{k=1}^{2} \beta_{2,k}^{\texttt{wave1}} \texttt{treat}_i^k + \sum_{k=1}^{2} \beta_{3,k}^{\texttt{wave1}} \left(\texttt{treat}_i^k \times \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}] \right) \right) \\ &+ \mathbb{1}_{\texttt{wave2}} \times \left(\beta_1^{\texttt{wave2}} \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}] + \sum_{k=1}^{2} \beta_{2,k}^{\texttt{wave2}} \texttt{treat}_i^k + \sum_{k=1}^{2} \beta_{3,k}^{\texttt{wave2}} \left(\texttt{treat}_i^k \times \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}] \right) \right) \\ &+ \mathbb{1}_{\texttt{wave3}} \times \left(\beta_1^{\texttt{wave3}} \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}] + \sum_{k=1}^{2} \beta_{2,k}^{\texttt{wave3}} \texttt{treat}_i^k + \sum_{k=1}^{2} \beta_{3,k}^{\texttt{wave3}} \left(\texttt{treat}_i^k \times \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}] \right) \right) + \varepsilon_i, \end{aligned} \tag{C.2}$$

for $Z = \{\pi, \pi^2, u\}$ with those who participated in all three waves of the surveys (937 out of 2,763).[12] By comparing the regression coefficients on the interaction terms between the treatment dummies with prior expectations across three waves ($\beta_{3,k}^{\texttt{wave1}} - \beta_3^{\texttt{wave3}}$), we examine if participants learn through surveys.

Table C.2 shows the estimation results from equation (C.2). First, columns 1-3 in Table C.2 show clear treatment effects of information provisions on expected price inflation rates in the subsequent waves.[13] When respondents receive information about either current CPI inflation rates or hourly earnings inflation rates, they revise their expectations about price inflation rates significantly by putting smaller weights on their priors. The information treatment effects with CPI inflation treatment are of similar magnitudes between the first and the second waves but they become much smaller in the third wave. In contrast, the information treatment effects with hourly earnings treatment are similar between the first and the third waves and they are imprecisely estimated in the second wave.

[12] We followed up with participants in the two treatment groups (CPI and hourly earnings group) and one control group (air quality index group) in the second and third waves. Among 3,979 participants in the first wave, 2,763 of them are in these groups.

[13] See Appendix C.3 the estimation results with the full sample who participated in either wave 2 or wave 3.

Table C.2: Effects of information treatments on price inflation, wage inflation, and unemployment expectations (Wave 1-3)

Dependent variable:	Price inflation ($Z = \pi$)				Wage inflation ($Z = \pi^2$)				Unemployment rate ($Z = u$)			
$\mathbb{E}_{it}^{post}[Z_{t+12}]$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Wave 1 ×												
treat_cpi	1.49***	1.50***	1.46***	1.60***	1.58***	1.35***	0.09	0.40*	-0.76***	-0.76***	-0.30	-0.74***
	(0.28)	(0.28)	(0.26)	(0.27)	(0.23)	(0.24)	(0.19)	(0.22)	(0.23)	(0.24)	(0.22)	(0.23)
treat_wage	1.10***	1.05***	0.93***	1.12***	2.97***	2.88***	3.91***	2.96***	-0.01	-0.08	0.06	0.03
	(0.26)	(0.26)	(0.24)	(0.25)	(0.22)	(0.23)	(0.18)	(0.21)	(0.24)	(0.25)	(0.24)	(0.24)
treat_cpi × $\mathbb{E}_{it}^{prior}[Z_{t+12}]$	-0.22***	-0.24***	-0.21***	-0.24***	-0.18***	-0.10***	-0.01	-0.22***	0.14***	0.14***	0.04	0.14***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
treat_wage × $\mathbb{E}_{it}^{prior}[Z_{t+12}]$	-0.10***	-0.10***	-0.08**	-0.10***	-0.23***	-0.19***	-0.78***	-0.15***	-0.01	0.00	-0.06*	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Wave 2 ×												
treat_cpi	1.75***	1.71***	1.83***	1.84***	0.90***	0.70***	0.97***	0.46**	-0.42*	-0.55**	-0.38	-0.39
	(0.27)	(0.27)	(0.29)	(0.28)	(0.22)	(0.23)	(0.20)	(0.23)	(0.23)	(0.24)	(0.25)	(0.25)
treat_wage	0.38	0.31	0.26	0.24	2.38***	2.24***	3.36***	2.48***	0.93***	0.91***	0.91***	0.71***
	(0.26)	(0.26)	(0.28)	(0.26)	(0.22)	(0.23)	(0.19)	(0.21)	(0.24)	(0.25)	(0.26)	(0.25)
treat_cpi × $\mathbb{E}_{it}^{prior}[Z_{t+12}]$	-0.26***	-0.26***	-0.28***	-0.28***	-0.31***	-0.30***	-0.31***	-0.25***	0.10***	0.12***	0.08**	0.08**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
treat_wage × $\mathbb{E}_{it}^{prior}[Z_{t+12}]$	-0.04	-0.03	-0.01	-0.02	-0.54***	-0.53***	-0.69***	-0.59***	-0.17***	-0.17***	-0.17***	-0.15***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Wave 3 ×												
treat_cpi	1.31***	1.13***	0.89***	1.05***	0.82***	0.54**	0.16	0.08	-0.20	-0.25	-0.43*	-0.21
	(0.27)	(0.27)	(0.26)	(0.27)	(0.22)	(0.23)	(0.18)	(0.21)	(0.23)	(0.25)	(0.23)	(0.25)
treat_wage	1.04***	0.97***	1.14***	0.89***	2.01***	1.96***	2.91***	1.93***	-0.08	-0.18	0.46**	0.14
	(0.25)	(0.26)	(0.24)	(0.25)	(0.22)	(0.23)	(0.17)	(0.21)	(0.24)	(0.25)	(0.23)	(0.24)
treat_cpi × $\mathbb{E}_{it}^{prior}[Z_{t+12}]$	-0.08**	-0.06*	-0.01	-0.04	-0.36***	-0.30***	-0.08***	-0.13***	0.06*	0.06*	0.09***	0.07*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
treat_wage × $\mathbb{E}_{it}^{prior}[Z_{t+12}]$	-0.16***	-0.15***	-0.10***	-0.10***	-0.40***	-0.40***	-0.65***	-0.40***	-0.01	0.02	-0.11***	-0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Sample	All	All	Numerate	Consistent	All	All	Numerate	Consistent	All	All	Numerate	Consistent
N	2922	2849	2018	2440	2925	2852	2019	2443	2925	2852	2019	2443
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Notes: This table presents the Huber-Robust regression output from equation (C.2). For each outcome variable specified in the header, the first column reports results without controls, the second column adds control variables, and the third column restricts the sample to highly numerate respondents only (who answered all the numerical competence questions correctly). Control variables are female, age, age^2, white, whether cohabiting or not, whether having a child or not, full-time employed or not, logarithmic monthly spending on gas, hours working at MTurk, education level, frequency of checking news, and income). The control group refers to those who have received irrelevant information such as the air quality index in Seattle or Covid-19 vaccination rates. Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We can observe similar patterns from columns 4-6 in Table C.2. While we observe clear information treatment effects from the follow-up surveys, the information treatment effects become smaller in the third wave. That is, at least for highly numerate respondents, the information treatment effects of CPI treatment and/or hourly earnings treatment become smaller in the third wave as they learn through participating in surveys.

Finally, we observe such a pattern from columns 7-9 in Table C.2. Across all waves, respondents further corroborated their priors on unemployment expectations when they received CPI inflation signals. The regression coefficients on the interaction terms between CPI treatment and prior unemployment expectations are statistically significantly positive across all three waves, but the magnitudes become smaller in the follow-up surveys. The information treatment effects of hourly earnings treatment on unemployment expectations, on the other hand, are only significant and negative in the second wave. They are imprecisely estimated in the first and the third waves for all respondents, but they are statistically significantly negative for highly numerate respondents, demonstrating information treatment effects.

C.3 Information Treatment Effects From Wave 2 & Wave 3

Lastly, we present the treatment effects of information provision from the second and the third waves of the survey with full observations including those who have participated in either wave 1 and wave 2 or wave 1 and wave 3 only. Table C.3 and C.4 show the results. Consistent with

the results in section C, they show clear information treatment effects. At the same time, however, the information treatment effects of CPI inflation rates become smaller for the price inflation and unemployment expectations in the third wave. In contrast, the information treatment effects on hourly earnings inflation expectations are of similar magnitudes across the three waves across various treatments.

Table C.3: Effects of information treatments on posterior expectations from Wave 2

Dependent variable:	Price inflation ($Z = \pi$)				Wage inflation ($Z = \pi^w$)				Unemployment rate ($Z = u$)			
$\mathbb{E}_{it}^{\texttt{post}}[Z_{t+12}]$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
`treat_cpi`	2.21***	2.13***	1.94***	2.27***	1.06***	1.29***	1.13***	1.34***	-0.37	-0.43	-0.57**	-0.14
	(0.29)	(0.30)	(0.30)	(0.29)	(0.25)	(0.26)	(0.26)	(0.24)	(0.30)	(0.32)	(0.29)	(0.30)
`treat_wage`	0.89***	0.80***	0.30	0.80***	1.66***	2.09***	3.01***	2.66***	0.62**	0.61*	0.64**	0.52*
	(0.28)	(0.30)	(0.30)	(0.27)	(0.25)	(0.25)	(0.25)	(0.23)	(0.30)	(0.32)	(0.29)	(0.30)
`treat_cpi` $\times$ $\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.36***	-0.35***	-0.29***	-0.34***	-0.17***	-0.32***	-0.37***	-0.42***	0.09**	0.11***	0.12***	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)
`treat_wage` $\times$ $\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.17***	-0.16***	-0.03	-0.12***	-0.22***	-0.40***	-0.64***	-0.57***	-0.12***	-0.12***	-0.13***	-0.10***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)
$\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	0.80***	0.80***	0.88***	0.89***	0.40***	0.57***	0.85***	0.75***	0.83***	0.83***	0.84***	0.89***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Sample	All	All	Numerate	Consistent	All	All	Numerate	Consistent	All	All	Numerate	Consistent
N	1752	1680	841	1289	1756	1683	841	1292	1756	1683	841	1292
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Notes: This table presents the Huber-Robust regression output for respondents who participated in the second wave of the survey from equation (2). For each outcome variable specified in the header, the first column reports results without controls, the second column adds control variables, and the third column restricts the sample to highly numerate respondents only (who answered all the numerical competence questions correctly). Control variables are female, age, age^2, white, whether cohabiting or not, whether having a child or not, full-time employed or not, logarithmic monthly spending on gas, hours working at MTurk, education level, frequency of checking news, and income). The control group refers to those who have received irrelevant information such as the air quality index in Seattle or Covid-19 vaccination rates. Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.4: Effects of information treatments on posterior expectations from Wave 3

