

Spillovers in Macroeconomic Expectations and Labor Supply: Implications for Wage-Price Spirals*

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Abstract

How do agents form their macroeconomic expectations and how do they incorporate them into their economic decisions? Do they think about each variable independently or do they revise expectations jointly? Using experimental evidence from the U.S. online labor market, we show that when people receive one relevant piece of information, they simultaneously update their expectations about multiple macroeconomic variables. For example, when people receive information about the price inflation rate, they revise not only their price inflation expectations but also their aggregate wage growth and unemployment expectations. Exploiting exogenous variation in expectations arising from randomized information provision, we document that such simultaneous revision of expectations has important implications for the likelihood of wage-price spirals. Specifically, we show that, after controlling for wage growth and unemployment rate expectations, higher price inflation expectations result in a downward revision of reservation wages, implying that households perceive inflation as a bad signal about the economy. These results suggest that the risk of wage-price spirals was limited in the U.S. in 2022, despite the high inflation rates.

Keywords: inflation expectations, information spillovers, labor supply, wage-price spiral, 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

Understanding how agents form macroeconomic expectations and how they incorporate them into their economic decisions is key to influential economic models. Since the rational expectations revolution, substantial progress has been made in answering this question, with particular attention devoted to inflation expectations. This focus is unsurprising, given that inflation expectations are an important indicator for central banks when designing monetary policy. The recent surge in inflation rates has highlighted gaps in understanding the role of inflation expectations in household behavior. As can be seen from the quote above, central bankers worldwide, especially in the U.S., were concerned that elevated levels of price inflation could become entrenched in long-term inflation expectations. Persistently high inflation could encourage workers to demand higher wages to offset the decline in purchasing power, potentially resulting in wage-price spirals.

Whether an elevated inflation rate results in a wage-price spiral depends on answers to two questions: i) how workers form their expectations and macroeconomic outlook, and ii) how they incorporate these expectations into their labor market behavior. Although spillovers between wage and price inflation have been widely discussed in recent years, there has been no direct causal evidence of the relationship between expectations and individuals’ labor market decisions. Such analysis is challenging because the research requires information on subjective expectations about the economy and labor supply preferences. Even if such information can be obtained from observational data, variations in subjective expectations about future economic variables are unlikely to be exogenous. Similarly, observed individuals’ decisions could reflect many unobserved factors researchers cannot directly control for.

Building on the advances in the literature on randomized information provision, we overcome these challenges by designing and running an experiment in an online labor market. Throughout the experiment, we observe the simultaneous revision of multiple macroeconomic expectations, including price inflation expectations, in response to a single exogenously provided piece of information. We then document how households adjust their reservation wages due to the revision of macroeconomic expectations. This allows us to provide the first identified evidence of the effect of inflation expectations on labor supply, which is critical for understanding wage-price spirals.

We implemented the experiment on Amazon Mechanical Turk (MTurk, hereafter) in April-July 2022.¹ Since MTurk is an online labor market for on-demand tasks, rather than posing hypothetical questions about labor supply response to shifts in macroeconomic expectations, we designed the experiment to capture the *actual* labor supply responses by credibly offering workers future employment based on the conditions they provided. Specifically, we offered workers participation in a series of short forecasting and

¹During this period, the U.S. experienced exceptionally high inflation rates. In June 2022, CPI inflation reached its highest level since 1982 at 8.9%. 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.

text transcription tasks about macroeconomic variables, resembling a typical MTurk on-demand task. Using *randomized* information provision, we generated exogenous shifts in workers' macroeconomic expectations, which allows us to identify causal effects on workers' behavior (see Haaland, Roth, and Wohlfart, 2023). Specifically, we examine i) how workers update their expectations about macroeconomic variables,² and ii) how the resulting revision of expectations affects labor supply, measured by reservation wages and desired employment duration in our project.

The experiment results show that, in response to information treatments, participants meaningfully revised their expectations about price inflation, wage inflation, and unemployment rates. Importantly, when respondents received one relevant signal, they updated their expectations across all macroeconomic variables *jointly*. For example, upon receiving information about the current CPI inflation rate, respondents updated not only their price inflation expectations but also their wage inflation expectations and unemployment expectations. Similarly, they updated their price inflation and unemployment rate expectations when provided with information about aggregate hourly earnings inflation rates. The spillovers between macroeconomic expectations provide insights into households' subjective models of the economy (Andre et al., 2022). In line with the wage-price spiral theory, there are positive spillovers between price and wage inflation expectations: an upward revision of one variable triggers an upward revision of another. However, unemployment rate expectations also respond positively to the revision of price inflation expectations, which contradicts the relationship predicted by the conventional Phillips curve. In the language of economic models, such a positive relationship implies a supply-side or stagflationary view of inflation (Kamdar, 2019; Andre et al., 2022; Coibion et al., 2023; McClure et al., 2023).

The exogenous variation in expectations resulting from a randomized information treatment allows us to analyze the causal relationship between inflation expectations and labor supply, thus testing the predictions of the wage-price spiral theory. If an upward revision of inflation expectations leads to an increase in pay workers demand to take on a job, this would provide evidence in favor of the wage-price spiral theory. We elicit labor supply preferences by asking about the desired pay and duration of employment with us working on a similar task.

We find that, in response to exogenous variation in macroeconomic expectations, MTurk workers adjust their labor supply preferences, particularly reservation wages, but this response is not consistent with the wage-price spiral theory. When workers update their wage inflation expectations upwards, they increase their reservation wages. However, when workers adjust their price inflation expectations upwards, they rather *decrease* their reservation wages. We attribute this decrease in reservation wages to the stagflationary view of U.S. households. That is, households associate higher inflation with a negative economic outlook (Kamdar, 2019; Binder, 2020). This pessimistic outlook about economic prospects induces them to reduce the minimum reward necessary for accepting a job offer. We do not find a statistically significant effect of macroeconomic expectations about any variable on the desired duration of employment in our project. Given that most respondents expressed interest in working with us for as many months as possible, we have little variation in this outcome and cannot detect a statistically significant effect.

Overall, our results suggest that, contrary to policymakers' concerns, the risk of the wage-price spiral in the U.S. was limited during the summer of 2022. While higher wage inflation expectations raise reservation wages, higher price inflation expectations tend to decrease reservation wages at the same time, partially offsetting the initial shock.

²Our randomized information treatments refer to information about price inflation, wage inflation, unemployment rate, or variables that are not relevant to the macroeconomic outlook.

Contribution to Literature. Our paper contributes to several strands of literature. First, it expands the literature on the formation of macroeconomic expectations and the relationship between them (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., 2022; Weber et al., 2023) by documenting spillovers between expectations about price inflation, wage inflation, and unemployment rate when provided with information about only one of them. Another distinguishing feature of our experiment is that it was implemented during the high inflation period when workers had more incentives to be informed about inflation and pay attention to information about it.

Second, we contribute to the literature on the effects of macroeconomic expectations on individual decisions (see, for example, Armona, Fuster, and Zafar, 2019; Armantier et al., 2016; Bontan and Perez-Truglia, 2020; Coibion, Gorodnichenko, and Weber, 2022; Coibion et al., 2019; Hajdini et al., 2023; Belot, Kircher, and Muller, 2022). To our knowledge, our paper is the first study to empirically examine the *direct* causal relationship between inflation expectations and labor supply. We show that, after controlling for aggregate wage inflation expectations, an increase in price inflation expectations *reduces* reservation wages. Our paper also builds on and contributes to methodological literature on designing randomized information provision experiments to account for the effect of potential spillovers between expectations (see Haaland, Roth, and Wohlfart, 2023). Otherwise, the results may be subject to omitted variable bias arising due to the revision of expectations that are not accounted for in the analysis.

Third, our paper contributes to the literature studying wage-price 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 (Blanchard, 1986). Previous empirical studies have relied on observational data across different countries that suffer from inherent endogeneity (see, for example, Kandil, 2003; Boissay et al., 2022). Our paper exploits exogenous variation in subjective expectations and hence provides identified causal evidence.

Finally, our paper contributes to the literature on subjective models of the economy that guide the behavior of non-expert economic agents (Andre et al., 2022). Our results suggest that the U.S. households behave in accordance with their subjective models which differs from standard economic models. In particular, they believe that an increase in inflation leads to a higher unemployment rate, in line with the supply-side view of inflation (Kamdar, 2019; McClure et al., 2023). Consequently, they reduce their reservation wages, likely to insure against uncertainty in future labor markets.

Clearly, understanding how households adjust their labor supply in response to inflation expectations is important for policy discussions and communications. For example, many central banks have made enormous efforts to control inflation expectations in 2022-2023. According to Andre et al. (2022), providing contextual cues about the demand versus supply nature of the shock substantially affects households' thoughts about propagation mechanisms. Our results suggest that in a situation when wage-price spirals are a concern, it is advantageous that policymakers clearly communicate that contractionary monetary policy is intended to *reduce* inflation which will likely *increase* unemployment rate. This would ensure that households moderate their wage demands thus contributing to curbing inflationary pressure.

The remainder of the paper is organized as follows. Section 2 describes the survey and experimental design. Section 3 presents the treatment effects of information provision on subjective expectations and discusses information spillovers between them. Section 4 then examines how changes in expectations affect labor supply preferences and discusses implications for the wage-price spiral theory. Finally, Section 5 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 training 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%.³ 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. 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.⁴

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 F.

