Beliefs Under Lockdown: Causal Evidence on Inflation Expectations from China

Zhiyong Fan[*] Aina Puig[†] Xuguang Simon Sheng[‡]

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Abstract

This paper studies how lockdown policies shape household inflation expectations and their responses to information treatments, using the first national survey of inflation expectations in China. The study exploits spatial variation in local lockdown policies during the COVID-19 pandemic to identify the causal impact of the policy environment on expectation formation. We find that households systematically overestimate inflation but respond to information treatments in a manner consistent with Bayesian updating. Households under lockdown exhibit higher inflation expectations and respond more strongly to policy-based information – particularly China's inflation target – suggesting greater trust in government institutions, while households not in lockdown are more sensitive to negative economic news. The effects of information treatments vary with decision-making behavior and price salience, and have implications for households' planned spending versus saving.

JEL classification: E31, E52, C83, D84
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[*]Renmin University of China

[†]Pace University

[‡]American University. The authors thank Olivier Coibion, Francesco D'Acunto, and Yuriy Gorodnichenko for valuable discussions, comments, and suggestions. All views and remaining errors in the paper are of the authors and are not necessarily those of the individuals or groups listed above.

1 Introduction

Inflation exhibited unusually high volatility during the COVID-19 pandemic. Households experienced these inflationary dynamics in markedly different ways depending on their country context and the varying degrees of lockdown restrictions they faced. As a large emerging market economy with a distinct lockdown policy response, China offers a unique lens through which to examine these inflationary experiences. This heterogeneity in inflation exposure raises important questions for central banks, which increasingly recognize the critical role that household expectations play in the transmission of monetary policy. Substantial research has examined how central banks can influence expectations under normal conditions in developed economies (Coibion et al. 2022; Coibion et al. 2023b). Much less is known about the effectiveness of such targeting strategies during periods of restricted mobility and heightened uncertainty, particularly in emerging market economies like China.

This paper investigates household macroeconomic expectations and the impact of information treatments during lockdown restrictions using the first national expectations survey in China. We analyze household responses to the Survey of Household Inflation Expectations in China in September 2022. The study capitalizes on China's unique policy environment, notably the geographic variation in lockdown policies during the COVID-19 pandemic, to identify the causal impact of lockdown exposure on household expectations.

Three key features distinguish this survey and setting. First, it is conducted in a emerging market economy, contrasting the extensively documented studies based in developed economies and offering novel insights on emerging market contexts. We provide several practical insights on the sample age distribution and question design for surveys on macroeconomics expectations in emerging market economies. Second, this survey captures a distinct macroeconomic environment. China faced deflationary concerns during the survey period, in contrast to the inflationary pressures in most countries covered in the existing literature. Third, China's localized lockdown policies, where some cities were under restrictions while others were not, provide natural spatial variation that enables causal identification of how information treatments influence expectations under different policy conditions.

We test the influence of different information treatments about future economic and pandemic developments on household expectations using a randomized control trial (RCT). We randomly assign the survey sample to five equally sized groups and present four groups with varying statements: two on a potential US economic contraction, one on the inflation target in China, and one on Covid cases in China. This allows us to investigate whether households react differently to each of these topics. We observe that the distribution of inflation expectations is multi-modal, suggesting deep disagreement among households. However, when provided with the official inflation target, expectations shift toward the policy value, illustrating the power of targeted policy communication.

We estimate the causal effect of information treatments on inflation expectations by respondent lockdown status. Estimates are presented for the overall sample and at the intensive margin. The intensive margin is the sample that makes a revision in their expectations post-treatment (Dräger et al. 2024). We find that households update their expectations in a Bayesian manner, but that weights placed on treatments vary by lockdown status based on which information signal is trusted. Lockdown households place more weight on domestic policy signals (inflation target), than on international or general news. Their expectations decrease more after receiving information on the inflation target, suggesting greater institutional trust, potentially shaped by more direct exposure to strong government intervention. In contrast, non-lockdown households react more to "bad news" about the economy or Covid cases, likely due to heightened surprise or uncertainty during this crisis pandemic period. Therefore, lockdown raises the precision of policy signals and lowers the salience of bad news.

Finally, we evaluate how other respondent characteristics interact with lockdown status to drive inflation expectations. Some households exhibit a theoretically inconsistent relationship between the inflation rate and economic growth. Other respondent characteristics include responsibility in making decisions about prices, capital, and wages in their jobs or reliance on salient prices. We also explore how inflation expectations shape household spending plans and expectations of income and employment.

1.1 Related literature

This paper contributes to the growing literature that uses RCTs to analyze the effects of information provision such as central bank communications on inflation expectations and consumption behavior (Armantier et al. 2016; Lamla and Vinogradov 2019; D'Acunto et al. 2021; Coibion et al. 2022; Dräger et al. 2024; Binder et al. 2024a). These studies consistently find that households update their macroeconomic expectations in response to new information. In our case, we show that Chinese household responsiveness to treatments varies significantly with their lockdown status, underscoring the importance of context in expectation formation.

Our findings offer new perspectives on how environmental conditions shape expectation formation and responses to information, contributing to the broader literature on expectations during uncertain times such as the COVID-19 pandemic (Dräger et al. 2016; Binder 2020; Bui et al. 2023; Dräger et al. 2024). Our study is particularly related to Armantier et al. (2021) and Coibion et al. (2025), which analyze how lockdown status affected U.S. household inflation expectations. Whereas Coibion et al. (2025) find that lockdowns lowered inflation expectations and raised uncertainty, we find the opposite pattern in mid-pandemic China: lockdowns were associated with *higher* inflation expectations and *lower* uncertainty.

Our work introduces a new source of high-quality, national survey data from China, a country that remains largely understudied in the macroeconomic expectations RCT literature. While most prior studies focus on the U.S. and European countries, only one existing RCT explores Chinese household expectations (An et al. 2023). An et al. (2023) focuses on gas prices following the war in Ukraine in four major cities of China. In contrast, our study leverages nationwide sampling and covers a broader range of macroeconomic topics. This project also delivers methodological contributions by offering practical lessons for conducting expectation surveys in emerging market economies, addressing issues such as sampling biases, age representation, and question design.

A strand of the literature on macroeconomic expectations emphasizes the role of monetary policy in shaping the degree of disagreement in inflation expectations (Falck et al. 2021). Policy actions can influence the modality of the distribution of expectations, affecting whether expectations become more dispersed or more concentrated around particular values (Adrian et al. 2021). Mankiw et al. (2003) describes the bimodality of the inflation expectations distribution resulting from one group revising expectations in line with aggregate data while another group maintains relatively higher expectations. Baker et al. (2020) find that natural disaster shocks lead to more attentive agents and lower dispersion of forecasts. Adrian et al. (2021) demonstrate that certain policy can restore the modality of a distribution to a unimodal optimal equilibrium. Our paper bridges the literature on expectation modality and policy communication by showing how information treatments and environmental context (lockdowns) jointly shape the distribution of expectations.

Another strand of the literature on consumer expectations highlights the role of price salience in shaping aggregate inflation expectations. Empirical evidence shows that household inflation expectations are disproportionately influenced by frequently purchased or highly visible goods, such as groceries (Cavallo et al. 2017; D'Acunto et al. 2021; Dietrich 2024), gasoline and energy (Binder et al. 2024b; Hajdini et al. 2024; Jo and Klopack 2025), and other salient categories (Ahn et al. 2024). We find that price salience also matters in the Chinese context, as individuals assign greater weight to food price inflation than overall inflation when forming post-treatment inflation expectations.

This paper also relates to the literature studying the causal effect of inflation expectations on household spending and wages (Roth and Wohlfart 2020; Duca-Radu et al. 2021; Jordà and Nechio 2023; Coibion et al. 2023a; Coibion et al. 2023b; Jain et al. 2024). In China, we find that higher inflation expectations lead households to expect lower durable spending and higher typical spending without changes in employment expectations.

2 Survey design

We use data from the Survey of Household Inflation Expectations in China – the first of its kind to be implemented nationwide. This survey is a joint effort between American University and Renmin University of China. The national survey has two waves, which collect rich demographic and economic data via WeChat (China's most widely used online platform). The first wave, in May 2022, surveyed 10,538 individuals and the second wave, in September 2022, surveyed 6,835 individuals.

Our experience conducting this national survey in China offers practical insights for implementing macroeconomic expectations surveys in emerging market economies. We address two key objectives in our survey design: the importance of matching the sample's age distribution to national demographics, and the effective collection of inflation expectations. The survey was administered on the largest online platform in China to maximize population coverage. Despite this, reaching older respondents proved challenging, highlighting a common limitation of online survey methods in developing country contexts. We correct for the differences in the age distribution of respondents in the survey versus in the national population with survey sampling weights (see Appendix A). We also determine that eliciting inflation expectations as point estimates, rather than a probability distribution, significantly improved data quality in the second wave of the survey in Appendix B. For this reason, we focus on data from the second wave of the survey moving forward.

In this paper, we focus on the results from the survey in September 2022.[1] We drop individuals who have repeated survey responses, whose survey time is less than 1 minute or over 30 minutes, and whose inflation expectations are larger than 1000%. The survey contains

[1]See the full questionnaire in Appendix M.

an attention check question to identify any respondents rushing through the survey.[2] We also omit respondents that fail this attention check from our analysis. This leaves our final sample of 5,989 individuals.

The sample matches the national demographics of China in terms of gender, but over-represents young and educated households. Table 1 shows that about half of sample respondents are female, aged below 27, or are college educated. About 80% of respondents reside in urban towns or cities. The majority of the sample, 60%, is employed and 84% of monthly incomes fall between 2000-9999 yuan. We construct sample weights to improve national representativeness. Our weights adjust the sample to population statistics by gender, age, education, and urban residence.

Table 1: Sample summary statistics

	Mean	SD	Min	Max
Female	0.514	0.500	0	1
Age	27.043	8.268	15	80
Education level college or more	0.499	0.500	0	1
Urban	0.807	0.395	0	1
Employed	0.605	0.489	0	1
Monthly personal income (if employed), ¥				
<2000	0.055	0.228	0	1
2000 to 4999	0.439	0.496	0	1
5000 to 9999	0.402	0.490	0	1
>10000	0.104	0.305	0	1
Lockdown status				
Not in lockdown	0.622	0.485	0	1
Recently (but not currently) in lockdown	0.213	0.409	0	1
Currently in lockdown	0.165	0.371	0	1

Note: This table displays the mean, standard deviation, minimum, and maximum values of variables in the survey sample of September 2022. Variable means are proportions of the sample, except for the age variable, which is the mean level of respondent age.

The survey is designed to elicit perceptions and expectations regarding price changes and spending behavior. It includes a set of randomized information treatments about the U.S. economy, Chinese inflation policy, and COVID trends. Pre- and post-treatment questions enable us to identify treatment effects on expectations.

2.1 Identification of lockdowns

The second wave of the survey was administered during a period when Chinese lockdowns were implemented locally, not nationally. This geographic variation in individual lockdown status makes China a good case study to estimate the causal effects of lockdowns and enables

[2]We ask respondents to give us their employment status at the beginning and end of the survey. We classify a failed attention check as those whose reported status does not match between these two questions.

a quasi-experimental identification strategy. There is important variation in lockdown groups in our sample. Table 1 shows that of sampled respondents, 62.2% are not in lockdown, 21.3% recently exited lockdown, and 16.5% are currently in lockdown.

We exploit the variation in lockdown orders in our sample and ask several questions on work, productivity, and the economy. Of those in lockdown, 55% report that they work from home (WFH) and the rest that they work at their usual workplace. Ideally, households prefer to WFH 3-4 days per week. Individuals report a higher ideal number of WFH days if they were recently or are currently in lockdown.

We find that lockdowns alter both work behavior and economic expectations. Those in lockdown report reduced working hours and productivity. For example, productivity dropped for one-third of respondents, and hours worked declined by 2-3 hours on average during lockdowns. Individuals also on average report working 1.4 fewer hours immediately after lockdown compared to when they were not in lockdown. Only 50-57% report that their productivity was maintained during lockdown. These real economy effects are important for interpreting changes in expectations.

3 Expectations and information treatments by lockdown status

3.1 Unconditional expectations

Respondents were asked a series of questions about their inflation perceptions and expectations in China. To capture perceived inflation, we first ask whether the individual thinks prices have changed over the past 12 months and then elicit a point estimate of the percentage change in prices. We ask these questions for food prices and for overall prices in the economy. We adjust the previously mentioned questions to elicit changes in prices over the next 12 months, rather than the past 12 months, to collect inflation expectations. Lastly, we calculate respondent uncertainty in their inflation expectations via a Likert scale of confidence in their estimate ranging from 1 to 10.

Households in China tend to overestimate inflation. Actual annual CPI inflation was 2.8% in September 2022 and 0% in September 2023.[3] Table 2 shows that individuals perceive food inflation to be 5.45% and overall inflation to be 5.81% on average. Inflation expectations were also elevated at 4.16% on average. Respondents are generally certain in their expectations, with an average uncertainty score of 7 out of 10.

There are important demographic differences in inflation experiences. Individuals who are men, college-educated, and live in urban areas have higher inflation perceptions and expectations.[4] These demographic groups also report lower uncertainty in their expectations. Respondents who were currently or recently in lockdown on average report inflation perceptions that are 0.2-0.4 pp higher than those not in lockdown. Lockdown individuals also report higher inflation expectations compared to not-locked down individuals; 4.44%

[3]Annual CPI inflation is of a particular month compared to the same month of the previous year.

[4]The fact that highly educated individuals predict higher inflation expectations than others in our sample is unusual. This is likely driven by the higher share of college-educated individuals who are male, urban, and in lockdown rather than by their educational level. In our sample, inflation expectations are lowest for college-educated women, then non-college-educated women, then non-college-educated men, and highest for college-educated men. Among the college-educated, 86% are urban residents. Also, individuals with college degrees are more likely to be in lockdown (40%) than those without college degrees (32%).

Table 2: Inflation perceptions and pre-treatment expectations by demographic

	π_{pcvd}^{food}		π_{pcvd}		π_{prior}		Uncertainty π_{prior}	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
All	5.45	5.51	5.81	5.70	4.16	5.06	6.92	2.28
Sex								
Male	5.72	5.47	6.14	5.68	4.43	5.05	7.30	2.17
Female	5.17	5.53	5.45	5.71	3.86	5.05	6.51	2.32
Education								
Non-college	4.93	4.98	5.17	5.18	3.71	4.59	6.89	2.35
College	7.23	6.72	7.80	6.73	5.64	6.14	7.02	1.94
Location								
Urban	5.71	5.76	6.23	5.94	4.41	5.28	6.99	2.21
Rural	4.89	4.89	4.86	5.01	3.62	4.51	6.78	2.40
Lockdown								
Not	5.39	5.37	5.67	5.56	4.02	4.89	6.85	2.26
Now or recent	5.59	5.78	6.09	5.98	4.44	5.37	7.04	2.31

Note: This table shows perceived inflation (π_{pcvd}) for food and the overall economy, pre-treatment inflation expectations (π_{prior}), and uncertainty (where 1 denotes not confident at all, and 10 denotes extremely confident) in inflation expectations. Statistics are computed using sample weights. Expectations are truncated at the 5 and 95 percentiles and use Huber weights.

versus 4.02% respectively. Individuals in lockdown additionally have lower uncertainty in their inflation expectations than those not in lockdown.[5]

3.2 Expectations and economic growth

Households likely have a relationship in mind between the inflation rate and economic growth. In economic theory, higher inflation expectations should be associated with higher growth expectations. However, household expectations do not always correspond to theory. Dräger et al. (2016) find that expectations become less consistent with theory during recessions or periods of volatility. Binder (2020) similarly finds that consumers often associate bad times in the Covid-19 pandemic with high inflation.

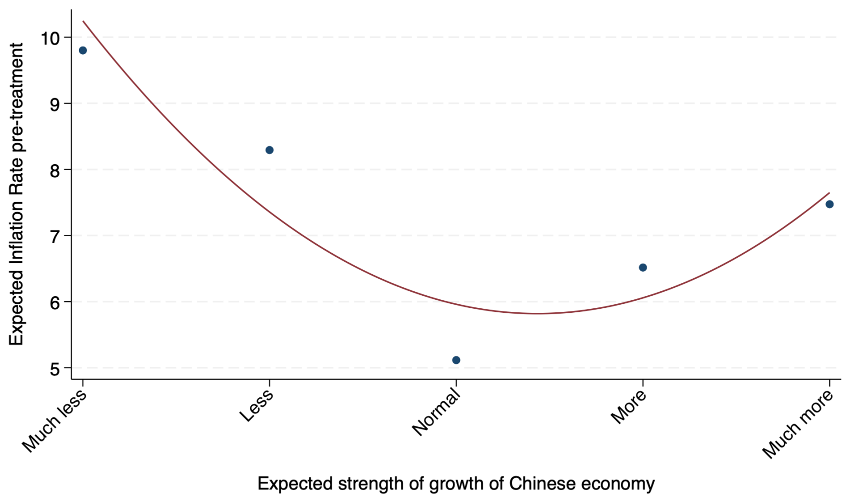
We explore how expectations relate to perceptions of economic growth. In our survey, respondents are asked their expectations for Chinese economic growth over the next 12 months. Answer choices are “much less strongly than normal”, “less strongly than normal”, “normal”, “more strongly than normal”, and “much more strongly than normal”.