Dependent variable:	Price inflation ($Z = \pi$)				Wage inflation ($Z = \pi^w$)				Unemployment rate ($Z = u$)			
$\mathbb{E}_{it}^{\texttt{post}}[Z_{t+12}]$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
`treat_cpi`	1.58***	1.49***	1.34***	1.07***	1.06***	0.75***	0.70***	0.35*	0.17	0.14	-0.03	0.20
	(0.32)	(0.33)	(0.30)	(0.32)	(0.23)	(0.24)	(0.21)	(0.21)	(0.30)	(0.33)	(0.30)	(0.29)
`treat_wage`	1.58***	1.49***	1.34***	1.07***	1.06***	0.75***	0.70***	0.35*	0.17	0.14	-0.03	0.20
	(0.32)	(0.33)	(0.30)	(0.32)	(0.23)	(0.24)	(0.21)	(0.21)	(0.30)	(0.33)	(0.30)	(0.29)
`treat_cpi` $\times$ $\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.18***	-0.18***	-0.09***	-0.12***	-0.40***	-0.33***	-0.26***	-0.17***	-0.02	-0.02	0.01	-0.01
	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)
`treat_wage` $\times$ $\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.18***	-0.17***	-0.14***	-0.10***	-0.43***	-0.44***	-0.54***	-0.44***	-0.01	0.01	-0.09**	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)
$\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	0.73***	0.74***	0.85***	0.81***	0.71***	0.66***	0.80***	0.77***	0.93***	0.91***	0.95***	0.95***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Sample	All	All	Numerate	Consistent	All	All	Numerate	Consistent	All	All	Numerate	Consistent
N	1470	1434	1039	1144	1472	1436	1041	1146	1472	1436	1041	1146
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Notes: This table presents the Huber-Robust regression output for respondents who participated in the second wave of the survey from equation (2). For each outcome variable specified in the header, the first column reports results without controls, the second column adds control variables, and the third column restricts the sample to highly numerate respondents only (who answered all the numerical competence questions correctly). Control variables are female, age, age^2, white, whether cohabiting or not, whether having a child or not, full-time employed or not, logarithmic monthly spending on gas, hours working at MTurk, education level, frequency of checking news, and income). The control group refers to those who have received irrelevant information such as the air quality index in Seattle or Covid-19 vaccination rates. Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Robustness Checks

D.1 Adjusted of $p-$values for Multiple Hypothesis Testing

First, we provide the same regression results with the adjusted p-values for multiple hypothesis testing. In the second stage, we are interested in three parameter values per each regression equation. The regression coefficients on the forecast revisions in price and wage inflation rates, and unemployment rates with two dependent variables: the desired duration of employment and the reservation wages. To minimize the likelihood of false rejections with multiple hypothesis testing, we use Westfall-Young stepdown adjusted p-values using `wyoung` command in STATA. This controls the familywise error rate (FWER) and allow for dependence amongst p-values. The results are reported in Table D.1

Table D.1: Effects of expectations on MTurk labor supply with adjusted p-values

	Desired Duration (in months)						Reservation Wages (in cents)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Continuous posteriors												
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	-0.02	-0.03	-0.01	-0.01	-0.02	-0.03	-0.49	0.15	-1.14*	-0.47	-1.62*	-1.25**
	(0.82)	(0.92)	(0.61)	(0.89)	(0.36)	(0.45)	(0.31)	(0.92)	(0.07)	(0.31)	(0.07)	(0.07)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	0.01	0.00	-0.02	-0.02	-0.00	-0.01	1.87***	2.22***	0.99***	0.72	0.82	1.09
	(0.79)	(0.97)	(0.25)	(0.53)	(0.50)	(0.45)	(0.01)	(0.00)	(0.01)	(0.15)	(0.13)	(0.13)
$\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	-0.02	-0.01	-0.04	-0.02	0.01	0.01	-1.45	0.18	0.32	-1.45**	0.51	0.28
	(0.82)	(0.92)	(0.68)	(0.89)	(0.50)	(0.45)	(0.25)	(0.92)	(0.91)	(0.05)	(0.71)	(0.93)
N	4,135	4,079	2,960	2,887	2,983	2,918	3,526	3,485	2,428	2,368	2,447	2,377
Sample	All	All	Numerate	Numerate	Consistent	Consistent	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	13.58	13.23	15.72	15.57	15.42	15.61	13.07	12.17	16.73	15.47	13.63	15.60
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	13.49	12.34	16.52	18.65	23.03	19.26	19.09	17.27	41.27	32.33	37.72	30.37
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	27.51	21.35	32.42	26.42	34.54	29.79	28.74	21.39	31.56	44.71	37.28	36.75
Panel B: Broad regime changes												
$\texttt{Regime}^{\pi}$	-0.21*	-0.13	-0.18	-0.08	-0.08	-0.07	-11.03***	-3.06	-14.26***	-2.07	-13.45***	-7.99
	(0.24)	(0.54)	(0.52)	(0.82)	(0.86)	(0.79)	(0.02)	(0.25)	(0.00)	(0.74)	(0.04)	(0.60)
$\texttt{Regime}^{\pi^w}$	-0.01	-0.12	-0.10	-0.22*	0.01	-0.10	9.81***	10.18***	9.13**	6.35*	7.37**	6.45*
	(0.95)	(0.81)	(0.52)	(0.49)	(0.93)	(0.79)	(0.02)	(0.00)	(0.02)	(0.06)	(0.04)	(0.26)
$\texttt{Regime}^{u}$	-0.08	0.08	-0.26	-0.09	0.20	0.16	-6.05	3.89	1.22	9.39	6.18	7.08
	(0.93)	(0.82)	(0.52)	(0.82)	(0.66)	(0.63)	(0.34)	(0.99)	(0.99)	(0.74)	(0.44)	(0.60)
N	4,135	4,056	2,960	2,877	2,983	2,915	3,624	3,575	2,510	2,456	2,518	2,461
Sample	All	All	Numerate	Numerate	Consistent	Consistent	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
F-stat for $\texttt{Regime}^{\pi}$	60.02	47.21	26.58	23.69	30.79	30.39	55.59	40.86	26.38	20.76	24.25	23.06
F-stat for $\texttt{Regime}^{\pi^w}$	64.21	65.34	44.07	44.16	44.08	42.42	53.20	52.95	34.90	35.22	31.71	28.62
F-stat for $\texttt{Regime}^{u}$	18.80	14.49	16.94	13.50	21.10	18.41	20.97	15.31	38.34	26.94	30.19	23.16

Notes: This table presents the regression output to estimate the effects of expectations on MTurk labor supply with the *adjusted* p-values in parentheses. To minimize the likelihood of false rejections with multiple hypothesis testing, we use Westfall-Young stepdown adjusted p-values using `wyoung` command in STATA. Panel A shows the results from equation (3) and Panel B shows the results from equation (5). We instrument the revisions in expectations with the treatment dummies of CPI inflation rates, hourly earnings inflation rates, and unemployment rates, the interactions of prior price inflation expectations with the CPI inflation treatment dummies and with the hourly earnings inflation treatment dummies, the interactions of prior wage inflation expectations with the CPI inflation treatment dummies and with the hourly earnings treatment dummies, and the interaction of unemployment treatment dummies with prior expected unemployment rates. Highly numerate respondents are those who answered all the numerical competence check questions correctly. For reservation wage questions, respondents were initially asked to provide their answers within specified ranges and then provide detailed numerical values. Consistent respondents are those who provided answers that matched between these two questions. Kleibergen and Paap (2006) rk Wald F-statistics for weak identification tests are reported. We use the geometric average of the weights generated from the Huber-robust regressions for each variable of interest in the first stage to control for outliers of the variables regarding expectations. To control for outliers for reservation wages in the second stage, we use a jackknife approach. See Appendix F for details about the treatment of outliers.

Results in Panel A of Table D.1 replicate the results in Sections 4.2 and 4.1. They are similar to the baseline results. In terms of the desired duration of employment on MTurk project, the results point to a statistically insignificant effect of macroeconomic expectations on employment duration. As to the reservation wages, a positive effect of wage inflation expectations and negative effect of price inflation expectations are largely robust to adjusted $p-$values with multiple hypothesis testing. Results in Panel B of Table D.1 also closely matches the results in Table 7 about broad regime changes.

D.2 Alternative Instruments

Next, we provide the estimation results with a different set of instrumental variables. In addition to the instruments we have in Section 4, we add the interaction of $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$ with the treatment dummy for unemployment rates, the interaction of $\mathbb{E}_{it}^{\texttt{post}}[\pi^{w}_{t+12}]$ with the treatment dummy for unemployment rates, and the interactions of $\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$ with the treatment dummies for CPI and hourly earnings inflation rates to the set of instruments. That is, our full set of instruments are now: $\Delta\mathbb{E}_{it}^{\texttt{post-prior}}[Z_{t+12}]$ for $Z \in \{\pi, \pi^2, u\}$ with the following set of IVs: $\texttt{treat\_cpi}_{it}$, $\texttt{treat\_wage}_{it}$, $\texttt{treat\_unemp}_{it}$, $(\texttt{treat\_cpi}_{it} \times \mathbb{E}_{it}^{\texttt{prior}}[\pi_{t+12}])$, $(\texttt{treat\_cpi}_{it} \times \mathbb{E}_{it}^{\texttt{prior}}[\pi^{w}_{t+12}])$, $(\texttt{treat\_wage}_{it} \times \mathbb{E}_{it}^{\texttt{prior}}[\pi^{w}_{t+12}])$,
$(\texttt{treat\_wage}_{it} \times \mathbb{E}_{it}^{\texttt{prior}}[\pi_{t+12}])$, $(\texttt{treat\_unemp}_{it} \times \mathbb{E}_{it}^{\texttt{prior}}[u_{t+12}])$,
$(\texttt{treat\_unemp}_{it} \times \mathbb{E}_{it}^{\texttt{prior}}[\pi_{t+12}])$, $(\texttt{treat\_unemp}_{it} \times \mathbb{E}_{it}^{\texttt{prior}}[\pi^{w}_{t+12}])$,
$(\texttt{treat\_cpi}_{it} \times \mathbb{E}_{it}^{\texttt{prior}}[u_{t+12}])$, and $(\texttt{treat\_wage}_{it} \times \mathbb{E}_{it}^{\texttt{prior}}[u_{t+12}])$.

