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, cross-learning, labor supply, wage-price spiral, randomized control trial

JEL Codes: E31, C83, D84, 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 the interactions 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 it requires data 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, individual decisions could reflect many unobserved factors that 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 causal 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] Specifically, we offered MTurk workers the opportunity to complete a series of short

[1] During this period, the U.S. experienced exceptionally high inflation rates. In June 2022, CPI inflation reached its

forecasting and text transcription tasks related to price inflation expectations, wage inflation expectations, and unemployment rate expectations, resembling a typical MTurk on-demand task. Using *randomized* information provision, we generated exogenous shifts in workers' expectations about these macroeconomic variables, which allows us to identify causal effects on workers' behavior (see Haaland, Roth, and Wohlfart, 2023). We examine i) how workers update their expectations about macroeconomic variables, and ii) how the resulting revision of expectations affects labor supply, measured by reservation wages and desired employment duration in our project. While existing research relies on eliciting labor supply preferences using answers to *hypothetical* questions about labor supply response to shifts in macroeconomic expectations, our experimental setting allows us to capture the *actual* labor supply response. To incentivize MTurk workers to truthfully reveal their labor supply preferences, we credibly offered them future employment based on the conditions they provided.

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*, a phenomenon commonly referred to as *cross-learning*. For example, upon receiving information about the current CPI inflation rate, respondents updated not only their price inflation expectations but also their wage inflation and unemployment expectations. Similarly, they updated their price inflation and unemployment rate expectations when provided with information about aggregate hourly earnings inflation rates. The interactions between macroeconomic expectations provide insights into households' subjective models of the economy (Andre et al., 2022). In line with wage-price spiral theory, we find evidence of cross-learning between price and wage inflation expectations: an upward revision of one variable triggers an upward revision of the other. However, while price inflation expectations respond positively to revisions in unemployment expectations, the opposite is not true. This result contradicts the relationship predicted by the conventional Phillips curve and is broadly consistent with 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 the 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 reward 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 terms of employment on a similar project in the future.

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

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.

inflation expectations upwards, they *decrease* their reservation wages. We attribute this decrease in reservation wages to a worsening economic outlook due to inflation (Kamdar, 2019; Binder, 2020; Binetti, Nuzzi, and Stantcheva, 2024). 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.

Contribution to Literature. Our paper contributes to several strands of literature. First, it expands the literature on the formation of macroeconomic expectations and the relationships between them (see, for example, Armantier et al., 2016; Binder, 2020; Cavallo, Cruces, and Perez-Truglia, 2017; Coibion et al., 2021; Coibion, Gorodnichenko, and Weber, 2022; Weber et al., 2023) by documenting *cross-learning* between expectations about price inflation, wage inflation, and the unemployment rate when provided with information about only one of these variables.

To the best of our knowledge, our paper provides the most comprehensive coverage to date on the role of joint updating in macroeconomic expectations. According to Dafoe, Zhang, and Caughey (2018), if manipulating beliefs about a particular attribute affects a background attribute that may be relevant for the outcome of interest, it would violate the Information Equivalence assumption, which is necessary to estimate the causal effect of the information treatment. Haaland, Roth, and Wohlfart (2023) argue that such cross-learning may complicate or invalidate the interpretation of IV estimates exploiting randomized information provision unless the specification controls for posterior expectations of variables that could be indirectly affected by the treatment. So far, this issue has received limited attention in the empirical literature. While several papers measure the effect of information treatments about one variable on expectations about another variable, they do not examine the implications of such updating for decision-making (e.g., Roth and Wohlfart, 2020; Link et al., 2023; Hajdini et al., 2024; Jain, Kostyshyna, and Zhang, 2024).

Our setting allows us not only to document the effect of information provision on expectations about multiple macroeconomic variables and measure the pass-through between them but also to compare how results change depending on various specifications frequently encountered in the literature (for example, specifications lacking control for posterior expectations that can be affected by the treatment). Our results suggest that mishandling simultaneous updating of multiple expectations can significantly distort the findings.

Second, we contribute to the literature on the effects of macroeconomic expectations on individual decisions, specifically labor supply. In this context, labor market behavior has received relatively less attention than household consumption-saving decisions (e.g., D'Acunto, Hoang,

and Weber, 2015; Burke and Ozdagli, 2021; Vellekoop and Wiederholt, 2019; Coibion et al., 2023; Coibion, Gorodnichenko, and Weber, 2022) and housing investment decisions (e.g., Armona, Fuster, and Zafar, 2019; Bottan and Perez-Truglia, 2024). Several papers document that higher price inflation expectations increase the probability of job transitions, likely as an attempt to alleviate nominal rigidity (Bostanci, Koru, and Villalvazo, 2022; Pilossoph and Ryngaert, 2022; Hajdini et al., 2024). However, existing papers focus either on observational evidence or on self-reported responses to hypothetical questions. For example, Hajdini et al. (2024) study the planned changes in labor market behavior in the following months, and Pilossoph and Ryngaert (2022) complement the analysis of observational data with a hypothetical scenario about job search in a low versus high inflation setting. To our knowledge, our paper is the first study to empirically examine the *direct* causal relationship between inflation expectations and *actual* reservation wages. We show that, after controlling for aggregate wage inflation expectations, an increase in price inflation expectations *reduces* reservation wages. Such a labor supply response to inflation is consistent with recent evidence from Guerreiro et al. (2024) and Stantcheva (2024), which shows that workers avoid asking for a pay raise due to inflation unless the expected benefits outweigh the perceived costs. Instead, they engage in other ways to mitigate the real income decline, such as taking on an additional job.

Third, our paper contributes to the literature studying wage-price spirals and the role of workers expectations in generating these spirals. A large theoretical literature justifies how wage-price spirals can emerge and explores their policy implications, particularly how they can be effectively addressed (*e.g.*, Lucas and Rapping, 1969; Blanchard, 1986; Lorenzoni and Werning, 2023). However, previous macroeconomic studies have relied on observational data from different countries, which often suffer from inherent endogeneity (see, for example, Kandil, 2003; Boissay et al., 2022). Empirical evidence on the microfoundations of wage-price spirals, particularly the likelihood of workers demanding higher wages in response to anticipated price increases, remains limited. The existing literature primarily focuses on the relationship between realized inflation and the equilibrium outcomes of collective bargaining (Card, 1990; Christofides and Oswald, 1992; Cukierman and Lippi, 1999). By providing experimental evidence on the effect of expected inflation on the reservation wages of individual workers during a high inflation period, our paper evaluates the microfoundations of wage-price spiral theory.

Finally, our paper contributes to the literature on subjective models of the macroeconomy that guide the behavior of non-expert economic agents (Roth and Wohlfart, 2020; Andre et al., 2022, 2023). Recent literature provides insights into subjective models of the economy by exposing households to well-defined macroeconomic shocks and studying their perceived responses regarding inflation and unemployment (Andre et al., 2022; Binetti, Nuzzi, and Stantcheva, 2024). Our results complement this literature by providing evidence on how households shift their overall economic perspective and labor supply decisions in response to a single piece of relevant information about the macroeconomic environment–similar to what they would have learned from the news. Our findings indicate that households' subjective models differ from standard economic models. Consistent with prior literature, we find support for the supply-side or stagflationary

view of inflation among U.S. households (Kamdar, 2019; McClure et al., 2023). However, we also show that the positive link between expected inflation and unemployment is not symmetric, as inflation expectations have a small and statistically insignificant effect on unemployment expectations. The fact that respondents reduce their reservation wages in response to higher price inflation expectations, as if to insure against uncertainty in future labor markets, corroborates the story that households perceive inflation as a bad signal about the economy. Such a labor supply response to inflation could potentially weaken the wage-price spiral.

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 cross-learning 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) and Stantcheva (2023).

2.1 Survey Design

We implemented our survey via Amazon Mechanical Turk (MTurk), a crowdsourcing website for hiring remotely-located crowd workers to perform on-demand tasks, called HITs (Human Intelligence Tasks), in exchange for monetary rewards.[2] We posted our HITs on MTurk in April and May 2022 for the first wave of our survey. The workers self-selected into participation based on a brief description stating that the reward for completing this HIT is $1.50 and the average completion time is 10-15 minutes. We informed participants that the purpose of the HIT was to train a machine learning forecasting algorithm in order to motivate them to carefully answer forecasting questions and avoid experimenter demand effects. To ensure data quality, 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 U.S. economic variables, we restricted our sample to residents of the U.S. (*i.e.* those registered on 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]

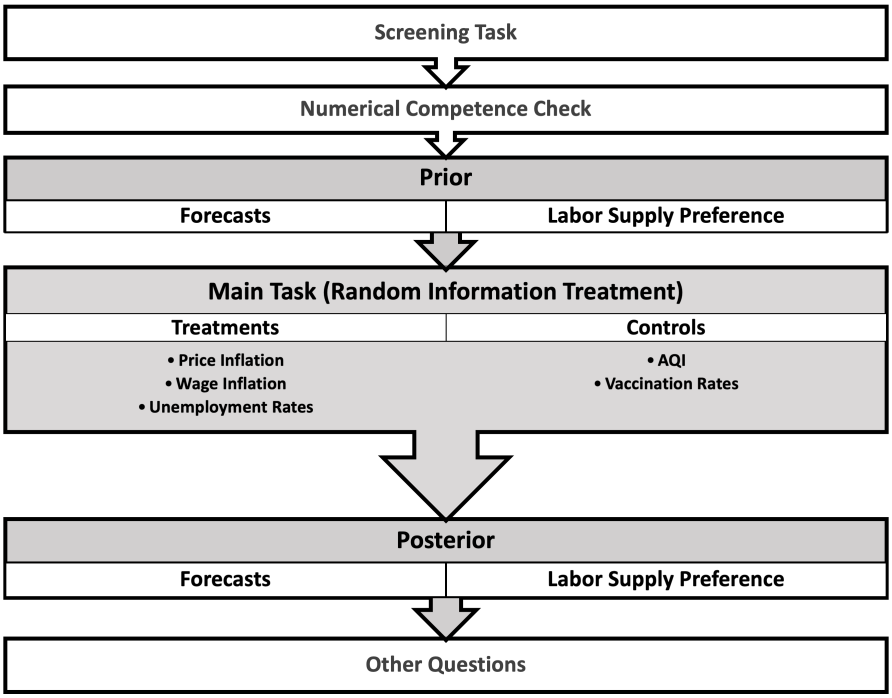
[2] See Dube et al. (2020) for an overview of findings on labor supply on MTurk.

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

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

Our survey consists of six blocks. Figure 1 summarizes our survey flow. The survey begins with a screening task and a numerical competence check. These are followed by the main part of the survey, which allows us to compare the initial forecasts and labor supply preferences with their revised versions. 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 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 Online Appendix[5].

Figure 1: Survey flow



Randomization was administered at the HIT allocation stage. In other words, we repeatedly posted batches of HITs that were identical in all parts except for the "Main Task" and the order of questions about expectations in the prior and posterior blocks. For each respondent who completed a HIT, we recorded an anonymized version of their ID, which was used to block them from participating in other HITs in the same wave and to enable them to participate in the follow-up HITs.

[5]The Online Appendix is available HERE.

Screening Task. Our survey starts with a screening task. The screening task follows a format similar to that of the main task, which is related to the information treatment. It tests participants' ability to accurately transcribe information from a screenshot. If participants answered the screening task incorrectly, they were directed to the end of the survey. If the answer was correct, they were prompted to participate in the rest of the survey. We included the screening task to ensure that only those who thoughtfully provided their best answers participated in the survey. Out of 10,758 MTurkers who attempted to participate in our survey, 7,457 passed the screening task and 5,487 completed the first wave of the survey. Most attrition occurred early in the survey due to inaccurate answers to the screening task or reluctance to complete numerical competence checks. Consequently, attrition is not systemically correlated with the information treatments (see Appendix A.1).

Numerical Competence Check. Upon successful completion of the screening task, participants were prompted to solve a few mathematical problems to evaluate their numerical competence. These questions assessed respondents' ability to convert pay per 10 minutes to hourly pay and to evaluate percentage changes based on absolute changes. Although respondents could proceed and complete our survey even if they answered these questions incorrectly, we included them to understand how many respondents were comfortable interpreting information treatments. In our sample, approximately 87% of participants answered at least two questions correctly, and about 75% answered all three questions correctly.