We observe a V-shaped relationship between respondent expectations of inflation and

[5]Kim and Binder (2023) find that individuals who closely follow the news or are aware of inflation report lower inflation uncertainty. We expect that respondents under Chinese lockdown were more exposed to inflation-related news, which at the time was predominantly negative. This heightened exposure may have contributed to higher inflation expectations and lower uncertainty among lockdown respondents.

economic growth.[6] Figure 1 shows that individuals with the highest and lowest inflation expectations anticipate the most extreme changes in growth, both positive and negative. In contrast, respondents with relatively lower inflation expectations also expect "normal" growth. The fact that part of the sample expects both higher inflation and lower growth is inconsistent with theory. This inconsistency likely reflects the confusion introduced by supply shocks during the pandemic.

Figure 1: Expectations of inflation versus economic growth



Note: This figure shows a binscatter plot of expectations of inflation pre-treatment and economic growth. Expectations of growth are elicited in reference to normal growth: for example, "much less" is presented to respondents as "much less strongly than normal". Plot uses sample weights.

In Appendix C we test several mechanisms for the V-shape relationship. This relationship holds when controlling for household characteristics such as age, sex, college education, urban residence, and employment. We also do not find a difference in this relationship between respondent lockdown status or information treatment.

3.3 Information treatments

After respondents have answered questions on their demographics and baseline expectations, they are randomly assigned to five equally sized groups for the information treatment. The first group is the control and does not receive any information. The other four groups are presented with different statements on the US economy, the US and Chinese inflation policy, and the rate of COVID cases in China. The specific treatment groups are as follows:

> *<u>Group 1:</u> Control group.*
> *<u>Group 2 (Treatment 1):</u> The probability of a recession in the United States over the next year is estimated to be about 40%.*

[6] The shape is consistent if plotting post-treatment, rather than prior, inflation expectations.

Group 3 (Treatment 2): The U.S. central bank has raised interest rates rapidly in recent months (by 1.5 percentage points), raising fears of a slowdown in the U.S. economy over the next year.
Group 4 (Treatment 3): The national legislature has set a target for inflation in China to be 3% in 2022.
Group 5 (Treatment 4): The Institute for Health Metrics and Evaluation (IHME) projects that the daily number of deaths from Covid in China will rise from about 3 per day to over 300 per day by November 2022.

This RCT design allows us to identify the causal effects of receiving this information on expectations. The two treatments on the US economy are important to understand the international effects of the US on Chinese households. Treatment 3 enables us to analyze the impact of Chinese institutions on households. Our analysis of Treatment 4 explores the interaction between the Covid pandemic developments and lockdowns on household economic expectations.

3.4 Prior versus post-treatment expectations

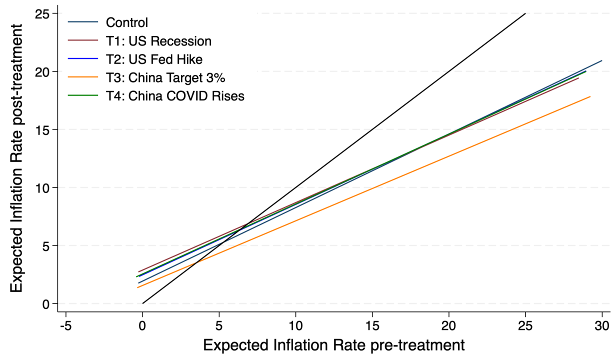
We ask respondents to report their inflation expectations before and after these treatments to study whether the receipt of this information influences how people view the economy. We expect to find that households respond to treatments as Bayesians, placing some weight on their priors and some weight on the information. This behavior should lead to a convergence in beliefs on expectations.

We construct binscatter plots showing the relationship between respondents' prior and post-treatment inflation expectations. Figure 2 displays the figures for the overall sample. We observe a slope of less than one for all treatment groups, even the control, which could reflect the uncertain pandemic and lockdown environment of the survey collection period. The slope of the relationship is flatter for several treatment groups compared to the control group, suggesting that the average treated household puts a lower-than-one weight on their priors (pre-treatment) when forming posteriors (post-treatment). The China Target 3% treatment group has a particularly flatter slope compared to the control.

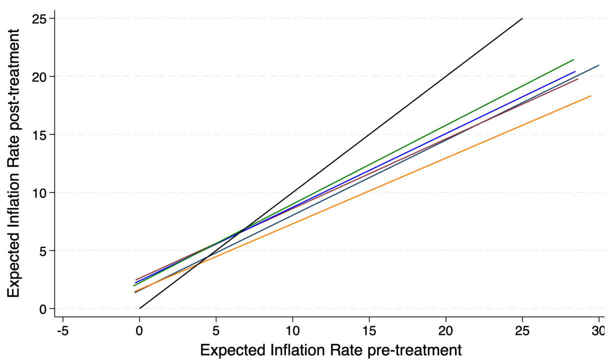
The relationship between prior and post-treatment inflation expectations varies by lockdown status. Figure 2b shows that individuals not in lockdown have a similar relationship to the general sample. In contrast, Figure 2c shows a much flatter slope, indicating that the information treatments reduce households' reliance on their prior beliefs even more for those in lockdown, who especially revise down their posterior expectations compared to the control group. This is suggestive evidence that treatments likely have differential effects on households based on their lockdown status. We formally test this hypothesis in the next section.

Appendix D contains binscatter plots showing the relationship between respondents' prior and posterior inflation expectations for the subsample that revises their post-treatment expectations (the intensive margin). More than half of the sample, 53%, updates their expectations post-treatment. The slope of the relationship for all households, plotted in Appendix D(a), is flatter for all groups compared to the overall sample since all households in this figure make revisions. The US Recession, China Target 3%, and China COVID Rises treatment groups have particularly flatter slopes compared to the control.

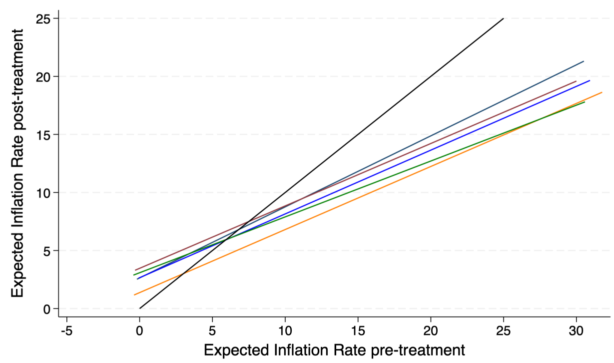
Figure 2: Binscatter plots of prior and post-treatment inflation expectations



(a) All



(b) No lockdown



(c) Lockdown

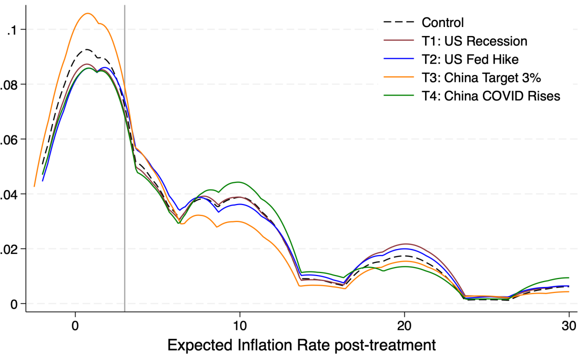
Note: These figures show the relationship between pre- and post-treatment inflation expectations for the overall sample. Figure (a) displays the plot for all households, Figure (b) represents households not in lockdown, and Figure (c) represents households recently or currently in lockdown. The solid black line is the 45-degree line. Plots use sample weights.

3.5 The modality of inflation expectations

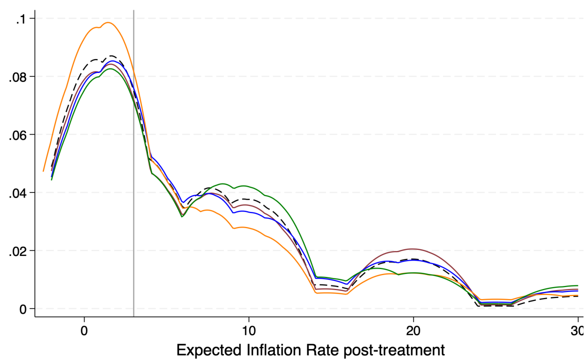
The distribution of inflation expectations changes following certain treatments. Figure 3a plots the distribution separately for each treatment group. The expectations of the control and most treatment groups are multi-modal, with common modes at 3%, 10%, and 20%. This finding illustrates that during a pandemic period, which served as a shock to the economy, there is deep disagreement in household revisions of expectations. One group revises their expectations in line with the aggregate data, while another group maintains their relatively higher expectations in line with Mankiw et al. (2003).

When provided with the official inflation target (Treatment 3), expectations shift toward the policy value and a more uni-modal distribution. The distribution of Treatment 3 in Figure 3a is more concentrated at lower values that are closer to the target value of 3% shared in the treatment statement. Respondents therefore have lower expectations following this treatment compared to the control and other treatments. This behavioral response

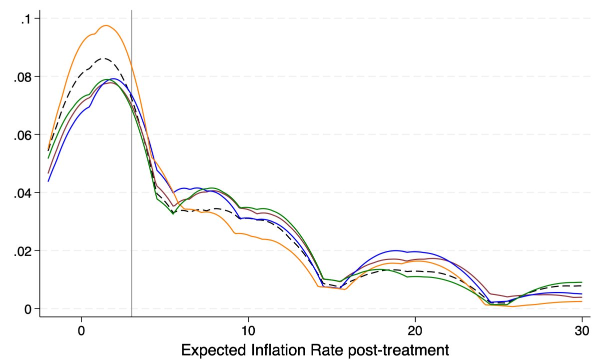
Figure 3: Distribution of post-treatment inflation expectations



(a) All



(b) No lockdown



(c) Lockdown

Note: These figures show the kernel densities of post-treatment inflation expectations by treatment group. Figure (a) displays the plot for all households, Figure (b) represents households not in lockdown, and Figure (c) represents households recently or currently in lockdown. Vertical grey line is at 3%. Plots use sample weights.

illustrates the power of targeted policy communication (Adrian et al. 2021). In our case, it is optimal to reduce inflation disagreement and align household expectations with economy aggregate values and government policy objectives.

The distribution of post-treatment inflation expectations differ by lockdown status. Figure 3b displays the distribution for respondents not in lockdown, which is similar to the overall sample. Figure 3c illustrates that individuals in lockdown have a flatter distribution of expectations after receiving information on the US Recession, US Fed Hike, or China COVID Rises compared to the control group.

Appendix E shows several distribution statistics of the density plots in Figure 3. The distribution of expectations among respondents who receive the China Target 3% treatment has a lower mean and standard deviation but relatively higher kurtosis and skewness compared with other groups, indicating greater asymmetry in the distribution of expectations following this treatment.

The distribution statistics of the subsample not in lockdown mirror those of the all households, while those in lockdown differ. The commonality among groups by lockdown status is that the distribution of respondents receiving the China Target 3% treatment has a relatively lower mean and standard deviation. However, the mean and standard deviation of expectations are especially elevated for respondents in lockdown who received the US Recession, US Fed Hike, and China COVID Rises treatments.

We also conduct non-parametric tests of the difference in distribution of post-treatment inflation expectations by treatment groups. The two-sample Kolmogorov-Smirnov tests show that the distribution of the China Target 3% treatment group is significantly different from that of all other groups, with this group having smaller values than the others.[7]

Figure 4 shows the distribution of respondent uncertainty in their inflation expectations. Uncertainty is measured on a Likert scale ranging from 1 to 10, where 1 indicates high uncertainty and 10 indicates high certainty. There is no clear difference in uncertainty by treatment groups for the overall sample. Respondents report that they are relatively certain in their expectations, with the majority of ratings above a level 5 out of 10.

We find differences in post-treatment inflation expectation uncertainty by respondent lockdown status. Figure 4b shows that individuals not in lockdown have a similar uncertainty distribution as the overall sample. However, individuals in lockdown are more certain about their expectations after receiving the China Target 3% treatment. In Figure 4c, the distribution for this treatment peaks above the others at a level of 7-8 and has a narrower left tail at lower values on the scale.

This distributional evidence highlights the role that targeted policy communication can play in shaping both the level and uncertainty of inflation expectations among households. The China Target 3% treatment leads to a notable shift toward lower, more policy-aligned expectations and a more concentrated, asymmetric distribution. This treatment also appears to lower respondent uncertainty, especially among those in lockdown, suggesting that credible and salient policy messaging may also bolster individuals' certainty in their economic outlooks.

4 Causal impact of information treatments

4.1 Overall effects

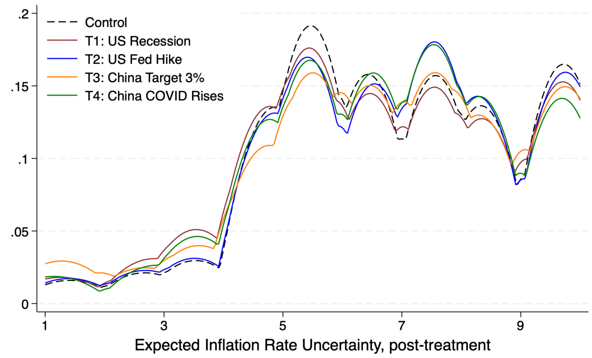
We exploit variation in assignment across groups to estimate the causal impact of the treatments on inflation expectations. Specifically, we run the following regression to examine respondents' reactions to the information signals:

$$\pi_{j,post} = \alpha + \sum_{k=2}^{5} \beta_k T_{j,k} + \delta \pi_{j,prior} + \sum_{k=2}^{5} \gamma_k T_{j,k} \times \pi_{j,prior} + \boldsymbol{X_j} \boldsymbol{\psi} + \epsilon_j, \tag{1}$$

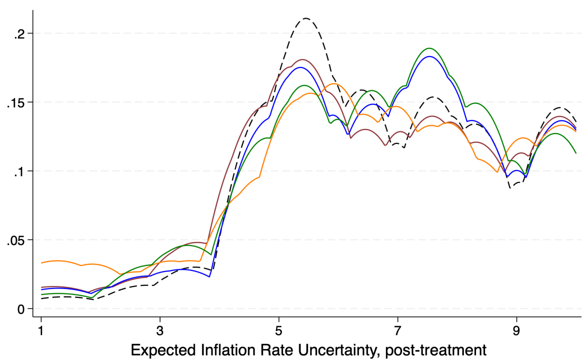
where π_{post} and π_{prior} are post-treatment and prior inflation expectations, respectively, of each respondent j. The four information treatments are captured by T relative to the

[7]The p-values of the Kolmogorov-Smirnov test between the Control and China Target 3% treatment group is 0.021, and the p-values of the tests between the China Target 3% and other treatment groups are less than 0.001.

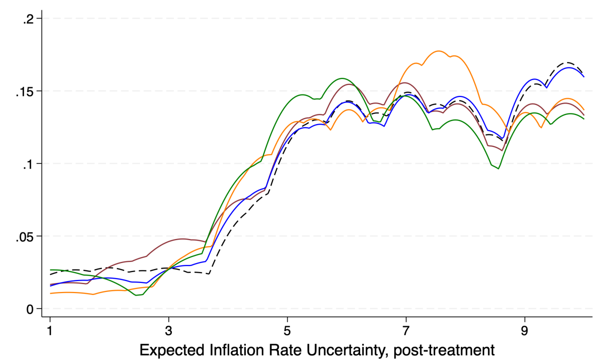
Figure 4: Distribution of post-treatment inflation expectation uncertainty



(a) Overall sample



(b) No lockdown



(c) Lockdown

Note: This figure shows the kernel densities of post-treatment inflation expectation uncertainty by treatment group. Respondents report their uncertainty in their expectations on a Likert scale ranging from 1 to 10, where 1 is high uncertainty and 10 indicates high certainty. Figure (a) is for the overall sample, while figures (b) and (c) are by lockdown status. Plot uses sample weights.

control. The vector of control variables, ψ, includes a quadratic polynomial in age and indicator variables for sex, college education, urban residence, employment, and lockdown status.

We employ several methods to control for outliers in our sample. First, we truncate all inflation expectations at the 5th and 95th percentiles so that they lie within the range of -5% to 30%. Second, we present estimates of both OLS and Huber (1964) robust regressions that systematically control for outliers.