Table D.2 shows the regression results from the same regression models of equations (3) and (5) with these instrumental variables. As can be seen from Panel A of Table D.2, the results are consistent with those in the main text with smaller Kleibergen and Paap (2006) rk Wald F-statistics for weak identification tests. Higher unemployment expectations are associated with a higher desired duration of employment. Higher wage inflation expectations increase reservation wages. In contrast, higher price inflation expectations rather decrease reservation wages for highly numerate respondents.

Panel B of Table D.2 shows that the results are consistent with the baseline results for broad regime changes in Section 5.2. Broad changes in inflation and unemployment regime do not affect the desired duration of employment. Moreover, the last four columns show that as respondents revise their broad regime about hourly earnings inflation expectation *upwards*, they increase their reservation wages. In contrast, the upward revision of price inflation expectations is associated with the decrease in reservation wages. Similarly, the upward forecast revisions of unemployment rates are associated with lower reservation wages.

Table D.2: Effects of expectations on MTurk labor supply with additional instruments

	Desired Duration (in months)						Reservation Wages (in cents)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Continuous posteriors												
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	-0.02	-0.03	-0.00	-0.01	-0.02	-0.03	-0.64	-0.42	-0.99*	-0.55	-1.35**	-1.10*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.62)	(0.61)	(0.58)	(0.57)	(0.65)	(0.65)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	-0.00	-0.00	-0.02	-0.03	-0.00	-0.01	2.00***	2.24***	1.15***	1.08**	0.92*	1.78**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.63)	(0.59)	(0.40)	(0.50)	(0.48)	(0.70)
$\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	-0.01	0.01	-0.02	-0.01	0.02	0.03	-1.66*	0.17	-0.40	0.99	-0.03	-0.31
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.87)	(0.98)	(0.80)	(0.73)	(0.68)	(0.90)
N	4,140	4,059	2,973	2,876	2,993	2,908	3,505	3,451	2,389	2,324	2,407	2,280
Sample	All	All	Numerate	Numerate	Consistent	Consistent	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	8.30	8.24	9.91	9.61	10.38	10.49	8.50	8.25	9.81	9.45	8.78	6.87
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	8.59	8.12	10.82	11.51	14.14	13.09	11.87	11.40	25.30	16.86	23.38	9.02
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	18.32	15.01	19.12	16.36	20.53	19.29	16.55	11.56	20.39	20.91	21.94	11.17
Panel B: Broad regime changes												
$\texttt{Regime}^{\pi}$	-0.17	-0.13	-0.09	-0.03	0.01	0.03	-12.99***	-6.45*	-13.51***	-5.92	-12.38***	-4.96
	(0.11)	(0.11)	(0.15)	(0.16)	(0.15)	(0.15)	(3.44)	(3.47)	(4.27)	(4.30)	(4.29)	(4.07)
$\texttt{Regime}^{\pi^w}$	-0.00	-0.06	-0.06	-0.14	-0.01	-0.10	11.02***	11.09***	6.06*	3.15	3.37	5.32
	(0.10)	(0.10)	(0.12)	(0.12)	(0.11)	(0.11)	(3.25)	(3.15)	(3.31)	(3.27)	(3.24)	(3.27)
$\texttt{Regime}^{u}$	-0.11	-0.03	-0.13	-0.02	0.29	0.32	-6.41	1.81	-7.37	-4.11	3.21	-0.60
	(0.19)	(0.21)	(0.20)	(0.22)	(0.19)	(0.20)	(5.90)	(6.67)	(5.11)	(5.18)	(4.89)	(5.49)
N	4,140	4,087	2,973	2,889	2,993	2,920	3,645	3,598	2,507	2,456	2,505	1,439
Sample	All	All	Numerate	Numerate	Consistent	Consistent	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
F-stat for $\texttt{Regime}^{\pi}$	50.07	42.52	24.49	21.23	30.04	25.75	43.04	40.04	20.82	21.41	23.41	24.76
F-stat for $\texttt{Regime}^{\pi^w}$	41.04	40.79	28.80	26.94	35.08	33.71	34.27	35.42	30.91	31.19	34.53	33.05
F-stat for $\texttt{Regime}^{u}$	12.55	9.89	10.38	8.46	12.83	10.57	14.01	10.17	20.24	17.14	25.16	14.81

This table presents the regression output to estimate the effects of expectations on MTurk labor supply. Panel A shows the results from equation (3) and Panel B shows the results from equation (5). We instrument the revisions in expectations with the treatment dummies of CPI inflation rates, hourly earnings inflation rates, and unemployment rates, the interactions of prior price inflation expectations with the CPI inflation treatment dummies and with the hourly earnings inflation treatment dummies, the interactions of prior wage inflation expectations with the CPI inflation treatment dummies and with the hourly earnings treatment dummies, the interaction of unemployment treatment dummies with prior expected unemployment rates, the interaction of prior price inflation expectations with the treatment dummy for unemployment rates, the interaction of prior wage inflation expectations with the treatment dummy for unemployment rates, and the interactions of prior expected unemployment rates with the treatment dummies for CPI and hourly earnings inflation rates. Heteroskedasticity-robust-standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Highly numerate respondents are those who answered all the numerical competence check questions correctly. For reservation wage questions, respondents were initially asked to provide their answers within specified ranges and then provide detailed numerical values. Consistent respondents are those who provided answers that matched between these two questions. Kleibergen and Paap (2006) rk Wald F-statistics for weak identification tests are reported. We use the geometric average of the weights generated from the Huber-robust regressions for each variable of interest in the first stage to control for outliers of the variables regarding expectations. To control for outliers for reservation wages in the second stage, we use a jackknife approach. See Appendix F for the treatment of outliers.

E Effects on Offline Labor Supply

The discussion in Section 4.1 and 4.2 focuses on the effect of macroeconomic expectations on *online* labor supply preferences. This section complements these results by examining the effect on preferences in *offline* labor markets. We elicited offline labor supply preferences by asking additional questions at the end of the survey. For the sake of survey time, we did not ask respondents about offline labor supply before the information treatment, which limits the amount of variation available relative to the previous analysis.

We asked respondents about offline labor supply along both extensive and intensive margins. For the extensive margin, we asked respondents to elicit subjective probabilities of changes in labor market status in the next 4 months (e.g., being employed with the same employer, changing

employers, becoming self-employed, becoming unemployed, or exiting the labor force). Table E.1 reports the results. Not surprisingly, respondents with higher unemployment rate expectations have a significantly lower subjective probability of being in the labor force both in the overall sample and in a subsample of numerate and/or consistent respondents. Respondents with higher wage inflation expectations *tend to* have higher subjective probabilities of being employed, while imprecisely estimated. At the same time, respondents with higher price inflation expectations tend to be pessimistic about their chances of being employed, especially the numerate ones. These results are consistent with a story that households interpret an increase in inflation as an indicator of deteriorating economic conditions.

Table E.1: Effects of macroeconomic expectations on the subjective probability of being in the labor force

	Prob. of Being in the Labor Force					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	0.08	0.06	-0.47	-0.22	-0.32	-0.19
	(0.42)	(0.34)	(0.35)	(0.26)	(0.34)	(0.28)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	-0.02	-0.05	0.59**	0.14	0.21	-0.04
	(0.45)	(0.39)	(0.26)	(0.15)	(0.29)	(0.29)
$\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	-6.03***	-2.57***	-3.96***	-1.12***	-3.42***	-2.04***
	(0.69)	(0.51)	(0.41)	(0.33)	(0.42)	(0.42)
N	3,340	3,300	2,281	2,209	2,288	2,214
Sample	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	13.85	11.63	16.90	17.12	16.58	18.07
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	16.40	11.13	31.15	45.26	29.95	21.74
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	21.54	15.08	35.64	24.34	33.14	24.52

Notes: This table presents the regression results for the effect of macroeconomic expectations on the subjective probability of being employed or self-employed in the next 4 months according to the following equation:

$$\begin{aligned} P_{it}(\texttt{employed}) =& \beta_0 + \beta_1 \mathbb{E}_{it}^{\text{post}}[\pi_{t+12}] + \beta_2 \mathbb{E}_{it}^{\text{post}}[\pi_{t+12}^{w}] + \beta_3 \mathbb{E}_{it}^{\text{post}}[u_{t+12}] \\ &+ \gamma_1 \mathbb{E}_{it}^{\text{prior}}[\pi_{t+12}] + \gamma_2 \mathbb{E}_{it}^{\text{prior}}[\pi_{t+12}^{w}] + \gamma_3 \mathbb{E}_{it}^{\text{prior}}[u_{t+12}] + \mathbf{X}_{it}'\delta + \varepsilon_i \end{aligned}$$

We instrument the posterior expectations with the treatment dummies of CPI inflation rates, hourly earnings inflation rates, and unemployment rates, the interactions of prior price inflation expectations with the CPI inflation treatment dummies and with the hourly earnings inflation treatment dummies, the interactions of prior wage inflation expectations with the CPI inflation treatment dummies and with the hourly earnings treatment dummies, and the interaction of unemployment treatment dummies with prior expected unemployment rates. Highly numerate respondents in columns 3-4 are those who answered all the numerical competence check questions correctly. Respondents were initially asked to provide their answers within specified ranges and then provide detailed numerical values for reservation wage questions. We refer to respondents as consistent, if they provided answers that matched between these two questions. Heteroskedasticity-robust-standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Kleibergen and Paap (2006) rk Wald F-statistics for weak identification tests are reported. We use the geometric average of the weights generated from the Huber-robust regressions for each variable of interest in the first stage to control for outliers of the variables regarding expectations. To control for outliers in the second stage, we use a jackknife approach. See Appendix F for details about the treatment of outliers.