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 information on the terms (reservation rewards and duration of employment) under which respondents were willing to accept and complete follow-up HITs. First, we asked what the smallest reward would be 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. At the HIT allocation stage, respondents were randomly allocated into one of the five groups: three treatment groups and two control groups. Each group was provided with a different information treatment in the form of a text transcription task. Specifically, respondents were asked to transcribe information from a screenshot into a table. The information referred to official data about either macroeconomic variables of interest (price inflation, hourly earnings inflation, and unemployment rate for the treatment groups) or variables unrelated to the macroeconomic situation (air quality index in Seattle and Covid-19 vaccination rates for the control groups). Our identification strategy exploits exogenous variation in macroeconomic expectations for respondents in the treatment groups, *i.e.*, those provided with pertinent information, relative to those in the control groups. Examples of screenshots are available in Appendix E. For instance, participants assigned to the price inflation group were prompted with 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 the 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 incorrect transcription of the screenshot information would result in no payment for the entire HIT. We also included attention-check questions to verify the recall rates after completing 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) as well as other variables in the control group (air quality in Seattle and Covid-19 vaccination rates) again. We used similar but slightly different wording to avoid asking exactly the same questions. We then asked about their reservation wages and desired duration of employment again, using 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, and number of children. Furthermore, we asked some hypothetical labor supply questions regarding their day jobs in *of-*

fline 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 signaled to participants that answers to forecasting questions are very important for the project's success. The actual purpose of the survey 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, full disclosure could bias respondents' answers about labor supply decisions. Second, we wanted MTurkers to understand that our project is ongoing and involves follow-up HITs over a few months. Because MTurk is an *actual* labor market, we expected participants to believe that we would follow up with them based on their answers for the desired terms (rewards and duration), thereby encouraging them to provide their best answers. This approach 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 offering them an opportunity to work with us in the following month at the rate they requested. We extended follow-up invitations to 2,763 wave 1 respondents in two treatment groups (CPI and hourly earnings group) and one control group (AQI). Among them, 1,450 (about 52%) participated in the second and/or third waves, and 937 of them participated in all three waves.[6]

2.3 Descriptive Statistics

Table 1 provides descriptive statistics about 4,614 unique respondents.[7] 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. However, our respondents are more educated compared to the U.S. population, as is typical for MTurkers.[8] About 75% have a 4-year college degree or more. About 83% are either employed full-time or part-time. In other words, most of them have day jobs and not many use MTurk as their major income source. Nonetheless, they spend an average of 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.

[6] Appendix Table A.3 summarizes attrition from participation in the follow-up waves of the survey and Appendix Table A.5 reports the descriptive statistics.

[7] The analysis sample excludes 873 duplicate responses that occurred because respondents accepted multiple HITs posted simultaneously, circumventing our ID-blocking algorithm for repeat completions. For respondents who completed multiple HITs, we retained only their first response in the analysis. Given that HITs were identical by design, the treatment arm in which a respondent opted in first should be plausibly random, and including the first response should not distort results for wave 1. However, multiple treatments could have distorted expectations updating in the follow-up waves. Therefore, we excluded respondents who took up multiple treatments from follow-up analysis.

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

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. However, 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%, more than double the actual unemployment rate of around 3.5% in April and May 2022.[9] The average desired duration of employment on a monthly HIT like ours is 3.78 months, and the median respondent showed interest in working on such a HIT for the maximum offered duration. The average reservation wage is about $1 per 10 minutes of work, which is consistent with the reward for this HIT. Descriptive statistics about respondents in the second and the third waves are similar to those in Table 1 (see Appendix Table A.5).

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
cohabiting	0.70	0.00	1.00	1.00	0.46
number of children	0.97	0.00	1.00	2.00	1.10
monthly spending on food	$704.40	$150.00	$300.00	$600.00	$2591.86
monthly spending on gas	$289.68	$40.00	$100.00	$200.00	$1756.90
$\mathbb{E}_t^{\texttt{prior}}[\pi_{t+12}]$	6.12	1.00	5.00	10.00	8.12
$\mathbb{E}_t^{\texttt{prior}}[\pi_{t+12}^w]$	7.22	1.00	4.00	10.00	11.31
$\mathbb{E}_t^{\texttt{prior}}[u_{t+12}]$	7.24	4.46	6.45	9.20	3.80
$\Delta^{\texttt{post-prior}}\mathbb{E}_t[\pi_{t+12}]$	0.53	-1.80	0.00	3.00	7.58
$\Delta^{\texttt{post-prior}}\mathbb{E}_t[\pi_{t+12}^w]$	-0.92	-3.00	0.00	2.00	11.60
$\Delta^{\texttt{post-prior}}\mathbb{E}_t[u_{t+12}]$	0.89	-1.18	0	1.96	5.01
$\mathbb{E}_t^{\texttt{prior}}[\texttt{duration}_{t+1}]$	3.76	2.00	5.00	5.00	1.53
$\mathbb{E}_t^{\texttt{prior}}[\texttt{reservation wages}_{t+1}]$	1.00	0.50	1.00	1.25	0.54
Observations	4,614				

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

Respondents across treatment arms vary in terms of demographic characteristics and prior expectations. This happens because we did not condition treatment allocation on observables, and randomization does not automatically ensure covariate balance in a single trial, potentially resulting in random confounding (Deaton and Cartwright, 2018). The main reason for the variation in observable characteristics is the fact that different people work on MTurk at different times.[10] We account for this by controlling for the day and time of survey fixed effects in all specifications, which explains most of the statistically significant differences across treatment arms (see Appendix Table A.4). To further mitigate the impact of potential covariate imbalance on our results, we include an extensive set of controls in the analysis. In addition to demographic and labor market characteristics, we control for prior expectations in all specifications to ensure that treatment is exogenous to the worker's preferences and information set.

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 examine if respondents update their expectations when they receive a relevant signal compared 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 and 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 indirect effect of information treatments, or cross-learning, *i.e.*, the revision of expectations about one macroeconomic variable in response to information about another macroeconomic variable. We then discuss the implications of cross-learning for understanding households' subjective models of the 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).

[10] The differences in demographic characteristics of MTurkers by day and time are evident from https://demographics.mturk-tracker.com//yearOfBirth/all.

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.[11] Comparing expectations revisions 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.[12] 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 the 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 or unemployment rate placed a lower weight on their respective priors and a higher weight on the signal than those in the control group.

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

[11] Respondents 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.

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

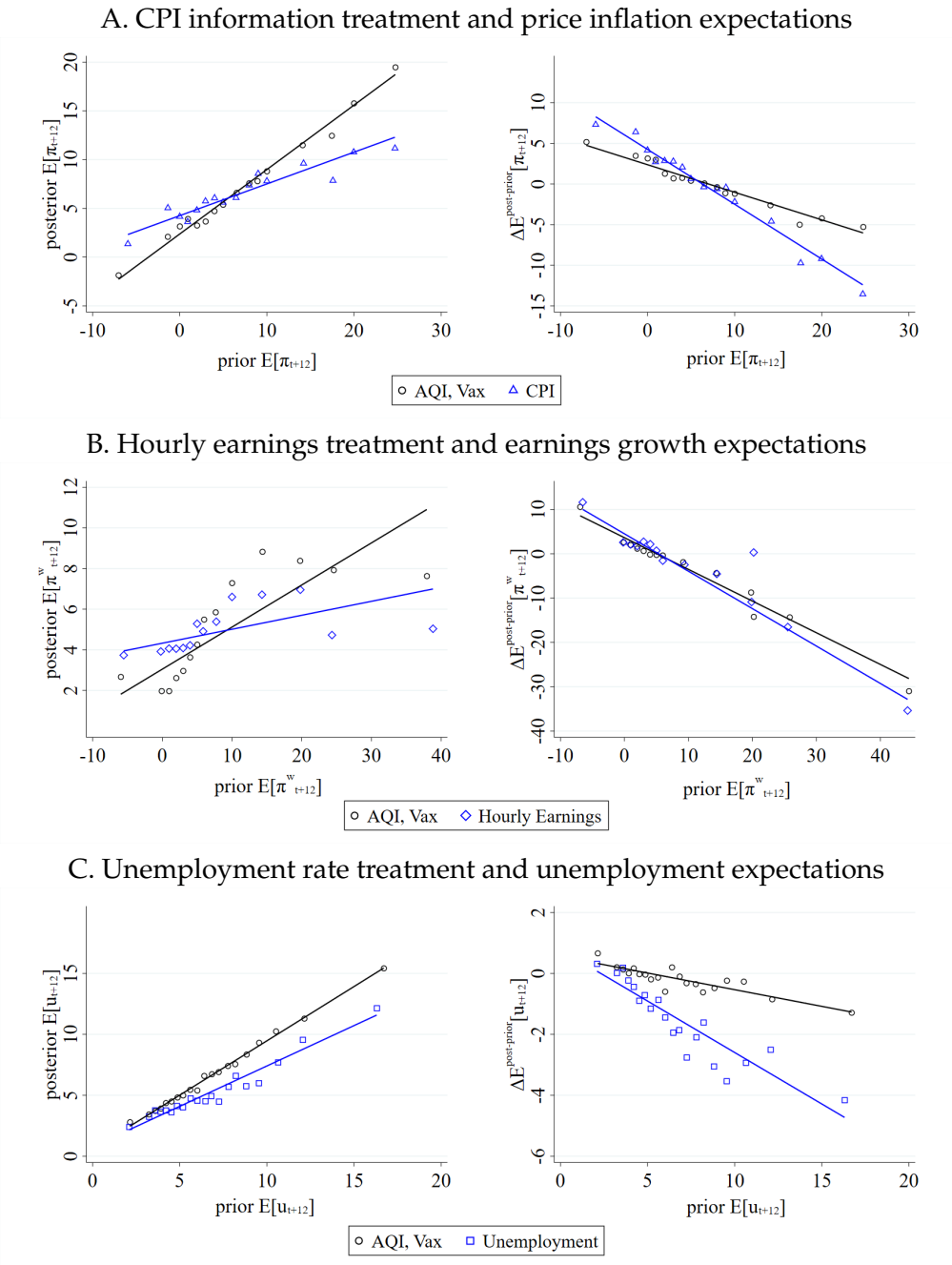
$$\mathbb{E}^{\text{post}}[Z_{t+12}] = (1-\alpha)\mathbb{E}^{\text{prior}}[Z_{t+12}] + \alpha\ Signal$$

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

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

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.

unemployment rate expectations:

$$\mathbb{E}_{it}^{\text{post}}[Z_{t+12}] = \alpha_0 + \alpha_1 \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}] + \alpha_2 \texttt{treat}_i^Z + \alpha_3 \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}] \times \texttt{treat}_i^Z + \mathbf{X}_i'\gamma + \varepsilon_i \quad (1)$$

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 $\texttt{treat}_i^Z$ is a treatment dummy denoting if a respondent i is in the treatment group that received a signal about variable Z. In other words, 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, Gorodnichenko, and Weber (2022), Coibion et al. (2023), Hajdini et al. (2024) 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 posterior price inflation, wage inflation, and unemployment expectations

Dependent variable:	Price inflation ($Z = \pi$)				Wage inflation ($Z = \pi^w$)				Unemployment rate ($Z = u$)			
$\mathbb{E}_{it}^{\text{post}}[Z_{t+12}]$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
treat_cpi	1.97***	2.09***	2.18***	2.47***								
	(0.23)	(0.53)	(0.53)	(0.49)								
treat_wage					1.29***	1.61***	2.34***	2.43***				
					(0.19)	(0.47)	(0.48)	(0.44)				
treat_unemp									0.05	-0.01	0.67**	0.47
									(0.23)	(0.33)	(0.33)	(0.30)
treat_cpi × $\mathbb{E}_{it}^{\text{prior}}[Z_{t+12}]$	-0.32***	-0.30***	-0.31***	-0.34***								
	(0.02)	(0.02)	(0.02)	(0.02)								
treat_wage × $\mathbb{E}_{it}^{\text{prior}}[Z_{t+12}]$					-0.16***	-0.15***	-0.32***	-0.26***				
					(0.01)	(0.01)	(0.02)	(0.02)				
treat_unemp × $\mathbb{E}_{it}^{\text{prior}}[Z_{t+12}]$									-0.19***	-0.18***	-0.30***	-0.28***
									(0.03)	(0.03)	(0.03)	(0.03)
$\mathbb{E}_{it}^{\text{prior}}[Z_{t+12}]$	0.62***	0.64***	0.74***	0.77***	0.22***	0.21***	0.40***	0.35***	0.88***	0.89***	0.92***	0.92***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(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 (who provided consistent answers to reservation wage questions asking first about a desired range and then desired level of pay). Control variables are female, age, age^2, white, whether cohabiting or not, whether having a child or not, full-time employed or not, logarithmic monthly spending on food, hours working at MTurk, 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 0.62-0.77 by 0.30-0.34 points. For wage inflation expectations (columns 5-8), respondents reduce the weight on prior from 0.21-0.40 by 0.15-0.32 points. Finally, for unemploy-

ment expectations (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 0.19-0.30 points. These results support the conclusion that information treatments effectively induce respondents to revise their expectations as intended.