Table 3 reports estimates of equation (1) for the overall sample, the intensive margin (households that revise their priors after treatment), and the extensive margin (likelihood of updating expectations). We find that Chinese households expect significantly higher inflation after news of a looming U.S. recession: the USRec treatment raises posterior expectations by 0.6-1.9 percentage points relative to the control. While this treatment does not change the likelihood of updating expectations, its effect persists among households at the intensive

Table 3: Treatment effects on inflation expectations

	Post-treatment inflation expectations					
	Overall sample		Extensive margin		Intensive margin	
	(1)	(2)	(3)	(4)	(5)	(6)
USRec	0.950**	0.609**	0.063	0.160	1.907***	1.163***
	(0.397)	(0.252)	(0.039)	(0.100)	(0.722)	(0.330)
USHike	0.524	0.099	0.049	0.124	0.378	0.335
	(0.409)	(0.224)	(0.039)	(0.100)	(0.757)	(0.303)
CTarget	-0.364	-0.295	0.049	0.124	-1.161*	-0.257
	(0.359)	(0.222)	(0.039)	(0.101)	(0.662)	(0.295)
CCOVID	0.654	0.335	0.033	0.085	1.237*	0.623*
	(0.419)	(0.258)	(0.040)	(0.103)	(0.737)	(0.341)
π_{prior}	0.631***	0.711***	0.009***	0.024***	0.332***	0.377***
	(0.040)	(0.026)	(0.003)	(0.007)	(0.054)	(0.025)
USRec × π_{prior}	-0.053	-0.020	-0.005	-0.013	-0.163**	-0.156***
	(0.059)	(0.040)	(0.004)	(0.010)	(0.076)	(0.037)
USHike × π_{prior}	-0.027	0.021	-0.005	-0.012	-0.017	-0.115***
	(0.058)	(0.035)	(0.004)	(0.010)	(0.079)	(0.038)
CTarget × π_{prior}	-0.080	-0.085**	-0.001	-0.001	-0.075	-0.230***
	(0.061)	(0.041)	(0.004)	(0.010)	(0.078)	(0.036)
CCOVID × π_{prior}	-0.034	-0.008	-0.005	-0.013	-0.110	-0.099**
	(0.065)	(0.039)	(0.004)	(0.010)	(0.084)	(0.038)
Constant	-1.511	-1.045	0.696***	0.499*	0.072	0.808
	(1.060)	(0.730)	(0.102)	(0.261)	(1.860)	(0.915)
N	5,181	5,174	5,181	5,181	2,637	2,535
Adj. R^2	0.429	0.601	0.016		0.115	0.270
Pseudo R^2				0.014		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Model	OLS	Huber	OLS	Probit	OLS	Huber

Note: This table shows estimates of equation (1) using the overall sample in columns (1) and (2) and the intensive margin subsample that revises their priors following the treatment in columns (5) and (6). Columns (3) and (4) are estimates of the extensive margin likelihood of revising expectations post-treatment. The treatment groups are abbreviated as: "USRec" for the US Recession, "USHike" for the US Fed Hike, "CTarget" for China Target Inflation 3%, and "CCOVID" for China COVID Rises. Huber (1964) robust regressions endogenously account for outliers. Regressions use sampling weights with inflation expectations truncated at the 5th and 95th percentiles. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

margin. Other treatments do not show strong effects overall or at the extensive margin; however, at the intensive margin, respondents lower their expectations after the CTarget treatment and raise them after the CCOVID treatment.

Households update expectations in a Bayesian manner, placing considerable weight on their priors (0.631 in column 1), but this weight declines when they receive new information.

The reduction is especially pronounced at the intensive margin, and the interaction between treatments and priors is negative and significant, showing that households rely less on their priors after treatment. Notably, they react far more strongly to domestic policy signals: the decline in the weight on priors is about twice as large for the inflation target as for the U.S. recession or COVID news (column 6). This indicates that Chinese households view domestic policy information as more influential than international or general news when forming their inflation expectations.

4.2 Lockdown heterogeneity in the causal impact of information treatments

In this section, we investigate whether respondent lockdown status influences the estimated effects of our treatments on inflation expectations. We exploit variation in both treatment assignment and lockdown status to identify the causal impact of information signals by expanding equation (1):

$$\begin{aligned}\pi_{j,post} = \alpha + \sum_{k=2}^{5} \beta_k T_{j,k} + \delta \pi_{j,prior} + \sum_{k=2}^{5} \gamma_k T_{j,k} \times \pi_{j,prior} + \phi Lockdown_j \\ + \sum_{k=2}^{5} \zeta_k T_{j,k} \times Lockdown_j + \boldsymbol{X_j \psi} + \epsilon_j,\end{aligned} \tag{2}$$

where *Lockdown* is an indicator variable equal to 1 if the respondent was recently or is currently in lockdown and equal to 0 if not in lockdown.[8] The vector of control variables, ψ, includes a quadratic polynomial in age and indicator variables for sex, college education, urban residence, and employment.

Chinese households not in lockdown expect higher inflation from all "bad news" about the economy, including information on a looming US recession, US interest rate hike, or increase in COVID cases. Table 4 column 1 shows that post-treatment inflation expectations are 1.086, 0.926, and 1.127 percentage points (pp) higher than the control in response to information on the US recession, rate hike, and COVID cases. Individuals are more likely to update their expectations following the USHike treatment compared to the control. We also find that the overall sample behavior holds for individuals in the intensive margin.

[8] Estimates for individuals recently or currently in lockdown have the same sign. We pool these groups to increase statistical power and for ease of the discussion of results.

Table 4: Treatment effects on inflation expectations

	Post-treatment inflation expectations					
	Overall sample		Extensive margin		Intensive margin	
	(1)	(2)	(3)	(4)	(5)	(6)
USRec	1.086**	0.714**	0.064	0.163	2.168***	1.022***
	(0.445)	(0.294)	(0.045)	(0.115)	(0.778)	(0.383)
USHike	0.926**	0.423	0.077*	0.196*	1.049	0.290
	(0.450)	(0.264)	(0.044)	(0.114)	(0.791)	(0.343)
CTarget	0.063	-0.069	0.049	0.125	-0.085	-0.164
	(0.421)	(0.264)	(0.045)	(0.116)	(0.761)	(0.355)
CCOVID	1.127**	0.497*	0.044	0.114	2.224***	0.688*
	(0.495)	(0.301)	(0.046)	(0.117)	(0.818)	(0.403)
π_{prior}	0.633***	0.712***	0.009***	0.024***	0.338***	0.378***
	(0.040)	(0.026)	(0.003)	(0.007)	(0.055)	(0.025)
USRec × π_{prior}	-0.055	-0.023	-0.005	-0.013	-0.170**	-0.156***
	(0.059)	(0.040)	(0.004)	(0.010)	(0.077)	(0.037)
USHike × π_{prior}	-0.029	0.019	-0.005	-0.012	-0.023	-0.120***
	(0.058)	(0.035)	(0.004)	(0.010)	(0.080)	(0.038)
CTarget × π_{prior}	-0.081	-0.087**	-0.001	-0.002	-0.082	-0.231***
	(0.062)	(0.041)	(0.004)	(0.010)	(0.079)	(0.036)
CCOVID × π_{prior}	-0.035	-0.010	-0.005	-0.014	-0.113	-0.100***
	(0.064)	(0.039)	(0.004)	(0.010)	(0.083)	(0.039)
Lockdown	0.844	0.546*	0.037	0.094	1.595*	-0.003
	(0.515)	(0.331)	(0.045)	(0.115)	(0.893)	(0.401)
USRec × Lockdown	-0.389	-0.295	-0.003	-0.008	-0.636	0.443
	(0.752)	(0.476)	(0.063)	(0.162)	(1.265)	(0.588)
USHike × Lockdown	-1.240*	-1.019**	-0.091	-0.231	-1.908	0.195
	(0.741)	(0.443)	(0.063)	(0.161)	(1.351)	(0.558)
CTarget × Lockdown	-1.280*	-0.690	0.001	0.000	-2.913**	-0.208
	(0.690)	(0.467)	(0.063)	(0.162)	(1.135)	(0.517)
CCOVID × Lockdown	-1.460*	-0.487	-0.033	-0.085	-2.880**	-0.137
	(0.786)	(0.475)	(0.064)	(0.164)	(1.318)	(0.595)
Constant	-1.883*	-1.266*	0.682***	0.463*	-0.583	0.825
	(1.070)	(0.746)	(0.103)	(0.263)	(1.864)	(0.929)
N	5,181	5,174	5,181	5,181	2,637	2,536
Adj. R^2	0.430	0.599	0.017		0.119	0.268
Pseudo R^2				0.015		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Model	OLS	Huber	OLS	Probit	OLS	Huber

Note: This table shows estimates of equation (2) using the overall sample in columns (1) and (2) and the intensive margin subsample that revises their priors following the treatment in columns (5) and (6). Columns (3) and (4) are estimates of the extensive margin likelihood of revising expectations post-treatment. The treatment groups are abbreviated as: "USRec" for the US Recession, "USHike" for the US Fed Hike, "CTarget" for China Target Inflation 3%, and "CCOVID" for China COVID Rises. Huber (1964) robust regressions endogenously account for outliers. Regressions use sampling weights with inflation expectations truncated at the 5th and 95th percentiles. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The estimates in Table 4 indicate that lockdown status does, in fact, significantly alter the effects of information signals on inflation expectations. Respondents in lockdown have higher inflation expectations in the overall sample and intensive margin compared to those not in lockdown, but there is no difference in the likelihood of revising between the two groups. Those in lockdown also show a stronger belief in policy credibility. Their inflation expectations decrease more after receiving information on the inflation target, suggesting greater institutional trust. In contrast, non-lockdown households react more to "bad news" about the economy. Their higher inflation expectations following these treatments are likely due to heightened surprise or uncertainty.

The post-treatment expectations of lockdown households converge to the aggregate more than non-lockdown households in response to information about the inflation target. Our estimates in Table 4 column 1 show that households in lockdown receiving the China Target treatment have 0.436 pp lower expectations compared to households receiving this treatment and not in lockdown.[9] This difference is larger in the intensive margin, with estimates in column 5 presenting a difference of 1.318 pp. The fact that lockdown households react more than non-lockdown households to information on the target shows their trust in institutions to achieve a lower inflation rate. This trust in institutions, higher among lockdown households likely due to their greater exposure to strong government lockdown intervention, reduces their uncertainty and leads to lower inflation expectations.

4.2.1 Lockdown counterfactual

Before receiving information treatments, respondents are asked several hypothetical questions on their expectations and lockdown status. These questions provide a counterfactual scenario to study how households view the relationship between their expectations and lockdowns. We ask individuals who are not in lockdown to imagine being in lockdown, and vice versa. The questions are as follows:

Q.H1 Imagine that your community were [not] in lockdown, would you change your forecasts for "overall prices in the economy over the next 12 months"?

A. Yes (go to Q.H2)
B. No

Q.H2 In that case, over the next 12 months, if your community were [not] in lockdown, do you think overall prices in the economy

A. would go up (go to Q.H3)
B. would stay the same, or
C. would go down (go to Q.H3)?

Q.H3 Over the next 12 months, if your community were [not] in lockdown, by what percentage do you think overall prices in the economy would go [up / down]? _____ %

[9] The value of -0.436 is the sum of coefficients for $Lockdown$ (0.844) and $CTarget \times Lockdown$ (-1.280). In the intensive margin, the value is $-1.318 = 1.595 - 2.913$.

Households update their expectations in response to both counterfactual scenarios. Approximately half (51%) of households not in lockdown report that they would change their inflation forecast if they were in lockdown. Of those who change their forecast, 82% expect higher inflation than their current lockdown state. Almost three quarters (72%) of households in lockdown would change their forecast if they were hypothetically not in lockdown. Inflation forecasts are revised down by 63% of respondents who make revisions. Households thus expect higher (lower) inflation rates if they were hypothetically in (not in) lockdown compared to their current status not in (in) lockdown.

The magnitude of revisions is asymmetric by hypothetical lockdown. The revisions of individuals considering being in lockdown are on average 7.2 pp upward, whereas the revisions of individuals considering not being in lockdown average 1.5 pp downward. Thus, lockdown-induced inflation fears are stronger in magnitude than relief from lifting restrictions. This shows the asymmetry both in probability and in scale of inflation expectation revisions.

We estimate that inflation expectation elasticities to lockdown status are larger under the counterfactual status scenario. Table 5 Panel A shows average inflation expectations of respondents by actual and hypothetical lockdown status. The inflation expectations of respondents in lockdown are on average 10% (0.42 pp) higher than those not in lockdown. However, expectations jump when respondents imagine changing from not in lockdown to in lockdown. In the counterfactual, the inflation expectations of respondents hypothetically in lockdown are 124% (5.10 pp) higher than those hypothetically not in lockdown.

We also test differences in respondent revisions in expectations following the counterfactual by lockdown status. First, we test the likelihood of making a revision in inflation expectation in the counterfactual scenario. Second, we test the likelihood of an upward revision in expectations given that a revision occurred. Lastly, we estimate the magnitude of the revision as the difference in expectation from the counterfactual and the actual prior. We run regressions for each outcome - an indicator for a revision, an indicator for an upward revision, and the magnitude of the revision - on the lockdown status indicator and the control variables in equation (2).

Respondents considering being in lockdown are more likely to revise their expectations and revise them upward compared to respondents considering not being in lockdown. Table 5 Panel B shows that respondents hypothetically in lockdown are 24% more likely to revise their expectations and are 44.4% more likely to make an upward rather than downward revision. The magnitude of the revision by lockdown status is approximately 8.27 pp when controlling for other respondent characteristics. The fact that this estimate is almost the same size as the raw difference in averages (7.2 pp upward versus 1.5 pp downward) demonstrates that almost all of the difference in revisions is due to lockdown status rather than other demographic characteristics of respondents.

The results from this counterfactual exercise provide direct supporting evidence that households believe lockdowns themselves drive higher inflation expectations. This view is in line with our main results in Table 4. Respondents are therefore consciously linking lockdown status and inflation beliefs, rather than mechanically updating their expectations in Table 4. The fact that a majority of respondents revise their forecasts following each change in lockdown status suggests expectations are not strongly anchored.

Table 5: Inflation expectations in the lockdown status counterfactual

Panel A: Descriptive Statistics				
	π_{prior}		π^{cf}_{prior}	
	Mean	SD	Mean	SD
Lockdown: Not	4.02	4.89	9.20	8.45
Lockdown: Now or recent	4.44	5.37	4.10	7.10

Panel B: Regression Results			
	(1)	(2)	(3)
	Revision	Upward revision	$\Delta\pi^{cf}_{prior}$
Lockdown: Now (CF)	0.240***	0.444***	8.270***
	(0.032)	(0.041)	(0.533)
N	2,267	1,731	2,267
Adj. R^2			0.102
Pseudo R^2	0.059	0.119	
Controls	Yes	Yes	Yes
Model	Probit	Probit	Huber

Note: Panel A shows statistics for actual pre-treatment inflation expectations (π_{prior}) and counterfactual inflation expectations (π^{cf}_{prior}). Expectations are truncated at the 5 and 95 percentiles and use Huber (1964) robust weights. Panel B shows estimates of (1) likelihood of revising expectations in the counterfactual, (2) likelihood of the revision being upward, (3) the change in pre-treatment expectations between the counterfactual and actual scenarios on lockdown status. Estimates in columns 1 and 2 are the marginal effects. "Lockdown: Now (CF)" is the group of respondents not in lockdown whose counterfactual is to be in lockdown. Huber (1964) robust regressions endogenously account for outliers. Regressions use sampling weights with inflation expectations truncated at the 5th and 95th percentiles. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3 Is the causal impact of information treatments in lockdown different for decision-makers?

In the survey, we inquire about respondents' involvement in decision-making in their employment. Approximately a quarter, 28%, of respondents report making any decision in their employment. Specifically, we examine those who make decisions about prices, capital, or wages at work, referring to them as 'decision-makers' throughout the analysis. Since we are interested in how different respondents form expectations, we focus on individuals whose jobs involve thinking about price expectations.[10] Out of the respondents who report making any type of decision, 62% report making decisions on capital, prices, or wages.

We are first interested in estimating whether decision-makers respond differently to treatments when constructing their inflation expectations compared to those who do not make

[10]Respondents are asked to report if in their current job they make decisions on hiring/firing workers, setting prices, capital expenditures, wages/salaries, and marketing or sales. We do not find that individuals who report making decisions on hiring/firing workers and marketing/sales respond to information differently than individuals who are not decision-makers.

decisions.[11] We find that decision-makers rely more on their priors than others when receiving information treatments, as evidenced by the positive coefficients on the triple interaction of treatments, decision-makers, and inflation priors in Appendix Table F2. We also observe significant effects following the US recession and Fed hike treatments in the extensive margin. Overall, individuals who make decisions place greater trust in their priors than others but recognize the need to adjust them when those priors are relatively high.