Similarly, we examine the effects of macroeconomic expectations on the subjective probability of being employed by a different employer. Table E.2 presents the results of this analysis. Interestingly, respondents with higher price inflation expectations have a significantly higher subjective probability of being employed by a different employer among numerate and/or consistent respondents. This suggests two potential explanations. First, households may perceive rising inflation as an indicator of a deteriorating economic landscape, leading them to assess the risk of job loss and hence forced to switch to a different employer as higher. This again aligns with a story of a stagflationary view of the U.S. households. Second, households with higher price inflation

expectations may be inclined to seek employment with other employers offering higher salaries. This is because the wages of existing workers tend to be stickier, while those of new hires tend to be more cyclical. A similar empirical finding is presented in Hajdini et al. (2022b); Pilossoph and Ryngaert (2022); Bostanci, Koru, and Villalvazo (2022). On the other hand, respondents with higher wage inflation expectations tend to have lower subjective probabilities of being employed by a different employer. Again, this result implies that households either perceive a lower risk of job loss or are disinclined to change employers. Lastly, respondents with higher unemployment expectations have a significantly greater subjective probability of being employed by a different employer. This suggests that with a worse economic outlook, households tend to perceive the risk of job loss as elevated.

Table E.2: Effects of macroeconomic expectations on the subjective probability of being employed by a different employer

	Prob. of Employed By a Different Employer					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	0.47	0.42	1.02***	0.43*	0.75**	0.63**
	(0.33)	(0.29)	(0.33)	(0.24)	(0.31)	(0.30)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	-0.35	-0.38	-0.89***	-0.37	-0.57**	-0.55**
	(0.34)	(0.27)	(0.32)	(0.23)	(0.25)	(0.24)
$\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	2.57***	1.46***	1.85***	0.84***	1.89***	1.15***
	(0.39)	(0.36)	(0.34)	(0.27)	(0.35)	(0.30)
N	3,109	3,072	2,128	2,093	2,039	2,026
Sample	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	7.46	7.33	7.91	9.04	9.23	8.50
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	10.46	10.34	11.22	12.54	20.58	15.63
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	18.69	15.31	26.66	29.24	25.60	26.96

Notes: This table presents the regression results for the effect of macroeconomic expectations on the subjective reported probability of being employed by a different employer in the next 4 months according to the following equation:

$$P_{it}(\texttt{employed by a different employer}) = \beta_0 + \beta_1 \mathbb{E}_{it}^{\text{post}}[\pi_{t+12}] + \beta_2 \mathbb{E}_{it}^{\text{post}}[\pi_{t+12}^{w}] + \beta_3 \mathbb{E}_{it}^{\text{post}}[u_{t+12}] + \gamma_1 \mathbb{E}_{it}^{\text{prior}}[\pi_{t+12}] + \gamma_2 \mathbb{E}_{it}^{\text{prior}}[\pi_{t+12}^{w}] + \gamma_3 \mathbb{E}_{it}^{\text{prior}}[u_{t+12}] + \mathbf{X}_{it}'\delta + \varepsilon_i$$

We instrument the posterior expectations with the treatment dummies of CPI inflation rates, hourly earnings inflation rates, and unemployment rates, the interactions of prior price inflation expectations with the CPI inflation treatment dummies and with the hourly earnings inflation treatment dummies, the interactions of prior wage inflation expectations with the CPI inflation treatment dummies and with the hourly earnings treatment dummies, and the interaction of unemployment treatment dummies with prior expected unemployment rates. Highly numerate respondents in columns 3-4 are those who answered all the numerical competence check questions correctly. Respondents were initially asked to provide their answers within specified ranges and then provide detailed numerical values for reservation wage questions. We refer to respondents as consistent, if they provided answers that matched between these two questions. Heteroskedasticity-robust-standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Kleibergen and Paap (2006) rk Wald F-statistics for weak identification tests are reported. We use the geometric average of the weights generated from the Huber-robust regressions for each variable of interest in the first stage to control for outliers of the variables regarding expectations. To control for outliers in the second stage, we use a jackknife approach. See Appendix F for details about the treatment of outliers.

Offline labor supply preferences along the intensive margin refer to a desire to change the number of hours worked per week. It is obtained from questions about how many hours respondents work per week on day jobs, whether they would like to change those hours, and by how much. According to Table E.3, workers with higher unemployment expectations are more likely to be interested in increasing hours worked per week, likely due to precautionary mechanisms. A one percentage point increase in expected unemployment rates increases the probability of desir-

ing more working hours by 3-6 percent. A one percentage point increase in inflation expectations has no effect or decreases the probability of desiring more working hours by up to 1 percent. As expected, as wage inflation increases, respondents want to work more in their day jobs. While imprecisely estimated, one percentage point increase in wage inflation expectations increases the probability of desiring more working hours by one percent. This adjustment is likely driven by an interplay of income and substitution effects.

Table E.3: Effects of macroeconomic expectations on desired hours worked

	$\mathbb{1}_{\texttt{Increase Hours}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	-0.01	-0.01	0.00	-0.01	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	0.01	0.01*	0.01	0.01*	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
$\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	0.04***	0.05***	0.06***	0.04***	0.05***	0.03*
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
N	3,073	3,039	2,080	2,033	2,017	1,988
Sample	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	8.29	7.98	12.94	11.39	10.25	8.03
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	11.58	11.62	16.62	17.96	20.29	14.34
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	15.44	9.82	12.61	11.92	15.02	10.34

Notes: This table presents the regression results for the effect of macroeconomic expectations on the desired number of hours worked according to the following equation:

$$\begin{aligned}\mathbb{1}_{it}(\texttt{increase hours}) =& \beta_0 + \beta_1 \mathbb{E}_{it}^{\text{post}}[\pi_{t+12}] + \beta_2 \mathbb{E}_{it}^{\text{post}}[\pi_{t+12}^{w}] + \beta_3 \mathbb{E}_{it}^{\text{post}}[u_{t+12}] + \theta\, \texttt{hours}_{it} \\ &+ \gamma_1 \mathbb{E}_{it}^{\text{prior}}[\pi_{t+12}] + \gamma_2 \mathbb{E}_{it}^{\text{prior}}[\pi_{t+12}^{w}] + \gamma_3 \mathbb{E}_{it}^{\text{prior}}[u_{t+12}] + \mathbf{X}_{it}'\delta + \varepsilon_i\end{aligned}$$

We instrument the posterior expectations with the treatment dummies of CPI inflation rates, hourly earnings inflation rates, and unemployment rates, the interactions of prior price inflation expectations with the CPI inflation treatment dummies and with the hourly earnings inflation treatment dummies, the interactions of prior wage inflation expectations with the CPI inflation treatment dummies and with the hourly earnings treatment dummies, and the interaction of unemployment treatment dummies with prior expected unemployment rates. Highly numerate respondents in columns 3-4 are those who answered all the numerical competence check questions correctly. Respondents were initially asked to provide their answers within specified ranges and then provide detailed numerical values for reservation wage questions. We refer to respondents as consistent, if they provided answers that matched between these two questions. Heteroskedasticity-robust-standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Kleibergen and Paap (2006) rk Wald F-statistics for weak identification tests are reported. We use the geometric average of the weights generated from the Huber-robust regressions for each variable of interest in the first stage to control for outliers of the variables regarding expectations. To control for outliers in the second stage, we use a jackknife approach. See Appendix F for details about the treatment of outliers.

F Treatment of Outliers

To deal with outliers in expectations and labor supply data, we use the strategy following Coibion et al. (2019). To be more specific, we use the Huber-robust regression in the first stage with `rreg` command in STATA.[14] In this process, we generate weights to deal with outliers in the subjective expectations data. We run the second stage using the weights generated from the first stage. Because we run three first-stage regressions with posterior price, wage inflation expectations, and expected unemployment rates, we have three weights generated from the first stage. We take the geometric average over the three weights and use it in the second stage.

To further remove the influence of outliers in the second stage for a reservation wage variable, we use the jackknife approach in the second stage. That is, we calculate the regression coefficients by dropping one observation each to find influential observations. We then drop observations as long as they move the regression coefficients on posterior expectations by a magnitude greater than 0.05.[15]

[14] For more detail, see help for STATA's `rreg` command. Or see Appendix C of Coibion et al. (2019).

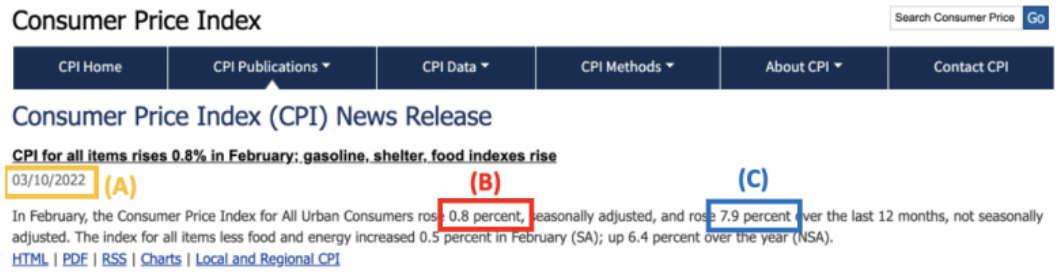
[15] Besley, Kuh, and Welsch (1980) suggests to use the threshold of $2/\sqrt{N}$, where N is the number of observations. After dropping the duplicated observations, we have 4,614 observations in the first wave. This corresponds to the threshold of 0.0294. We pick a higher number to drop a smaller number of observations. Our results are robust to the choice of this value from 0.05 to 0.10.

G Examples of the Main Task

Treatment groups

Figure G.1: Example of text transcription task: CPI inflation rate

Based on the information from this screenshot, please fill the table below it.