The information treatment was the most successful at shifting household wage inflation expectations as households placed less than 40% weight on their prior expectations. It was also quite successful in shifting price inflation expectations with up to 77% weight placed on prior expectations. Unemployment expectations were the most anchored with over 80% weight placed on prior expectations. At the same time, each information treatment induced statistically significant shifts in relevant expectations. Overall, the analysis of direct treatment effects suggests that information treatment worked as intended.

3.2 Cross-Learning Between 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 is assumed to affect *only* expectations about price inflation and to have no effect on expectations about other variables. However, since many macroeconomic phenomena are interrelated, macroeconomic expectations about one variable may be responsive to signals about other macroeconomic variables. Moreover, cross-learning between price and wage inflation expectations is essential for the theory of wage-price spirals. To examine whether such cross-learning is 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., the wage growth rate or unemployment rate).

Graphical Evidence The graphical evidence regarding the direct and indirect effects of information treatments on macroeconomic expectations is summarized in Appendix B. As expected, there is indeed substantial cross-learning 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, cross-learning is limited for unemployment expectations, as they are largely unresponsive to signals about the wage inflation rate.

Regression Analysis To document the role of cross-learning 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 $Z = \{\pi, \pi^w, u\}$.

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

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 $\texttt{treat} \times \mathbb{E}_{it}^{\texttt{prior}}[\pi_{t+12}]$). The implied weight on the prior price inflation expectation falls from 0.63-0.76 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 decreased 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 work on the effects of information treatment on inflation expectations (see, for example, Binder, 2020; Cavallo, Cruces, and Perez-Truglia, 2017; Coibion, Gorodnichenko, and Weber, 2022; Coibion 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 0.22-0.38 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).

Cross-learning is 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. When provided with information about the current unemployment rate, respondents significantly revised their unemployment rate expectations toward the signal (the implied weight on the prior expectations decreased from 0.87-0.91 by 0.14-0.26). 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 (Kamdar, 2019; Andre et al., 2022), where the inflation-unemployment tradeoff in macroeconomic policies plays a limited role (Binetti, Nuzzi, and Stantcheva, 2024).

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

Dependent variable:	Price inflation ($Z = \pi$)				Wage inflation ($Z = \pi^w$)				Unemployment rate ($Z = u$)			
$\mathbb{E}_{it}^{post}[Z_{t+12}]$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
treat_cpi	2.02***	2.06***	2.17***	2.40***	0.89***	0.90*	1.61***	1.30***	-0.11	-0.54	-0.79**	-0.59*
	(0.23)	(0.53)	(0.55)	(0.50)	(0.20)	(0.48)	(0.51)	(0.45)	(0.22)	(0.36)	(0.33)	(0.32)
treat_wage	1.21***	1.36**	1.65***	1.91***	1.28***	1.59***	2.28***	2.46***	-0.12	-0.48	-0.28	-0.19
	(0.22)	(0.53)	(0.55)	(0.50)	(0.20)	(0.48)	(0.52)	(0.46)	(0.22)	(0.36)	(0.34)	(0.32)
treat_unemp	-0.25	0.22	0.73	0.10	-0.34	0.50	1.20**	1.00**	-0.19	-0.34	0.43	0.32
	(0.27)	(0.54)	(0.57)	(0.52)	(0.23)	(0.49)	(0.53)	(0.47)	(0.26)	(0.38)	(0.37)	(0.34)
treat_cpi $\times$ $\mathbb{E}_{it}^{prior}[Z_{t+12}]$	-0.33***	-0.30***	-0.31***	-0.34***	-0.15***	-0.16***	-0.30***	-0.26***	0.09***	0.11***	0.11***	0.11***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
treat_wage $\times$ $\mathbb{E}_{it}^{prior}[Z_{t+12}]$	-0.26***	-0.25***	-0.31***	-0.29***	-0.16***	-0.15***	-0.30***	-0.26***	0.04	0.06*	-0.01	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
treat_unemp $\times$ $\mathbb{E}_{it}^{prior}[Z_{t+12}]$	-0.08***	-0.07**	-0.04	-0.11***	-0.07***	-0.07***	-0.22***	-0.17***	-0.14***	-0.11***	-0.26***	-0.25***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
$\mathbb{E}_{it}^{prior}[Z_{t+12}]$	0.63***	0.63***	0.73***	0.76***	0.23***	0.22***	0.38***	0.35***	0.87***	0.87***	0.91***	0.91***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Sample	All	All	Numerate	Consistent	All	All	Numerate	Consistent	All	All	Numerate	Consistent
N	4611	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, age^2, white, whether cohabiting or not, whether having a child or not, full-time employed or not, logarithmic monthly spending on food, hours working at MTurk, 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.

While information treatments induce respondents to revise macroeconomic expectations in the short run, the data for the follow-up waves show that these effects persist over a longer horizon 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. 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).

3.3 Pass-Through From and to Inflation Expectations

The results in Section 3.2 suggest that MTurkers update expectations about multiple variables in response to one piece of relevant information. However, the estimates are not convenient to interpret numerically because they do not imply a clear mapping from expectations about one variable to expectations about another variable.

This section examines the effect of updating expectations about variable $Y = \{\pi, \pi^w, u\}$ through expectations about other variable Z. We estimate it by comparing the responses of expectations about variable Y of workers who received information about variable $Z \neq Y$ with those of workers in the control group using the 2SLS approach. The second stage is estimated using Equation

(3), and the first stage is estimated using Equation (1). The results are reported in Table 4.

$$\mathbb{E}_{it}^{\text{post}}[Y_{t+12}] = \beta_0 + \beta_1 \mathbb{E}_{it}^{\text{post}}[Z_{t+12}] + \beta_2 \mathbb{E}_{it}^{\text{prior}}[Y_{t+12}] + \beta_3 \mathbb{E}_{it}^{\text{prior}}[Z_{t+12}] + \mathbf{X}_{it}'\delta + \nu_i \tag{3}$$

Panel A of Table 4 shows that there is a 22-38% pass-through from wage inflation expectations to price inflation expectations. The pass-through is smaller for numerate respondents and those with consistent answers to reservation wage questions, but it remains statistically significant in most specifications. Panel B shows that the pass-through from price inflation expectations to wage inflation expectations is 26-36%, and it is statistically significant in all specifications. This estimate is only slightly higher than 20% pass-through from price inflation expectations to expected personal income growth according to Hajdini et al. (2024). Assuming that pass-through to subjective income growth expectations is similar in our sample, this result suggests that respondents perceive aggregate wages to grow somewhat faster than their earnings. The fact that it is the highest for numerate respondents suggests that they are most likely to perceive price inflation as an essential factor for wage-setting.

Table 4: Pass-Through Between Macroeconomic Expectations

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: *Pass-through to* $\mathbb{E}_{it}^{post}[\pi_{t+12}]$						
from						
$\mathbb{E}_{it}^{\text{post}}[\pi_{t+12}^{w}]$	0.31**	0.38***	0.24***	0.26***	0.22**	0.19
	(0.13)	(0.15)	(0.09)	(0.09)	(0.11)	(0.12)
$\mathbb{E}_{it}^{\text{post}}[u_{t+12}]$	0.55***	0.34	0.38***	0.30	0.40***	0.20
	(0.17)	(0.61)	(0.14)	(0.28)	(0.13)	(0.27)
Panel B: *Pass-through to* $\mathbb{E}_{it}^{post}[\pi_{t+12}^{w}]$						
from						
$\mathbb{E}_{it}^{\text{post}}[\pi_{t+12}]$	0.26***	0.27***	0.36***	0.36***	0.25***	0.26***
	(0.09)	(0.09)	(0.10)	(0.10)	(0.09)	(0.09)
$\mathbb{E}_{it}^{\text{post}}[u_{t+12}]$	0.48***	0.33	0.19	0.18	0.26**	0.07
	(0.17)	(0.69)	(0.16)	(0.36)	(0.13)	(0.29)
Panel C: *Pass-through to* $\mathbb{E}_{it}^{post}[u_{t+12}]$						
from						
$\mathbb{E}_{it}^{\text{post}}[\pi_{t+12}]$	-0.04	-0.03	-0.08*	-0.06	-0.01	-0.02
	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
$\mathbb{E}_{it}^{\text{post}}[\pi_{t+12}^{w}]$	-0.10	-0.18**	-0.04	-0.03	-0.09*	-0.11*
	(0.08)	(0.09)	(0.04)	(0.04)	(0.05)	(0.06)
Sample	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes

Notes: This table presents the Huber-Robust regression output from equation (3) summarizing the pass-through of expectations about the variable specified in the row to the variable specified in the panel subtitle. Control variables include female, age, age^2, white, whether cohabiting or not, whether having a child or not, full-time employed or not, logarithmic monthly spending on food, hours working on 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.

The pass-through from unemployment expectations to price inflation expectations is even larger, up to 55%, but it may be partially driven by differences in observables, as the effect becomes statistically insignificant after accounting for controls.[13]. Unemployment expectations also have a significant pass-through to wage inflation expectations in some specifications but it also becomes insignificant after accounting for controls. A positive effect of unemployment expectations on either price or wage inflation contradicts the downward-sloped Phillips curve. However, at least in the numerate sample, such a relationship is not statistically significant. Additionally, the pass-through is not symmetric: according to Panel C, unemployment expectations are largely unresponsive to either price or wage inflation expectations and the statistically significant coefficients have a negative sign. Our result about largely asymmetric pass-through between inflation and unemployment expectations contrasts with the existing evidence about the joint response of inflation and unemployment expectations to various shocks (Andre et al., 2022; Binetti, Nuzzi, and Stantcheva, 2024). Since we do not provide respondents with a well-defined shock, a portion of the observed asymmetry could be driven by heterogeneity in beliefs about shocks underlying a particular inflation pattern. Another explanation is that the aggregate unemployment rate is not very relevant measure of aggregate economic performance for those employed online.

Economic Implications The presence of cross-learning has important implications for understanding the behavior of economic agents. The fact that households revise their expectations about *multiple* macroeconomic variables when provided with 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 for the likelihood that overall economic situation will deteriorate 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 cross-learning between macroeconomic expectations, i.e., the analysis of household behavior under the assumption that only 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 cross-learning between macroeconomic expectations on labor supply decisions and discusses their implications for understanding the risks of wage-price spirals for inflation dynamics in the U.S. in 2022.

[13]The correlation between inflation and unemployment expectations is consistently positive and robust to accounting for controls (see Appendix B.3)

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 is nontrivial cross-learning 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:

$$\begin{aligned} Y_{it}^{\texttt{post}} = \beta_0 &+ \beta_1 \mathbb{E}_{it}^{\text{post}}[\pi_{t+12}] + \beta_2 \mathbb{E}_{it}^{\text{post}}[\pi_{t+12}^{w}] + \beta_3 \mathbb{E}_{it}^{\text{post}}[u_{t+12}] \\ &+ \gamma_0 Y_{it}^{\texttt{prior}} + \gamma_1 \mathbb{E}_{it}^{\text{prior}}[\pi_{t+12}] + \gamma_2 \mathbb{E}_{it}^{\text{prior}}[\pi_{t+12}^{w}] + \gamma_3 \mathbb{E}_{it}^{\text{prior}}[u_{t+12}] + \mathbf{X}_{it}'\delta + \eta_i \end{aligned} \tag{4}$$

where $Y_{it} = \{\overline{\texttt{rw}}_{it,t+\texttt{dur}_t}^{\texttt{post}}, \texttt{dur}_{it}^{\texttt{post}}\}$ 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 (4), 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.[14] 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 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

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

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.

Table 5: Effects of expectations on reservation wages

	Reservation Wages (in cents)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	-0.87	0.07	-1.39**	-1.21**	-1.47**	-1.24*
	(0.76)	(0.83)	(0.56)	(0.61)	(0.67)	(0.72)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	2.39***	1.46**	0.87**	0.64*	0.65	0.51
	(0.83)	(0.71)	(0.36)	(0.35)	(0.43)	(0.47)
$\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	-1.81*	1.78	0.61	1.21	0.10	1.84*
	(0.96)	(1.88)	(0.76)	(1.11)	(0.72)	(1.06)
N	3,330	3,330	2,280	2,280	2,305	2,305
Sample	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	10.33	14.90	16.35	25.32	13.30	21.87
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	15.01	17.54	37.62	63.20	37.18	44.92
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	25.64	8.68	32.13	23.29	32.95	22.92

Notes: This table presents the regression output to estimate the effects of expectations on reservation wages in the online labor market according to Equation (4). We instrument the posterior expectations with treatment dummies and their interactions with the priors, as specified in footnote 14. The numerate sample consists of respondents who answered all the numerical competence check questions correctly. The consistent sample consists of respondents who provided consistent answers to distinct reservation wage questions. Sanderson and Windmeijer (2016) multivariate F-statistics 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 5 reports the effect of posterior macroeconomic expectations on the reservation wages per 10 minutes of respondents' time, accounting for the presence of cross-learning. 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 results in a 1.46-2.39 cent reservation wage increase per 10 minutes in the overall sample and a 0.64-0.87 cent increase in the numerate sample. This corresponds to about a 0.6 to 2.5 *percent* increase given the average/median reward per 10 minutes of $1. Yet, in the consistent sample, where respondents likely thought about reservation wage questions more carefully and recognized that wages in the online markets are set in a particular way, expected wage inflation has no statistically significant effect on reservation wages. 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.[15] 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.