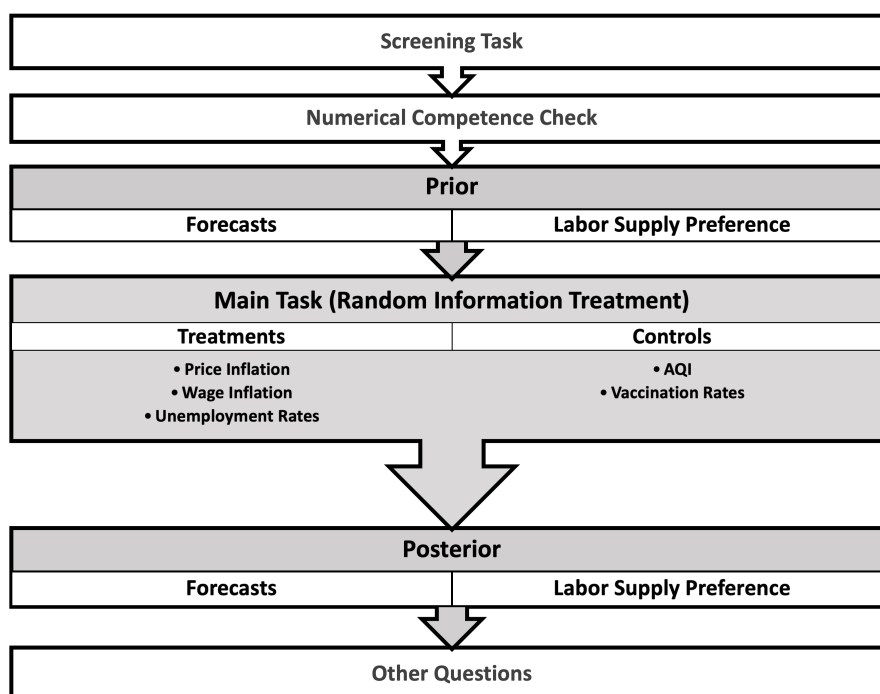
Screening Task. Our survey starts with a screening task. The screening task is of a similar format to the main task related to the information treatment. It tests participants’ ability to transcribe information from a screenshot accurately. If participants answered the screening task incorrectly, they 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.

³Requesters 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.

⁴Attrition from the attempt to the completion is not systemically correlated with the treatment arms (see Appendix Table A.1 and A.2 for details).

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 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 E. 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 E.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 E.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×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 3,979 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.⁵

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.⁶ About 75% of them have a 4-year college degree or more. About 83% 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 20.39 hours per week working on MTurk. Their households spend \$724 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 7.20%, 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 2022.⁷ The average desired duration of

⁵Appendix Table A.3 summarizes attrition from participation in the follow-up waves of the survey.

⁶Our survey has numerical competency check questions. It is more likely that those who are more comfortable with numbers tend to complete our surveys.

⁷When we asked about their expected unemployment rates, we gave information about the lowest and highest unemployment rates between 2019 and 2021.

employment on a monthly HIT like ours is 3.78 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
$\mathbb{E}_t^{\text{prior}}[\pi_{t+12}]$	6.12	1.00	5.00	10.00	8.12
$\mathbb{E}_t^{\text{prior}}[\pi_{t+12}^w]$	7.22	1.00	4.00	10.00	11.31
$\mathbb{E}_t^{\text{prior}}[u_{t+12}]$	7.24	4.46	6.45	9.20	3.80
$\Delta^{\text{post-prior}}\mathbb{E}_t[\pi_{t+12}]$	0.53	-1.80	0.00	3.00	7.58
$\Delta^{\text{post-prior}}\mathbb{E}_t[\pi_{t+12}^w]$	-0.92	-3.00	0.00	2.00	11.60
$\Delta^{\text{post-prior}}\mathbb{E}_t[u_{t+12}]$	0.89	-1.18	0	1.96	5.01
$\mathbb{E}_t^{\text{prior}}[\text{duration}_{t+1}]$	3.76	2.00	5.00	5.00	1.53
$\mathbb{E}_t^{\text{prior}}[\text{reservation wages}_{t+1}]$	1.00	0.50	1.00	1.25	0.54
Observations	4,614				

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.

First, we examine the direct effect of information treatments, i.e., the revision of expectations about a given macroeconomic variable in response to information about this variable. Next, we study the role of information spillovers, i.e., the revision of expectations about one macroeconomic variable in response to information about another macroeconomic variable. We then discuss the implications of the presence of information spillovers for understanding households' subjective model of economy.

3.1 Direct Effect of Information Provision on Subjective Expectations

Does information about the CPI inflation rate received through a text transcription task induce workers to revise their price inflation expectations? What about information and expectations regarding other macroeconomic variables? To answer these questions, we study how expectations regarding a given variable change in response to information provision about that variable in the treatment group relative to the control group. To illustrate the revision of expectations, we first analyze binned scatter plots of respondents' posterior expectations and their revisions against their priors (Figure 2), and then perform regression analysis (Table 2).

Graphical Evidence Panel A of Figure 2 illustrates the revision of 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 either the air quality index or Covid-19 vaccination rate. If respondents in the treatment group find the provided information useful, then we would observe larger revisions of their expectations compared to the control group, which received information largely irrelevant to macroeconomic conditions. If respondents in the treatment group did not pay attention to the information about inflation they received, they should behave similarly to the control group.⁸ Comparing expectations revision relative to the control group allows us to isolate the effect of interest, illustrated by the difference between black and blue lines.

The left graph of panel A shows that respondents who received information about the current CPI inflation rate change their posterior expectations about price inflation more than those in the control group. This suggests that, in line with Bayesian updating, respondents in the treatment group place much smaller weights on their priors.⁹ 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 revise their expectations toward the signal by placing a higher weight on the signal and decreasing weight on the prior. The right graph of panel A points to a similar conclusion.

Results in panel A of Figure 2 suggest that despite the high salience of information about inflation during the analyzed period, respondents paid attention to publicly available information about inflation. The same is true for wage growth and unemployment rate. Panels B and C of Figure 2 show that respondents who received relevant information about past earnings growth (unemployment rate) placed a lower weight on their respective priors and a higher weight on the signal than those in the control group.

⁸Respondents in the treatment and control groups may adjust their posterior forecasts as a result of slight change in the wording of prior and posterior questions.

⁹To 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:

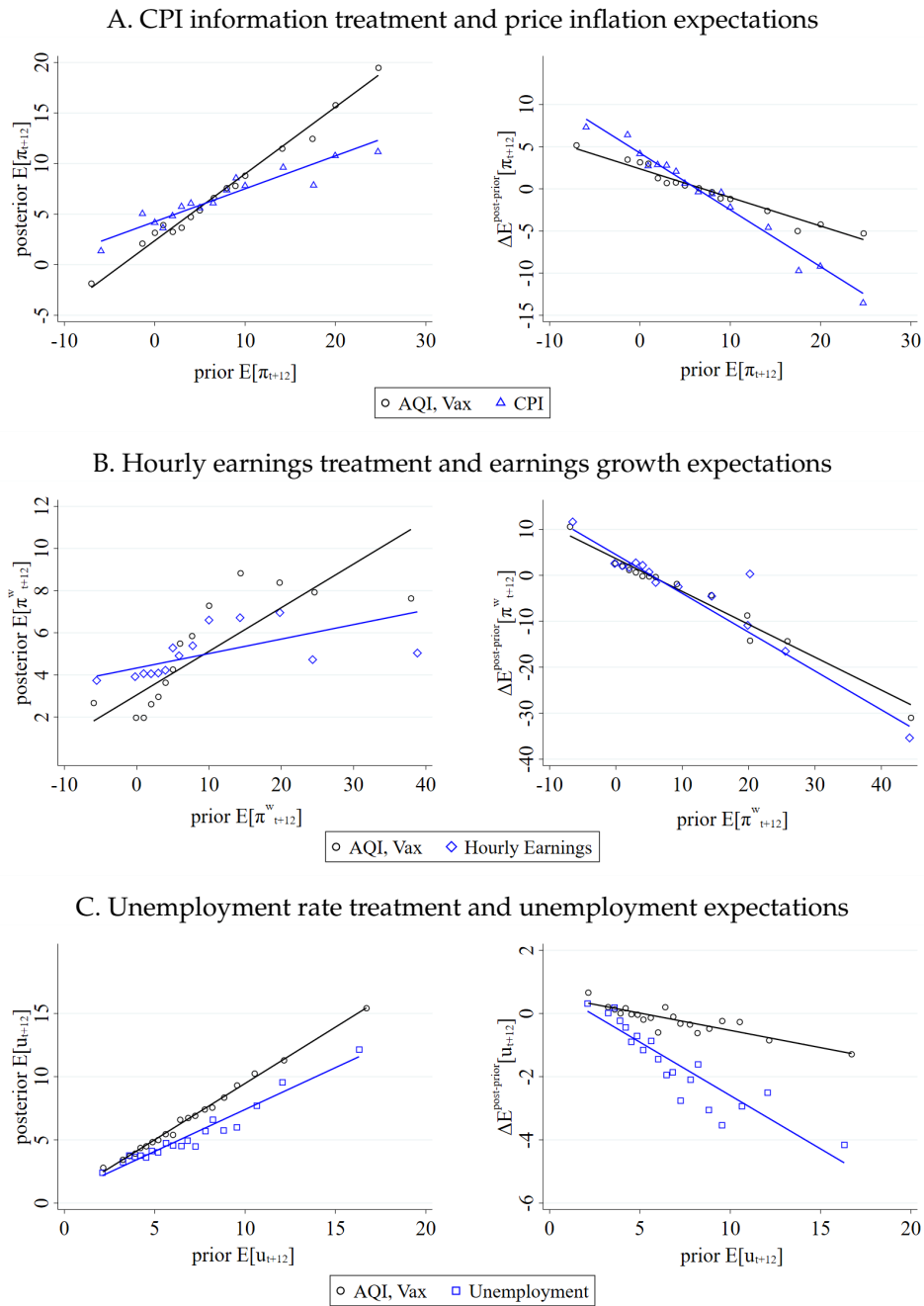
$$\mathbb{E}^{\text{post}}[Z_{t+12}] = (1 - \alpha)\mathbb{E}^{\text{prior}}[Z_{t+12}] + \alpha \textit{Signal}$$

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

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

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

Figure 2: Effects of information treatments on macroeconomic 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 (the right panel, on y -axis) against their priors (on x -axis) to illustrate the effect of 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.