Source: https://www.bls.gov/cpi/news.htm

Table

	Date of the news report	CPI inflation rate	
	mm/dd/yyyy (A)	in March 2022, in percent (B)	over the last 12 months, in percent (C)
Your answer			

Figure G.2: Example of text transcription task: Hourly earnings

D. Based on the information from this screenshot, please fill the table below it.

Table B-3. Average hourly and weekly earnings of all employees on private nonfarm p

ESTABLISHMENT DATA
Table B-3. Average hourly and weekly earnings of all employees on private nonfarm payrolls by industry sector, seasona

Industry	Average hourly earnings			
	Mar. 2021 (B)	Jan. 2022	Feb. 2022(P)	Mar. 2022(P) (C)
Total private	$30.06	$31.56	$31.60	$31.73
Goods-producing	30.45	31.91	31.88	31.97
Mining and logging	34.30	35.90	35.75	35.75
Construction	32.24	33.87	33.94	34.07
Manufacturing	29.20	30.57	30.46	30.55
Private service-providing	29.97	31.48	31.54	31.67
Trade, transportation, and utilities	25.83	27.14	27.26	27.44
Information	44.06	44.77	45.18	45.17
Financial activities	39.77	40.88	40.87	41.19
Professional and business services	35.80	37.92	37.97	38.18
Education and health services	29.46	31.22	31.25	31.24
Leisure and hospitality	17.60	19.43	19.45	19.68
Other services	27.22	28.37	28.31	28.18

Footnotes
(P) Preliminary

Last Modified Date April 01, 2022 (A)

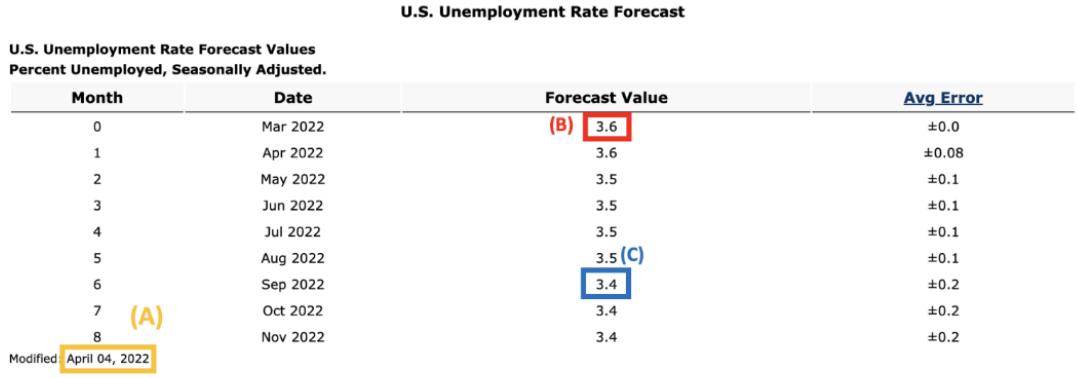
Source: https://www.bls.gov/news.release/empsit.t19.htm#ces_table3.f.p

Table.

	Date when table was last modified mm/dd/yyyy (A)	Average hourly earnings of all employees in the private sector in the U.S. (omit $ symbol) in March **2021** (B)	in March **2022** (C)
Your answer			

Figure G.3: Example of text transcription task: Unemployment rate

Based on the information from this screenshot, please fill the table below it.



U.S. Unemployment Rate Forecast

U.S. Unemployment Rate Forecast Values
Percent Unemployed, Seasonally Adjusted.

Month	Date	Forecast Value	Avg Error
0	Mar 2022	(B) 3.6	±0.0
1	Apr 2022	3.6	±0.08
2	May 2022	3.5	±0.1
3	Jun 2022	3.5	±0.1
4	Jul 2022	3.5	±0.1
5	Aug 2022	3.5 (C)	±0.1
6	Sep 2022	3.4	±0.2
7 (A)	Oct 2022	3.4	±0.2
8	Nov 2022	3.4	±0.2

Modified April 04, 2022

Source: https://www.forecasts.org/unemploy.htm

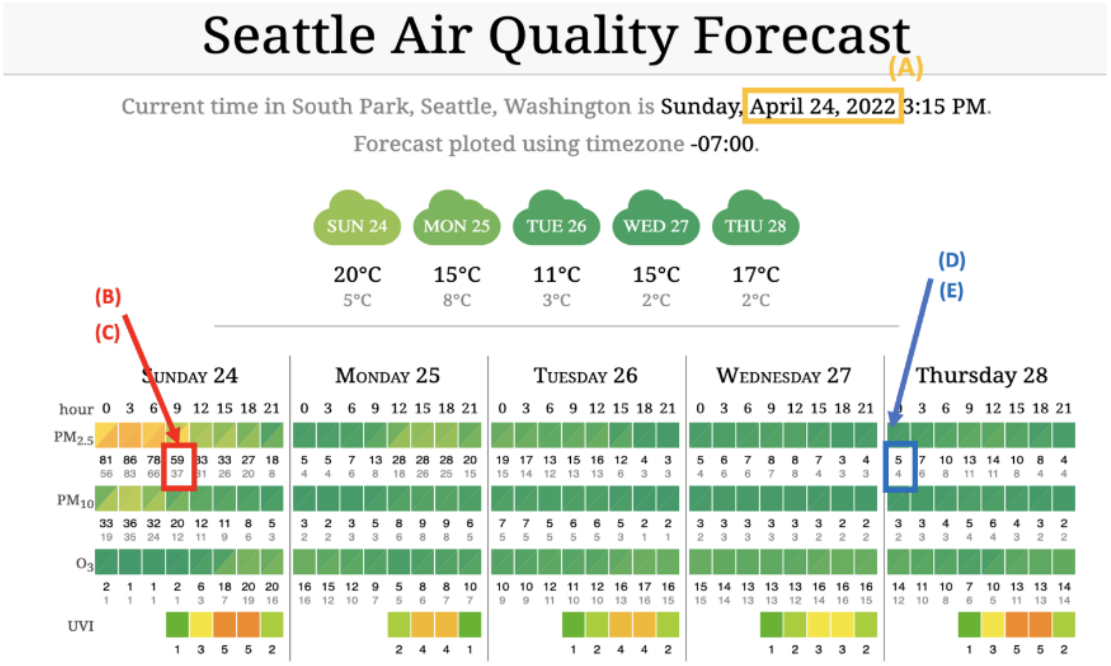
Table.

	Date when the table is last modified mm/dd/yyyy **(A)**	Unemployment rate in the **previous month**, in percent **(B)**	Unemployment rate forecast in **six months**, in percent **(C)**
Your answer			

Control groups

Figure G.4: Example of text transcription task: Air quality index

Based on the information from this screenshot, please fill the table below it.



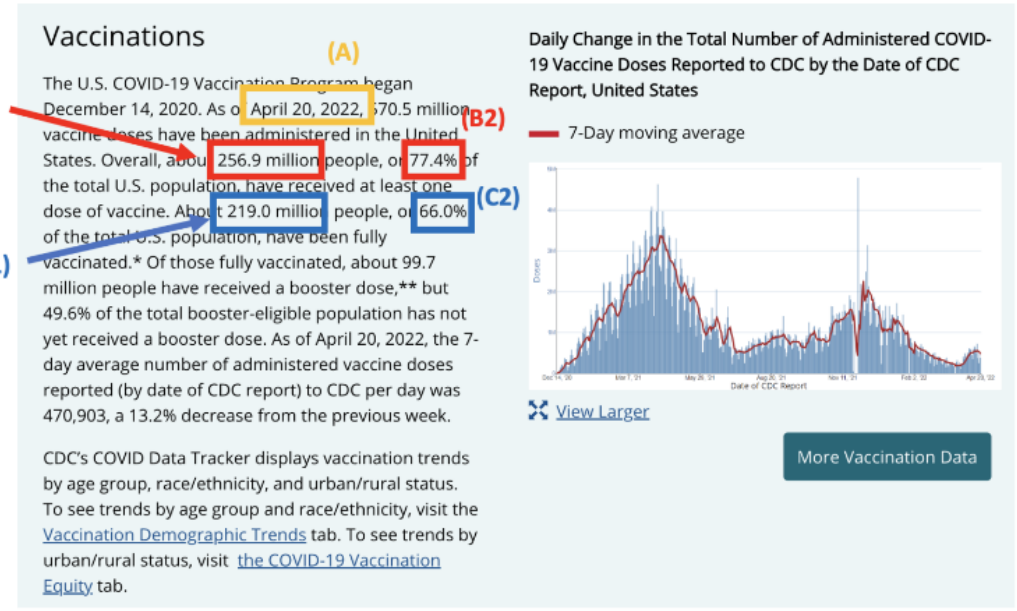
Source: https://aqicn.org/forecast/seattle/

Table.

	Date of the forecast	What is the air quality index (PM 2.5) at 12 pm on the day of the forecast?		What is the forecast for the air quality index (PM 2.5) at 12 pm in 4 days?	
	mm/dd/yyyy (A)	High (B)	Low (C)	High (D)	Low (E)
Your answer					

Figure G.5: Example of text transcription task: Covid-19 vaccination rate

D. Based on the information from this screenshot, please fill the table below it.



Source: https://www.cdc.gov/coronavirus/2019-ncov/covid-data/covidview/index.html

Table.

	Date of the report	Total COVID Vaccination Rates (At least one dose)		Total COVID Vaccination Rates (Fully Vaccniated)	
	mm/dd/yyyy (A)	Count (in millions) (B1)	Percent of the US Population (B2)	Count (in millions) (C1)	Percent of the US Population (C2)
Your answer					

Note. Ignore % symbol during transcription.

H Survey Questions

Start of Block: Description

Consent

CONSENT TO PARTICIPATE IN HIT "SHORT SURVEY + FORECASTING TASK"

Please find below information about this HIT for you to carefully consider when deciding about whether to participate. Please ask questions about any of the information you do not understand before you decide whether to participate.

Contact Information:
EpiLS Study Team
Email: Epilsstudyteam@tufts.edu
Phone: 617-627-3560

We are collecting data for training a machine learning forecasting model. Once our study is completed, we will provide you with full information.

In this task, in addition to answering several questions about you and your experience, we ask you to:
1) Transcribe the statistical information from a screenshot
2) Record your own forecasts based on the information provided.

Before the main task, you will be asked to do a short screening task on transcribing text from a screenshot. Only after you complete the screening task accurately, you will be eligible to proceed with the remainder of the study.

It takes about 10-15 minutes to complete this HIT.

Once your HIT is approved, you will be paid $1.50.

HIT approval decision will be based on the following three criteria: i) survey completion, ii) accuracy of transcription, and iii) quality of your answers. If your answers are meaningful, you transcribe the information accurately, and you complete the survey, your HIT will be approved.

This HIT includes a few numerical competence checks and transcription of text from a screenshot. They are designed for working on a computer. Some of the tasks might not be mobile-friendly and may cause eye strain.

Participation is completely voluntary. You have the right to quit this HIT at any point. If you quit

before completing the survey, however, your HIT will not be approved, and you will not be paid. The data collected to the point of withdrawal will be discarded.

We will take measures to protect your privacy and confidentiality. Although your Mechanical Turk Worker ID will be used to distribute the payment to you, we will not store your worker ID with your survey responses. We will not collect any personally identifiable information except for the encrypted version of your Amazon worker ID. Our research team will have access only to encrypted ID and your anonymized answers which will be stored on password-protected computers. De-identified data will be retained indefinitely for possible use in future research.

Despite taking steps to protect your privacy, we can never fully guarantee your privacy. If you tell us something that makes us believe that you or others have been or may be harmed due to participation in this HIT, we may report that information to the appropriate agencies. Individuals and organizations responsible for conducting or monitoring this study may be permitted to access and inspect the research records. This includes Tufts SBER IRB or Berkeley OPHS.