[15]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

The unemployment rate, after controlling for other macroeconomic expectations, does not have a statistically significant effect on reservation wages except for the consistent sample.

Effects on Desired Duration of Employment on MTurk In addition to asking workers about the pay they would be willing to accept for 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. In contrast to reservation wages, macroeconomic expectations do not significantly affect the probability that workers want to increase the employment duration *with us* after the information treatment (Appendix Table C.1).[16] This result, however, should not be interpreted as the absence of an 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.

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. However, the results still provide insight into how inflation expectations may affect offline labor market behavior. The main result is that for numerate workers and workers who provided consistent answers to reservation wage questions, higher price inflation expectations imply a significantly higher subjective probability of being employed by a different employer (Table 6). On the other hand, respondents with higher wage inflation expectations report a lower subjective probability 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.[17] These findings are consistent with the evidence in the literature that higher inflation expectations increase the likelihood of job-to-job transitions (Hajdini et al., 2024; Pilossoph and Ryngaert, 2022; Bostanci, Koru, and Villalvazo, 2022).

4.2 Evidence From Alternative Specifications

The results discussed in Section 4.1 account for the role of cross-learning between macroeconomic expectations. However, unlike Equation (4), 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. A common reason for such an assump-

provide detailed numerical values. We refer to respondents as consistent if they provided answers that matched these two questions.

[16] This result is robust to the use of the alternative dependent variable, the desired duration of employment *in months*.

[17] Appendix Table C.2 also provides suggestive evidence that higher price inflation expectations may increase the subjective probability of non-employment, but the magnitude of the coefficients is much smaller than for unemployment expectations.

Table 6: Effects of macroeconomic expectations on the subjective probability of switching to a different employer

	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	0.71*	0.46	1.04***	0.44	0.94**	0.63*
	(0.36)	(0.30)	(0.36)	(0.28)	(0.38)	(0.36)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	-0.53	-0.22	-1.01***	-0.43*	-0.74***	-0.68**
	(0.37)	(0.31)	(0.33)	(0.24)	(0.28)	(0.27)
$\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	2.30***	1.20**	1.84***	0.28	1.81***	0.98***
	(0.35)	(0.51)	(0.37)	(0.38)	(0.30)	(0.36)
N	2,946	2,946	1,967	1,967	1,935	1,935
Sample	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	5.69	7.98	6.66	11.94	7.30	10.01
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	7.78	7.81	11.66	13.22	14.94	16.92
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	15.79	9.04	24.71	23.64	24.77	24.46

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

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

We instrument the posterior expectations with treatment dummies and their interactions with the priors, as specified in footnote 14. The numerate sample consists of respondents who answered all the numerical competence check questions correctly. The consistent sample consists of respondents who provided consistent answers to distinct reservation wage questions.Heteroskedasticity-robust-standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sanderson and Windmeijer (2016) multivariate F-statistics 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.

tion is the limitations of the data. In the presence of cross-learning, such a strategy could result in omitted variable bias that may critically affect the conclusions.

This section discusses how the results for the reservation wages in Table 5 would change if we deviated from our preferred specification by excluding variables capturing the simultaneous revision of expectations that are commonly omitted by researchers. Table 7 reports the results for the effect of price inflation expectations.

Panel A exploits only the variation in updating expectations in a single treatment arm relative to the control group. Consistent with our preferred specification, the results suggest that higher inflation expectations decrease reservation wages by up to 2%. However, it is less precisely estimated due to the smaller sample size. Another issue is that it pools together the direct and indirect effects of inflation expectations on reservation wages. Given the discussion in Section 3.2, wage inflation expectations are an omitted variable positively correlated with both reservation wages and price inflation expectations. Therefore, the coefficients in Panel A suffer from an upward bias.

Panel B relaxes the limitation of the small sample size by using data from all treatment arms, not only the treatment arm of interest, but it considers those receiving information about macroeconomic variables other than price inflation as similar to the control group. Similar to Panel A, it would provide an unbiased coefficient of the effect of inflation expectations on labor supply only if

Table 7: Effect of price inflation expectations on reservation wages based on alternative specifications

	Reservation Wages (in cents)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Single treatment arm vs control group					
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$ (IV)	-1.10	-0.59	-1.23	-1.26	-1.97**	-1.51*
	(0.93)	(0.94)	(0.78)	(0.82)	(0.98)	(0.91)
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	21.04	35.99	25.61	49.19	20.28	47.04
N	2,078	2,078	1,439	1,439	1,421	1,421
Panel B	Other treatment arms considered as a control group					
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$ (IV)	-2.78***	-1.19	-1.84*	-1.87	-3.33**	-2.14*
	(1.07)	(1.19)	(1.09)	(1.29)	(1.44)	(1.17)
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	26.71	29.61	18.20	24.54	16.82	41.18
N	3,330	3,330	2,280	2,280	2,305	2,305
Panel C	All treatment arms without posterior controls					
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$ (IV)	-0.83	-0.29	-1.10**	-1.13**	-1.42**	-1.24*
	(0.57)	(0.63)	(0.49)	(0.54)	(0.63)	(0.67)
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	28.15	38.73	34.99	57.33	27.88	44.67
N	3,330	3,330	2,280	2,280	2,305	2,305
Panel D	All treatment arms with posterior controls					
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$ (IV)	-0.92	-0.35	-1.17**	-1.27**	-1.49**	-1.37*
	(0.62)	(0.69)	(0.54)	(0.59)	(0.68)	(0.72)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	0.15	0.15	0.06	0.24	0.24	0.30
	(0.23)	(0.24)	(0.22)	(0.21)	(0.25)	(0.24)
$\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	-0.82***	-0.36	-0.62*	-0.50	-0.41	-0.19
	(0.24)	(0.24)	(0.34)	(0.35)	(0.36)	(0.37)
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	23.32	32.67	29.62	48.52	23.75	39.46
N	3,330	3,330	2,280	2,280	2,305	2,305
Sample	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes

Notes: This table presents the regression output to estimate the relationship between price inflation expectations and reservation wages in the online labor market. Panel A presents the results for equation $Y_{it}^{\texttt{post}} = \beta_0 + \beta_1 \mathbb{E}_{it}^{\text{post}}[\pi_{t+12}] + \gamma_0 Y_{it}^{\texttt{prior}} + \gamma_1 \mathbb{E}_{it}^{\text{prior}}[\pi_{t+12}] + \mathbf{X}_{it}'\delta + \eta_i$ while instrumenting for $\mathbb{E}_{it}^{\text{post}}[\pi_{t+12}]$ with the CPI inflation rate treatment dummy and its interaction with the prior price inflation expectations. Panel A isolates the responses from the CPI inflation rate treatment arm relative to the control group. Panel B estimates the same equation as Panel A using the same instruments but includes responses from all the treatment arms. Panel B also controls for prior wage inflation and unemployment expectations. Panel C is similar to Panel B except for the expanded set of instruments which consists of treatment dummies for CPI inflation rates, hourly earnings inflation rates, and unemployment rates, and their interactions with prior price inflation expectations. Panel D extends Panel C by including controls for posterior wage inflation expectations and unemployment expectations. The first stage F-statistics are reported. We use weights from the Huber-robust regressions for price inflation expectations to control for outliers in expectations revision. The outliers at the second stage are addressed implicitly by restricting attention to the same respondents as in Table 5 to retain a consistent sample. See Appendix D for details about the treatment of outliers.

omitted posterior expectations were not related to price inflation expectations (*i.e.*, in the absence of cross-learning). This approach yields larger negative coefficients on price inflation expectations than in Panel A and in our preferred specification due to omitting the fact that the revision of expectations about variables other than price inflation may respond to information treatments

pooled together in a "control" group. Panel C extends the set of instruments for inflation expectations by including treatment dummies relevant to wage and unemployment expectations. It yields results quite similar to the preferred specification, but the validity of results depends on the correlation structure across expectation variables.

Finally, as recommended by Haaland, Roth, and Wohlfart (2023), Panel D incorporates the controls for posterior expectations about other variables that could be affected by the information treatment to avoid omitted variable bias. Controlling for posterior expectations also partially addresses the concern of violating the Information Equivalence assumption according to Dafoe, Zhang, and Caughey (2018). This approach yields a coefficient for price inflation expectations of a similar magnitude as in Table 5, implying that an upward revision of inflation expectations reduces reservation wages by almost 1.5%.

The estimates from alternative specifications for wage inflation expectations are reported in Table 8. Similar to price inflation expectations, the results in Panel A for wage inflation expectations differ from those in the preferred specification. They are less statistically significant and biased downward. Extending the sample size in Panel B and expanding the instrument set in Panel C does not solve the problem. However, including controls for posterior expectations for price inflation and unemployment rate generates results more similar to the preferred specification.

Interestingly, the coefficient on unemployment expectations in Panel D of Tables 7 and 8 is negative and statistically significant, whereas in all specifications of Table C.3, it is positive and not statistically significant. This corroborates the conclusion that aggregate unemployment expectations, although negatively associated with reservation wages, do not significantly affect reservation wages in the online labor market.

4.3 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 Sections 3.2 and 3.3, if households do not adjust their wage demands in response to changes 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 5). This result suggests that rather than demanding that employers compensate them for the decline in the 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.

The reluctance to ask for higher pay even when the costs of doing so are minimal could be explained by workers prioritizing obtaining an additional job opportunity over marginal increases in pay at this job in an uncertain economic environment.

Table 8: Effect of wage inflation expectations on reservation wages based on alternative specifications

	Reservation Wages (in cents)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A			Single treatment arm vs control group			
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$ (IV)	2.01	1.88	0.31	0.45	-0.08	0.07
	(1.35)	(1.29)	(0.49)	(0.47)	(0.55)	(0.56)
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	32.02	27.32	127.12	181.15	129.55	128.47
N	2,180	2,180	1,495	1,495	1,529	1,529
Panel B			Other treatment arms considered as a control group			
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$ (IV)	3.02*	2.50	0.17	0.54	0.10	0.06
	(1.62)	(2.59)	(0.73)	(0.70)	(0.63)	(0.70)
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	37.82	9.36	77.82	71.15	136.29	101.61
N	3,330	3,330	2,280	2,280	2,305	2,305
Panel C			All treatment arms without posterior controls			
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$ (IV)	1.86***	1.30**	0.49	0.29	0.30	0.11
	(0.67)	(0.64)	(0.31)	(0.31)	(0.41)	(0.47)
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	31.71	40.14	114.25	190.62	95.68	90.24
N	3,330	3,330	2,280	2,280	2,305	2,305
Panel D			All treatment arms with posterior controls			
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	-0.64***	-0.32	-0.57***	-0.41**	-0.59***	-0.37*
	(0.23)	(0.20)	(0.19)	(0.18)	(0.20)	(0.20)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$ (IV)	2.19***	1.37**	0.59*	0.38	0.45	0.22
	(0.75)	(0.70)	(0.33)	(0.33)	(0.43)	(0.49)
$\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	-0.86***	-0.35	-0.74**	-0.61*	-0.44	-0.29
	(0.24)	(0.25)	(0.35)	(0.36)	(0.37)	(0.37)
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	26.40	35.33	99.49	167.96	88.41	83.62
N	3,330	3,330	2,280	2,280	2,305	2,305
Sample	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes

Notes: This table presents the regression output to estimate the relationship between wage inflation expectations and reservation wages in the online labor market. Panel A presents the results for equation $Y_{it}^{\texttt{post}} = \beta_0 + \beta_1 \mathbb{E}_{it}^{\text{post}}[\pi_{t+12}^{w}] + \gamma_0 Y_{it}^{\texttt{prior}} + \gamma_1 \mathbb{E}_{it}^{\text{prior}}[\pi_{t+12}^{w}] + \mathbf{X}_{it}'\delta + \eta_i$ while instrumenting for $\mathbb{E}_{it}^{\text{post}}[\pi_{t+12}^{w}]$ with the hourly earnings growth rate treatment dummy and its interaction with the prior wage inflation expectations. Panel A isolates the responses from the hourly earnings inflation rate treatment arm relative to the control group. Panel B estimates the same equation as Panel A using the same instruments but it includes responses from all the treatment arms. Panel B also controls for prior price inflation and unemployment expectations. Panel C is similar to Panel B except for the expanded set of instruments which consists of treatment dummies of CPI inflation rates, hourly earnings inflation rates, and unemployment rates, and their interactions with prior wage inflation expectations. Panel D extends Panel C by including controls for posterior price inflation expectations and unemployment expectations. The first stage F-statistics are reported. We use weights from the Huber-robust regressions for price inflation expectations to control for outliers in expectations revision. The outliers at the second stage are addressed implicitly by restricting attention to the same respondents as in Table 5 to retain a consistent sample. See Appendix D for details about the treatment of outliers.