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 for price inflation expectations, wage inflation expectations, and unemployment rate expectations:

$$\mathbb{E}_{it}^{\text{post}}[Z_{t+12}] = \alpha_0 + \alpha_1 \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}] + \alpha_2 \text{treat}_i^Z + \alpha_3 \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}] \times \text{treat}_i^Z + \varepsilon_i \quad (1)$$

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 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. (2023) and others, we use Huber-Robust regressions to control for outliers. The results are summarized in Table 2.

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

Dependent variable: $\mathbb{E}_{it}^{\text{post}}[Z_{t+12}]$	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)
treat_cpi	1.97*** (0.23)	1.71*** (0.26)	1.64*** (0.27)	1.98*** (0.26)								
treat_wage					1.29*** (0.19)	1.32*** (0.22)	2.13*** (0.23)	2.12*** (0.21)				
treat_unemp									0.05 (0.23)	0.06 (0.24)	0.77*** (0.24)	0.46** (0.22)
treat_cpi \times $\mathbb{E}_{it}^{\text{prior}}[Z_{t+12}]$	-0.32*** (0.02)	-0.30*** (0.02)	-0.31*** (0.02)	-0.34*** (0.02)								
treat_wage \times $\mathbb{E}_{it}^{\text{prior}}[Z_{t+12}]$					-0.16*** (0.01)	-0.15*** (0.01)	-0.31*** (0.02)	-0.27*** (0.02)				
treat_unemp \times $\mathbb{E}_{it}^{\text{prior}}[Z_{t+12}]$									-0.19*** (0.03)	-0.19*** (0.03)	-0.31*** (0.03)	-0.28*** (0.03)
$\mathbb{E}_{it}^{\text{prior}}[Z_{t+12}]$	0.62*** (0.01)	0.63*** (0.01)	0.74*** (0.01)	0.76*** (0.01)	0.22*** (0.01)	0.21*** (0.01)	0.39*** (0.01)	0.35*** (0.01)	0.88*** (0.01)	0.89*** (0.01)	0.92*** (0.02)	0.92*** (0.01)
Sample	All	All	Numerate	Consistent	All	All	Numerate	Consistent	All	All	Numerate	Consistent
N	2860	2849	2106	2100	2881	2870	2100	2198	2445	2437	1814	1893
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, age², 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, education level, frequency of checking news, income group, and launch time fixed effects. The control group refers to those who have received irrelevant information such as the air quality index in Seattle or Covid-19 vaccination rates.

Columns 1-4 of Table 2 show the effect of information treatment about the CPI inflation rate on the revision of price inflation expectations. When respondents are provided with information about the current CPI inflation rates, their implied weight on prior price inflation expectations decreases from 0.62-0.76 to 0.30-0.43 by 0.30-0.34 points. The results in columns 5-8 show similar results. On average, respondents reduce the weight on prior wage inflation expectations from 0.21-0.39 by 0.15-0.31 points. Finally, according

to columns 9-12, when workers receive information about the unemployment rate forecast, they decrease the weight they assign to their priors from 0.88-0.92 by about 0.19-0.31 points. These results support the conclusion that information treatments effectively induce respondents to revise their expectations as intended.

Overall, the analysis of direct treatment effects suggests that information treatment worked as intended. Workers in the treatment groups paid attention to the information they received and considered it when revising macroeconomic expectations. Therefore, our experiment succeeded in generating exogenous shifts in macroeconomic expectations.

3.2 Information Spillovers in Subjective Expectations

The previous results assume that information about a given macroeconomic variable affects expectations only about this variable. For example, a signal about the CPI inflation rate affects *only* price inflation expectations but not other forms of expectations. However, since many macroeconomic phenomena are interrelated, revisions of macroeconomic expectations about one variable may be responsive to signals about other macroeconomic variables. For example, [Coibion, Gorodnichenko, and Weber \(2022\)](#) document that information about the unemployment rate has a significant effect on the revision of price inflation expectations of U.S. households. Similarly, the spillovers between price and wage inflation expectations are essential for the theory of the wage-price spirals. To examine whether such spillovers are present in our experiment, we analyze how respondents revise their expectations about one macroeconomic variable (e.g., price inflation expectations) when they receive a signal about another variable (e.g., wage growth rate or unemployment rate).

Graphical Evidence The graphical evidence regarding the direct and indirect effects of information treatments on macroeconomic expectations are summarized in Appendix B. As expected, there are indeed substantial information spillovers across macroeconomic expectations. A signal about hourly earnings growth results in a similar revision of price inflation expectations as a signal about the CPI inflation rate (Appendix Figure B.1). 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 both the CPI inflation rate and unemployment rate (Appendix Figure B.2). However, information spillovers are limited for unemployment expectations, as they are largely unresponsive to signals about the wage inflation rate.

Regression Analysis To document the role of information spillovers across macroeconomic expectations quantitatively, we augment the previous regression specification to account for the fact that a signal about one macroeconomic variable may affect expectations about other macroeconomic variables. Specifically, we incorporate in Equation (1) indicator variables for multiple information treatments and their interactions with the prior expectations of the variable of interest for $Z = \{\pi, \pi^w, u\}$.

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

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. The estimates for the effect of information treatment on CPI inflation rate are similar to those in Table 2: 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 (indicated by the negative and statistically significant coefficient on $\text{treat} \times \mathbb{E}_{it}^{\text{prior}}[\pi_{t+12}]$). The implied weight on the prior price inflation expectation falls from 0.36-0.76 by 0.25-0.34 points for respondents who received information about either the CPI inflation rate or hourly earnings growth rate. When respondents received information about the unemployment rate, they decrease the weight on their priors but by a smaller amount of 0.04-0.11 points. In other words, even though workers are more responsive to the direct signals about each variable, they 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., 2023).

We observe similar patterns for hourly earnings inflation expectations (columns 5-8 of Table 3). Respondents in the treatment groups placed significantly smaller weights on their priors than respondents in the control group. The implied weight on the prior wage inflation expectations falls from 0.22-0.37 by 0.15-0.30 for respondents who received information either about hourly earnings growth or about the CPI inflation rate. A signal about the unemployment rate also reduced the weight on prior wage inflation expectations but by a smaller amount (0.07-0.22).

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 ($Z = u$)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\mathbb{E}_{it}^{\text{post}}[Z_{t+12}]$												
treat_cpi	2.02*** (0.23)	1.80*** (0.25)	1.71*** (0.27)	2.05*** (0.26)	0.89*** (0.20)	0.69*** (0.22)	1.27*** (0.24)	1.14*** (0.22)	-0.11 (0.22)	-0.43* (0.23)	-0.47** (0.22)	-0.51** (0.22)
treat_wage	1.21*** (0.22)	1.09*** (0.24)	1.42*** (0.26)	1.68*** (0.24)	1.28*** (0.20)	1.24*** (0.22)	2.00*** (0.24)	2.09*** (0.21)	-0.12 (0.22)	-0.40* (0.24)	-0.02 (0.23)	-0.27 (0.22)
treat_unemp	-0.25 (0.27)	-0.23 (0.29)	-0.29 (0.30)	-0.03 (0.28)	-0.34 (0.23)	-0.24 (0.25)	0.51* (0.27)	0.47* (0.24)	-0.19 (0.26)	-0.32 (0.27)	0.54** (0.25)	0.36 (0.25)
$\text{treat_cpi} \times \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}]$	-0.33*** (0.02)	-0.30*** (0.02)	-0.31*** (0.02)	-0.34*** (0.02)	-0.15*** (0.01)	-0.16*** (0.01)	-0.30*** (0.02)	-0.27*** (0.02)	0.09*** (0.03)	0.11*** (0.03)	0.10*** (0.03)	0.11*** (0.03)
$\text{treat_wage} \times \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}]$	-0.26*** (0.02)	-0.25*** (0.02)	-0.31*** (0.02)	-0.29*** (0.02)	-0.16*** (0.02)	-0.15*** (0.02)	-0.30*** (0.02)	-0.27*** (0.02)	0.04 (0.03)	0.06** (0.03)	-0.01 (0.03)	0.02 (0.03)
$\text{treat_unemp} \times \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}]$	-0.08*** (0.03)	-0.07** (0.03)	-0.04 (0.03)	-0.11*** (0.03)	-0.07*** (0.02)	-0.07*** (0.02)	-0.22*** (0.02)	-0.18*** (0.02)	-0.14*** (0.03)	-0.12*** (0.03)	-0.27*** (0.03)	-0.25*** (0.03)
$\mathbb{E}_{it}^{\text{prior}}[Z_{t+12}]$	0.63*** (0.01)	0.63*** (0.01)	0.73*** (0.01)	0.76*** (0.01)	0.23*** (0.01)	0.22*** (0.01)	0.37*** (0.01)	0.35*** (0.01)	0.87*** (0.02)	0.87*** (0.02)	0.91*** (0.02)	0.91*** (0.02)
Sample	All	All	Numerate	Consistent	All	All	Numerate	Consistent	All	All	Numerate	Consistent
N	4611	4595	3381	3447	4614	4598	3382	3449	4614	4598	3382	3449
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, age², 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, education level, frequency of checking news, income group, and launch time fixed effects. The control group refers to those who have received irrelevant information such as the air quality index in Seattle or Covid-19 vaccination rates.