Next, we estimate whether decision-makers respond differently to treatments according to their lockdown status compared to those who do not make decisions. To examine this, equation (2) is adapted to include interactions between an indicator for making decisions, lockdown, and treatment groups:

$$\begin{aligned}\pi_{j,post} = \alpha + \sum_{k=2}^{5} \beta_k T_{j,k} + \delta\pi_{j,prior} + \sum_{k=2}^{5} \gamma_k T_{j,k} \times \pi_{j,prior} + \phi Lockdown_j + \chi makedec_j \\ + \sum_{k=2}^{5} \zeta_k T_{j,k} \times Lockdown_j + \sum_{k=2}^{5} \omega_k T_{j,k} \times makedec_j + \lambda Lockdown_j \times makedec_j \\ + \sum_{k=2}^{5} \Delta_k T_{j,k} \times Lockdown_j \times makedec_j + \boldsymbol{X_j \psi} + \epsilon_j,\end{aligned} \tag{3}$$

where *makedec* is an indicator variable equal to 1 if the individual is a decision-maker in their current job. Differences between decision-makers and non-decision-makers are captured by ω_k for expectations following different treatments and by λ for weights placed on lockdown. The triple interaction coefficients Δ_k indicates the degree to which decision-makers are influenced by their lockdown status following treatments than non-decision-makers.

We find that decision-makers revise down their inflation expectations more than others in lockdown when receiving information treatments, as evidenced by the negative coefficients on the triple interaction of treatments, lockdown, and decision-makers in Table 6.[12] Decision-makers especially decrease their expectations following information on the inflation target. Lockdown respondents who make decisions also react less to information on "bad news" about the economy. Individuals who make decisions therefore not only rely on their priors, but also greater trust in institutional policy than others when in lockdown.

4.4 Salient prices and the reliance on priors by lockdown status

We next study the salience of prices on inflation expectations. Specifically, we compare estimates of the impact of prior inflation expectations on post-treatment inflation expectations with the impacts of past inflation experiences and expectations of food prices. In addition to economy-wide inflation expectations, respondents are asked about their perceived inflation experiences and expectations for food inflation (see Section 3.1). The overall inflation expectations that respondents report are positively correlated with their perceived inflation (0.5) and highly correlated with their food inflation expectations (0.74). Households in lockdown

[11] To examine this, we expand equation (1) to include interactions between an indicator for making decisions, prior expectations, and treatment groups. See Appendix F for details.

[12] See the full table in Appendix G.

Table 6: Treatment effects on inflation expectations by decision-making and lockdown status

	Post-treatment inflation expectations					
	Overall sample		Extensive margin		Intensive margin	
	(1)	(2)	(3)	(4)	(5)	(6)
USRec × Lockdown × *makedec*	-2.670	-2.430**	-0.015	-0.044	-5.042	-4.956*
	(2.009)	(1.228)	(0.153)	(0.390)	(3.289)	(2.897)
USHike × Lockdown × *makedec*	-2.472	-1.810	0.292*	0.733*	-6.508**	-6.195**
	(1.809)	(1.128)	(0.150)	(0.384)	(3.182)	(2.730)
CTarget × Lockdown × *makedec*	-2.556	-1.645	0.050	0.117	-5.916**	-5.710**
	(1.790)	(1.148)	(0.150)	(0.387)	(3.005)	(2.571)
CCOVID × Lockdown × *makedec*	-2.477	-1.112	0.049	0.118	-7.254**	-6.541**
	(2.008)	(1.166)	(0.153)	(0.393)	(3.198)	(2.729)
N	5,181	5,175	5,181	5,181	2,637	2,637
Adj. R^2	0.431	0.591	0.017		0.123	0.142
Pseudo R^2				0.017		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Model	OLS	Huber	OLS	Probit	OLS	Huber

Note: This table shows estimates of the coefficient Δ_k in equation (3). Full table in Appendix G. Estimates for the overall sample in columns (1) and (2) and the intensive margin subsample that revises their priors following the treatment in columns (5) and (6). Columns (3) and (4) are estimates of the extensive margin likelihood of revising expectations post-treatment. The treatment groups are abbreviated as: "USRec" for the US Recession, "USHike" for the US Fed Hike, "CTarget" for China Target Inflation 3%, and "CCOVID" for China COVID Rises. Huber (1964) robust regressions endogenously account for outliers. Regressions use sampling weights with inflation expectations truncated at the 5th and 95th percentiles. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

have higher food inflation expectations than those not in lockdown on average, but past inflation perceptions are similar.[13]

The role of alternative pre-treatment inflation measures in shaping households' post-treatment expectations is analyzed to better understand the drivers of expectation changes. The alternative measures include pre-treatment inflation expectations for changes in food prices, perceived overall inflation, and perceived inflation of food prices. We estimate the effect of each alternative measure separately. Equation (1) is adjusted to include the alternative measure and an interaction of the measure with the information treatments.

Prior food inflation expectations are more important than overall inflation expectations in determining post-treatment inflation expectations (see Appendix H). We find that respondents place a weight that is approximately twice larger on prior food inflation expectations than overall inflation expectations. The decrease in respondent reliance on priors following treatment is larger on food than overall expectations.

Households weight their perceived inflation less than their prior expectations when reporting their post-treatment expectations. Appendix H displays estimates of weights on priors that are approximately five times larger than perceived inflation in the overall sample,

[13]These summary statistics by lockdown status are intuitive given that individuals in lockdown have relatively higher overall inflation expectations and that there is a strong positive correlation between overall and food inflation. Additionally, inflation over the past 12 months should be similar for all households given that lockdowns were not prevalent in September 2021 in China.

but weights that are similar in size for the intensive margin. We also find that households increase their reliance on their perceived overall and food inflation following information on a likely US recession and increase in COVID cases.

Given that salient prices affect expectations differently, we examine whether lockdown status alters how individuals respond to treatments based on various inflation measures. We estimate the following regression for each measure to capture price salience:

$$\begin{aligned}\pi_{j,post} = \alpha &+ \sum_{k=2}^{5} \beta_k T_{j,k} + \delta \pi_j + \sum_{k=2}^{5} \gamma_k T_{j,k} \times \pi_j + \phi Lockdown_j + \lambda \pi_j \times Lockdown_j \\ &+ \sum_{k=2}^{5} \zeta_k T_{j,k} \times Lockdown_j + \sum_{k=2}^{5} \Delta_k T_{j,k} \times Lockdown_j \times \pi_j + \boldsymbol{X_j \psi} + \epsilon_j,\end{aligned} \tag{4}$$

where π is prior inflation expectations π_{prior}, prior food inflation expectations π_{prior}^{food}, perceived inflation π_{pcvd}, or perceived food inflation π_{pcvd}^{food}. The coefficient Δ_k captures whether lockdown changes how strongly people rely on each inflation measure versus the information treatments when reporting post-treatment inflation expectations.

We find that individuals in lockdown rely less on their priors than those not in lockdown when forming post-treatment inflation expectations. Table 7 reports the estimated coefficients on the triple interaction term in equation (4) for each pre-treatment inflation measure.[14] The coefficients are negative for all inflation measures, but especially significant for prior food inflation expectations and perceived inflation. Therefore, among all treatments, lockdown participants updated their inflation expectations more strongly. Table 7 shows that a 1 pp higher prior predicts up to 0.4 pp less in post-treatment expectations for lockdown versus non-lockdown participants, indicating weaker anchoring to prior beliefs.

While lockdown individuals report relatively higher food inflation expectations, they rely less on this prior following receipt of the treatment. The negative and statistically significant coefficient on the triple interaction indicates that their post-treatment expectations are less anchored to pre-existing food inflation beliefs. In contrast, non-lockdown respondents exhibit a stronger persistence of prior food inflation beliefs, suggesting a higher degree of expectation rigidity. This pattern complements estimates in Appendix H showing higher reliance on food than overall economy inflation expectations. Our results show that lockdown mitigates the price salience estimates by weakening the link between prior food inflation expectations and post-treatment overall inflation expectations. These results complement our analysis in Table 4 showing a differential response to information treatments by lockdown status.

4.5 Lockdown policy and information precision across economic contexts

Lockdown status substantially reshapes how households process economic information. The heterogeneous effects we document show that pandemic restrictions act as a natural experiment for studying how environmental conditions influence the precision and salience of information. We find that lockdown households have higher inflation expectations and stronger responsiveness to policy-target signals. These patterns suggest that lockdown conditions

[14] Appendix I contains full regression estimates using the π_{prior} measure.

Table 7: Treatment effects on inflation expectations by inflation measure and lockdown status

	Post-treatment inflation expectations							
	π_{prior}		π^{food}_{prior}		π_{pcvd}		π^{food}_{pcvd}	
	Overall sample (1)	Intensive margin (2)	Overall sample (3)	Intensive margin (4)	Overall sample (5)	Intensive margin (6)	Overall sample (7)	Intensive margin (8)
USRec × L × π	-0.079	0.141	-0.179***	-0.079	-0.015	0.155	-0.035	-0.007
	(0.088)	(0.160)	(0.055)	(0.154)	(0.069)	(0.138)	(0.080)	(0.156)
USHike × L × π	-0.192**	0.063	-0.124**	-0.320*	-0.165***	-0.143	-0.075	-0.242*
	(0.078)	(0.155)	(0.058)	(0.179)	(0.063)	(0.143)	(0.068)	(0.137)
CTarget × L × π	-0.125	0.184	-0.141**	-0.026	-0.153**	-0.115	-0.112	-0.139
	(0.086)	(0.153)	(0.066)	(0.149)	(0.067)	(0.127)	(0.073)	(0.137)
CCOVID × L × π	-0.070	-0.083	-0.125**	-0.400**	-0.029	-0.161	-0.062	-0.353**
	(0.084)	(0.152)	(0.060)	(0.165)	(0.075)	(0.158)	(0.079)	(0.154)
N	5,174	2,637	5,033	2,569	4,941	2,510	5,007	2,549
Adj. R^2	0.600	0.144	0.736	0.327	0.613	0.272	0.619	0.264
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows overall sample and intensive margin estimates of coefficient Δ_k in equation (4), where L is *Lockdown*. The treatment groups are abbreviated as: "USRec" for the US Recession, "USHike" for the US Fed Hike, "CTarget" for China Target Inflation 3%, and "CCOVID" for China COVID Rises. The regressions each use a different measure of inflation, π, specified in the header of the column (π_{prior}, π^{food}_{prior}, π_{pcvd}, π^{food}_{pcvd}). See Appendix I for full regression estimates using the π_{prior} measure. Estimates are generated from Huber robust regressions using sampling weights with inflation expectations truncated at the 5th and 95th percentiles. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

heightened attention to official communications and increased confidence in institutional sources, thereby raising the precision of policy signals. Lockdowns in mid-pandemic China appear to have created an information-constrained environment in which households more actively responded to policy news.

The effect of lockdowns on macroeconomics expectations is not uniform across countries. Our findings contrast to US evidence in Coibion et al. (2025), where households in lockdown reported lower expectations and higher uncertainty. The divergence in estimates suggests that belief formation depends on the structure of the informational environment and the credibility of macroeconomic institutions. In countries where policy communication is centralized and widely trusted, such as our Chinese context, lockdowns can strengthen the influence of public signals. In environments with more dispersed or contested information, lockdowns may instead amplify ambiguity, leading to more uncertain expectations. Our results are consistent with Armantier et al. (2021), who observe elevated expectations during the US lockdown period. This indicates that information channels can dominate uncertainty responses under certain conditions.

These mechanisms have broader implications beyond the Chinese context. They highlight that the effects of lockdowns on expectation formation are context-dependent, operating through changes in attention, trust, and perceived information precision. This framework helps explain why similar pandemic-related restrictions generated divergent expectation dynamics in emerging versus advanced economies.

5 Bayesian updating under lockdown

This section presents a stylized model of Bayesian updating extended to study household belief formation under lockdown status. We use this model to rationalize our empirical findings on inflation expectations and relate these estimates to structural parameters.

We model households as Bayesian learners who combine a prior with new information: a domestic policy signal (s_{pol}) or a bad-news signal (s_{bad}). Lockdown status $L \in \{0, 1\}$, with 1 indicating lockdown, modifies the precision and credibility of each signal.

5.1 Model setup

Let the latent next-period inflation be $\theta \equiv \pi_{t+1}$. Households hold a Normal prior

$$\theta \sim \mathcal{N}\big(\mu_p,\ \sigma_p^2(L)\big), \qquad \lambda_p(L) \equiv \sigma_p^{-2}(L),$$

and observe a noisy signal centered on the state:

$$s_{pol} = \theta + \varepsilon_{pol} \qquad or \qquad s_{bad} = \theta + \varepsilon_{bad},$$

with independent noises.

Policy target credibility and external "bad news" scale signal *precisions* through lockdown-dependent multipliers:

$$\lambda_{pol}(L) = \tau(L)\,\sigma_{pol}^{-2}, \qquad \lambda_{bad}(L) = \eta(L)\,\sigma_{bad}^{-2},$$

with $\tau(1) > \tau(0)$ (policy target more credible under lockdown) and $\eta(1) < \eta(0)$ (external/bad news less salient under lockdown).

Given the signals, the posterior for θ is Normal with

$$E(\theta \mid s_j, L) = \omega_p(L)\,\mu_p \ + \ \omega_j(L)\,s_j,$$

$$Var(\theta \mid s_j, L) = \Big[\lambda_p(L) + \lambda_j(L)\Big]^{-1}, \qquad j \in \{pol, bad\}$$

where the weights are precision shares

$$\omega_p(L) = \frac{\lambda_p(L)}{\lambda_p(L) + \lambda_j(L)}, \qquad \omega_j(L) = \frac{\lambda_j(L)}{\lambda_p(L) + \lambda_j(L)} \tag{5}$$

5.2 Matching empirical estimates to structural parameters

We next map our empirical estimates from the earlier section to signal credibility. In equation (1), we estimate the weight that households allocate to their prior expectations versus the information treatment when forming post-treatment expectations: $\pi_i^{post} = \alpha + \delta\,\pi_i^{prior} + \sum_k \gamma_k T_{ik} \times \pi_i^{prior} + \varepsilon_i$. The $\hat{\delta}$ coefficient on the prior represents the weight allocated to prior inflation expectations, while the $\hat{\gamma}_k$ coefficients capture the change in the weight on the prior due to new information. Therefore, $1 - (\hat{\delta} + \hat{\gamma}_k)$ represents the weight on new information, or the empirical Kalman gain.

Under the Gaussian updating model,

$$1-\delta(L)-\gamma_{pol}(L)=\omega_{pol}(L), \qquad 1-\delta(L)-\gamma_{bad}(L)=\omega_{bad}(L).$$

Since posterior weights satisfy equation (5), the ratio of signal precisions is identified as:

$$\lambda_{pol}(L)/\lambda_{bad}(L)=\frac{\omega_{pol}(L)}{1-\omega_{pol}(L)}\Big/\frac{\omega_{bad}(L)}{1-\omega_{bad}(L)}=\frac{1-\delta(L)-\gamma_{pol}(L)}{\delta(L)+\gamma_{pol}(L)}\Big/\frac{1-\delta(L)-\gamma_{bad}(L)}{\delta(L)+\gamma_{bad}(L)}$$

The relative precision of signals between lockdown groups is therefore as follows:

$$\frac{\lambda_{pol}(1)/\lambda_{bad}(1)}{\lambda_{pol}(0)/\lambda_{bad}(0)}=\frac{\frac{1-\delta(1)-\gamma_{pol}(1)}{\delta(1)+\gamma_{pol}(1)}\Big/\frac{1-\delta(1)-\gamma_{bad}(1)}{\delta(1)+\gamma_{bad}(1)}}{\frac{1-\delta(0)-\gamma_{pol}(0)}{\delta(0)+\gamma_{pol}(0)}\Big/\frac{1-\delta(0)-\gamma_{bad}(0)}{\delta(0)+\gamma_{bad}(0)}} \tag{6}$$

We calculate the lockdown ratio of relative precision between signals in equation (6) using our survey data. Equation (1) is estimated for households by lockdown status with Huber robust regressions (see Appendix L). The estimated δ and γ coefficients are then combined to calculate the difference in relative precision by lockdown group. We compare the precision of the $CTarget$ policy treatment relative to each bad news signal ($USRec$, $USHike$, and $CCOVID$) by lockdown status.

Our estimated slopes confirm that the effective credibility of policy signals is 3.8% higher under lockdown. Table 8 shows that the policy signal is 19.8% and 24.9% more credible than the $USRec$ and $CCOVID$ signals, respectively. The policy signal is more precise than the $USHike$ signal for non-lockdown households.

Table 8: Relative precision between policy and bad news signals

Bad news signal type	Relative precision
$USRec$	1.198
$USHike$	0.735
$CCOVID$	1.249
Average of bad signals	1.038

Note: This table displays empirical estimates of the relative precision between the policy signal (the $CTarget$ treatment) and various bad news signals (the $USRec$, $USHike$, and $CCOVID$ treatments) by lockdown status. The treatment groups are abbreviated as: "USRec" for the US Recession, "USHike" for the US Fed Hike, "CTarget" for China Target Inflation 3%, and "CCOVID" for China COVID Rises. The relative precision is calculated according to equation (6). Estimates are from Huber robust regressions with output in Appendix L.