Role of Cross-Learning The results discussed in Sections 4.1 and 4.2 demonstrate that omitting the presence of cross-learning across macroeconomic expectations may substantially distort the results. Therefore, selecting proper specifications is essential. Controlling for posterior expectations of variables that may be affected by the information treatment, as in Panel D, is a valid approach to mitigate the bias due to cross-learning. At the same time, restricting the attention to only one treatment and control arms, as implemented in Panel A, is not a reliable approach when cross-learning is present. The challenge is that in order to verify that cross-learning is not relevant in a specific context, researchers need a solid theoretical background or empirical evidence. The latter can be obtained by incorporating additional questions about expectations for variables that could be affected by the treatment.

5 Discussion and Conclusions

We use experimental evidence to document interactions 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 cross-learning between various expectations provides insights into the subjective model of the economy that households use to make economic decisions.

While the pass-through between price and wage inflation expectations is rather symmetric, pass-through between price inflation and unemployment expectations is asymmetric. A significant pass-through from price inflation expectations to aggregate expected wage growth contrasts with Hajdini et al. (2024) who find no statistically significant effect of information treatments about inflation on personal income growth expectations. This indicates that households realize that wage growth could lead to inflation. The weak causal link from inflation expectations to unemployment expectations also contrasts with the findings in the literature about the joint response of inflation to hypothetical shock scenarios (Andre et al., 2022; Binetti, Nuzzi, and Stantcheva, 2024). It implies that households tend to perceive inflation as a consequence of high unemployment rather than a cause. Overall, our results suggest that, consistent with the stagflationary view, news about an inflation increase induces workers to cautiously revise their economic outlook.

Next, exploiting the experimental variation in macroeconomic expectations, we document several results about the effects of expectations on labor supply. First, we find that higher wage inflation expectations increase reservation wages for numerate respondents. Second, higher price inflation expectations appear to *decrease* reservation wages, whereas higher unemployment expectations do not consistently affect reservation wages. Third, omitting cross-learning between macroeconomic expectations, which generates omitted variable bias in this setting, could significantly distort the results suggesting no statistically significant effect of 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 increase with 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. However, Guerreiro et al. (2024) and Binetti, Nuzzi, and Stantcheva (2024) also find that workers are reluctant to demand pay increases to compensate for inflation. Such a labor supply response implies that news about high inflation induces workers to behave more cautiously, prioritizing the ability to secure additional income in the future over marginally increasing pay, thereby partially muting the first link in the wage-price spiral.

It is important to keep in mind that our results are based on the experiments conducted on Amazon MTurk, an online labor market with distinctive features compared to offline labor markets. One possible concern is that MTurk workers could be significantly different from the broader U.S. population. However, while workers in our sample are younger and more educated than the general U.S. population, they are quite similar in other dimensions. Additionally, prior research shows that experiments conducted on MTurk have a high degree of replicability (Horton, Rand, and Zeckhauser, 2011; Haaland, Roth, and Wohlfart, 2023). Another possible concern is that MTurk is more flexible: it is much easier for workers to adjust their labor supply in online labor markets than in offline labor markets. On the one hand, from this perspective, MTurk workers represent those on the margin of adjustment—individuals who are of particular concern to policymakers. On the other hand, due to low entry and exit costs, online jobs are often considered secondary and thus have a less tangible effect on workers' earnings compared to offline jobs. Therefore, the labor supply response in offline markets could differ from that in online markets. The magnitude of such a difference is left for our future work.

We propose to consider our results from the following perspective. If workers generally had a mindset to demand pay increases commensurate with inflation, they should do so across all settings. Information processing costs should reduce the probability of doing so, but adjusting the default $ 1.00 pay for the inflation rate should be straightforward for people who can interpret and calculate percentages. Moreover, in this particular setting, the cost of demanding higher pay

is low because there are many outside options available to workers so general equilibrium effects should play a minimal role. The fact that workers did not ask for higher pay on MTurk indicates that the behavioral pattern of asking for higher pay commensurate with inflation increase does not uniformly hold in the population. Therefore, it is plausible to assume that the MTurk workers under study do not immediately associate an increase in inflation as a trigger to demand higher pay either on MTurk or in other settings. Moreover, MTurkers are more educated than the average U.S. worker. Therefore, even though the results are derived from a particular part of the population, these results are useful.

References

Andre, Peter, Ingar Haaland, Christopher Roth, and Johannes Wohlfart. 2023. "Narratives about the Macroeconomy." Tech. rep.

Andre, Peter, Carlo Pizzinelli, Christopher Roth, and Johannes Wohlfart. 2022. "Subjective models of the macroeconomy: Evidence from experts and representative samples." *The Review of Economic Studies* 89 (6):2958–2991.

Armantier, Olivier, Scott Nelson, Giorgio Topa, Wilbert Van der Klaauw, and Basit Zafar. 2016. "The price is right: Updating inflation expectations in a randomized price information experiment." *Review of Economics and Statistics* 98 (3):503–523.

Armona, Luis, Andreas Fuster, and Basit Zafar. 2019. "Home price expectations and behaviour: Evidence from a randomized information experiment." *The Review of Economic Studies* 86 (4):1371–1410.

Belsley, David A, Edwin Kuh, and Roy E Welsch. 1980. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. John Wiley & Sons.

Binder, Carola. 2020. "Coronavirus Fears and Macroeconomic Expectations." *Review of Economics and Statistics* 102 (4):721–730.

Binder, Carola and Gwangmin Kim. 2020. "Learning-Through-Survey in Inflation Expectations,." *American Economic Journal: Macroeconomics* .

Binetti, Alberto, Francesco Nuzzi, and Stefanie Stantcheva. 2024. "People's Understanding of Inflation." Tech. rep., National Bureau of Economic Research.

Blanchard, Olivier J. 1986. "The wage price spiral." *The Quarterly Journal of Economics* 101 (3):543–565.

Boissay, Frederic, Fiorella De Fiore, Deniz Igan, Albert Pierres Tejada, Daniel Rees et al. 2022. "Are major advanced economies on the verge of a wage-price spiral?" Tech. rep., Bank for International Settlements.

Bostanci, Gorkem, Omer Koru, and Sergio Villalvazo. 2022. "Changing Jobs to Fight Inflation: Labor Market Reactions to Inflationary Shocks." Tech. rep.

Bottan, Nicolas L and Ricardo Perez-Truglia. 2024. "Betting on the house: Subjective expectations and market choices." *American Economic Journal: Applied Economics* (forthcoming).

Burke, Mary A and Ali Ozdagli. 2021. "Household inflation expectations and consumer spending: evidence from panel data." *Review of Economics and Statistics* :1–45.

Card, David. 1990. "Unexpected inflation, real wages, and employment determination in union contracts." *American Economic Review* 80:669–688.

Cavallo, Alberto, Guillermo Cruces, and Ricardo Perez-Truglia. 2017. "Inflation expectations, learning, and supermarket prices: Evidence from survey experiments." *American Economic Journal: Macroeconomics* 9 (3):1–35.

Christofides, Louis N and Andrew J Oswald. 1992. "Real wage determination and rent-sharing in collective bargaining agreements." *The Quarterly Journal of Economics* 107 (3):985–1002.

Coibion, Olivier, Dimitris Georgarakos, Yuriy Gorodnichenko, and Maarten Van Rooij. 2023. "How does consumption respond to news about inflation? Field evidence from a randomized control trial." *American Economic Journal: Macroeconomics* 15 (3):109–152.

Coibion, Olivier, Yuriy Gorodnichenko, Saten Kumar, and Jane Ryngaert. 2021. "Do You Know that I Know that You Know? Higher-Order Beliefs in Survey Data." *The Quarterly Journal of Economics* 136 (3):1387–1446.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber. 2022. "Monetary policy communications and their effects on household inflation expectations." *Journal of Political Economy* 130 (6):1537–1584.

Cukierman, Alex and Francesco Lippi. 1999. "Central bank independence, centralization of wage bargaining, inflation and unemployment: Theory and some evidence." *European Economic Review* 43 (7):1395–1434.

Dafoe, Allan, Baobao Zhang, and Devin Caughey. 2018. "Information equivalence in survey experiments." *Political Analysis* 26 (4):399–416.

Deaton, Angus and Nancy Cartwright. 2018. "Understanding and misunderstanding randomized controlled trials." *Social Science & Medicine* 210:2–21.

D'Acunto, Francesco, Daniel Hoang, and Michael Weber. 2015. "Inflation expectations and consumption expenditure." *Chicago Booth Global Markets Working Paper Series* .

Dube, Arindrajit, Jeff Jacobs, Suresh Naidu, and Siddharth Suri. 2020. "Monopsony in online labor markets." *American Economic Review: Insights* 2 (1):33–46.

Guerreiro, Joao, Jonathon Hazell, Chen Lian, and Christina Patterson. 2024. "Why Do Workers Dislike Inflation? Wage Erosion and Conflict Costs." Tech. rep., Discussion paper, Working Paper.

Haaland, Ingar, Christopher Roth, and Johannes Wohlfart. 2023. "Designing information provision experiments." *Journal of Economic Literature* 61 (1):3–40.

Hajdini, Ina, Edward S. Knotek, John Leer, Mathieu Pedemonte, Robert W. Rich, and Raphael Schoenle. 2024. "Low Passthrough from Inflation Expectations to Income Growth Expectations: Why People Dislike Inflation." .

Horton, John J., David G. Rand, and Richard J. Zeckhauser. 2011. "The online laboratory: Conducting experiments in a real labor market." *Experimental Economics* 14:399–425.

Jain, Monica, Olena Kostyshyna, and Xu Zhang. 2024. "How do people view wage and price inflation?" *Journal of Monetary Economics* :103552.

Kamdar, Rupal. 2019. "The Inattentive Consumer: Sentiment and Expectations." Working paper.

Kandil, Ms Magda E. 2003. *The wage-price spiral: industrial country evidence and implications*. International Monetary Fund.

Link, Sebastian, Andreas Peichl, Christopher Roth, and Johannes Wohlfart. 2023. "Information frictions among firms and households." *Journal of Monetary Economics* 135:99–115.

Lorenzoni, Guido and Iván Werning. 2023. "Wage price spirals." *Brookings Papers in Economic Activity* .

Lucas, Robert E. and Leonard A Rapping. 1969. "Real Wages, Employment, and Inflation." *Journal of Political Economy* 77 (5):721–754.

McClure, Ethan ML, Vitaliia Yaremko, Olivier Coibion, and Yuriy Gorodnichenko. 2023. "The Macroeconomic Expectations of US Managers." *Journal of Money, Credit and Banking* forthcoming.

Pilossoph, Laura and Jane M. Ryngaert. 2022. "Job Search, Wages, and Inflation." Tech. rep.

Roth, Christopher and Johannes Wohlfart. 2020. "How do expectations about the macroeconomy affect personal expectations and behavior?" *Review of Economics and Statistics* 102 (4):731–748.

Sanderson, Eleanor and Frank Windmeijer. 2016. "A weak instrument F-test in linear IV models with multiple endogenous variables." *Journal of Econometrics* 190 (2):212–221.

Stantcheva, Stefanie. 2023. "How to run surveys: A guide to creating your own identifying variation and revealing the invisible." *Annual Review of Economics* 15 (1):205–234.

———. 2024. "Why do we dislike inflation?" *Brookings Papers in Economic Activity* .

Vellekoop, Nathanael and Mirko Wiederholt. 2019. "Inflation expectations and choices of households." .

Weber, Michael, Bernardo Candia, Tiziano Ropele, Rodrigo Lluberas, Serafin Frache, Brent H. Meyer, Saten Kumar, Yuriy Gorodnichenko, Dimitris Georgarakos, Olivier Coibion, Geoff Kenny, and Jorge Ponce. 2023. "Tell Me Something I Dont Already Know: Learning in Low and High-Inflation Settings." Tech. rep., National Bureau of Economic Research.