Information spillovers are also evident for unemployment expectations (columns 9-12 of Table 3), but to a lesser extent, as unemployment rate expectations are largely not responsive to signals about wage inflation rates. However, information about price inflation has quite a substantial and surprising effect on unemployment expectations. 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 decreased from 0.87-0.91 by 0.14-0.27). However, when provided with information about the current price inflation rate, they significantly revised their unemployment expectations *away* from the signal (the implied weight on the prior expectations *increased* by 0.09-0.11). We attribute this pattern to a subjective model of the economy that workers use to rationalize the information they were provided with. They tend to think that when inflation rates are higher, unemployment rates tend to increase as well. This is consistent with a stagflationary view of inflation (see, for example, Kamdar, 2019; Binder, 2020).

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). Specifically, 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 the 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 in the past. We also find evidence of “learning-through-survey” effects Binder and Kim (2020). Although we find statistically significant information treatment effects across all three waves, the magnitude of the effect decreases in the third wave likely because participants were better informed about the situation after the first two waves (see Table C.2 in Appendix C.2).

Economic Implications The presence of information spillovers has important implications for understanding the behavior of economic agents. The fact that households revise their expectations about *multiple* macroeconomic variables when provided only one piece of relevant information makes it more challenging to infer their response to a particular shock. Rather than responding to an isolated shock, households appear to be responding to a series of shocks inferred based on a subjective model of the economy (Andre et al., 2022). For example, the stagflationary or supply-side view of inflation documented in prior literature (see Kamdar, 2019; Binder, 2020; McClure et al., 2023) means that when households decide how to adjust their behavior relative to the previous period, they account not only for the fact that higher inflation reduces their real income but also that the unemployment rate is likely to increase as well. Results in Table 3 also suggest that this “subjective model” also predicts higher wage growth thus partially offsetting pessimism about the rise in inflation and unemployment.

Omission of spillovers in macroeconomic expectations, i.e., the analysis of household behavior under the assumption that only the direct effects of information provision matter for decision-making, may result in omitted variable bias, leading to misleading conclusions about the way expectations affect households’ economic decisions. The next section documents the role of information spillovers across macroeconomic expectations in the case of labor supply decisions and discusses their implications for understanding the risks of wage-price spirals for inflation dynamics in the U.S. in 2022.

4 Application to Labor Supply and Wage-Price Spirals

In this section, we examine the *causal* relationship between inflation expectations and labor supply. As we discussed earlier, subjective expectations about future economic variables are unlikely to be exogenous. Many unobserved factors affect both expectations and individuals' behavior, including labor supply decisions. To overcome these issues, we use an instrumental variable approach that exploits exogenous variation in expectations due to randomized information treatments.

4.1 Effect of Inflation Expectations on Labor Supply

In Section 3.2, we established that there are nontrivial information spillovers between macroeconomic expectations: when provided with *one* relevant piece of information about the economy, respondents update their expectations about *all* relevant variables. In particular, when respondents received information about CPI inflation rates, they updated their expectations about price inflation rates, wage inflation, and unemployment rates. Since expectations about each of these macroeconomic variables could affect labor supply decisions, we estimate the regression model with all the measured expectations (price, wage, and unemployment rates) as endogenous variables in the second-stage equation:

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

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

Due to inherent endogeneity 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 and hourly earnings treatment dummies, the interaction of prior hourly earnings inflation expectations with the CPI treatment and hourly earnings treatment dummies, and the interaction of prior unemployment expectations with unemployment treatment dummy.¹⁰ The parameters of our interest are β_1 - β_3 's.

Effects on MTurk Reservation Wages The main advantage of running an experiment in MTurk is the fact that it allows us to credibly offer employment on terms elicited by workers. This enables us to measure workers' reservation wages as the lowest pay they would be willing to accept to work on our project in the future. We use this information to examine the effect of inflation expectations on the reservation wages of MTurk workers. A question of particular interest is whether workers who received information about the currently high price inflation rates revise their reservation wages upward to account for the decline in the purchasing power of their earnings, as predicted by the wage-price spiral theory.

¹⁰In 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: treat_cpi_{it} , treat_wage_{it} , treat_unemp_{it} , $(\text{treat_cpi}_{it} \times \mathbb{E}_{it}^{\text{prior}}[\pi_{t+12}])$, $(\text{treat_cpi}_{it} \times \mathbb{E}_{it}^{\text{prior}}[\pi_{t+12}^w])$, $(\text{treat_wage}_{it} \times \mathbb{E}_{it}^{\text{prior}}[\pi_{t+12}^w])$, $(\text{treat_wage}_{it} \times \mathbb{E}_{it}^{\text{prior}}[\pi_{t+12}])$, and $(\text{treat_unemp}_{it} \times \mathbb{E}_{it}^{\text{prior}}[u_{t+12}])$.

Table 4: Effects of expectations on reservation wages

	Reservation Wages (in cents)					
	(1)	(2)	(3)	(4)	(5)	(6)
$E_{it}^{\text{post}}[\pi_{t+12}]$	-0.77 (0.66)	-0.18 (0.62)	-1.49*** (0.57)	-0.82 (0.55)	-1.50** (0.68)	-1.10* (0.63)
$E_{it}^{\text{post}}[\pi_{t+12}^w]$	1.99*** (0.68)	1.91*** (0.66)	1.04*** (0.34)	0.54* (0.32)	0.89** (0.43)	0.88* (0.48)
$E_{it}^{\text{post}}[u_{t+12}]$	-1.82* (0.95)	-0.30 (0.97)	0.59 (0.80)	0.59 (0.65)	0.03 (0.67)	-0.23 (0.72)
<i>N</i>	3,487	3,488	2,362	2,348	2,396	2,416
Sample	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes
F-stat for $E_{it}^{\text{post}}[\pi_{t+12}]$	12.51	14.06	15.81	16.34	13.60	13.98
F-stat for $E_{it}^{\text{post}}[\pi_{t+12}^w]$	17.54	17.18	40.75	44.61	38.47	29.55
F-stat for $E_{it}^{\text{post}}[u_{t+12}]$	25.13	20.24	30.40	41.73	32.69	32.75

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 D for details about the treatment of outliers.

Table 4 reports the effect of posterior macroeconomic expectations on the reservation wages per 10 minutes of respondents' time, accounting for the presence of information spillovers. The results 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 0.88-1.99 cent increase in their reservation wages per ten minutes. This corresponds to about a 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 highly numerate respondents and respondents who provided consistent answers to reservation wage questions.¹¹ A 1 percentage point increase in the expected price inflation rate is associated with up to a 1.50 cent *decrease* (1.5%) in nominal reservation wages on average. The unemployment rate, after controlling for other macroeconomic expectations, does not have a statistically significant effect on reservation wages.

Effects on Desired Duration of Employment on MTurk In addition to asking workers about the pay they would be willing to work on a 10-minute forecasting task similar to ours in the future, we also asked about the number of periods (from 0 to 5 months) they would be willing to participate in the task. An indicator variable denoting whether respondents increased the desired employment duration after the information

¹¹Highly 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.

treatment is the dependent variable in the results summarized in Table 5.¹²

In contrast to reservation wages, macroeconomic expectations do not significantly affect the desired duration of employment *with us*. This result, however, should not be interpreted as the absence of the effect on overall labor supply for two reasons. First, since most workers would like to work on our project for as long as possible (see Table 1), there is little variation in both prior and posterior duration. Second, workers may change their desired terms of employment with other employers, both in the online and offline settings.

Table 5: Effects of expectations on desired duration of employment

	$\mathbb{1}_{\text{increase the desired duration of employment}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_{it}^{\text{post}}[\pi_{t+12}]$	0.002 (0.003)	-0.000 (0.003)	0.003 (0.003)	-0.001 (0.003)	0.003 (0.003)	0.002 (0.003)
$\mathbb{E}_{it}^{\text{post}}[\pi_{t+12}^w]$	0.004 (0.005)	-0.007 (0.005)	-0.003 (0.002)	-0.004** (0.002)	-0.002 (0.002)	-0.003* (0.002)
$\mathbb{E}_{it}^{\text{post}}[u_{t+12}]$	0.003 (0.004)	-0.005 (0.006)	-0.001 (0.002)	-0.005 (0.004)	-0.000 (0.003)	0.000 (0.004)
N	3,573	3,556	2,440	2,429	2,457	2,473
Sample	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes
F-stat for $\mathbb{E}_{it}^{\text{post}}[\pi_{t+12}]$	14.95	16.45	19.87	21.66	18.66	21.63
F-stat for $\mathbb{E}_{it}^{\text{post}}[\pi_{t+12}^w]$	16.21	15.30	66.53	68.59	66.54	68.26
F-stat for $\mathbb{E}_{it}^{\text{post}}[u_{t+12}]$	31.54	24.79	38.59	31.42	42.59	33.39

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.