6 Effects of inflation expectations on future spending and employment

Inflation expectations are of policy relevance due to their impact on household spending and employment outcomes. In our survey, respondents are asked their expectations spending on durable goods, typical monthly spending, income, and job loss. Analysis of the impact of inflation expectations on these outcomes is difficult due to their endogenous relationship. We use the random assignment of information treatments to identify exogenous variation in inflation expectations following Coibion et al. (2023a). The instrumental variables specification used to estimate these effects is detailed in Appendix J. Although our analysis relies on planned rather than realized spending, stated spending intentions are strong predictors of subsequent expenditure behavior, suggesting that they provide a reliable measure of underlying consumption responses (Colarieti et al. 2024).

We find that higher inflation expectations influence household spending. Appendix Table J3 shows that higher inflation expectations cause households to be more likely to expect higher future typical monthly spending. Households in lockdown are more likely to plan to purchase durable goods than households not in lockdown. On average, however, inflation expectations lead households to plan to purchase fewer durables. Appendix Table J4 shows a detailed breakdown of types of durable goods that households plan to purchase. An increase in inflation expectations causes households to significantly decrease planned house, car, TV, and refrigerator purchases while increasing their planned saving. Households in lockdown report planning to purchase more household goods such as computers and TVs, and decreasing their saving.

Building on the estimated lockdown household behaviors, we next examine whether the effects of inflation expectations on planned spending and employment differ by lockdown status (see Appendix K). For most outcomes, we find no significant heterogeneity. As shown in Table 9, the interaction between lockdown status and post-treatment expectations is generally insignificant. The instruments are sufficiently strong for inference, with first-stage F-statistics exceeding the Stock and Watson (2012) threshold of 10. We also report the LM and Hansen J statistics, both indicating a strong and valid instrument set across all specifications.

Table 9 shows that inflation expectations affect planned spending but not employment-related expectations. Higher post-treatment expectations increase planned monthly spending (Panel A) and reduce planned durable purchases (Panel B). These effects are not significantly moderated by lockdown status. Lockdown individuals display slightly higher intended durable purchases and lower intended savings, but the coefficients are imprecisely estimated. Inflation expectations do not significantly affect income or job-loss expectations, although lockdown individuals report higher perceived job-loss risk (Panel A, column 5).

7 Conclusion

Macroeconomic expectations and policy communications vary by economic environment. Understanding household beliefs under lockdown is essential for effective monetary policy and anchoring expectations. China's localized lockdown policies provide the opportunity to study these mechanisms. We capture beliefs in this quasi-experimental setting in the first national survey on macroeconomic expectations in China; the Survey of Household Inflation Expectations. The first two survey waves provide practical insights for implementing macroeconomic expectations surveys in emerging market economies, as we note the importance of matching the age distribution and eliciting expectations in a simple manner.

This paper shows that lockdown status affects household inflation expectations and their

Table 9: Inflation expectations effects on spending and employment expectations by lockdown status

Panel A: Spending and Employment

	(1) Durables	(2) Durables ind	(3) Spending	(4) Exp Income	(5) Job loss
π_{post}	-0.017	-0.011	1.000***	-0.055	0.000
	(0.012)	(0.007)	(0.121)	(0.101)	(0.042)
Lockdown × π_{post}	0.005	0.000	0.215*	-0.058	-0.006
	(0.012)	(0.006)	(0.126)	(0.109)	(0.040)
Lockdown	0.100	0.067*	-0.957	0.245	0.904***
	(0.084)	(0.040)	(0.708)	(0.595)	(0.293)
N	4,838	4,843	4,648	4,554	3,006
Adj. R^2	0.063	0.067	0.123	0.017	0.051
Fstat 1-stage (π_{post})	12.232	12.211	13.431	11.873	9.164
Fstat 1-stage (L×π_{post})	18.255	18.044	16.666	15.601	12.404
Kleibergen–Paap LM stat	179.436	183.192	178.554	168.326	128.652
p-value LM statistic	0.000	0.000	0.000	0.000	0.000
Hansen J stat	4.226	7.515	20.083	27.456	19.331
p-value J stat	0.998	0.962	0.217	0.037	0.252
Controls	Yes	Yes	Yes	Yes	Yes

Panel B: Detailed Durables

	House	Car	Computer	TV	Fridge	Cell	Save
π_{post}	-0.012***	-0.011***	-0.001	-0.005**	-0.008***	-0.002	0.011
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.006)	(0.007)
Lockdown × π_{post}	0.006*	0.004	0.003	-0.000	0.004	-0.005	-0.000
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)
Lockdown	-0.028	0.004	0.027	0.033	-0.009	0.049	-0.067*
	(0.024)	(0.029)	(0.021)	(0.021)	(0.021)	(0.039)	(0.040)
N	4,837	4,838	4,837	4,836	4,831	4,839	4,843
Adj. R^2	0.015	0.015	0.061	0.012	0.004	0.031	0.067
Fstat 1-stage (π_{post})	12.864	12.320	13.206	12.918	12.908	12.746	12.211
Fstat 1-stage (L×π_{post})	17.251	18.350	17.299	17.741	17.290	18.565	18.044
Kleibergen–Paap LM stat	180.001	177.778	185.433	183.276	183.257	180.671	183.192
p-value LM statistic	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hansen J stat	11.582	8.575	7.196	9.891	22.374	10.618	7.515
p-value J stat	0.772	0.930	0.969	0.872	0.132	0.832	0.962
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows estimates of 2SLS Huber robust regressions (details in Appendix K). The dependent variable in Panel A column (1) is the number of durable goods planned to be purchased, while column (2) is an indicator whether any durable good is planned to be purchased. Panel A column (3) is the expected change in typical monthly spending, column (4) is the expected change in monthly income, and column (5) is the likelihood of job loss for employed individuals. Panel B displays regressions on planned durable spending categories. First stage instruments include exogenous variation in post-treatment expectations due to the information treatments and perceived inflation. All regressions use a jackknife procedure to account for outliers and use weights from Huber (1964) robust regressions as well as population weights. Heteroscedasticity-robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

responses to information on policy and bad news. We find that Chinese households tend to overestimate the level of inflation. Informing households about China's inflation target helps reduce their inflation expectations, which is consistent with Bayesian learning. Furthermore, we estimate that lockdown amplifies the credibility of domestic policy communication and dampens the influence of bad news. This result extends to the differences in behaviors of respondents with differing levels of professional knowledge regarding prices and wages, as well as varying reliance on alternative measures of inflation.

Our findings highlight the potential for expectation surveys to inform both monetary policy design and communication strategies in periods of heightened uncertainty and crisis. Establishing a regular household survey on inflation expectations in China would facilitate deeper research into the dynamics of expectation formation and the transmission of policy information in emerging markets.

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A Appendix: Matching the age distribution in emerging market economy surveys

One of our objectives when sampling individuals was in aligning the survey sample with the Chinese population age distribution. Ensuring that survey respondents reflect the broader population is essential for producing representative aggregate statistics. We conducted our survey online to maintain comparability with existing literature on macroeconomic expectations.

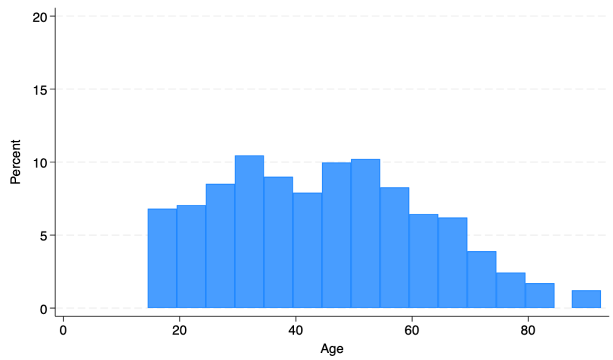
Even when using a dominant platform like WeChat to reach respondents, older households remain underrepresented in the sample relative to the national population. In China, the average age is approximately 38. The age distribution is relatively flat due to population aging, with similar proportions of individuals aged 20 and 60 shown in Figure A1a. In contrast, the average ages of respondents in our two survey waves are 26 and 27, respectively. As shown in Figures A1b and A1c, our survey waves sample a larger proportion of younger individuals compared to the national age distribution.

We correct for the differences in the age distribution of respondents in the survey versus in the national population with survey sampling weights. We construct weights to match the fraction of the population over the age of 25. We assign the threshold weight at age 25 to ensure we have enough observations in each bin to conduct our analysis. A higher age threshold, such as at age 30 or 35, assigns a large weight on the few older-age individuals in our sample; skewing the estimates towards the responses of these few individuals. Therefore, sampling weights by age may not fully correct for this bias.

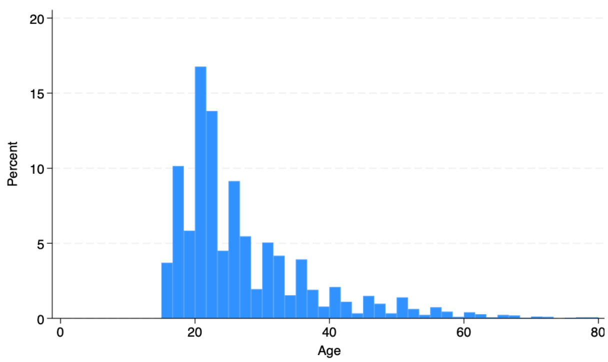
It is important to consider this challenge when designing online surveys in emerging market economies where the young population predominantly uses the internet. Sampling weights by age are necessary in these country contexts for estimates to represent aggregate national behavior. In China in 2018, 40.22% of adults age 60 and older had access to the internet and 18.27% used it regularly (Hu and Xu 2024). In contrast, in a high-income country with extensive collection of household expectations such as the US, over 80% of individuals age 65 and above say they regularly use the internet (Pew Research Center 2024). Adjusting sampling behavior to sample a wider age distribution is thus especially important in emerging market economy surveys on expectations. It may even be optimal to design surveys both online with on-site to ensure the collection of responses from these demographic groups.[15]

[15] On-site survey collection is prevalent in emerging market economies (United Nations 2005; Stantcheva 2022). However, this survey design is new to surveys eliciting macroeconomic expectations as so far they are collected online.

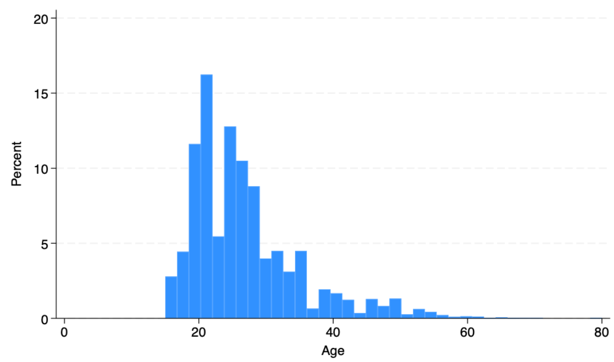
Figure A1: Age distribution in population versus survey



(a) China population



(b) Survey, May



(c) Survey, September

Note: These figures show the age distributions (15+) of the population in China (chart a), and the survey waves collected in May (chart b) and September (chart c) 2022. The source of data for the population age distribution is the United Nations Economic and Social Commission for Asia and the Pacific for 2020.

B Appendix: Eliciting inflation expectations in emerging market economy surveys

Financial literacy can influence how individuals report their inflation expectations. In designing our survey, we tested alternative formulations of questions on macroeconomic expectations and found that their effectiveness depends on respondents' familiarity with statistical concepts. Similar RCTs conducted in the United States and the Netherlands elicit expectations using probability-based questions. Following this approach, in the first round of our survey we asked respondents to assign probabilities to different potential inflation outcomes. The exact wording of the questions was as follows:

Survey wave 1, May 2022

Q.I1A What do you think are low, medium and high possible inflation rates for China over the next twelve months?

Low:	____ %
Medium:	____ %
High:	____ %

Q.I2A What do you think is the probability that inflation over the next twelve months ends up at the low, medium and high levels that you just picked? These probabilities should sum to 100%.

Probability of low inflation:	____ %
Probability of medium inflation:	____ %
Probability of high inflation:	____ %

Many respondents in our sample did not understand how to answer these probability questions. Table B1 shows summary statistics of the responses to the two probability questions.[16] While the majority of respondents provide inflation rate expectations near the China central bank target rate of 3%, many provide unusually large values. The maximum values provided for the low, medium, and high inflation rates are 100%, 200%, and 300%, respectively, as shown in Table B1. A large number of respondents also provide inflation rates that are not in sequential order. For example, some give expectations of their "high" inflation rate that are lower than their "low" inflation rate. Another problem is that 48% of individuals do not answer Q.I2A by providing probabilities that in total sum to 100%. The last row in Table B1 displays that total probabilities range from 0% to 300%, which makes these responses unusable for our analysis.

Responses to probabilistic forecasting questions reveal significant comprehension challenges among respondents. Overall, only 43% of respondents in the sample provided valid answers to both question Q.I1A (by giving sequential values) and question Q.I2A (by reporting probabilities that sum to 100%). Individuals who provided these valid answers more often hold college degrees, have higher incomes, and reside in urban locations. While den-

[16] For this first survey wave, we omit duplicated observations and responses whose duration was shorter than a minute or longer than 30 minutes in length. This leaves a total sample of 9,412 individuals.

Table B1: Summary statistics of responses to probability inflation expectations questions

	Mean	SD	Min	Median	Max
Q.I1A Possible low inflation rate	7.822	12.739	0	3.000	100
Q.I1A Possible medium inflation rate	10.979	14.064	0	5.000	200
Q.I1A Possible high inflation rate	15.688	20.425	0	10.000	300
Q.I2A Sum of probabilities	82.526	50.904	0	100.000	300

Note: This table shows summary statistics for questions eliciting inflation expectations in the first survey wave in May 2022.

sity forecasting is well understood by professional forecasters and individuals in high-income countries, such questions often prove challenging for respondents in typical emerging market economy contexts. This suggests potential limitations in survey comprehension or familiarity with probabilistic reasoning in these settings.

To improve respondent comprehension and data quality, the second wave of the survey revised the inflation expectation questions. Instead of asking for full density forecasts, we elicited a point estimate of expected inflation along with a measure of respondent uncertainty in that estimate. The inflation expectation questions in the second wave were as follows:

Survey wave 2, September 2022

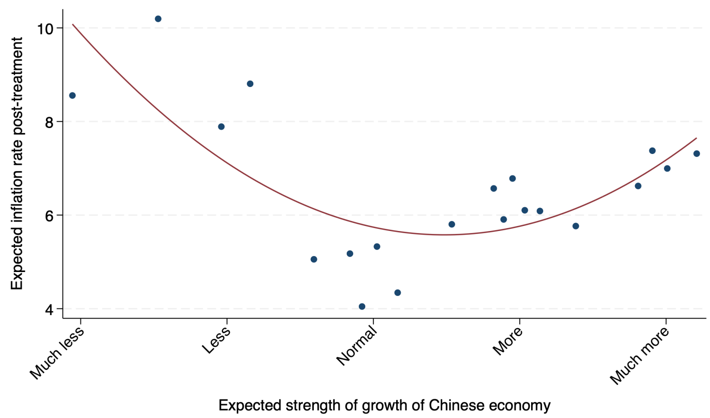
Q.I1B Over the next 12 months, do you think overall prices in the economy
A. will go up
B. will stay the same, or
C. will go down?

Q.I2B Over the next 12 months, by what percentage do you think overall prices in the economy will go [up/down] ? _____ *%*

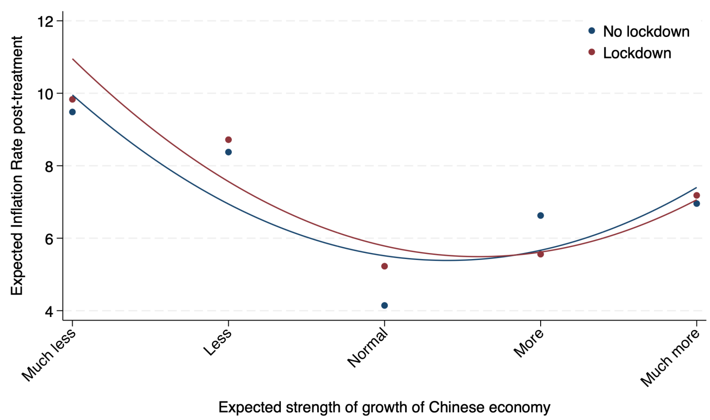
Q.I3B On a scale ranging from 1 to 10, how confident are you in your prediction where 1 denotes not confident at all, and 10 denotes extremely confident? _____

The revised questions were easier for respondents to answer and provided a direct measure of their confidence in their own expectations. This approach eliminates the need to infer uncertainty from complex density forecasts, which can be difficult for respondents unfamiliar with probabilistic reasoning. These findings highlight the importance of using simplified survey formats in such contexts.