Appendix

A Data Description

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	-0.012	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 the air quality transcription task asked workers to record five numbers rather than three as is the case for the treatment groups (CPI and Wage). 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 analysis for wave 1

Figure A.1 shows the prior and posterior macroeconomic expectations in the unprocessed data pooled across all treatment and control groups. It indicates that there is indeed a shift in distribution before and after treatment.

Figure A.1: Prior and posterior expectations

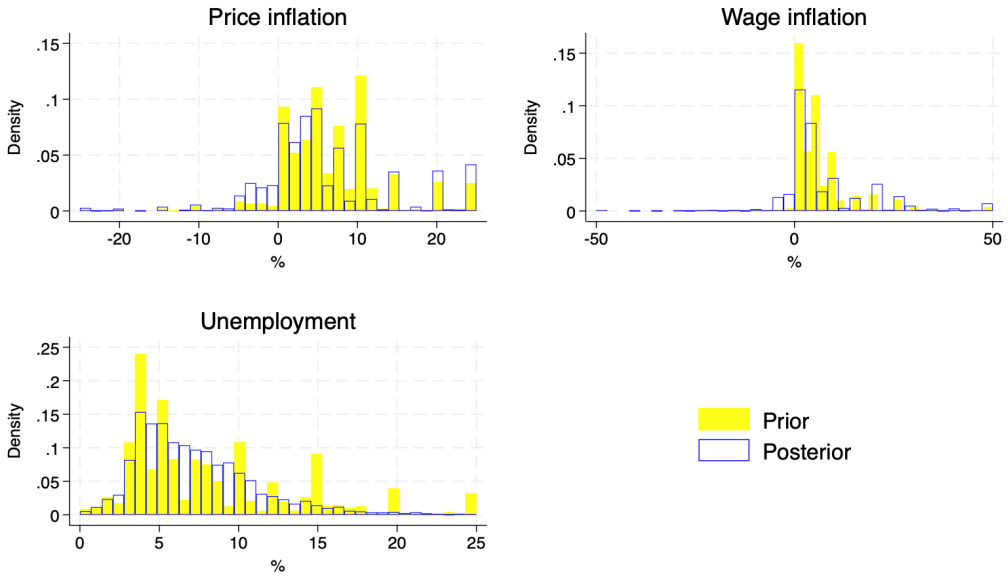


Figure A.2 reveals that, despite the randomization, there is some heterogeneity in distributions of prior expectations by treatment arm which is likely driven by the fact that different demographic groups work on MTurk at different moments in time. We address this heterogeneity by controlling for time of survey fixed effect as well as prior expectations.

Figure A.2: Distribution of prior expectations by treatment arms

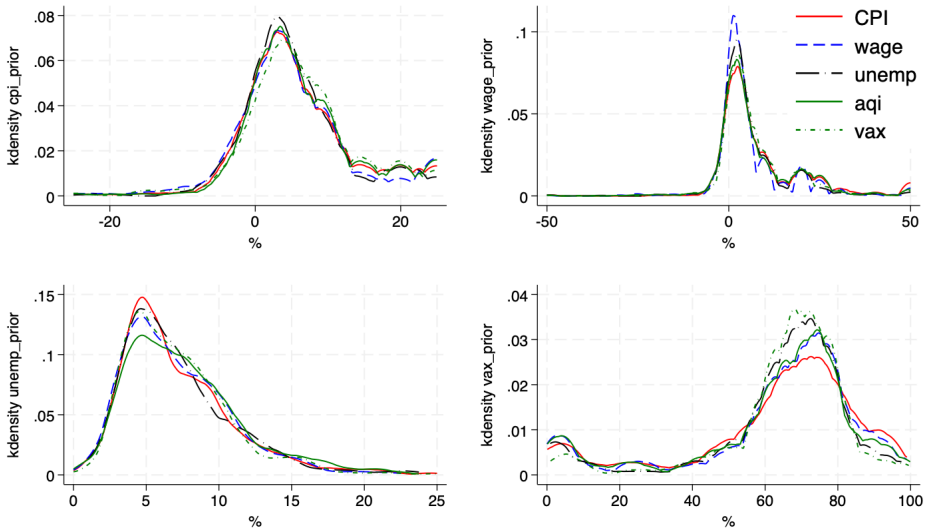


Table A.4 shows that after controlling for survey launch time fixed effects, differences in prior expectations and other demographic characteristics become largely statistically insignificant except for age, monthly spending, and hours worked on MTurk. Those in the unemployment treatment group also appear to have a larger desired duration of employment on our project and lower prior reservation wage. To account for the remaining imbalances, in all specifications, we control for prior expectations and, where relevant, we control for prior reservation wages. In addition, we report the results with an extensive set of demographic controls.

Table A.4: Covariate balance across treatment arms in wave 1

Variable	(1) treat_cpi	(2) treat_wage	(3) treat_unemp	(4) control
age	43.41	-3.07**	-2.00	-4.12***
	(0.88)	(1.25)	(1.25)	(1.31)
female	0.52	0.06	-0.00	-0.03
	(0.04)	(0.05)	(0.05)	(0.05)
white	0.76	0.03	0.05	-0.03
	(0.03)	(0.04)	(0.04)	(0.04)
with college degree	0.68	-0.06	0.07	-0.02
	(0.03)	(0.04)	(0.04)	(0.05)
employed	0.74	0.05	0.05	0.02
	(0.03)	(0.04)	(0.04)	(0.04)
full-time employed	0.62	0.03	0.06	0.00
	(0.03)	(0.05)	(0.05)	(0.05)
cohabiting	0.61	0.03	0.06	-0.01
	(0.03)	(0.05)	(0.05)	(0.05)
number of children	0.45	0.07	0.01	-0.07
	(0.04)	(0.05)	(0.05)	(0.05)
log(monthly spending on food)	5.72	-0.44***	-0.50***	0.07
	(0.11)	(0.16)	(0.16)	(0.17)
log(monthly spending on gas)	4.40	-0.53***	-0.29	-0.02
	(0.13)	(0.19)	(0.19)	(0.20)
log(weekly MTurk hours)	2.44	0.06	-0.07	-0.28***
	(0.07)	(0.10)	(0.10)	(0.10)
$\mathbb{E}_t^{\texttt{prior}}[\pi_{t+12}]$	6.32	-1.02	-0.81	0.84
	(0.60)	(0.85)	(0.85)	(0.89)
$\mathbb{E}_t^{\texttt{prior}}[\pi^w_{t+12}]$	7.29	-0.74	-1.36	-1.83
	(0.82)	(1.17)	(1.18)	(1.23)
$\mathbb{E}_t^{\texttt{prior}}[u_{t+12}]$	6.83	-0.09	0.15	0.76*
	(0.28)	(0.40)	(0.40)	(0.42)
$\mathbb{E}_t^{\texttt{prior}}[vax_{t+12}]$	64.47	-4.20*	-3.93	2.51
	(1.71)	(2.43)	(2.44)	(2.56)
$\mathbb{E}_t^{\texttt{prior}}[aqi_good_{t+1}]$	0.62	-0.04	0.09*	0.00
	(0.04)	(0.05)	(0.05)	(0.05)
$\mathbb{E}_t^{\texttt{prior}}[\texttt{duration}_{t+1}]$	3.99	0.04	-0.37**	0.31*
	(0.11)	(0.16)	(0.16)	(0.16)
$\mathbb{E}_t^{\texttt{prior}}[\texttt{reservation wages}_{t+1}]$	105.73	-0.59	-13.75**	7.15
	(3.97)	(5.64)	(5.67)	(5.91)
N	4614			

Notes: Table reports coefficients from regression of pre-determined and pre-treatment variables on treatment dummies after controlling only for time of survey fixed effects. The first column reports the CPI treatment group's average value (intercept). The remaining columns report the difference in values for the other treatment and control groups (slope coefficients). Heteroskedasticity-robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All values in the first columns are statistically significant at 0.01 level, the symbols are omitted for exposition purposes.

A.3 Descriptive statistics (follow-up surveys)

Table A.5 below provides descriptive statistics about respondents who participated in the second and third waves. Table A.5 shows that they are similar to those from the first wave of the survey in Section 2.3.

Table A.5: Descriptive Statistics (Wave 2&3)

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

Wave 3 (July 2022)	Mean	Percentiles			Std. Dev.
		p25	p50	p75	
age	40.79	31.00	39.00	49.00	12.22
female	0.49	0.00	0.00	1.00	0.50
white	0.81	0.00	1.00	1.00	0.39
with college degree	0.74	1.00	1.00	1.00	0.44
employed	0.82	1.00	1.00	1.00	0.38
full-time employed	0.67	0.00	1.00	1.00	0.47
number of children	0.89	0.00	1.00	2.00	1.10
monthly spending on food	$519.16	$150.00	$350.00	$560.00	1165.40
monthly spending on gas	$205.74	$50.00	$120.00	$225.00	361.07
$\mathbb{E}_t^{\texttt{prior}}[\pi_{t+12}]$	4.85	1.00	4.00	9.00	7.78
$\mathbb{E}_t^{\texttt{prior}}[\pi^w_{t+12}]$	5.32	1.00	3.00	6.00	9.43
$\mathbb{E}_t^{\texttt{prior}}[u_{t+12}]$	6.96	4.23	6.20	8.90	3.47
$\mathbb{E}_t^{\texttt{prior}}[\texttt{duration}_{t+1}]$	3.97	3.00	5.00	5.00	1.44
$\mathbb{E}_t^{\texttt{prior}}[\texttt{reservation wages}_{t+1}]$	0.98	0.50	1.00	1.25	0.54
Observations	1,472				

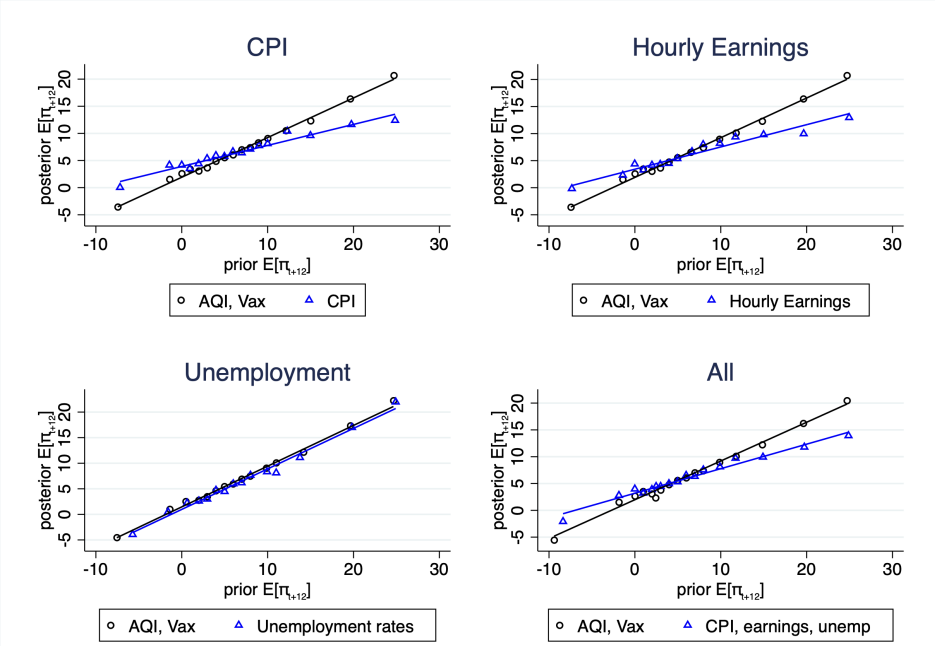
B Effects of Information Treatment on Subjective Expectations

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

B.1 Graphical Illustration of Information Treatment Effects

This section presents binned scatter plots of respondents' posterior expectations against their priors by each treatment (CPI inflation, hourly earnings inflation, unemployment, and all three pooled together). Consistent with the discussion in Section 3, Figure B.1 shows that respondents 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 the CPI and hourly earnings treatment arms. Respondents adjust their weights towards the signal the most when they have received the information about the CPI inflation.