Effects on Offline Labor Market Preferences 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 available variation relative to the previous analysis. The results suggest that inflation expectations may affect offline labor market behavior. Table 6 shows that for numerate workers and workers who provided consistent answers to reservation wage questions, higher price inflation expectations imply a significantly higher probability of being employed by a different employer. This result is consistent with findings of Hajdini et al. (2023); 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. Lastly, respondents with higher unemployment expectations have a significantly greater subjective probability of being employed by a different employer. Similarly, workers with higher aggregate unemployment expectations tend to be pessimistic about their chances of being employed in the future.

¹²Our results are robust to the use of the alternative dependent variable, the desired duration of employment *in months*.

Table 6: 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)
$\mathbb{E}_{it}^{\text{post}}[\pi_{t+12}]$	0.47 (0.33)	0.42 (0.29)	1.02*** (0.33)	0.43* (0.24)	0.75** (0.31)	0.63** (0.30)
$\mathbb{E}_{it}^{\text{post}}[\pi_{t+12}^w]$	-0.35 (0.34)	-0.38 (0.27)	-0.89*** (0.32)	-0.37 (0.23)	-0.57** (0.25)	-0.55** (0.24)
$\mathbb{E}_{it}^{\text{post}}[u_{t+12}]$	2.57*** (0.39)	1.46*** (0.36)	1.85*** (0.34)	0.84*** (0.27)	1.89*** (0.35)	1.15*** (0.30)
<i>N</i>	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 $\mathbb{E}_{it}^{\text{post}}[\pi_{t+12}]$	7.46	7.33	7.91	9.04	9.23	8.50
F-stat for $\mathbb{E}_{it}^{\text{post}}[\pi_{t+12}^w]$	10.46	10.34	11.22	12.54	20.58	15.63
F-stat for $\mathbb{E}_{it}^{\text{post}}[u_{t+12}]$	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:

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

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 D for details about the treatment of outliers.

4.2 Implications for Wage-Price Spirals

The feedback loop between price inflation expectations, wage inflation expectations, and worker's wage demands is essential for the persistence of wage-price spirals. While we have documented the feedback loop between price inflation expectations and wage inflation expectations in Section 3.2, if households do not adjust their wage demands in response to change in expectations, even high price inflation is unlikely to trigger persistent wage-price spirals. The results in Section 4.1 suggest limited risks of wage-price spirals.

On the one hand, when workers receive information that price inflation is higher than expected, they increase both price and wage inflation expectations (Table 3). On the other hand, while the resulting increase in wage inflation expectations raises workers' reservation wages, an increase in price inflation expectations reduces reservation wages (Table 4). This result suggests that rather than demanding that employers compensate them for the decline in purchasing power of their earnings due to price inflation, workers are willing to accept lower pay to secure employment. The fact that workers exhibit a supply-side view of inflation, i.e., they interpret inflation as a bad signal about the economy, partially explains the observed countervailing effect of inflation expectations on reservation wages, which reduces the likelihood of a wage-price spiral.

Role of Information Spillovers The results discussed in Section 4.1 account for the role of spillovers across macroeconomic expectations. However, unlike the specification (3), a conventional approach in the literature is to treat only the expectation variable of interest as endogenous. All other expectation variables are either treated as exogenous or entirely omitted from the analysis. In the presence of information spillovers, such a strategy could result in omitted variable bias that may critically affect the conclusions.

To understand the role of omitting spillovers across macroeconomic expectations, we replicated the results in 4.1 following the conventional approach of treating only one expectations variable as exogenous at a time. When only wage inflation expectations are treated as an endogenous variable, the IV results suggest that wage inflation expectations do not have a statistically significant effect on reservation wages. For all respondents, the point estimates are positive but an order of magnitude smaller relative to the specification when all three sets of expectations are treated as endogenous. For numerate respondents as well as those who provided consistent answers to reservation wage questions, the point estimates are even negative yet not statistically significant. Since wage and price inflation expectations are positively correlated, and given the negative effect of price inflation expectations on reservation wages, it is not surprising that omitting price inflation expectations from the regression generates a downward bias in the estimates for wage inflation expectations. When only price inflation expectations are treated as endogenous, the results also tend to be statistically insignificant in the sample of numerate respondents. The point estimates are still negative but tend to be smaller than the estimates in Table 4.

This exercise suggests that not accounting for the spillovers in the analysis of the effect of inflation expectations on reservation wages, substantially changes the conclusions about the risks of wage-price spirals. Rather than uncovering the fact that, for respondents who demonstrate competence at interpreting percentage changes, price and wage inflation expectations significantly affect reservation wages in the opposite directions, the results omitting spillovers show no statistically significant effect for either of them.

5 Discussion and Conclusions

We use experimental evidence to document spillovers between macroeconomic expectations and study their effect on labor supply preferences in an online labor market setting. 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 of the effect of inflation expectations on labor supply and suggest that the risks of wage-price spirals were limited in the U.S. in 2022 despite the 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., price inflation) respondents revise multiple expectations *jointly*. As expected, workers' price and wage inflation expectations tend to move together. However, contrary to conventional views, subjective price inflation expectations are positively correlated with unemployment expectations, implying a positively sloped "subjective Phillips curve". The nature of spillovers across various expectations provides insights into the subjective model of the economy which households use to make economic decisions. The stagflationary view of inflation makes workers behave more cautiously in response to news about inflation increases (see [Kamdar, 2019](#); [Binder, 2020](#)). This result suggests that the first chain of wage-price spirals could be partially muted with higher expected unemployment rates.

Next, exploiting the experimental variation in macroeconomic expectations, we document several results about the effects 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, omitting spillovers across macroeconomic expectations, which generates omitted variable bias in this setting, could significantly distort the results suggesting no statistically significant effect of either price or wage inflation expectations on MTurk reservation wages. Fourth, the desired duration of employment on our MTurk project does not significantly respond to changes in macroeconomic expectations; however, we cannot rule out that workers change their offline labor market preferences.

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.

It is important to keep in mind that 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. 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 them 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 → Wave2			Wave 1 → 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
$\mathbb{E}_t^{\text{prior}}[\pi_{t+12}]$	5.57	1.00	5.00	10.00	8.10
$\mathbb{E}_t^{\text{prior}}[\pi_{t+12}^w]$	5.78	1.00	3.00	8.00	9.93
$\mathbb{E}_t^{\text{prior}}[u_{t+12}]$	7.05	4.30	6.30	9.00	3.57
$\mathbb{E}_t^{\text{prior}}[\text{duration}_{t+1}]$	3.87	3.00	5.00	5.00	1.49
$\mathbb{E}_t^{\text{prior}}[\text{reservation wages}_{t+1}]$	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
$\mathbb{E}_t^{\text{prior}}[\pi_{t+12}]$	4.85	1.00	4.00	9.00	7.78
$\mathbb{E}_t^{\text{prior}}[\pi_{t+12}^w]$	5.32	1.00	3.00	6.00	9.43
$\mathbb{E}_t^{\text{prior}}[u_{t+12}]$	6.96	4.23	6.20	8.90	3.47
$\mathbb{E}_t^{\text{prior}}[\text{duration}_{t+1}]$	3.97	3.00	5.00	5.00	1.44
$\mathbb{E}_t^{\text{prior}}[\text{reservation wages}_{t+1}]$	0.98	0.50	1.00	1.25	0.54
Observations	1,472				

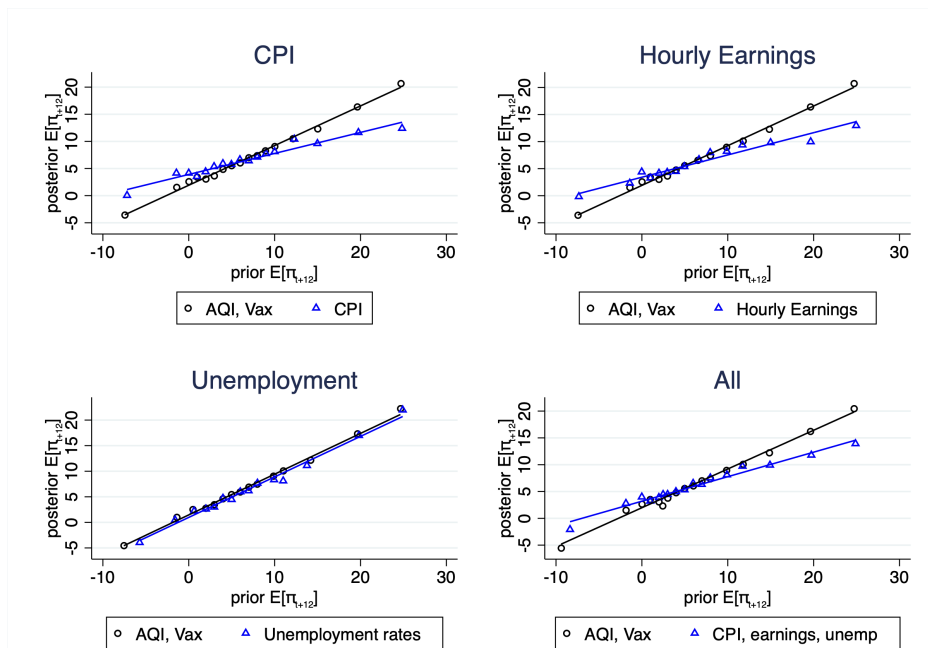
B Effects of Information Treatment on Subjective Expectations

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.