If you have questions and concerns, contact us. If you go to your Dashboard on MTurk, you can click “Contact Requester” and send us your message.

Institutional Review Boards (“IRB”) are overseeing this study. An IRB is a group of people who perform independent review of studies to ensure the rights and welfare of participants are protected. The research has been approved by IRB boards of the institutions with which researchers are affiliated – Tufts University (STUDY00002463) and University of California, Berkeley (CPHS Protocol 2022-01-14981). If you have questions about your rights or wish to speak with someone other than the research team, you may contact:

Tufts Social, Behavioral, and Educational Research IRB
75 Kneeland Street, Suite 623
Boston, MA 02111
617.627.8804
SBER@tufts.edu

Office for Protection of Human Subjects
University of California, Berkeley
1608 Fourth Street, Suite 220
Mail Code 5940
Berkeley CA, 94710-1749
510-642-7461
ophs@berkeley.edu

STATEMENT OF CONSENT

I have read and considered the information presented in this form. I confirm that I understand the purpose of the study and procedures. I understand that I may ask questions at any time and can withdraw my participation without prejudice. I have read this consent form.

By selecting “I agree,” you are consenting to participate in this study.

- ○ I agree
- ○ I disagree

End of Block: Description

Start of Block: Screening

Screening task Please enter the information from highlighted fields of the screenshot into a table below.

Table 4.2 Real gross domestic product by major demand category, 2000, 2010, 2020, and projected 2030
(Numbers in billions of chained 2012 dollars)

Category	2000	2010	2020 (B)	2030	Compound annual rate of change, 2000–10	Compound annual rate of change, 2010–20 (C)	Compound annual rate of change, 2020–30	Contribution to percent change in real GDP, 2000–10	Contribution to percent change in real GDP, 2010–20
Gross domestic product	$13,131.0	$15,598.7	$18,423.4	$23,029.8	1.7	1.7	2.3	1.7	1.7
Personal consumption expenditures	8,643.3	10,643.0	12,725.9	16,586.0	2.1	1.8	2.7	1.4	1.2
Gross private domestic investment	2,346.7	2,216.5	3,261.2	4,575.5	-0.6	3.9	3.4	-0.1	0.6
Exports	1,379.5	1,977.9	2,216.3	3,171.9	3.7	1.1	3.6	0.4	0.2
Imports(1)	1,930.3	2,543.8	3,142.6	5,098.3	2.8	2.1	5.0	0.4	0.4
Government consumption expenditures and gross investment	2,663.0	3,307.2	3,340.4	3,586.1	2.2	0.1	0.7	0.4	0.0

Footnotes:
(1) Imports are subtracted from the other components of GDP because they are not produced in the United States.
Note: Dash indicates data not computable or not applicable.
Source: Historical data: U.S. Bureau of Economic Analysis; Projected data: U.S. Bureau of Labor Statistics

Top

Last Modified Date September 8, 2021 (A)

Source: https://www.bls.gov/emp/tables/real-gdp-major-demand-category.htm#top

Note: If you transcribe the information incorrectly, you will NOT be permitted to proceed with this HIT.

Table

	Date when table was last modified	Gross Domestic Product in 2020	Compound annual rate of change (2010-20)
	mm/dd/yyyy (A)	in billions USD (B), (ignore all the symbols [e.g. $ and ,] except for decimal points .)	rate (C)
Your answer			

End of Block: Screening

Start of Block: Ba. Prior A - Reservation Wage

B1a The following three questions test your numerical competence.

Anna earns on average $1.00 per 10 minutes of work on MTurk. How much does Anna earn for an hour (60 minutes)?

_____

B2a John had earned $8.00 *per hour* before receiving a 5% raise. How much does John earn after the raise *per hour*?

_____

B3a A cafe has increased the price of a coffee from $2 to $2.5. How much has the price of a coffee increased *in percent*?

_____

B4a Suppose after completing a HIT on MTurk you are offered to participate in a follow-up task. What is the **smallest reward** for a 10-min HIT you would **accept** in **May 2022**? (in USD)

- 0.5
- 0.6
- 0.7
- 0.8
- 0.9
- 1.0
- 1.1
- 1.2
- 1.3
- 1.4
- 1.5
- I would accept a HIT that pays below 0.5 USD
- I would NOT accept any HIT that pays below 1.5 USD

Display This Question:

If Suppose after completing a HIT on MTurk you are offered to participate in a follow-up task. What... = I would accept a HIT that pays below 0.5 USD

Or Suppose after completing a HIT on MTurk you are offered to participate in a follow-up task. What... = I would NOT accept any HIT that pays below 1.5 USD

B5a What is the smallest reward you would accept for a 10-minute HIT?

- Pay for 10 minutes, USD

_____

B6a Would you accept work on a HIT that pays **$e{Selected Choice + 0.05} USD** per 10-min session in **May 2022**?

- ○ Yes
- ○ No

Display This Question:

If the answer to the above question = No

B6a1 What is the **smallest reward** you would **accept** for a 10-minute HIT in **May 2022**?

- ○ Pay for 10 minutes, USD

_____

B7a

How about a follow-up task that asks you to do a 10-minute HIT **two times -- in May and June 2022**. What is the **smallest reward** for **20 minutes** of your work that you would accept? (in USD)

- ○ 0.50
- ○ 0.60
- ○ 0.70
- ○ 0.80
- ○ 0.90
- ○ 1.00
- ○ 1.25
- ○ 1.50
- ○ 1.75
- ○ 2.00
- ○ 2.25
- ○ 2.50
- ○ 2.75
- ○ 3.00
- ○ 3.25
- ○ 3.50
- ○ 3.75
- ○ 4.00
- ○ 4.50

- ○ 5.00
- ○ 5.50
- ○ I would accept three HITs that pay less than 0.60 USD for 20 minutes
- ○ I would NOT accept three HITs that pay less than 5.50 USD for 20 minutes

B8a1 Suppose you could choose for how many months to work on a monthly hit paying ${your answer in B4a or in B5a} USD for 10 minutes of work. For how many **months** would you prefer to work?

- ○ 0
- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

End of Block: Bb. Prior A - Reservation Wage

Start of Block: C. Prior - Forecasts

C **FORECASTING TASK**

The next block of questions refers to the main forecasting task. If you are not certain about the answer to any of the following questions, please provide your **best guess**.

Note, we care about **your forecasts**. Therefore, if it is obvious that you have not given any thought to answering the questions and instead entered random numbers, we will not approve your HIT. As long as your answers are meaningful, your HIT will be approved.

To understand what we mean by a *meaningful answer,* see the question below.

C1
Suppose that the question asks "What do you think the average temperature is in Oahu, Hawaii, in **July**? (in Fahrenheit)" and your answer is **30**. Would your HIT be approved?

- Yes
- No

C2 What do you think is the average air quality index (AQI) in Seattle, USA was over the **past year**?

- Mostly good (AQI 0-50)
- Mostly moderate (AQI 51-100)
- Unhealthy for sensitive groups (AQI 101-150)
- Unhealthy (AQI 151-200)
- Very unhealthy (AQI 201-300)
- Hazardous (AQI 301-500)

C4 In your opinion, what is the percentage of the U.S. population that has received **at least one dose** of Covid vaccine by today?

_____

C5a In each of the scenarios below, what do you think the unemployment rate in the U.S. will be in **April 2023**?

Note: In February 2020, right before the pandemic, the unemployment rate was 3.5%. In April 2020 after the pandemic, the unemployment rate peaked at 14.7%.

- ○ The ***lowest*** possible unemployment rate
  _____
- ○ The ***median*** (or ***average***) unemployment rate
  _____
- ○ The ***highest*** possible unemployment rate
  _____

C5b For each of the scenarios below, please distribute 100 points to indicate how likely you think each unemployment rate will happen. The sum of the points you allocate should total to 100.

The likelihood of the ***lowest*** possible unemployment rate scenario : _____
The likelihood of the ***median*** unemployment rate scenario : _____
The likelihood of the ***highest*** possible unemployment rate scenario : _____
Total : _____

C3a In your opinion, what are the average **hourly** earnings of employees in the private sector in the U.S. in **April 2022**?

- ○ Average hourly earnings in April **2022**, USD _____

C3b In your opinion, will average **hourly** earnings of employees in the U.S. be higher or lower in April **2023** relative to today?

- ○ **Higher** than today
- ○ About the **same** as today
- ○ **Lower** than today

Display This Question:

*If In your opinion, will average hourly earnings of employees in the U.S. be higher or lower in Apri... = **Higher** than today*

C3_2a How much **higher** do you think the average hourly earnings in the U.S. will be in April 2023 relative to today (in percentage terms)?

If earnings double over a year, this corresponds to 100% increase. If earnings do not change, this corresponds to 0% increase. E.g., change from 20 to 40 USD corresponds to 100% increase. Change from 20 to 24 USD corresponds to 20% increase. Change from 20 to 21 USD corresponds to 5% increase. Change from 20.0 to 20.2 USD corresponds to 1% increase.

Increase in the average hourly earnings from April 2022 to April 2023:

- ○ in percent _____

Display This Question:

*If In your opinion, will average hourly earnings of employees in the U.S. be higher or lower in Apri... = **Lower** than today*

C3_2b How much **lower** do you think the average hourly earnings in the U.S. will be in April 2023 relative to today (in percentage terms)?

If earnings halved over a year, this corresponds to 50% decrease. If earnings do not change, this corresponds to 0% decrease. E.g., change from 20 to 10 USD corresponds to 50% decrease. Change from 20 to 16 USD corresponds to 20% decrease. Change from 20 to 19 USD corresponds to 5% decrease. Change from 20.0 to 19.8 USD corresponds to 1% decrease.

Decrease in the average hourly earnings from April 2022 to April 2023:

○ in percent _____

Display This Question:

*If In your opinion, will average hourly earnings of employees in the U.S. be higher or lower in Apri... = About the **same** as today*

C3_2c You have indicated that you expect that average hourly earnings in the U.S. will be about the same as today in April 2023. This could mean that the change equals zero percent or that the percent change is small. Please select a category that best describes your opinion.