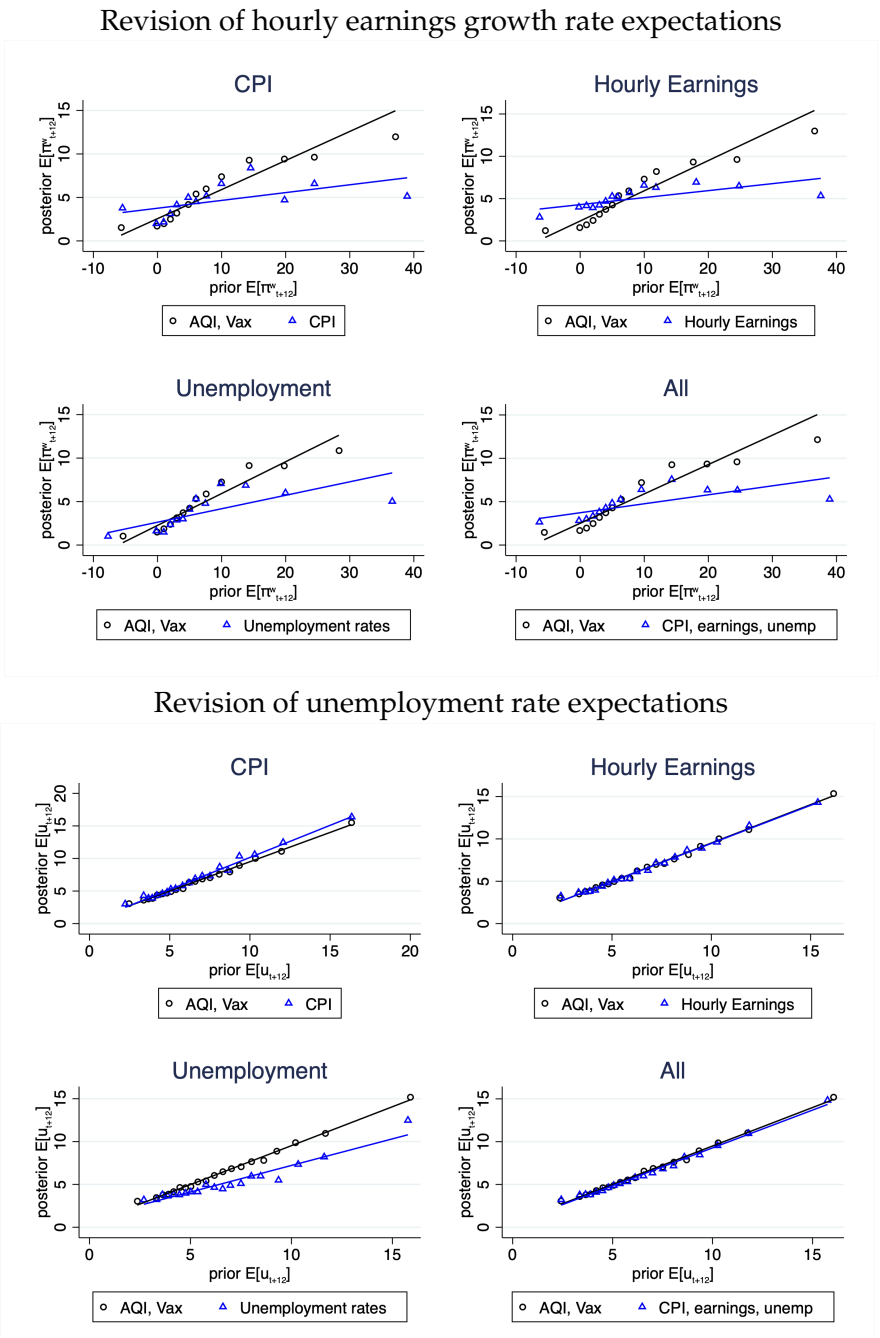
Figure B.1: Effects of information treatment on price inflation expectations



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 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.

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 with Regular Regressions

This section presents estimation results for Equation (2) with regular regressions, without using the Huber-Robust regressions to remove outliers in the first stage as is the case in the main text. In other words, Table B.1 is a regular regression version of Table 3 in the main text. Results are broadly consistent with those in Table 3 in the main text but more noisy due to the influence of outliers.

Table B.1: Effects of information treatments on the posterior price inflation, wage inflation, and unemployment expectations (multiple treatments with regular regressions)

Dependent variable:	Price inflation ($Z = \pi$)				Wage inflation ($Z = \pi^w$)				Unemployment rate ($Z = u$)			
$\mathbb{E}_{it}^{\texttt{post}}[Z_{t+12}]$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
treat_cpi	1.10***	1.05	0.57	1.51**	1.06***	1.21	1.51*	1.80**	1.64***	1.33**	1.20*	1.22*
	(0.33)	(0.64)	(0.69)	(0.68)	(0.35)	(0.75)	(0.88)	(0.75)	(0.49)	(0.62)	(0.73)	(0.71)
treat_wage	0.59*	0.64	0.17	0.92	1.37***	0.72	1.04	1.87***	0.55	0.17	-0.47	0.77
	(0.32)	(0.65)	(0.74)	(0.67)	(0.40)	(0.72)	(0.83)	(0.64)	(0.46)	(0.57)	(0.63)	(0.62)
treat_unemp	-0.64	-0.03	0.37	0.11	0.10	1.20	2.27**	1.53*	-2.27***	-1.70***	-1.43**	-1.82***
	(0.41)	(0.70)	(0.87)	(0.80)	(0.44)	(0.83)	(1.06)	(0.84)	(0.46)	(0.58)	(0.72)	(0.60)
$\texttt{treat_cpi} \times \mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.15***	-0.15***	-0.14***	-0.14***	-0.10***	-0.12***	-0.16***	-0.15***	-0.11*	-0.13*	-0.18**	-0.08
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.07)	(0.07)	(0.08)	(0.08)
$\texttt{treat_wage} \times \mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.12***	-0.13***	-0.14***	-0.14***	-0.06	-0.08	-0.15**	-0.20***	-0.00	0.00	0.05	-0.07
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)
$\texttt{treat_unemp} \times \mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	-0.01	-0.02	-0.01	-0.05	-0.08	-0.09*	-0.12*	-0.11*	0.15**	0.12*	0.08	0.09
	(0.05)	(0.05)	(0.07)	(0.06)	(0.05)	(0.05)	(0.06)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)
$\mathbb{E}_{it}^{\texttt{prior}}[Z_{t+12}]$	0.46***	0.47***	0.51***	0.53***	0.27***	0.26***	0.31***	0.31***	0.63***	0.60***	0.64***	0.65***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
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 *regular* regression output from equation (2). For each outcome variable specified in the header, the first column reports results without controls, the second column adds control variables, the third column restricts the sample to highly numerate respondents only (who answered all the numerical competence questions correctly), and the fourth column restricts the sample to consistent respondents only (For reservation wage questions, respondents were initially asked to provide their answers within specified ranges and then provide detailed numerical values. Consistent respondents are those who provided answers that matched these two questions). Control variables are female, age, age^2, white, whether cohabiting or not, whether having a child or not, full-time employed or not, logarithmic monthly spending on food, hours working at MTurk, 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.

B.3 Correlation Between Price Inflation and Unemployment Rates

This section reports OLS results for the relationship between price inflation and unemployment expectations. Table B.2 shows that price inflation expectations and unemployment expectations are consistently positively correlated both before and after the information treatment. The information treatment strengthened the correlation because the coefficients for posterior expectations across all treatment arms are larger than those for the control group only.

Table B.2: Association between expected price inflation and unemployment rates

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Association between price inflation and unemployment expectations						
Prior, all arms						
$\mathbb{E}_{it}^{prior}[u_{t+12}]$	0.21***	0.19***	0.21***	0.20***	0.19***	0.19***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Posterior, control arms						
$\mathbb{E}_{it}^{post}[u_{t+12}]$	0.25***	0.25***	0.25***	0.22***	0.26***	0.27***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Posterior, all arms						
$\mathbb{E}_{it}^{post}[u_{t+12}]$	0.27***	0.26***	0.30***	0.27***	0.25***	0.25***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Panel B: Association between unemployment and price inflation expectations						
Prior, all arms						
$\mathbb{E}_{it}^{prior}[\pi_{t+12}]$	0.05***	0.05***	0.05***	0.04***	0.05***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Posterior, control arms						
cpi_post	0.13***	0.11***	0.10***	0.08***	0.11***	0.10***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Posterior, all arms						
$\mathbb{E}_{it}^{post}[\pi_{t+12}]$	0.16***	0.14***	0.14***	0.12***	0.13***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Sample	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes

Notes: Panel A of the table presents Huber-robust regression output for equation $\mathbb{E}_{it}[\pi_{t+12}] = \alpha_0 + \alpha_1 \mathbb{E}_{it}[u_{t+12}] + X_i'\gamma + \varepsilon_i$. Panel B of the table reports Huber-robust regression output for equation $\mathbb{E}_{it}[u_{t+12}] = \alpha_0 + \alpha_1 \mathbb{E}_{it}[\pi_{t+12}] + X_i'\gamma + \varepsilon_i$. The numerate sample consists of respondents who answered all the numerical competence questions correctly. The consistent sample consists of respondents who provided matching answers to distinct reservation wage questions. Control variables are female, age, age^2, white, whether cohabiting or not, whether having a child or not, full-time employed or not, logarithmic monthly spending on food, hours working at MTurk, 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.

C Effects of Subjective Expectations on Labor Supply

This section supplements Section 4.

Table C.1: Effects of expectations on desired duration of employment

	$\mathbb{1}_{\texttt{increase the desired duration of employment}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	-0.00	-0.00	-0.00	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	0.00	-0.00	-0.00	-0.00*	-0.00	-0.00
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	0.01	-0.00	-0.00	-0.00	-0.00	-0.01
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
N	3,463	3,463	2,374	2,374	2,405	2,405
Sample	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	14.18	24.65	22.39	35.97	18.07	32.30
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	15.05	17.93	65.11	109.31	63.41	100.66
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	31.62	17.50	40.55	20.62	43.81	25.28

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 (4). We instrument the posterior expectations with treatment dummies and their interactions with the priors, as specified in footnote 14. The numerate sample consists of respondents who answered all the numerical competence check questions correctly. The consistent sample consists of respondents who provided consistent answers to distinct reservation wage questions. Sanderson and Windmeijer (2016) multivariate F-statistics 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 C.2: Effects of expectations on the subjective probability of becoming non-employed

	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	0.94	0.56	0.76**	0.06	0.48*	0.07
	(0.59)	(0.39)	(0.37)	(0.26)	(0.25)	(0.20)
$\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	-1.03**	-0.46	-0.83***	-0.16	-0.33	-0.12
	(0.47)	(0.31)	(0.27)	(0.20)	(0.34)	(0.31)
$\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	5.10***	3.19***	2.94***	0.83***	1.82***	0.88***
	(0.57)	(0.87)	(0.30)	(0.29)	(0.24)	(0.27)
N	2,736	2,736	1,802	1,802	1,778	1,778
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}]$	7.67	9.49	11.11	14.88	16.12	23.28
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[\pi_{t+12}^{w}]$	10.99	12.29	16.41	18.29	14.13	10.78
F-stat for $\mathbb{E}_{it}^{\texttt{post}}[u_{t+12}]$	20.11	9.14	37.16	30.35	33.27	37.40

Notes: This table presents the regression results for the effect of macroeconomic expectations on the subjective reported probability of becoming non-employed (unemployed or in the next 4 months according to the following equation:

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

We instrument the posterior expectations with treatment dummies and their interactions with the priors, as specified in footnote 14. The numerate sample consists of respondents who answered all the numerical competence check questions correctly. The consistent sample consists of respondents who provided consistent answers to distinct reservation wage questions.Heteroskedasticity-robust-standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sanderson and Windmeijer (2016) multivariate F-statistics 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.

C.1 Evidence from Alternative Specifications

This section discusses how our results about the reservation wages would change if we deviate from the baseline specification in Table 5 by excluding variables capturing simultaneous revision of expectations that are commonly omitted by the researchers.