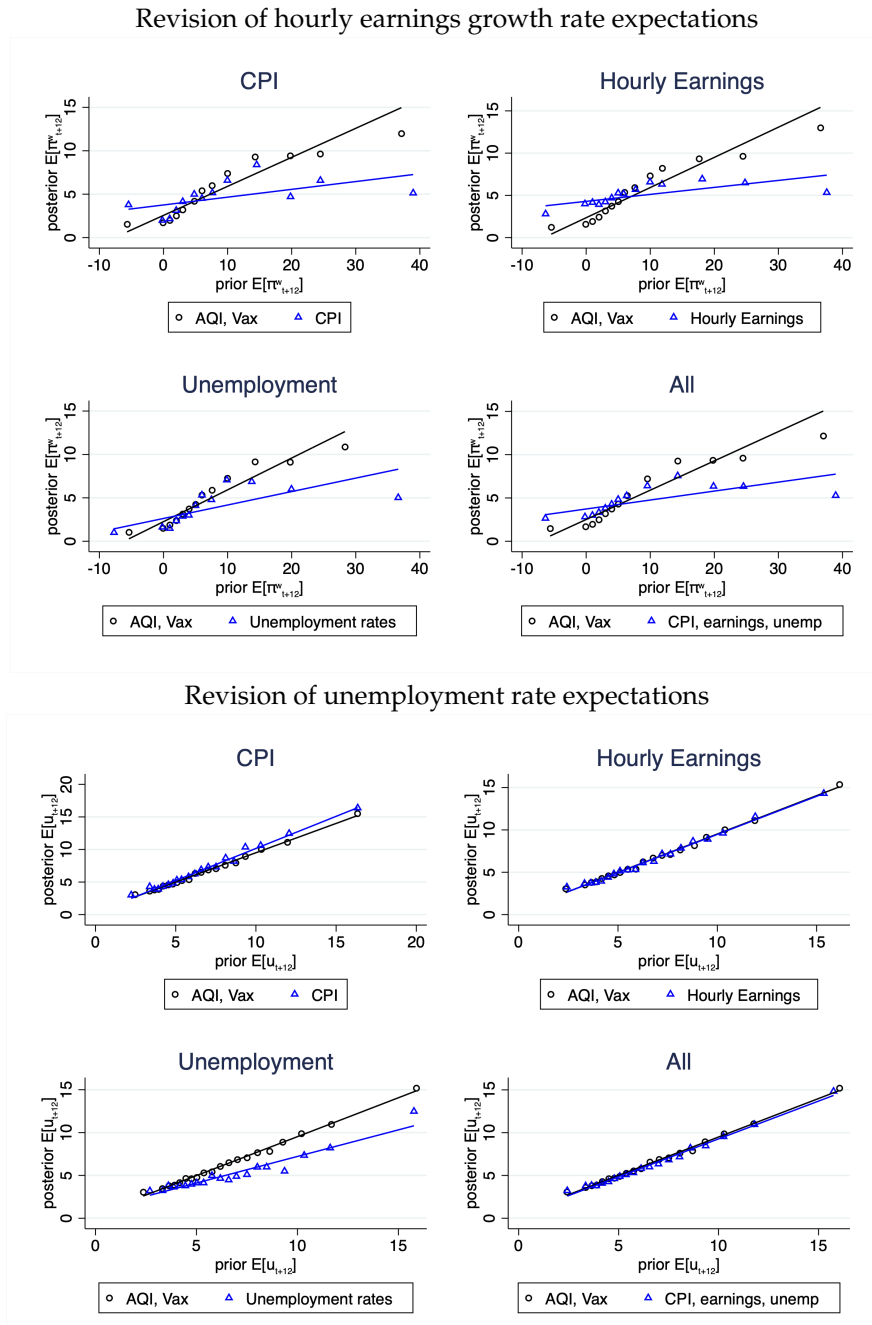
Figure B.1: Effects of information treatment on price inflation expectations



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 ?? . We extend the specification estimated there by introducing interaction terms of regime change indicators with prior expectations:

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

where 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 $\text{Regime Change}_i^\pi$ 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 $\text{Regime Change}_i^\pi$ equals to one. It will take on the value of zero otherwise. We define $\text{Regime Change}_i^{\pi^w}$ similarly. Meanwhile, because unemployment rates are defined differently, we define 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 ?? 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: Regime Change ^Z	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)
<i>treat_cpi</i>	0.089*** (0.019)	0.079*** (0.022)	0.054** (0.023)	0.078*** (0.023)	0.014 (0.020)	0.008 (0.024)	-0.010 (0.026)	-0.009 (0.026)	-0.023 (0.043)	-0.046 (0.051)	-0.082 (0.053)	-0.110** (0.052)
<i>treat_wage</i>	0.074*** (0.018)	0.080*** (0.021)	0.067*** (0.022)	0.095*** (0.022)	0.109*** (0.019)	0.128*** (0.023)	0.127*** (0.025)	0.135*** (0.024)	-0.021 (0.043)	-0.018 (0.052)	-0.026 (0.053)	-0.069 (0.051)
<i>treat_unemp</i>	-0.026 (0.022)	-0.004 (0.025)	0.012 (0.026)	-0.017 (0.025)	-0.051** (0.023)	-0.038 (0.026)	-0.049* (0.029)	-0.032 (0.029)	-0.211*** (0.050)	-0.079 (0.061)	-0.064 (0.061)	-0.209*** (0.059)
<i>treat_cpi</i> \times $\mathbb{E}_t^{\text{prior}}[Z_{t+12}]$	-0.005*** (0.002)	-0.004** (0.002)	-0.004** (0.002)	-0.005** (0.002)	0.003** (0.002)	0.004* (0.002)	0.004* (0.002)	0.005** (0.002)	0.012** (0.006)	0.014** (0.007)	0.017** (0.007)	0.021*** (0.007)
<i>treat_wage</i> \times $\mathbb{E}_t^{\text{prior}}[Z_{t+12}]$	-0.005** (0.002)	-0.006** (0.002)	-0.007*** (0.002)	-0.008*** (0.002)	-0.004** (0.002)	-0.003 (0.002)	-0.002 (0.002)	-0.002 (0.002)	0.004 (0.006)	-0.004 (0.007)	-0.006 (0.007)	0.000 (0.007)
<i>treat_unemp</i> \times $\mathbb{E}_t^{\text{prior}}[Z_{t+12}]$	0.000 (0.002)	-0.001 (0.003)	-0.001 (0.003)	-0.000 (0.003)	0.001 (0.002)	0.002 (0.003)	0.003 (0.003)	0.002 (0.003)	0.003 (0.007)	-0.019** (0.008)	-0.022*** (0.008)	-0.004 (0.008)
$\mathbb{E}_t^{\text{prior}}[Z_{t+12}]$	-0.021*** (0.001)	-0.018*** (0.001)	-0.018*** (0.001)	-0.017*** (0.001)	-0.019*** (0.001)	-0.021*** (0.001)	-0.021*** (0.001)	-0.021*** (0.001)	-0.014*** (0.003)	-0.008** (0.004)	-0.008* (0.004)	-0.012*** (0.004)
Sample	All	All	Numerate	Consistent	All	All	Numerate	Consistent	All	All	Numerate	Consistent
N	4535	3301	3292	3352	4462	3276	3226	3283	4282	3106	3080	3161
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, age², 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:

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

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: $\mathbb{E}_t^{\text{prior}2}[Z_{t+12}]$												
treat_cpi	0.01 (0.56)	-0.03 (0.56)	0.23 (0.65)	0.05 (0.60)	0.38 (0.36)	0.20 (0.39)	0.22 (0.47)	0.36 (0.42)	-0.42 (0.40)	-0.24 (0.41)	-0.32 (0.47)	-0.35 (0.43)
treat_wage	0.51 (0.55)	0.55 (0.55)	0.76 (0.63)	0.78 (0.58)	-0.19 (0.35)	-0.36 (0.38)	-0.66 (0.45)	-0.37 (0.40)	-0.10 (0.41)	0.00 (0.42)	0.16 (0.49)	-0.05 (0.44)
treat_cpi \times $\mathbb{E}_t^{\text{prior}}[Z_{t+12}]$	-0.05 (0.06)	-0.05 (0.06)	-0.07 (0.07)	-0.05 (0.06)	-0.06** (0.03)	-0.04 (0.03)	0.01 (0.04)	-0.04 (0.03)	-0.00 (0.05)	-0.03 (0.05)	-0.02 (0.06)	-0.00 (0.05)
treat_wage \times $\mathbb{E}_t^{\text{prior}}[Z_{t+12}]$	-0.18*** (0.05)	-0.19*** (0.05)	-0.19*** (0.06)	-0.22*** (0.06)	-0.03 (0.03)	0.01 (0.03)	-0.08** (0.04)	0.05 (0.03)	-0.01 (0.05)	-0.03 (0.05)	-0.08 (0.06)	-0.01 (0.06)
$\mathbb{E}_t^{\text{prior}}[Z_{t+12}]$	0.52*** (0.04)	0.53*** (0.04)	0.59*** (0.05)	0.59*** (0.04)	0.12*** (0.02)	0.11*** (0.02)	0.08*** (0.03)	0.13*** (0.02)	0.49*** (0.04)	0.45*** (0.04)	0.50*** (0.05)	0.47*** (0.04)
Sample N	All 1365	All 1340	Numerate 1031	Consistent 1170	All 1365	All 1340	Numerate 1031	Consistent 1170	All 1365	All 1340	Numerate 1031	Consistent 1170
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Part 2: Dependent variable: $\mathbb{E}_t^{\text{prior}3}[Z_{t+12}]$												
treat_cpi	0.70 (0.53)	0.57 (0.54)	0.18 (0.60)	0.05 (0.60)	0.31 (0.32)	0.08 (0.32)	0.39 (0.34)	0.36 (0.42)	-0.10 (0.41)	-0.15 (0.42)	-0.76* (0.46)	-0.35 (0.43)
treat_wage	0.47 (0.50)	0.39 (0.52)	0.60 (0.56)	0.78 (0.58)	0.10 (0.31)	0.01 (0.31)	0.48 (0.33)	-0.37 (0.40)	-1.18*** (0.42)	-1.04** (0.43)	-1.24*** (0.46)	-0.05 (0.44)
treat_cpi \times $\mathbb{E}_t^{\text{prior}}[Z_{t+12}]$	-0.11** (0.05)	-0.11** (0.05)	0.01 (0.06)	-0.05 (0.06)	-0.10*** (0.02)	-0.08*** (0.02)	-0.10*** (0.03)	-0.04 (0.03)	0.02 (0.05)	0.04 (0.05)	0.13** (0.06)	-0.00 (0.05)
treat_wage \times $\mathbb{E}_t^{\text{prior}}[Z_{t+12}]$	-0.17*** (0.05)	-0.18*** (0.05)	-0.16*** (0.05)	-0.22*** (0.06)	-0.07*** (0.03)	-0.05** (0.03)	-0.10*** (0.03)	-0.05 (0.03)	0.20*** (0.05)	0.18*** (0.05)	0.20*** (0.06)	-0.01 (0.06)
$\mathbb{E}_t^{\text{prior}}[Z_{t+12}]$	0.43*** (0.04)	0.43*** (0.04)	0.45*** (0.04)	0.59*** (0.04)	0.15*** (0.02)	0.13*** (0.02)	0.16*** (0.02)	0.13*** (0.02)	0.35*** (0.04)	0.32*** (0.04)	0.35*** (0.04)	0.47*** (0.04)
Sample N	All 1444	All 1416	Numerate 1140	Consistent 1170	All 1444	All 1416	Numerate 1140	Consistent 1170	All 1444	All 1416	Numerate 1140	Consistent 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, age², 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:

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

for $Z = \{\pi, \pi^2, u\}$ with those who participated in all three waves of the surveys (937 out of 2,763).¹³ By comparing the regression coefficients on the interaction terms between the treatment dummies with prior expectations across three waves ($\beta_{3,k}^{\text{wave1}} - \beta_{3,k}^{\text{wave3}}$), 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.¹⁴ 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.

¹³We 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.

¹⁴See 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 ($Z = u$)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$E_{it}^{\text{post}}[Z_{t+12}]$												
Wave 1 ×												
treat_cpi	1.49*** (0.28)	1.50*** (0.28)	1.46*** (0.26)	1.60*** (0.27)	1.58*** (0.23)	1.35*** (0.24)	0.09 (0.19)	0.40* (0.22)	-0.76*** (0.23)	-0.76*** (0.24)	-0.30 (0.22)	-0.74*** (0.23)
treat_wage	1.10*** (0.26)	1.05*** (0.26)	0.93*** (0.24)	1.12*** (0.25)	2.97*** (0.22)	2.88*** (0.23)	3.91*** (0.18)	2.96*** (0.21)	-0.01 (0.24)	-0.08 (0.25)	0.06 (0.24)	0.03 (0.24)
treat_cpi × $E_{it}^{\text{prior}}[Z_{t+12}]$	-0.22*** (0.03)	-0.24*** (0.03)	-0.21*** (0.03)	-0.24*** (0.03)	-0.18*** (0.02)	-0.10*** (0.02)	-0.01 (0.02)	-0.22*** (0.02)	0.14*** (0.03)	0.14*** (0.03)	0.04 (0.03)	0.14*** (0.03)
treat_wage × $E_{it}^{\text{prior}}[Z_{t+12}]$	-0.10*** (0.03)	-0.10*** (0.03)	-0.08** (0.03)	-0.10*** (0.03)	-0.23*** (0.02)	-0.19*** (0.03)	-0.78*** (0.02)	-0.15*** (0.02)	-0.01 (0.03)	0.00 (0.03)	-0.06* (0.03)	-0.02 (0.03)
Wave 2 ×												
treat_cpi	1.75*** (0.27)	1.71*** (0.27)	1.83*** (0.29)	1.84*** (0.28)	0.90*** (0.22)	0.70*** (0.23)	0.97*** (0.20)	0.46** (0.23)	-0.42* (0.23)	-0.55** (0.24)	-0.38 (0.25)	-0.39 (0.25)
treat_wage	0.38 (0.26)	0.31 (0.26)	0.26 (0.28)	0.24 (0.26)	2.38*** (0.22)	2.24*** (0.23)	3.36*** (0.19)	2.48*** (0.21)	0.93*** (0.24)	0.91*** (0.25)	0.91*** (0.26)	0.71*** (0.25)
treat_cpi × $E_{it}^{\text{prior}}[Z_{t+12}]$	-0.26*** (0.03)	-0.26*** (0.03)	-0.28*** (0.03)	-0.28*** (0.03)	-0.31*** (0.02)	-0.30*** (0.02)	-0.31*** (0.03)	-0.25*** (0.03)	0.10*** (0.03)	0.12*** (0.03)	0.08** (0.04)	0.08** (0.04)
treat_wage × $E_{it}^{\text{prior}}[Z_{t+12}]$	-0.04 (0.03)	-0.03 (0.03)	-0.01 (0.03)	-0.02 (0.03)	-0.54*** (0.03)	-0.53*** (0.03)	-0.69*** (0.03)	-0.59*** (0.03)	-0.17*** (0.03)	-0.17*** (0.03)	-0.17*** (0.04)	-0.15*** (0.04)
Wave 3 ×												
treat_cpi	1.31*** (0.27)	1.13*** (0.27)	0.89*** (0.26)	1.05*** (0.27)	0.82*** (0.22)	0.54** (0.23)	0.16 (0.18)	0.08 (0.21)	-0.20 (0.23)	-0.25 (0.25)	-0.43* (0.23)	-0.21 (0.25)
treat_wage	1.04*** (0.25)	0.97*** (0.26)	1.14*** (0.24)	0.89*** (0.25)	2.01*** (0.22)	1.96*** (0.23)	2.91*** (0.17)	1.93*** (0.21)	-0.08 (0.24)	-0.18 (0.25)	0.46** (0.23)	0.14 (0.24)
treat_cpi × $E_{it}^{\text{prior}}[Z_{t+12}]$	-0.08** (0.03)	-0.06* (0.03)	-0.01 (0.03)	-0.04 (0.03)	-0.36*** (0.02)	-0.30*** (0.03)	-0.08*** (0.02)	-0.13*** (0.03)	0.06* (0.03)	0.06* (0.03)	0.09*** (0.03)	0.07* (0.04)
treat_wage × $E_{it}^{\text{prior}}[Z_{t+12}]$	-0.16*** (0.03)	-0.15*** (0.03)	-0.10*** (0.03)	-0.10*** (0.03)	-0.40*** (0.03)	-0.40*** (0.03)	-0.65*** (0.02)	-0.40*** (0.03)	-0.01 (0.03)	0.02 (0.03)	-0.11*** (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, age², 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 ($Z = u$)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\mathbb{E}_i^{\text{post}}[Z_{t+12}]$												
treat_cpi	2.21*** (0.29)	2.13*** (0.30)	1.94*** (0.30)	2.27*** (0.29)	1.06*** (0.25)	1.29*** (0.26)	1.13*** (0.26)	1.34*** (0.24)	-0.37 (0.30)	-0.43 (0.32)	-0.57** (0.29)	-0.14 (0.30)
treat_wage	0.89*** (0.28)	0.80*** (0.30)	0.30 (0.30)	0.80*** (0.27)	1.66*** (0.25)	2.09*** (0.25)	3.01*** (0.25)	2.66*** (0.23)	0.62** (0.30)	0.61* (0.32)	0.64** (0.29)	0.52* (0.30)
treat_cpi \times $\mathbb{E}_i^{\text{prior}}[Z_{t+12}]$	-0.36*** (0.03)	-0.35*** (0.03)	-0.29*** (0.03)	-0.34*** (0.03)	-0.17*** (0.02)	-0.32*** (0.02)	-0.37*** (0.02)	-0.42*** (0.02)	0.09** (0.04)	0.11*** (0.04)	0.12*** (0.04)	0.05 (0.04)
treat_wage \times $\mathbb{E}_i^{\text{prior}}[Z_{t+12}]$	-0.17*** (0.03)	-0.16*** (0.03)	-0.03 (0.03)	-0.12*** (0.03)	-0.22*** (0.02)	-0.40*** (0.02)	-0.64*** (0.03)	-0.57*** (0.02)	-0.12*** (0.04)	-0.12*** (0.04)	-0.13*** (0.04)	-0.10*** (0.04)
$\mathbb{E}_i^{\text{prior}}[Z_{t+12}]$	0.80*** (0.02)	0.80*** (0.02)	0.88*** (0.02)	0.89*** (0.02)	0.40*** (0.02)	0.57*** (0.02)	0.85*** (0.02)	0.75*** (0.02)	0.83*** (0.03)	0.83*** (0.03)	0.84*** (0.03)	0.89*** (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, age², 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 ($Z = u$)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\mathbb{E}_i^{\text{post}}[Z_{t+12}]$												
treat_cpi	1.58*** (0.32)	1.49*** (0.33)	1.34*** (0.30)	1.07*** (0.32)	1.06*** (0.23)	0.75*** (0.24)	0.70*** (0.21)	0.35* (0.21)	0.17 (0.30)	0.14 (0.33)	-0.03 (0.30)	0.20 (0.29)
treat_wage	1.58*** (0.32)	1.49*** (0.33)	1.34*** (0.30)	1.07*** (0.32)	1.06*** (0.23)	0.75*** (0.24)	0.70*** (0.21)	0.35* (0.21)	0.17 (0.30)	0.14 (0.33)	-0.03 (0.30)	0.20 (0.29)
treat_cpi \times $\mathbb{E}_i^{\text{prior}}[Z_{t+12}]$	-0.18*** (0.03)	-0.18*** (0.04)	-0.09*** (0.03)	-0.12*** (0.03)	-0.40*** (0.02)	-0.33*** (0.02)	-0.26*** (0.02)	-0.17*** (0.02)	-0.02 (0.04)	-0.02 (0.04)	0.01 (0.04)	-0.01 (0.04)
treat_wage \times $\mathbb{E}_i^{\text{prior}}[Z_{t+12}]$	-0.18*** (0.03)	-0.17*** (0.03)	-0.14*** (0.03)	-0.10*** (0.03)	-0.43*** (0.02)	-0.44*** (0.02)	-0.54*** (0.02)	-0.44*** (0.02)	-0.01 (0.04)	0.01 (0.04)	-0.09** (0.04)	-0.02 (0.04)
$\mathbb{E}_i^{\text{prior}}[Z_{t+12}]$	0.73*** (0.03)	0.74*** (0.03)	0.85*** (0.02)	0.81*** (0.02)	0.71*** (0.02)	0.66*** (0.02)	0.80*** (0.02)	0.77*** (0.02)	0.93*** (0.03)	0.91*** (0.03)	0.95*** (0.03)	0.95*** (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, age², 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 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.¹⁵ 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 0.05.¹⁶