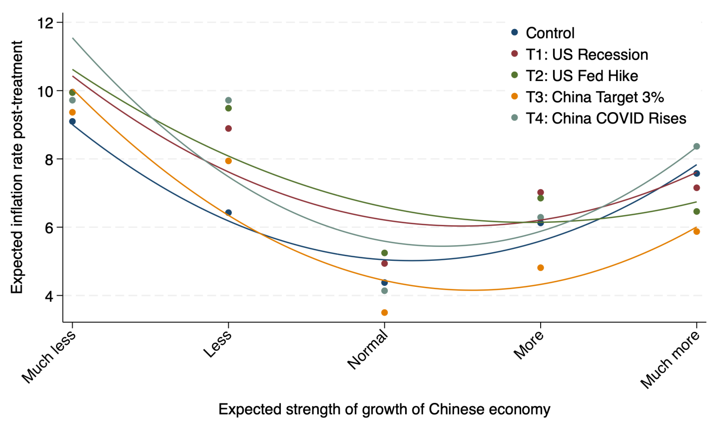
C Appendix: Expectations of inflation versus economic growth by subgroups



(a) Controls



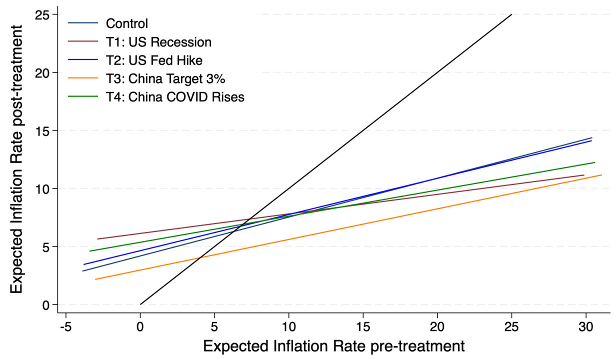
(b) Lockdown



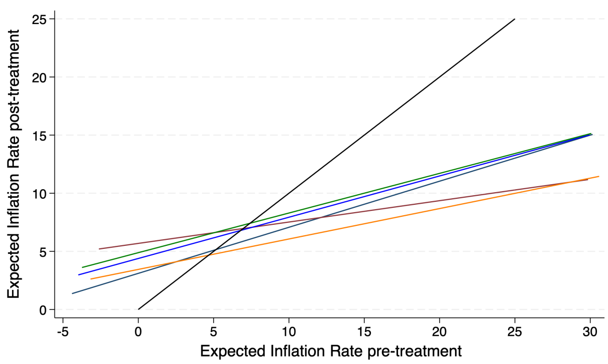
(c) Treatment

Note: These figures show binscatter plots of expectations of inflation post-treatment and economic growth. Expectations of growth are elicited in reference to normal growth: for example, "much less" is presented to respondents as "much less strongly than normal". Plots use sample weights.

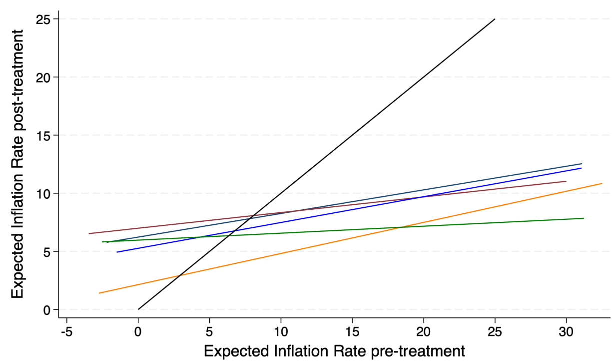
D Appendix: Intensive margin binscatter plots of prior and post-treatment inflation expectations



(a) All



(b) No lockdown



(c) Lockdown

Note: These figures show the relationship between pre- and post-treatment inflation expectations for the intensive margin sample (conditional on revising expectations). Figure (a) displays the plot for all households, Figure (b) represents households not in lockdown, and Figure (c) represents households recently or currently in lockdown. The solid black line is the 45-degree line. Plots use sample weights.

E Appendix: Distribution statistics of post-treatment inflation expectations

	Mean	SD	Kurtosis	Skewness
All sample				
Control	3.74	4.52	5.34	1.42
T1: US Recession	4.02	4.80	5.87	1.51
T2: US Fed Hike	3.83	4.34	5.46	1.39
T3: China Target 3%	3.24	4.21	6.42	1.65
T4: China COVID Rises	4.20	4.81	4.72	1.26
No lockdown				
Control	3.31	4.04	5.69	1.48
T1: US Recession	3.37	4.25	7.42	1.75
T2: US Fed Hike	3.22	3.71	5.11	1.34
T3: China Target 3%	2.76	3.67	6.91	1.66
T4: China COVID Rises	3.59	4.25	5.52	1.43
Lockdown				
Control	3.87	4.95	6.09	1.58
T1: US Recession	4.58	5.16	4.79	1.29
T2: US Fed Hike	4.47	5.00	5.45	1.42
T3: China Target 3%	3.71	4.75	6.04	1.65
T4: China COVID Rises	4.57	5.27	4.55	1.23

Note: This table shows post-treatment inflation expectations by treatment group and lockdown status. Expectations are truncated at the 5 and 95 percentiles and use Huber weights.

F Appendix: Treatment effects on inflation expectations by decision-making status

We run the following specification to estimating whether decision-makers respond differently to treatments when constructing their inflation expectations compared to those who do not make decisions:

$$\begin{aligned}\pi_{j,post} = \alpha + \sum_{k=2}^{5} \beta_k T_{j,k} + \delta\pi_{j,prior} + \sum_{k=2}^{5} \gamma_k T_{j,k} \times \pi_{j,prior} + \chi makedec_j + \lambda\pi_{j,prior} \times makedec_j \\ + \sum_{k=2}^{5} \zeta_k T_{j,k} \times makedec_j + \sum_{k=2}^{5} \Delta_k T_{j,k} \times makedec_j \times \pi_{j,prior} + \boldsymbol{X_j}\boldsymbol{\psi} + \epsilon_j,\end{aligned} \tag{7}$$

where *makedec* is an indicator variable equal to 1 if the individual is a decision-maker in their current job. Differences between decision-makers and non-decision-makers are captured by λ for weights placed on priors and by ζ_k for expectations following different treatments. The triple interaction coefficients Δ_k indicates the degree to which decision-makers rely more or less on their priors following treatments than non-decision-makers.

Table F2: Treatment effects on inflation expectations by decision-making status

	Post-treatment inflation expectations					
	Overall sample		Extensive margin		Intensive margin	
	(1)	(2)	(3)	(4)	(5)	(6)
USRec	1.120***	0.694**	0.044	0.111	2.069***	1.917***
	(0.407)	(0.273)	(0.044)	(0.111)	(0.750)	(0.683)
USHike	0.647	0.052	0.045	0.113	0.386	-0.224
	(0.435)	(0.239)	(0.044)	(0.112)	(0.813)	(0.623)
CTarget	-0.191	-0.243	0.053	0.133	-0.945	-1.015*
	(0.376)	(0.243)	(0.044)	(0.113)	(0.697)	(0.606)
CCOVID	1.024**	0.610**	0.043	0.109	1.441*	1.211*
	(0.455)	(0.287)	(0.045)	(0.116)	(0.772)	(0.682)
π_{prior}	0.673***	0.742***	0.007**	0.018**	0.361***	0.362***
	(0.041)	(0.028)	(0.003)	(0.008)	(0.059)	(0.053)
USRec × π_{prior}	-0.106*	-0.067	-0.002	-0.004	-0.193**	-0.188**
	(0.062)	(0.043)	(0.004)	(0.011)	(0.081)	(0.074)
USHike × π_{prior}	-0.075	-0.011	-0.002	-0.005	-0.038	-0.005
	(0.061)	(0.038)	(0.004)	(0.010)	(0.086)	(0.075)
CTarget × π_{prior}	-0.123*	-0.129***	0.001	0.003	-0.108	-0.122
	(0.064)	(0.045)	(0.004)	(0.011)	(0.085)	(0.075)
CCOVID × π_{prior}	-0.077	-0.061	-0.004	-0.011	-0.101	-0.103
	(0.069)	(0.043)	(0.004)	(0.011)	(0.091)	(0.078)
makedec	0.945	0.104	-0.037	-0.141	1.385	0.718
	(0.821)	(0.429)	(0.065)	(0.174)	(1.610)	(1.319)
makedec × π_{prior}	-0.239**	-0.170***	0.013***	0.047***	-0.128	-0.090
	(0.105)	(0.058)	(0.005)	(0.017)	(0.139)	(0.125)
USRec × *makedec*	-0.808	-0.457	0.107	0.318	-0.712	-0.284
	(1.235)	(0.675)	(0.095)	(0.245)	(2.207)	(1.885)
USHike × *makedec*	-0.682	0.251	0.023	0.106	0.240	1.389
	(1.127)	(0.627)	(0.095)	(0.245)	(2.085)	(1.745)
CTarget × *makedec*	-0.875	-0.291	-0.028	-0.026	-1.007	-0.291
	(1.049)	(0.568)	(0.094)	(0.248)	(1.957)	(1.659)
CCOVID × *makedec*	-1.914*	-1.374**	-0.055	-0.096	-0.163	0.194
	(1.124)	(0.608)	(0.095)	(0.251)	(2.284)	(1.865)
USRec × *makedec* × π_{prior}	0.308**	0.262***	-0.019**	-0.062***	0.138	0.116
	(0.155)	(0.091)	(0.008)	(0.024)	(0.218)	(0.200)
USHike × *makedec* × π_{prior}	0.297*	0.197**	-0.017**	-0.056**	0.070	-0.019
	(0.159)	(0.092)	(0.008)	(0.024)	(0.216)	(0.192)
CTarget × *makedec* × π_{prior}	0.241	0.258***	-0.009	-0.036	0.142	0.092
	(0.169)	(0.094)	(0.008)	(0.024)	(0.210)	(0.189)
CCOVID × *makedec* × π_{prior}	0.247	0.291***	-0.005	-0.026	-0.149	-0.163
	(0.169)	(0.087)	(0.008)	(0.025)	(0.209)	(0.187)
Constant	-1.702	-1.190	0.697***	0.502*	-0.176	1.032
	(1.073)	(0.732)	(0.104)	(0.265)	(1.891)	(1.639)
N	5,181	5,173	5,181	5,181	2,637	2,637
Adj. R^2	0.431	0.607	0.018		0.116	0.137
Pseudo R^2				0.017		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Model	OLS	Huber	OLS	Probit	OLS	Huber

Note: This table shows estimates of equation (7) for the overall sample in columns (1) and (2) and the intensive margin subsample that revises their priors following the treatment in columns (5) and (6). Columns (3) and (4) are estimates of the extensive margin likelihood of revising expectations post-treatment. The treatment groups are abbreviated as: "USRec" for the US Recession, "USHike" for the US Fed Hike, "CTarget" for China Target Inflation 3%, and "CCOVID" for China COVID Rises. Huber (1964) robust regressions endogenously account for outliers. Regressions use sampling weights with inflation expectations truncated at the 5th and 95th percentiles. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

G Appendix: Treatment effects on inflation expectations by decision-making and lockdown status

	Post-treatment inflation expectations					
	Overall sample		Extensive margin		Intensive margin	
	(1)	(2)	(3)	(4)	(5)	(6)
USRec	0.761*	0.465	0.067	0.173	1.668**	1.582**
	(0.460)	(0.313)	(0.048)	(0.123)	(0.826)	(0.754)
USHike	0.568	0.104	0.104**	0.266**	0.399	-0.023
	(0.470)	(0.279)	(0.047)	(0.121)	(0.834)	(0.687)
CTarget	-0.234	-0.336	0.064	0.164	-0.647	-0.779
	(0.443)	(0.284)	(0.047)	(0.123)	(0.824)	(0.714)
CCOVID	0.976*	0.424	0.059	0.152	1.775**	1.602**
	(0.522)	(0.327)	(0.049)	(0.126)	(0.862)	(0.780)
π_{prior}	0.632***	0.708***	0.009***	0.024***	0.329***	0.338***
	(0.040)	(0.026)	(0.003)	(0.007)	(0.056)	(0.049)
USRec × π_{prior}	-0.054	-0.028	-0.005	-0.013	-0.158**	-0.160**
	(0.059)	(0.040)	(0.004)	(0.010)	(0.077)	(0.070)
USHike × π_{prior}	-0.026	0.016	-0.005	-0.012	-0.009	0.009
	(0.058)	(0.036)	(0.004)	(0.010)	(0.081)	(0.071)
CTarget × π_{prior}	-0.079	-0.090**	-0.001	-0.002	-0.071	-0.094
	(0.061)	(0.041)	(0.004)	(0.010)	(0.079)	(0.070)
CCOVID × π_{prior}	-0.030	-0.011	-0.005	-0.013	-0.093	-0.105
	(0.064)	(0.040)	(0.004)	(0.010)	(0.084)	(0.072)
Lockdown	0.727	0.460	0.052	0.130	0.761	0.569
	(0.549)	(0.382)	(0.052)	(0.131)	(0.968)	(0.878)
USRec × Lockdown	-0.012	0.033	0.000	0.001	0.347	0.362
	(0.817)	(0.549)	(0.072)	(0.184)	(1.379)	(1.250)
USHike × Lockdown	-0.898	-0.754	-0.141*	-0.357*	-0.783	-1.016
	(0.832)	(0.507)	(0.072)	(0.185)	(1.552)	(1.199)
CTarget × Lockdown	-0.857	-0.452	0.002	0.005	-1.815	-1.345
	(0.734)	(0.534)	(0.073)	(0.187)	(1.231)	(1.094)
CCOVID × Lockdown	-0.935	-0.315	-0.034	-0.086	-1.320	-1.232
	(0.879)	(0.545)	(0.074)	(0.187)	(1.483)	(1.268)
makedec	-1.143*	-1.248**	0.085	0.220	-1.508	-1.617
	(0.641)	(0.521)	(0.070)	(0.179)	(1.050)	(0.994)
USRec × *makedec*	2.392**	2.143**	-0.012	-0.034	2.589	2.575
	(1.095)	(0.835)	(0.101)	(0.257)	(1.691)	(1.592)
USHike × *makedec*	2.476***	2.278***	-0.193**	-0.493**	3.980**	4.233**
	(0.957)	(0.708)	(0.098)	(0.250)	(1.794)	(1.663)
CTarget × *makedec*	2.087**	1.917***	-0.106	-0.272	3.231*	3.149**
	(0.939)	(0.686)	(0.102)	(0.262)	(1.794)	(1.534)
CCOVID × *makedec*	0.892	0.744	-0.102	-0.262	1.768	1.594
	(1.014)	(0.729)	(0.101)	(0.257)	(1.852)	(1.578)
Lockdown × *makedec*	0.966	0.786	-0.097	-0.240	4.036*	3.938**
	(1.382)	(0.817)	(0.106)	(0.273)	(2.289)	(1.963)
USRec × Lockdown × *makedec*	-2.670	-2.430**	-0.015	-0.044	-5.042	-4.956*
	(2.009)	(1.228)	(0.153)	(0.390)	(3.289)	(2.897)
USHike × Lockdown × *makedec*	-2.472	-1.810	0.292*	0.733*	-6.508**	-6.195**
	(1.809)	(1.128)	(0.150)	(0.384)	(3.182)	(2.730)
CTarget × Lockdown × *makedec*	-2.556	-1.645	0.050	0.117	-5.916**	-5.710**
	(1.790)	(1.148)	(0.150)	(0.387)	(3.005)	(2.571)
CCOVID × Lockdown × *makedec*	-2.477	-1.112	0.049	0.118	-7.254**	-6.541**
	(2.008)	(1.166)	(0.153)	(0.393)	(3.198)	(2.729)
Constant	-1.770*	-1.150	0.654***	0.391	-0.031	1.058
	(1.075)	(0.762)	(0.105)	(0.268)	(1.887)	(1.664)
N	5,181	5,175	5,181	5,181	2,637	2,637
Adj. R^2	0.431	0.591	0.017		0.123	0.142
Pseudo R^2				0.017		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Model	OLS	Huber	OLS	Probit	OLS	Huber

Note: This table shows estimates of equation (3) for the overall sample in columns (1) and (2) and the intensive margin subsample that revises their priors following the treatment in columns (5) and (6). Columns (3) and (4) are estimates of the extensive margin likelihood of revising expectations post-treatment. The treatment groups are abbreviated as: "USRec" for the US Recession, "USHike" for the US Fed Hike, "CTarget" for China Target Inflation 3%, and "CCOVID" for China COVID Rises. Huber (1964) robust regressions endogenously account for outliers. Regressions use sampling weights with inflation expectations truncated at the 5th and 95th percentiles. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

H Appendix: Treatment effects on inflation expectations by alternative inflation measure