Table C.3: Effect of unemployment expectations on reservation wages based on alternative specifications

	Reservation Wages (in cents)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Single treatment arm vs control group					
unemp_post (IV)	0.13	2.17	1.21	1.22	0.36	1.64
	(1.15)	(2.38)	(0.84)	(1.16)	(0.80)	(1.20)
F-stat for unemp_post	58.37	17.73	84.11	66.22	108.20	61.76
N	1,800	1,800	1,200	1,200	1,257	1,257
Panel B	Other treatment arms considered as a control group					
unemp_post (IV)	-0.06	2.32	0.65	1.27	-0.28	1.34
	(0.93)	(1.63)	(0.71)	(0.94)	(0.69)	(0.93)
F-stat for unemp_post	119.29	59.68	150.02	149.72	175.76	130.95
N	3,330	3,330	2,280	2,280	2,305	2,305
Panel C	All treatment arms without posterior controls					
unemp_post (IV)	-0.84	2.21	0.34	0.71	-0.40	1.28
	(0.92)	(1.63)	(0.71)	(0.95)	(0.69)	(0.93)
F-stat for unemp_post	61.26	31.47	75.97	78.49	88.31	66.93
N	3,330	3,330	2,280	2,280	2,305	2,305
Panel D	All treatment arms with posterior controls					
cpi_post	-0.35**	-0.21	-0.47***	-0.31*	-0.57***	-0.38**
	(0.16)	(0.15)	(0.18)	(0.17)	(0.19)	(0.19)
wage_post	0.16	0.27*	-0.00	0.12	0.03	0.08
	(0.17)	(0.16)	(0.19)	(0.17)	(0.21)	(0.21)
unemp_post (IV)	-0.71	2.10	0.40	0.62	-0.24	1.24
	(0.94)	(1.61)	(0.71)	(0.95)	(0.70)	(0.93)
F-stat for unemp_post	59.88	31.86	74.96	79.93	87.23	66.85
N	3,330	3,330	2,280	2,280	2,305	2,305
Sample	All	All	Numerate	Numerate	Consistent	Consistent
Controls	No	Yes	No	Yes	No	Yes

Notes: This table presents the regression output to estimate the relationship between unemployment expectations and reservation wages in the online labor market. Panel A presents the results for equation $Y_{it}^{\texttt{post}} = \beta_0 + \beta_1 \mathbb{E}_{it}^{\text{post}}[u_{t+12}] + \gamma_0 Y_{it}^{\texttt{prior}} + \gamma_1 \mathbb{E}_{it}^{\text{prior}}[u_{t+12}] + \mathbf{X}_{it}'\delta + \eta_i$ while instrumenting for $\mathbb{E}_{it}^{\text{post}}[u_{t+12}$ with the unemployment rate treatment dummy and its interaction with the prior unemployment expectations. Panel A isolates the responses from unemployment rate treatment arm relative to control group. Panel B estimates the same equation as Panel A using the same instruments but it includes responses from all the treatment arms. Panel B also controls for prior price inflation and wage inflation expectations. Panel C is similar to Panel B except for the expanded set of instruments which consists of treatment dummies of the unemployment rate and their interactions with prior unemployment expectations. Panel D extends Panel C by including controls for posterior price inflation expectations and wage inflation expectations. Sanderson and Windmeijer (2016) multivariate F-statistics are reported. We use weights from the Huber-robust regressions for unemployment expectations to control for outliers in expectations revision. The outliers at the second stage are addressed implicitly by restricting attention to the same respondents as in Table 5 to retain a consistent sample. See Appendix D for details about the treatment of outliers.

D Treatment of Outliers

To deal with outliers in expectations and labor supply data, we use the strategy following Coibion et al. (2023). To be more specific, we use the Huber-robust regression in the first stage with `rreg` command in STATA.[18] 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.[19]

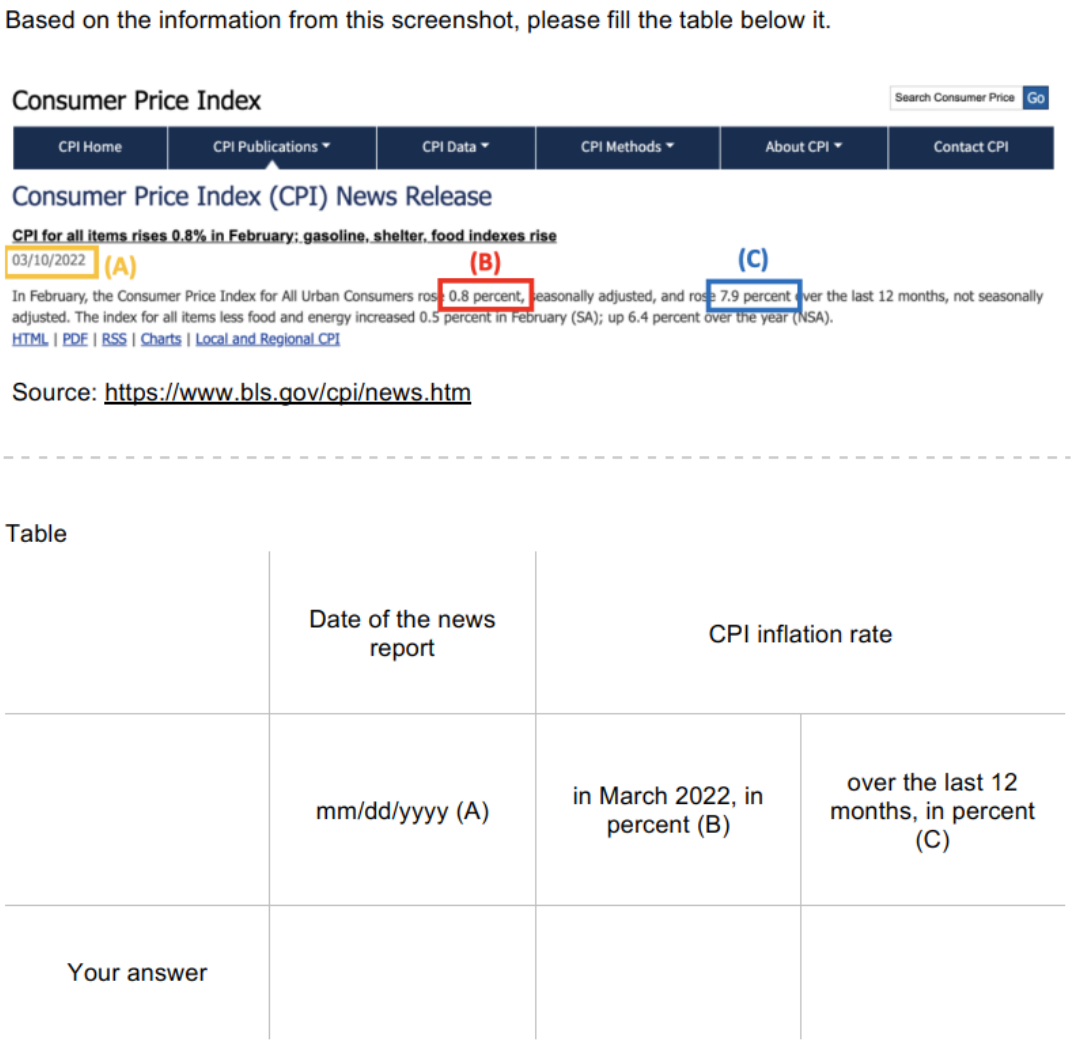
[18] For more detail, see help for STATA's `rreg` command. Or see Appendix C of Coibion et al. (2023).

[19] Belsley, 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



	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 p

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

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

Footnotes
(P) Preliminary

Last Modified Date April 01, 2022 (A)

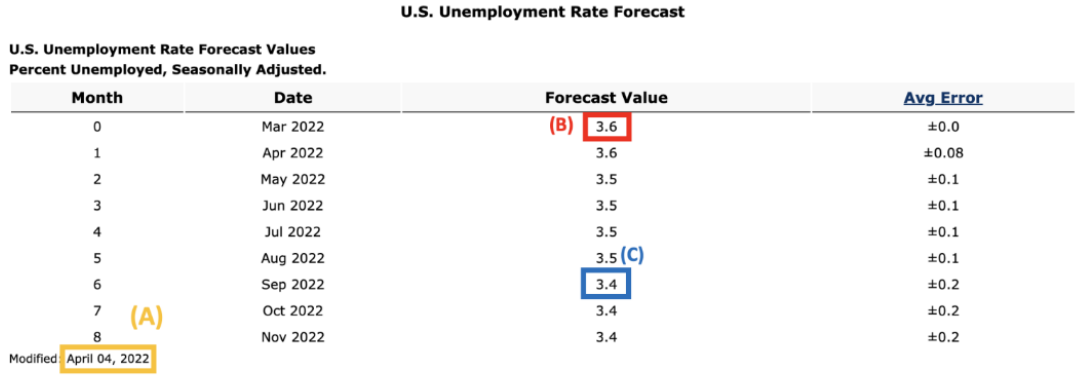
Source: https://www.bls.gov/news.release/empsit.t19.htm#ces_table3.f.p

Table.

	Date when table was last modified	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			

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

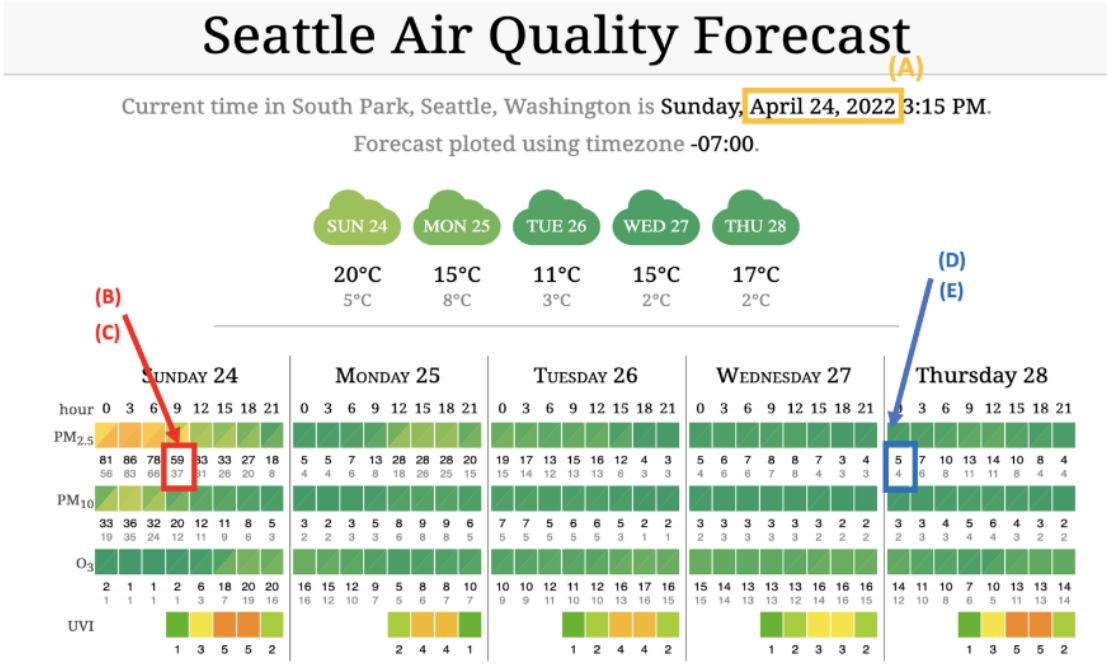
Table.

	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			

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.



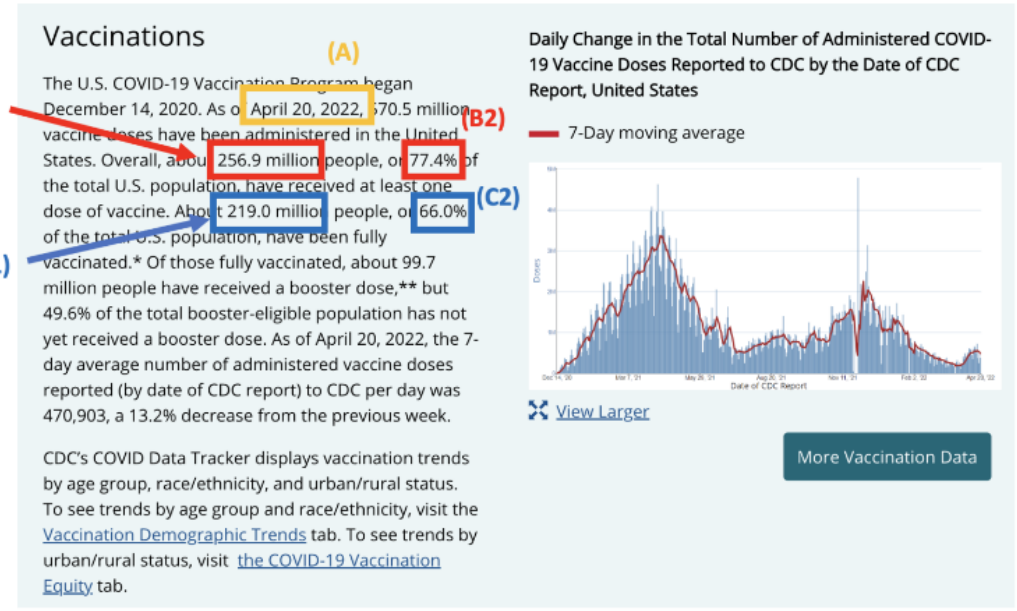
Source: https://aqicn.org/forecast/seattle/

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					

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.



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

Table.

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

Note. Ignore % symbol during transcription.