- ○ In April 2023 by 5% lower than today
- ○ In April 2023 by 4% lower than today
- ○ In April 2023 by 3% lower than today
- ○ In April 2023 by 2% lower than today
- ○ In April 2023 by 1% lower than today
- ○ In April 2023 exactly the same as today
- ○ In April 2023 by 1% higher than today
- ○ In April 2023 by 2% higher than today
- ○ In April 2023 by 3% higher than today
- ○ In April 2023 by 4% higher than today
- ○ In April 2023 by 5% higher than today

Page Break

C6a In your opinion, will **prices** in the U.S. be higher or lower in **April 2023** relative to today?

- ○ **Higher** than today
- ○ About the **same** as today
- ○ **Lower** than today

Display This Question:

*If In your opinion, will prices in the U.S. be higher or lower in April 2023 relative to today? = **Higher** than today*

C6a_1 How much do you think the **overall price level** in the U.S. will increase between April **2022** and April **2023** (in percentage terms)?

For example, if cost of a typical consumer basket increases from 1000 to 1250 USD, this corresponds to 25% increase in price level (or inflation rate). If cost of a consumer basket increases from 1000 to 1100 USD, this corresponds to 10% inflation rate. An increase of cost from 1000 to 1050 USD corresponds to 5% inflation rate, and increase from 1000 to 1020 USD means 2% increase in price level.

Increase in the overall price level from April 2022 to April 2023:

- ○ in percent _____

Display This Question:

*If In your opinion, will prices in the U.S. be higher or lower in April 2023 relative to today? = **Lower** than today*

C6a_2 How much do you think the **overall price level** in the U.S. will decrease between April **2022** and April **2023** (in percentage terms)?

For example, if cost of a typical consumer basket decreases from 1000 to 750 USD, this corresponds to 25% decrease in price level (or deflation rate, which is negative inflation rate). If cost of a consumer basket decreases from 1000 to 900 USD, this corresponds to 10% deflation rate. A decrease of cost from 1000 to 950 USD corresponds to 5% deflation rate, and decrease from 1000 to 989 USD means 2% decrease in price level.

Decrease in the overall price level from April 2022 to April 2023:

○ in percent _____

Page Break

Display This Question:

*If In your opinion, will prices in the U.S. be higher or lower in April 2023 relative to today? = About the **same** as today*

C6a_3 You have indicated that you expect that the overall price level in the U.S. will be about the same as today in April 2023. This could mean that the change equals zero percent or that the percent change is small. Please select a category that best describes your opinion.

- In April 2023 by 5% lower than today
- In April 2023 by 4% lower than today
- In April 2023 by 3% lower than today
- In April 2023 by 2% lower than today
- In April 2023 by 1% lower than today
- In April 2023 exactly the same as today
- In April 2023 by 1% higher than today
- In April 2023 by 2% higher than today
- In April 2023 by 3% higher than today
- In April 2023 by 4% higher than today
- In April 2023 by 5% higher than today

End of Block: C. Prior - Forecasts

Start of Block: D. Task

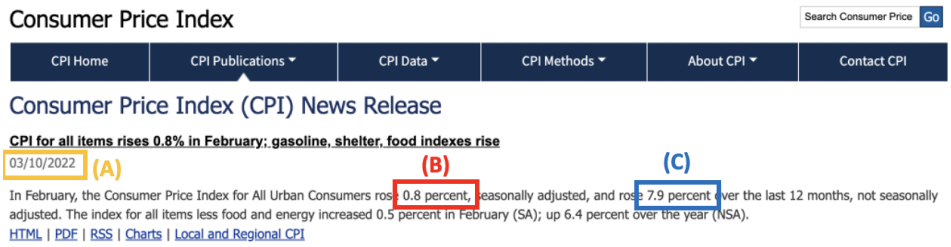
D

Recording Official Statistics

In the previous question, you answered that the overall price level in the U.S. will **change** by **${Your answer}% over the next 12 months.**

Next, we will ask you to fill a table with **official statistics** about the price level changes.

Based on the information from this screenshot, please fill the table below it.



Source: https://www.bls.gov/cpi/news.htm

Table

	Date of the news report	CPI inflation rate	
	mm/dd/yyyy (A)	in March 2022, in percent (B)	over the last 12 months, in percent (C)
Your answer			

Da You entered the following data based on the information from the screenshot:

Showing their transcription

If any data entry above is incorrect, please go back and enter correct information. Otherwise, proceed to the next questions.

We will NOT approve your HIT if you record the numbers from the screenshot *incorrectly*.

D2 According to the data you just entered, over the past 12 months, the overall price level in the U.S. has

- ○ decreased by 8.5%.
- ○ decreased by 1.2%.
- ○ not changed.
- ○ increased by 8.5%
- ○ increased by 1.2%

End of Block: D. Task

Start of Block: E. Posterior - Forecasts

E

Instructions:

Some of the following questions will ask you to forecast a change of a variable in the future in percentage terms (in other words, to provide your estimate of its growth rate).

For example, if the question asks about percentage change of average temperature in February 2023 relative to today and you think that it will be by 10% warmer in February 2023 than in February 2022 (i.e., the temperature will increase), enter “10.” If you think it will be by 10% colder in February 2023 than in February 2022 (i.e., the temperature will decrease), enter “-10”. If you think it will be about the same, enter “0.”

E1

After learning about the official statistics, by how much do you think the **overall price level** in the U.S. will change over the **next 12 months** relative to today (in percentage terms)?

If you think the overall price level will increase, enter a positive number. If you think it will decrease, then enter a negative number. If you think that the price level will not change, enter 0.

○ Price change over 12 months, percent
_____

Display This Question:

If If After learning about the official statistics, by how much do you think the overall price level in the U.S. will change over the next 12 months relative to today (in percentage terms)? Response Is Equal to 0

E1_a You have indicated that you expect that the overall price level in the U.S. will be about the same as today in 12 months. This could mean that the change equals zero percent or that the percent change is small. Please select a category that best describes your opinion.

- In April 2023 by 5% lower than today
- In April 2023 by 4% lower than today
- In April 2023 by 3% lower than today
- In April 2023 by 2% lower than today
- In April 2023 by 1% lower than today
- In April 2023 exactly the same as today
- In April 2023 by 1% higher than today
- In April 2023 by 2% higher than today
- In April 2023 by 3% higher than today
- In April 2023 by 4% higher than today
- In April 2023 by 5% higher than today

E2 By how much do you think the **average hourly earnings** in the U.S. will change **over the next 12 months** (in percentage terms)?

If you think the average hourly earnings will increase, enter a positive number. If you think they will decrease, then enter a negative number. If you think that the average hourly earnings will not change, enter 0.

- ○ Change in the average hourly earnings over the next 12 months, percent
  _____

Display This Question:

If If By how much do you think the average hourly earnings in the U.S. will change over the next 12 mon... Text Response Is Equal to 0

E2_a You have indicated that you expect that the average hourly earnings in the U.S. will be about the same as today in 12 months. This could mean that the change equals zero percent or that the percent change is small. Please select a category that best describes your opinion.

- ○ In April 2023 by 5% lower than today
- ○ In April 2023 by 4% lower than today
- ○ In April 2023 by 3% lower than today
- ○ In April 2023 by 2% lower than today
- ○ In April 2023 by 1% lower than today
- ○ In April 2023 exactly the same
- ○ In April 2023 by 1% higher than today
- ○ In April 2023 by 2% higher than today
- ○ In April 2023 by 3% higher than today
- ○ In April 2023 by 4% higher than today
- ○ In April 2023 by 5% higher than today

E3 What is your own forecast for the **Air Quality Index** in Seattle, USA **in 2 weeks**?

- ○ Good (AQI 0-50)
- ○ Moderate (AQI 51-100)
- ○ Unhealthy for sensitive groups (AQI 101-150)
- ○ Unhealthy (AQI 151-200)
- ○ Very unhealthy (AQI 201-300)
- ○ Hazardous (AQI 301-500)

E4 What share of the U.S. population will be **fully vaccinated** by the end of **May 2022**?

Fully vaccinated *means a person has received their primary series of COVID-19 vaccines (i.e. at least two doses of Moderna or Pfizer Biotech OR at least one dose of Johnson & Johnson's).*

_____

E5 What do you think the **unemployment rate** in the U.S. will be in **April 2023** (in percent)?

Note: In February 2020, right before the pandemic, the unemployment rate was 3.5%. In April 2020 after the pandemic, the unemployment rate peaked at 14.7%.

- ○ unemployment rate in April 2023
  _____

End of Block: E. Posterior - Forecasts

Start of Block: F. Posterior Wage

F1 Suppose in the future we offered you to perform a *similar task* you did today (but without numerical literacy questions) taking about **10 min** of your time once a month. I.e., you would record the information from the same website and provide your prediction based on it.

How many **months** would be you interested in working?

- ○ 0
- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

NOTE **WE MAY USE YOUR ANSWER TO THIS QUESTION TO OFFER YOU WORK ON FOLLOW-UP HITS.**

F2 In the previous question, you answered that you are willing to work on a *similar* 10-min task for ${your answer in F1} months, which corresponds to **$e{ 10 * your answer in F1}** minutes of your time. What is the **lowest** *total* reward that you would accept to work? (in USD)

- ○ $e{ 0.4 * your answer in F1}
- ○ $e{ 0.5 * your answer in F1}
- ○ $e{ 0.55 * your answer in F1}
- ○ $e{ 0.6 * your answer in F1}
- ○ $e{ 0.65 * your answer in F1}
- ○ $e{ 0.7 * your answer in F1}
- ○ $e{0.75 * your answer in F1}
- ○ $e{ 0.8 * your answer in F1}
- ○ $e{ 0.85 * your answer in F1}
- ○ $e{ 0.9 * your answer in F1}
- ○ $e{ 1 * your answer in F1}
- ○ $e{ 1.05 * your answer in F1}
- ○ $e{ 1.1 * your answer in F1}
- ○ $e{ 1.15 * your answer in F1}
- ○ $e{ 1.2 * your answer in F1}
- ○ $e{ 1.25 * your answer in F1}
- ○ $e{ 1.3 * your answer in F1}
- ○ $e{ 1.35 * your answer in F1}
- ○ $e{ 1.45 * your answer in F1}
- ○ $e{ 1.5 * your answer in F1}

- ○ $e{ 1.6 * your answer in F1}
- ○ $e{ 1.7 * your answer in F1}
- ○ $e{ 1.8 * your answer in F1}
- ○ $e{ 1.9 * your answer in F1}
- ○ $e{ 2 * your answer in F1}
- ○ Below $e{ 0.4 * your answer in F1}
- ○ Above $e{ 2 * your answer in F1}

NOTE **WE MAY USE YOUR ANSWER TO THIS QUESTION TO OFFER YOU WORK ON FOLLOW-UP HITS.**

Display This Question:

*If In the previous question, you answered that you are willing to work on a similar 10-min task for... != Below $e{ 0.4 * your answer in F1}*

*And In the previous question, you answered that you are willing to work on a similar 10-min task for... != Above $e{ 2 * your answer in F1}*

F3 Would you be willing to accept an offer to do ${your answer in F1} ten-minute HITs that pay you total amount of $e{your answer in F2 + 0.05} USD?