	Post-treatment inflation expectations					
	π^{food}_{prior}		π_{pcvd}		π^{food}_{pcvd}	
	Overall	Intensive	Overall	Intensive	Overall	Intensive
	(1)	(2)	(3)	(4)	(5)	(6)
USRec	0.368**	0.427*	0.271	-0.266	0.109	0.072
	(0.185)	(0.244)	(0.262)	(0.294)	(0.261)	(0.289)
USHike	0.132	0.115	0.170	-0.211	0.142	-0.379
	(0.175)	(0.230)	(0.250)	(0.289)	(0.242)	(0.279)
CTarget	-0.223	0.153	-0.160	-0.195	-0.427*	0.194
	(0.173)	(0.222)	(0.263)	(0.286)	(0.247)	(0.280)
CCOVID	0.271	0.442*	0.432	-0.239	0.023	-0.307
	(0.198)	(0.253)	(0.278)	(0.320)	(0.275)	(0.284)
π_{prior}	0.298***	-0.010	0.660***	0.225***	0.648***	0.209***
	(0.036)	(0.020)	(0.028)	(0.029)	(0.029)	(0.028)
USRec × π_{prior}	-0.117**	-0.029	-0.135***	-0.192***	-0.168***	-0.155***
	(0.054)	(0.029)	(0.050)	(0.039)	(0.051)	(0.037)
USHike × π_{prior}	0.130**	-0.028	-0.010	0.092**	-0.003	-0.014
	(0.055)	(0.028)	(0.042)	(0.040)	(0.043)	(0.039)
CTarget × π_{prior}	0.047	0.030	-0.121**	-0.153***	-0.087*	-0.079**
	(0.056)	(0.032)	(0.048)	(0.039)	(0.046)	(0.040)
CCOVID × π_{prior}	0.012	-0.076**	-0.057	-0.153***	-0.066	-0.089**
	(0.056)	(0.035)	(0.046)	(0.040)	(0.045)	(0.038)
π^{alt}	0.569***	0.764***	0.121***	0.214***	0.115***	0.293***
	(0.040)	(0.026)	(0.027)	(0.026)	(0.027)	(0.027)
USRec × π^{alt}	0.143**	0.083**	0.130***	0.408***	0.193***	0.275***
	(0.056)	(0.036)	(0.042)	(0.035)	(0.045)	(0.039)
USHike × π^{alt}	-0.155***	0.078**	-0.007	0.002	0.004	0.122***
	(0.058)	(0.039)	(0.036)	(0.037)	(0.037)	(0.039)
CTarget × π^{alt}	-0.162***	-0.507***	-0.017	-0.043	0.019	-0.217***
	(0.060)	(0.039)	(0.038)	(0.035)	(0.039)	(0.039)
CCOVID × π^{alt}	-0.020	-0.024	0.014	0.220***	0.106**	0.222***
	(0.059)	(0.043)	(0.041)	(0.040)	(0.043)	(0.040)
Constant	-1.084*	0.587	-1.404*	0.738	-0.815	0.774
	(0.576)	(0.683)	(0.732)	(0.793)	(0.718)	(0.754)
N	5,032	2,390	4,941	2,400	5,007	2,427
Adj. R^2	0.737	0.734	0.610	0.533	0.624	0.567
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows estimates of the overall sample and intensive margin for equation (1) adjusted to include the alternative measure and an interaction of the measure with the information treatments. The regressions use different alternative measures of inflation, π^{alt}, which is specified in the header of the column (π^{food}_{prior}, π_{pcvd}, π^{food}_{pcvd}). The treatment groups are abbreviated as: "USRec" for the US Recession, "USHike" for the US Fed Hike, "CTarget" for China Target Inflation 3%, and "CCOVID" for China COVID Rises. All estimates are of Huber (1964) robust regressions with inflation expectations truncated at the 5th and 95th percentiles. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

I Appendix: Treatment effects on inflation expectations, interaction between treatments, lockdown, and priors

	Post-treatment inflation expectations					
	Overall sample		Extensive margin		Intensive margin	
	(1)	(2)	(3)	(4)	(5)	(6)
USRec	1.050**	0.586*	0.072	0.183	2.534***	2.363***
	(0.430)	(0.302)	(0.048)	(0.124)	(0.787)	(0.728)
USHike	0.815*	0.092	0.094*	0.239*	1.229	0.799
	(0.442)	(0.269)	(0.048)	(0.123)	(0.805)	(0.678)
CTarget	0.100	-0.279	0.039	0.099	0.402	0.199
	(0.414)	(0.268)	(0.048)	(0.125)	(0.804)	(0.708)
CCOVID	0.698	0.388	0.050	0.128	1.869**	1.674**
	(0.443)	(0.313)	(0.050)	(0.128)	(0.821)	(0.752)
π_{prior}	0.644***	0.690***	0.010***	0.025***	0.394***	0.394***
	(0.041)	(0.030)	(0.003)	(0.008)	(0.057)	(0.052)
USRec × π_{prior}	-0.049	-0.003	-0.006	-0.016	-0.210**	-0.206***
	(0.065)	(0.047)	(0.005)	(0.012)	(0.084)	(0.078)
USHike × π_{prior}	-0.013	0.075*	-0.007	-0.018	-0.037	-0.013
	(0.064)	(0.041)	(0.004)	(0.012)	(0.090)	(0.081)
CTarget × π_{prior}	-0.086	-0.048	0.001	0.003	-0.139	-0.155*
	(0.073)	(0.050)	(0.005)	(0.012)	(0.095)	(0.084)
CCOVID × π_{prior}	0.029	0.008	-0.006	-0.016	-0.056	-0.067
	(0.062)	(0.047)	(0.005)	(0.013)	(0.089)	(0.077)
Lockdown	1.085*	0.118	0.048	0.124	3.086***	2.681***
	(0.626)	(0.357)	(0.058)	(0.149)	(1.144)	(1.003)
USRec × Lockdown	-0.238	0.127	-0.026	-0.069	-1.794	-1.586
	(0.930)	(0.552)	(0.082)	(0.209)	(1.631)	(1.450)
USHike × Lockdown	-0.860	0.079	-0.145*	-0.372*	-2.349	-2.451*
	(0.965)	(0.488)	(0.082)	(0.211)	(1.823)	(1.318)
CTarget × Lockdown	-1.380*	-0.029	0.034	0.085	-4.447***	-3.786***
	(0.798)	(0.479)	(0.083)	(0.213)	(1.391)	(1.220)
CCOVID × Lockdown	-0.241	-0.128	-0.050	-0.127	-2.153	-2.015
	(0.954)	(0.552)	(0.085)	(0.217)	(1.630)	(1.381)
Lockdown × π_{prior}	-0.037	0.081	-0.002	-0.005	-0.194	-0.178
	(0.100)	(0.058)	(0.006)	(0.015)	(0.128)	(0.118)
USRec × Lockdown × π_{prior}	-0.023	-0.079	0.004	0.009	0.147	0.141
	(0.139)	(0.088)	(0.008)	(0.021)	(0.173)	(0.160)
USHike × Lockdown × π_{prior}	-0.048	-0.192**	0.008	0.020	0.067	0.063
	(0.134)	(0.078)	(0.008)	(0.020)	(0.178)	(0.155)
CTarget × Lockdown × π_{prior}	0.016	-0.125	-0.005	-0.012	0.200	0.184
	(0.138)	(0.086)	(0.008)	(0.021)	(0.168)	(0.153)
CCOVID × Lockdown × π_{prior}	-0.162	-0.070	0.002	0.006	-0.085	-0.083
	(0.147)	(0.084)	(0.008)	(0.021)	(0.171)	(0.152)
Constant	-1.938*	-1.098	0.680***	0.459*	-1.071	0.135
	(1.059)	(0.742)	(0.104)	(0.264)	(1.858)	(1.642)
N	5,181	5,174	5,181	5,181	2,637	2,637
Adj. R^2	0.432	0.600	0.017		0.126	0.144
Pseudo R^2				0.016		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Model	OLS	Huber	OLS	Probit	OLS	Huber

Note: This table shows estimates of equation (4) with π_{prior} using the overall sample in columns (1) and (2) and the intensive margin subsample that revises their priors following the treatment in columns (5) and (6). Columns (3) and (4) are estimates of the extensive margin likelihood of revising expectations post-treatment. The treatment groups are abbreviated as: "USRec" for the US Recession, "USHike" for the US Fed Hike, "CTarget" for China Target Inflation 3%, and "CCOVID" for China COVID Rises. Huber (1964) robust regressions endogenously account for outliers. Regressions use sampling weights with inflation expectations truncated at the 5th and 95th percentiles. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

J Appendix: The causal effects of inflation expectations on additional outcomes

We estimate the causal effects of inflation expectations on planned spending and employment expectations using instrumental variable regressions. In the first stage, the planned spending or employment outcome P is regressed on inflation expectations and controls using a similar specification as equation (2):

$$P_{j,post} = \alpha_1 + \phi_1 \pi_{j,post} + \phi_2 \Delta\pi_{j,pcvdf} + \phi_3 \pi_{j,prior} + \phi_4 Lockdown_j + \boldsymbol{\zeta_j \psi} + \epsilon_j, \tag{8}$$

where P is planned durables purchases, expected changes in typical monthly spending or income, or expectations of job loss. The gap in perceived overall and food inflation, $\Delta\pi_{pcvdf}$, captures salience in food prices. We instrument post-treatment inflation expectations in the following second stage regressions:

$$\begin{aligned}\pi_{j,post} = \alpha_0 + \sum_{k=2}^{5} \beta_k T_{j,k} + \sum_{k=2}^{5} \gamma_k T_{j,k} \times \pi_{j,pcvd} + \eta \pi_{j,pcvd} + \sum_{k=2}^{5} \lambda_k T_{j,k} \times Lockdown_j \\ + \delta_1 \pi_{j,prior} + \delta_2 Lockdown_j + \boldsymbol{X_j \psi} + u_j,\end{aligned}$$

where the instrument vector of post-treatment inflation expectations is composed of the treatment indicators T, perceived overall inflation π_{pcvd}, their interaction, and the interaction of treatment and lockdown groups. We include the interactions of treatment and lockdown groups as instruments due to our Table 4 findings of differing inflation expectations by household lockdown status. The estimates are presented in Tables J3 and J4.

Table J3: Inflation expectations effects on spending and employment expectations

	(1) Durables	(2) Durables ind	(3) Spending	(4) Exp Income	(5) Job loss
π_{post}	-0.020*	-0.013*	1.004***	-0.048	-0.018
	(0.012)	(0.007)	(0.118)	(0.101)	(0.042)
	[-0.045,0.0006]	[-0.026,0.0003]	[0.783,1.242]	[-0.259,0.131]	[-0.088,0.076]
π_{prior}	0.009	0.005	-0.213**	0.015	0.040
	(0.008)	(0.005)	(0.088)	(0.073)	(0.029)
$\Delta\pi_{pcvdf}$	0.002	0.001	-0.026	-0.022	-0.010
	(0.003)	(0.001)	(0.029)	(0.024)	(0.010)
Lockdown	0.110***	0.068***	0.221	-0.196	0.861***
	(0.041)	(0.020)	(0.338)	(0.325)	(0.153)
Constant	0.415**	0.389***	4.589***	3.151*	5.842***
	(0.180)	(0.095)	(1.678)	(1.659)	(0.933)
N	4,837	4,842	4,648	4,557	3,006
Adj. R^2	0.062	0.065	0.145	0.019	0.048
KP Wald Fstat 1-stage	16.681	16.500	18.142	15.915	12.194
KP LM stat	176.651	181.028	180.535	165.323	125.546
p-value LM statistic	0.000	0.000	0.000	0.000	0.000
Hansen J stat	4.049	5.971	16.736	16.952	14.280
p-value J stat	0.983	0.918	0.160	0.151	0.283
p-value LR	0.065	0.056	< 0.001	0.512	0.896
Controls	Yes	Yes	Yes	Yes	Yes

Note: This table shows estimates of equation (8) using 2SLS Huber robust regressions. The dependent variable in column (1) is the number of durable goods planned to be purchased, while column (2) is an indicator whether any durable good is planned to be purchased. Column (3) is the expected change in typical monthly spending, column (4) is the expected change in monthly income, and column (5) is the likelihood of job loss for employed individuals. First stage instruments include exogenous variation in post-treatment expectations due to the information treatments and perceived inflation. All regressions use a jackknife procedure to account for outliers and use weights from Huber (1964) robust regressions as well as population weights. KP is Kleibergen-Paap. Heteroscedasticity-robust standard errors are reported in parentheses. Squared parentheses report p-values for the weak instruments robust test (conditional likelihood ratio test). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table J4: Inflation expectations effects on planned durable spending

	House	Car	Computer	TV	Fridge	Cell	Save
π_{post}	-0.010***	-0.013***	-0.003	-0.004**	-0.006***	-0.003	0.013*
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.006)	(0.007)
	[-0.016, -0.004]	[-0.022, -0.007]	[-0.006, 0.002]	[-0.008, -0.0008]	[-0.010, -0.001]	[-0.017, 0.007]	[-0.0003, 0.026]
π_{prior}	0.007***	0.009***	0.001	0.002	0.003*	-0.000	-0.005
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)
$\Delta\pi_{pcvdf}$	0.001	0.001	0.000	-0.000	0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lockdown	-0.001	0.018	0.033***	0.023**	0.009	0.018	-0.068***
	(0.012)	(0.015)	(0.011)	(0.011)	(0.011)	(0.020)	(0.020)
Constant	0.078	-0.048	0.075	-0.000	-0.079	0.407***	0.611***
	(0.050)	(0.058)	(0.048)	(0.045)	(0.049)	(0.088)	(0.095)
N	4,831	4,836	4,832	4,831	4,827	4,843	4,842
Adj. R^2	0.014	0.005	0.063	0.010	0.009	0.030	0.065
KP Wald Fstat 1-stage	17.744	16.194	17.540	17.428	17.586	17.750	16.500
KP LM stat	181.067	174.865	180.615	179.220	180.490	180.688	181.028
p-value LM statistic	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hansen J stat	5.115	7.908	10.430	9.431	15.309	11.448	5.971
p-value J stat	0.954	0.792	0.578	0.666	0.225	0.491	0.918
p-value LR	<0.001	<0.001	0.371	0.019	0.006	0.429	0.056
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows estimates of equation (8) using 2SLS Huber robust regressions. First stage instruments include exogenous variation in post-treatment expectations due to the information treatments and perceived inflation. All regressions use a jackknife procedure to account for outliers and use weights from Huber (1964) robust regressions as well as population weights. KP is Kleibergen-Paap. Heteroscedasticity-robust standard errors are reported in parentheses. Squared parentheses report p-values for the weak instruments robust test (conditional likelihood ratio test). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

K Appendix: The causal effects of inflation expectations on additional outcomes by lockdown status

We estimate the causal effects of inflation expectations on planned spending and employment expectations using instrumental variable regressions. In the first stage, the planned spending or employment outcome P is regressed on inflation expectations and controls using a similar specification as equation (2):

$$P_{j,post} = \alpha_1 + \phi_1 \pi_{j,post} + \phi_2 \Delta\pi_{j,pcvdf} + \phi_3 \pi_{j,prior} + \phi_4 Lockdown_j + \phi_5 Lockdown_j \times \pi_{j,post} + \boldsymbol{\zeta_j \psi} + \epsilon_j, \tag{9}$$

where P is planned durables purchases, expected changes in typical monthly spending or income, or expectations of job loss. The gap in perceived overall and food inflation, $\Delta\pi_{pcvdf}$, captures salience in food prices. The coefficient ϕ_5 measures differences in the effect of expectations on outcomes by lockdown status. We instrument post-treatment inflation expectations in the following second stage regressions:

$$\begin{aligned}\pi_{j,post} = \alpha_0 + \sum_{k=2}^{5} \beta_k T_{j,k} + \sum_{k=2}^{5} \gamma_k T_{j,k} \times \pi_{j,pcvd} + \eta \pi_{j,pcvd} + \sum_{k=2}^{5} \lambda_k T_{j,k} \times Lockdown_j \\ + \omega \pi_{j,pcvd} \times Lockdown_j + \sum_{k=2}^{5} \chi_k T_{j,k} \times \pi_{j,pcvd} \times Lockdown_j \\ + \delta_1 \pi_{j,prior} + \delta_2 Lockdown_j + \boldsymbol{X_j \psi} + u_j,\end{aligned}$$

$$\begin{aligned}Lockdown_j \times \pi_{j,post} = \alpha_0 + \sum_{k=2}^{5} \beta_k T_{j,k} + \sum_{k=2}^{5} \gamma_k T_{j,k} \times \pi_{j,pcvd} + \eta \pi_{j,pcvd} + \sum_{k=2}^{5} \lambda_k T_{j,k} \times Lockdown_j \\ + \omega \pi_{j,pcvd} \times Lockdown_j + \sum_{k=2}^{5} \chi_k T_{j,k} \times \pi_{j,pcvd} \times Lockdown_j \\ + \delta_1 \pi_{j,prior} + \delta_2 Lockdown_j + \boldsymbol{X_j \psi} + u_j,\end{aligned}$$

where the instrument vector of post-treatment inflation expectations is composed of the treatment indicators T, perceived overall inflation π_{pcvd}, their interaction, and the interaction of treatment, perceived overall inflation, and lockdown groups. We include the interactions of treatment and lockdown groups as instruments due to our Table 4 findings of differing inflation expectations by household lockdown status. The estimates are presented in Tables K5 and K6.