¹⁵For more detail, see help for STATA's `rreg` command. Or see Appendix C of [Coibion et al. \(2019\)](#).

¹⁶[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.

E Examples of the Main Task

Treatment groups

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

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

Consumer Price Index Search Consumer Price

CPI Home | CPI Publications | CPI Data | CPI Methods | About CPI | Contact CPI

Consumer Price Index (CPI) News Release

CPI for all items rises 0.8% in February; gasoline, shelter, food indexes rise

03/10/2022 (A) (B) (C)

In February, the Consumer Price Index for All Urban Consumers rose 0.8 percent, seasonally adjusted, and rose 7.9 percent over the last 12 months, not seasonally adjusted. The index for all items less food and energy increased 0.5 percent in February (SA); up 6.4 percent over the year (NSA).

[HTML](#) | [PDF](#) | [RSS](#) | [Charts](#) | [Local and Regional CPI](#)

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 E.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 payrolls by industry sector, seasonally adjusted

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

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	Average hourly earnings of all employees in the private sector in the U.S. (omit \$ symbol)	
	mm/dd/yyyy (A)	in March 2021 (B)	in March 2022 (C)
Your answer	<input type="text"/>	<input type="text"/>	<input type="text"/>

Figure E.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>

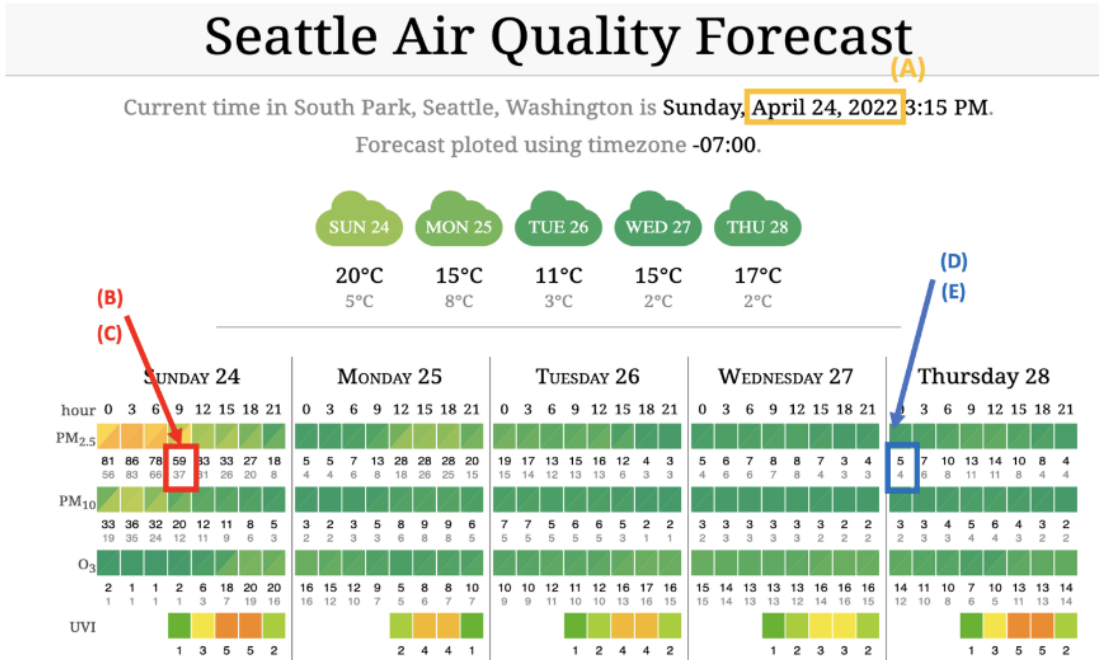
Table.

	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	<input type="text"/>	<input type="text"/>	<input type="text"/>

Control groups

Figure E.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	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>

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

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

Vaccinations

The U.S. COVID-19 Vaccination Program began December 14, 2020. As of April 20, 2022, 70.5 million vaccine doses have been administered in the United States. Overall, about 256.9 million people, or 77.4% of the total U.S. population, have received at least one dose of vaccine. About 219.0 million people, or 66.0% of the total U.S. population, have been fully vaccinated.* Of those fully vaccinated, about 99.7 million people have received a booster dose,** but 49.6% of the total booster-eligible population has not yet received a booster dose. As of April 20, 2022, the 7-day average number of administered vaccine doses reported (by date of CDC report) to CDC per day was 470,903, a 13.2% decrease from the previous week.

CDC's COVID Data Tracker displays vaccination trends by age group, race/ethnicity, and urban/rural status. To see trends by age group and race/ethnicity, visit the [Vaccination Demographic Trends](#) tab. To see trends by urban/rural status, visit [the COVID-19 Vaccination Equity](#) tab.

Daily Change in the Total Number of Administered COVID-19 Vaccine Doses Reported to CDC by the Date of CDC Report, United States

7-Day moving average

[View Larger](#)

[More Vaccination Data](#)

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

Table.

	Date of the report mm/dd/yyyy (A)	Total COVID Vaccination Rates (At least one dose)		Total COVID Vaccination Rates (Fully Vaccinated)	
		Count (in millions) (B1)	Percent of the US Population (B2)	Count (in millions) (C1)	Percent of the US Population (C2)
Your answer	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>

Note. Ignore % symbol during transcription.

F 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

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 $\$e\{\text{Selected Choice} + 0.05\}$ 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 $\text{\$}$ {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 April... = **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 April... =
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 April... =
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.

Consumer Price Index Search Consumer Price Go

CPI Home | CPI Publications | CPI Data | CPI Methods | About CPI | Contact CPI

Consumer Price Index (CPI) News Release

CPI for all items rises 0.8% in February; gasoline, shelter, food indexes rise

03/10/2022 (A) (B) (C)

In February, the Consumer Price Index for All Urban Consumers rose 0.8 percent, seasonally adjusted, and rose 7.9 percent over the last 12 months, not seasonally adjusted. The index for all items less food and energy increased 0.5 percent in February (SA); up 6.4 percent over the year (NSA).

[HTML](#) | [PDF](#) | [RSS](#) | [Charts](#) | [Local and Regional CPI](#)

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 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 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 $\$ \{ \text{your answer in F1} \}$ months, which corresponds to $\$ \{ 10 * \text{your answer in F1} \}$ minutes of your time. What is the **lowest total** reward that you would accept to work? (in USD)

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

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

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 $\$e\{0.4 * \text{your answer in F1}\}$

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

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

Yes

No

Display This Question:

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

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

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

F3_1 What is the smallest reward you would accept for $\$\{\text{your answer in F1}\}$ ten-minute HITs (total $\$e\{10 * \text{your answer in F1}\}$ 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 would... = fewer hours than today

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