- ○ Yes
- ○ No

Display This Question:

If Would you be willing to accept an offer to do ${your answer in F1} ten-minut... = No

*Or In the previous question, you answered that you are willing to work on a similar 10-min task for... = Below $e{ 0.4 * your answer in F1}*

*Or In the previous question, you answered that you are willing to work on a similar 10-min task for... = Above $e{ 2 * your answer in F1}*

F3_1 What is the smallest reward you would accept for ${your answer in F1} ten-minute HITs (total $e{ 10 * your answer in F1} minutes of your time)? (in USD)

- ○ The smallest reward you would accept _____

F4 What is the **smallest reward** for a **10-min** HIT you would **accept** for a *similar task* you did today in the next month?

- ○ 0.00 - 0.50
- ○ 0.51 - 0.60
- ○ 0.61 - 0.70
- ○ 0.71 - 0.80
- ○ 0.81 - 0.90
- ○ 0.91 - 1.00
- ○ 1.01 - 1.10
- ○ 1.11 - 1.20
- ○ 1.21 - 1.30
- ○ 1.31 - 1.40
- ○ 1.41 - 1.50
- ○ 1.51 - 1.60
- ○ 1.61 - 1.70
- ○ 1.71 - 1.80
- ○ 1.81 - 1.90
- ○ 1.91 - 2.00
- ○ I would NOT accept any HIT that pays below 2.0 USD

Display This Question:

If What is the smallest reward for a 10-min HIT you would accept for a similar task you did today in... = I would NOT accept any HIT that pays below 2.0 USD

F5 What is the **smallest reward** you would **accept** for a 10-minute HIT *similar* to this one in the next month?

○ Pay for 10 minutes, USD

_____

Display This Question:

If What is the smallest reward for a 10-min HIT you would accept for a similar task you did today in... != I would NOT accept any HIT that pays below 2.0 USD

F6 You answered that you would accept **${your answer in F4}** **USD** per 10-min session for a *similar task* you did today in the next month. Please specify the smallest amount that you would accept to work.

○ The smallest amount you would accept to work

_____

End of Block: F. Posterior Wage

Start of Block: G. Qualification and experience-related questions

G This is the last group of short questions. It refers to you and your work experience.

G1 Think about the amount of time you devote to work on MTurk. Is this more or less than 20 hours per week?

- ○ More than 20 hours per week
- ○ Less than 20 hours per week

G1a How many hours do you work on MTurk in a typical week?

_____

G2 Do you work on other crowdsourcing platforms in addition to MTurk?

- ○ Yes, regularly
- ○ Yes, occasionally
- ○ No

Display This Question:

If Do you work on other crowdsourcing platforms in addition to MTurk? != No

G2a How many hours per week do you usually work on other online platforms?

_____

G3 Do you have a day job in addition to MTurk?

- ○ Yes, a full-time job
- ○ Yes, a part-time job
- ○ No, but I am looking for one
- ○ No, and I am not interested in getting another job

Display This Question:
If Do you have a day job in addition to MTurk? = Yes, a full-time job
Or Do you have a day job in addition to MTurk? = Yes, a part-time job

G3a How many hours per week do you usually work on day job(s)?

- ○ <5
- ○ 5-10
- ○ 10-20
- ○ 20-30
- ○ 30-40
- ○ 40 or more

Display This Question:
If Do you have a day job in addition to MTurk? = Yes, a full-time job
Or Do you have a day job in addition to MTurk? = Yes, a part-time job

G3b You have selected that you work ${your answer in G3a} hours a week. Please specify the average hours you usually work per week on day jobs.

- ○ average hours you work per week
  _____

Display This Question:

If Do you have a day job in addition to MTurk? = Yes, a full-time job

Or Do you have a day job in addition to MTurk? = Yes, a part-time job

G3c If you could choose the number of hours you work each week, and taking into account how that would affect your income, how much would you choose to work in **May 2022**?

- ○ fewer hours than today
- ○ about the same hours
- ○ more hours than today

Display This Question:

If If you could choose the number of hours you work each week, and taking into account how that woul... = fewer hours than today

Or If you could choose the number of hours you work each week, and taking into account how that woul... = more hours than today

G3d How many hours a week would you choose to work on average in **May 2022**? Again, take into account how that would affect your income.

- ○ Desired work hours in May 2022

_____

Display This Question:

If Do you have a day job in addition to MTurk? = Yes, a full-time job

Or Do you have a day job in addition to MTurk? = Yes, a part-time job

G3e1 What do you think is the percent chance that **four months from now** you will be...

Please enter a percent 0-100 for each. If you are certain that some event is impossible (e.g. you start your own business), answer 0.

Employed with the same employer : _____
Employed with a different employer : _____
Self-employed : _____
Unemployed and actively looking for a new job : _____
Not employed and not looking for a new job : _____
Total : _____

Display This Question:

If Do you have a day job in addition to MTurk? = Yes, a full-time job

Or Do you have a day job in addition to MTurk? = Yes, a part-time job

G3f1 Suppose someone **offered you a job** in **May 2022** in line with your current work that **pays by 10% more** than your current job. Would you accept this offer?

- Yes
- No
- Don't know

Display This Question:

If Do you have a day job in addition to MTurk? = Yes, a full-time job

Or Do you have a day job in addition to MTurk? = Yes, a part-time job

G3f11 What is the **smallest** increase relative to your current pay should a new job offer for you to **accept** it in May 2022?

- 0-2%
- 2-5%
- 5-7%
- 7-10%
- 10-15%
- 15-20%
- 20-25%
- 25-30%
- >30%
- I am not interested in another job

Display This Question:

If Do you have a day job in addition to MTurk? = No, but I am looking for one

G3e2 What do you think is the **percent chance** that **four months from now** you will be... Please enter a percent 0-100 for each. If you are certain that some event is impossible (e.g. you start your own business), answer 0.

Employed : _____
Self-employed : _____
Unemployed and actively looking for a job : _____
Not employed and not looking for a job : _____
Total : _____

Display This Question:

If Do you have a day job in addition to MTurk? = No, but I am looking for one

G3f2 Suppose someone **offered you a job** in **May 2022** in line with your previous work. What the **smallest pay** should a new job offer **relative to your previous pay** for you to **accept** it?

- by 15% or more lower than previous pay
- 10-15% lower
- 7-10% lower
- 5-7% lower
- 2-5% lower
- 0-2% lower
- same as previous pay
- 0-2% higher
- 2-5% higher
- 5-7% higher
- 7-10% higher
- 10-15% higher
- > 15% higher

Display This Question:

If Do you have a day job in addition to MTurk? != No, and I am not interested in getting another job

And Do you have a day job in addition to MTurk? != No, but I am looking for one

G5 In what industry is your main job?

- ○ Agriculture, Forestry, Fishing or Hunting
- ○ Mining, Quarrying, or Oil and Gas Extraction
- ○ Utilities
- ○ Construction
- ○ Manufacturing
- ○ Wholesale Trade
- ○ Retail Trade
- ○ Transportation or Warehousing
- ○ Information Services (including Publishing or Media)
- ○ Banking, Finance, or Insurance
- ○ Real Estate, or Rental & Leasing Services
- ○ Professional, Technical, or Business Services
- ○ Education
- ○ Health Care or Social Assistance
- ○ Arts, Entertainment, or Recreation
- ○ Hotel, Accommodation, Restaurant, or Food Services
- ○ Other Services (except Government)
- ○ Government, including Military
- ○ Other: _____

Display This Question:

If Do you have a day job in addition to MTurk? = No, and I am not interested in getting another job

G5a Why are you not interested in getting a day job?

- ○ I earn enough online (1)
- ○ I need flexible schedule due to caregiving responsibilities (2)
- ○ I am retired (3)
- ○ I am a student (4)
- ○ Due to health concerns or disability (5)
- ○ Other: (6) _____

G6 What is your highest education level?

- ○ Less than high school
- ○ High school graduate
- ○ Some college
- ○ 2 year degree
- ○ Bachelor's or other 4 year degree
- ○ Master's or Professional degree
- ○ Doctorate/PhD

G7 How often during the usual week do you check news?

- ○ I don't usually read/watch news
- ○ Every day
- ○ Almost every day
- ○ A few days

G8a What is your gender?

- ○ Male (1)
- ○ Female (2)
- ○ Non-binary / third gender (3)
- ○ Prefer not to say (4)

G8b How old are you?

_____

G8c In which U.S. state do you currently reside?

(Multiple choice questions/ omitting options)

G8d What is your ethnicity?

- [ ] White
- [ ] Black or African American
- [ ] Hispanic or Latino
- [ ] Asian
- [ ] American Indian or Alaska Native
- [ ] Native Hawaiian or Pacific Islander
- [ ] Other
- [ ] Prefer not to answer

G9 Are you currently married or cohabiting?

- ○ Yes
- ○ No

Display This Question:
If Are you currently married or cohabiting? = No

G10 Have you ever been married?

- ○ Yes
- ○ No

G11 How many children under 18 do you have?

- ○ None
- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5
- ○ More than 5
- ○ Prefer not to answer

G12 What is your annual income?

- ○ Less than $10,000
- ○ $10,000 - $19,999
- ○ $20,000 - $29,999
- ○ $30,000 - $39,999
- ○ $40,000 - $49,999
- ○ $50,000 - $59,999
- ○ $60,000 - $69,999
- ○ $70,000 - $79,999
- ○ $80,000 - $89,999
- ○ $90,000 - $99,999
- ○ $100,000 - $149,999
- ○ $150,000 - $199,999
- ○ More than $200,000
- ○ Prefer not to answer

G13 Can you recall how much have you spent on following products last month?

	Monthly Spending
	In USD
Food (including grocery, beverages, dining-out, take-out food, etc.)	
Gasoline	

G14 Was it confusing to answer any questions or to complete any tasks in this HIT? If so, please explain.

_____

Completion

Your completion code is ${e://Field/compcode}.

End of Block: G. Qualification and experience-related questions