Table K5: Inflation expectations effects on spending and employment expectations by lockdown status

	(1) Durables	(2) DurablesI	(3) Spending	(4) Exp Income	(5) Job loss
π_{post}	-0.017	-0.011	1.000***	-0.055	0.000
	(0.012)	(0.007)	(0.121)	(0.101)	(0.042)
Lockdown × π_{post}	0.005	0.000	0.215*	-0.058	-0.006
	(0.012)	(0.006)	(0.126)	(0.109)	(0.040)
Lockdown	0.100	0.067*	-0.957	0.245	0.904***
	(0.084)	(0.040)	(0.708)	(0.595)	(0.293)
π_{prior}	0.007	0.004	-0.262***	0.040	0.029
	(0.008)	(0.005)	(0.092)	(0.073)	(0.029)
$\Delta\pi_{pcvdf}$	0.002	0.001	-0.013	-0.019	-0.013
	(0.003)	(0.001)	(0.031)	(0.024)	(0.011)
Constant	0.477**	0.393***	4.590***	3.061*	5.481***
	(0.185)	(0.094)	(1.700)	(1.631)	(0.891)
N	4,838	4,843	4,648	4,554	3,006
Adj. R^2	0.063	0.067	0.123	0.017	0.051
Fstat 1-stage (π_{post})	12.232	12.211	13.431	11.873	9.164
Fstat 1-stage (L×π_{post})	18.255	18.044	16.666	15.601	12.404
Kleibergen–Paap LM stat	179.436	183.192	178.554	168.326	128.652
p-value LM statistic	0.000	0.000	0.000	0.000	0.000
Hansen J stat	4.226	7.515	20.083	27.456	19.331
p-value J stat	0.998	0.962	0.217	0.037	0.252
Controls	Yes	Yes	Yes	Yes	Yes

Note: This table shows estimates of equation (9) using 2SLS Huber robust regressions. The dependent variable in column (1) is the number of durable goods planned to be purchased, while column (2) is an indicator whether any durable good is planned to be purchased. Column (3) is the expected change in typical monthly spending, column (4) is the expected change in monthly income, and column (5) is the likelihood of job loss for employed individuals. First stage instruments include exogenous variation in post-treatment expectations due to the information treatments and perceived inflation. All regressions use a jackknife procedure to account for outliers and use weights from Huber (1964) robust regressions as well as population weights. KP is Kleibergen-Paap. Heteroscedasticity-robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table K6: Inflation expectations effects on planned durable spending by lockdown status

	House	Car	Computer	TV	Fridge	Cell	Save
π_{post}	-0.012***	-0.011***	-0.001	-0.005**	-0.008***	-0.002	0.011
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.006)	(0.007)
Lockdown $\times$ π_{post}	0.006*	0.004	0.003	-0.000	0.004	-0.005	-0.000
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)
Lockdown	-0.028	0.004	0.027	0.033	-0.009	0.049	-0.067*
	(0.024)	(0.029)	(0.021)	(0.021)	(0.021)	(0.039)	(0.040)
π_{prior}	0.007***	0.007**	-0.001	0.002	0.004**	-0.000	-0.004
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)
$\Delta\pi_{pcvdf}$	0.001	0.001	0.000	-0.000	0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.099**	-0.038	0.067	0.007	-0.064	0.413***	0.607***
	(0.050)	(0.058)	(0.049)	(0.047)	(0.049)	(0.088)	(0.094)
N	4,837	4,838	4,837	4,836	4,831	4,839	4,843
Adj. R^2	0.015	0.015	0.061	0.012	0.004	0.031	0.067
Fstat 1-stage (π_{post})	12.864	12.320	13.206	12.918	12.908	12.746	12.211
Fstat 1-stage (L$\times\pi_{post}$)	17.251	18.350	17.299	17.741	17.290	18.565	18.044
Kleibergen–Paap LM stat	180.001	177.778	185.433	183.276	183.257	180.671	183.192
p-value LM statistic	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hansen J stat	11.582	8.575	7.196	9.891	22.374	10.618	7.515
p-value J stat	0.772	0.930	0.969	0.872	0.132	0.832	0.962
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows estimates of equation (9) using 2SLS Huber robust regressions. First stage instruments include exogenous variation in post-treatment expectations due to the information treatments and perceived inflation. All regressions use a jackknife procedure to account for outliers and use weights from Huber (1964) robust regressions as well as population weights. KP is Kleibergen-Paap. Heteroscedasticity-robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

L Appendix: Treatment effects on inflation expectations by lockdown status subsample

	Post-treatment inflation expectations	
	(1)	(2)
USRec	0.583*	0.750
	(0.303)	(0.470)
USHike	0.093	0.116
	(0.269)	(0.414)
CTarget	-0.291	-0.307
	(0.268)	(0.403)
CCOVID	0.379	0.267
	(0.313)	(0.454)
π_{prior}	0.691***	0.770***
	(0.030)	(0.048)
USRec × π_{prior}	-0.003	-0.092
	(0.047)	(0.074)
USHike × π_{prior}	0.074*	-0.115*
	(0.041)	(0.066)
CTarget × π_{prior}	-0.047	-0.181***
	(0.050)	(0.070)
CCOVID × π_{prior}	0.007	-0.074
	(0.047)	(0.070)
Constant	-1.571*	0.490
	(0.868)	(1.381)
N	3,249	1,925
Adj. R^2	0.618	0.560
Controls	Yes	Yes
Lockdown	No	Yes

Note: This table shows estimates of equation (1) for the subsample of non-lockdown respondents in column (1) and lockdown respondents in column (2). The treatment groups are abbreviated as: "USRec" for the US Recession, "USHike" for the US Fed Hike, "CTarget" for China Target Inflation 3%, and "CCOVID" for China COVID Rises. Estimates are from Huber (1964) robust regressions with inflation expectations truncated at the 5th and 95th percentiles. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

M Appendix: Survey Questionnaire

This survey was conducted in Mandarin. The questionnaire is translated into English below.

This survey is conducted on behalf of School of Economics, Renmin University of China. We want to learn about your perceptions and expectations about price changes. This survey takes about 10 minutes. Your responses are strictly confidential.

Part A: Background Information

1. Your gender?
   (a) Male
   (b) Female
2. Your age?
   ____
3. Your education background?
   (a) Middle school or less
   (b) High school
   (c) College or more
4. Residence over the past 12 months?
   (a) Local town or local city
   (b) Local village
5. Do you have a paid job?
   (a) Yes *(go to Q6)*
   (b) No *(go to Q10)*
6. Your personal monthly income?
   (a) less than ¥2000
   (b) ¥2000 to ¥4999
   (c) ¥5000 to ¥9999
   (d) ¥10000 or above
7. In your current job, do you... Please select all that apply.
   (a) Make decisions about hiring/firing workers
   (b) Make decisions about what prices to set
   (c) Make decisions about capital expenditures

(d) Make decisions about wages/salaries
(e) Make decisions about marketing or sales
(f) None of the above *[EXCLUSIVE]*

8. In your current job, do you supervise other people
   (a) Yes *(go to Q9)*
   (b) No *(go to Part B)*
9. How many people do you supervise?
   (a) Supervise 1 to 10 other people
   (b) Supervise 11 to 50 other people
   (c) Supervise more than 50 other people
10. Are you looking for a job now?
    (a) Yes *(go to Part B)*
    (b) No *(go to Q11)*
11. Here are a number of possible reasons why people who are not working choose not to look for work. Please select all that apply to you.
    (a) Homemaker
    (b) Raising children
    (c) Student
    (d) Retiree
    (e) Disabled, health issues
    (f) No financial need
    (g) Temporarily laid-off (expect to be recalled with the next 6 months)
    (h) Temporarily laid-off (do not expect to be recalled with the next 6 months)

<u>Part B: Views on changes in price level in the past 12 months</u>

The following questions will ask you about percent changes of things in the past.

12. Over the past 12 months, do you think overall prices in the economy
    (a) have gone up *(go to Q13)*,
    (b) have stayed the same, or *(go to Q15)*
    (c) have gone down *(go to Q14)*?

13. Over the past 12 months, by what percentage do you think overall prices in the economy have gone up?
_____ % *(go to Q15)*

14. Over the past 12 months, by what percentage do you think overall prices in the economy have gone down?
_____ %

15. Over the past 12 months, do you think food prices

    (a) have gone up *(go to Q16)*
    (b) have stayed the same, or *(go to Q18)*
    (c) have gone down *(go to Q17)*?

16. Over the past 12 months, by what percentage do you think food prices have gone up?
_____ % *(go to Q18)*

17. Over the past 12 months, by what percentage do you think food prices have gone down?
_____ %

18. What inflation rate do you think national authorities are trying to achieve?
_____ %

Part C: Expectations of changes in price level in the future

19. Over the next 12 months, do you think overall prices in the economy

    (a) will go up *(go to Q20)*
    (b) will stay the same, or *(go to Q22)*
    (c) will go down *(go to Q21)*?

20. Over the next 12 months, by what percentage do you think overall prices in the economy will go up?
_____ % *(go to Q22)*

21. Over the next 12 months, by what percentage do you think overall prices in the economy will go down?
_____ %

22. On a scale ranging from 1 to 10, how confident are you in your prediction where 1 denotes not confident at all, and 10 denotes extremely confident?
_____

23. Over the next 12 months, do you think food prices

    (a) will go up *(go to Q24)*

(b) will stay the same, or *(go to Q26)*
(c) will go down *(go to Q25)*?

24. Over the next 12 months, by what percentage do you think food prices will go up?
_____ % *(go to Q26)*

25. Over the next 12 months, by what percentage do you think food prices will go down?
_____ %

Part D: About the impact of lockdowns

26. Are you currently in lockdowns?
    (a) Yes *(go to Q27)*
    (b) No *(go to Q33)*

27. How long has been the lockdowns till today?
    (a) within a week
    (b) between 1-2 weeks
    (c) between 2-3 weeks
    (d) between 3-4 weeks
    (e) more than 4 weeks

28. When, do you think, the lockdowns will end?
    (a) within a week
    (b) between 1-2 weeks
    (c) between 2-3 weeks
    (d) between 3-4 weeks
    (e) more than 4 weeks
    (f) Don't know

29. Imagine that your community were not in lockdown, would you change your forecasts for "overall prices in the economy over the next 12 months"?
    (a) Yes *(go to Q30)*
    (b) No *(go to Part E)*

30. In that case, over the next 12 months, if your community were not in lockdown, do you think overall prices in the economy
    (a) would go up *(go to Q31)*
    (b) would stay the same, or *(go to Part E)*

(c) would go down *(go to Q32)*?

31. Over the next 12 months, if your community were not in lockdown, by what percentage do you think overall prices in the economy would go up?
_____ % *(go to Part E)*

32. Over the next 12 months, if your community were not in lockdown, by what percentage do you think overall prices in the economy will go down?
_____ % *(go to Part E)*

33. Has your community been in lockdown in the last 60 days?

    (a) Yes *(go to Q34)*
    (b) No *(go to Q44)*

34. Did you have a paid job during the lockdown?

    (a) Yes *(go to Q35)*
    (b) No *(go to Part E)*

35. During the lockdown, were you able to work

    (a) from home
    (b) at your usual place
    (c) at other places

36. How many hours did you work at home during the lockdown period relative to how many hours you had worked before the lockdown?

    (a) Fewer hours *(go to Q37)*
    (b) About the same amount of hours *(go to Q39)*
    (c) More hours *(go to Q38)*

37. Approximately how many fewer hours per week would you say you worked during the lockdown compared to before the lockdown?
_____ hours per week *(go to Q39)*

38. Approximately how many more hours per week would you say you worked during the lockdown compared to before the lockdown?
_____ hours per week

39. How many hours per day had you previously spent on commuting to work before the lockdown?

    (a) Less than 1 hour
    (b) Between 1 and 2 hours
    (c) Between 2 and 3 hours

(d) More than 3 hours

40. When working from home, were you more productive, less productive, or about the same as you had been before the lockdowns?

    (a) Less productive *(go to Q41)*
    (b) About the same productivity *(go to Q43)*
    (c) More productive *(go to Q42)*

41. Approximately how much less productive were you while working from home during the lockdown? Please select your answer, expressed in percentage terms.

    (a) 1%-20%
    (b) 21%-40%
    (c) 41%-60%
    (d) 61%-80%
    (e) 81%-99%

    (go to Q43)

42. Approximately how much more productive were you while working from home during the lockdown? Please select your answer, expressed in percentage terms.

    (a) 1%-20%
    (b) 21%-40%
    (c) 41%-60%
    (d) 61%-80%
    (e) 81%-99%
    (f) More than 100%

43. After the lockdown ended, how many days per week would you ideally like to continue working from home?
    _____ days *(go to Part E)*

44. Imagine that your community were in lockdown, would you change your forecasts for "overall prices in the economy over the next 12 months"?

    (a) Yes *(go to Q45)*
    (b) No *(go to Q48)*

45. In that case, over the next 12 months, if your community was in lockdown, do you think overall prices in the economy

    (a) would go up *(go to Q46)*,

(b) would stay the same, or *(go to Q48)*

(c) would go down *(go to Q47)*?

46. Over the next 12 months, if your community was in lockdown, by what percentage do you think overall prices in the economy would go up?
_____ % *(go to Q48)*

47. Over the next 12 months, if your community was in lockdown, by what percentage do you think overall prices in the economy would go down?
_____ %

48. Do you have a paid job?

    (a) Yes *(go to Q49)*

    (b) No *(go to Part E)*

49. How many hours have you been working recently relative to when lockdowns started being applied in some parts of China recently?

    (a) Fewer hours *(go to Q50)*

    (b) About the same amount of hours *(go to Q52)*

    (c) More hours *(go to Q51)*

50. Approximately how many <u>fewer hours per week</u> would you say you have been working recently compared to before lockdowns started being put in place in China recently?
_____ hours per week *(go to Q52)*

51. Approximately how many <u>more hours per week</u> would you say you have been working recently compared to before lockdowns started being put in place in China recently?
_____ hours per week

52. How many hours <u>per day</u> do you typically spending on commuting to work?

    (a) Less than 1 hour

    (b) Between 1 and 2 hours

    (c) Between 2 and 3 hours

    (d) More than 3 hours

53. Since recent lockdowns have been imposed in some parts of China, are you more productive, less productive, or about the same as you were before the lockdowns?

    (a) Less productive *(go to Q54)*

    (b) About the same productivity *(go to Q56)*

    (c) More productive *(go to Q55)*

54. Approximately how much less productive have you been while working since the lockdown? Please select your answer, expressed in percentage terms.

    (a) 1%-20%
    (b) 21%-40%
    (c) 41%-60%
    (d) 61%-80%
    (e) 81%-99%

    (go to Q56)

55. Approximately how much more productive have you been while working since the lockdown? Please select your answer, expressed in percentage terms.

    (a) 1%-20%
    (b) 21%-40%
    (c) 41%-60%
    (d) 61%-80%
    (e) 81%-99%

56. How many days per week would you ideally like to work from home if that was possible for your job?
    _____ days

Part E: Information Treatments

[Randomly assign respondents to five equally sized groups:]

Group 1: *Control group, goes straight to Q57.*
Group 2: The probability of a recession in the United States over the next year is estimated to be about 40%. *(go to Q57)*
Group 3: The U.S. central bank has raised interest rates rapidly in recent months (by 1.5 percentage points), raising fears of a slowdown in the U.S. economy over the next year. *(go to Q57)*
Group 4: The national legislature has set a target for inflation in China to be 3% in 2022. *(go to Q57)*
Group 5: The Institute for Health Metrics and Evaluation (IHME) projects that the daily number of deaths from Covid is China will rise from about 3 per day to over 300 per day by November 2022. *(go to Q57)*

Part F: Follow-up questions

57. Do you think overall prices in the economy over the next 12 months

    (a) will go up *(go to Q58)*

(b) will stay the same, or *(go to Q60)*
(c) will go down *(go to Q59)*?

58. Over the next 12 months, by what percentage do you think overall prices in the economy will go up?
_____ % *(go to Q60)*

59. Over the next 12 months, by what percentage do you think overall prices in the economy will go down?
_____ %

60. On a scale ranging from 1 to 10, how confident are you in your prediction where 1 denotes not confident at all, and 10 denotes extremely confident?
_____

61. In the next 12 months, which of the following do you plan to purchase? (Select all that apply.)
    (a) A house
    (b) A car
    (c) A computer
    (d) A television
    (e) A refrigerator
    (f) A cellphone
    (g) None of the above

62. Over the next 12 months, do you expect your typical monthly spending to
    (a) increase *(go to Q63)*
    (b) stay the same, or *(go to Q65)*
    (c) decrease *(go to Q64)*?

63. Over the next 12 months, by how much your typical monthly spending will increase?
_____ % *(go to Q65)*

64. Over the next 12 months, by how much your typical monthly spending will decrease?
_____ %

65. How strongly do you expect the Chinese economy to grow over the next twelve months?
    (a) much more strongly than normal
    (b) more strongly than normal
    (c) normal
    (d) less strongly than normal

(e) much less strongly than normal

66. Over the next 12 months, do you expect your income to

    (a) increase *(go to Q67)*
    (b) stay the same, or *(go to Q69)*
    (c) decrease *(go to Q68)*?

67. Over the next 12 months, by how much your income will increase?
    _____ % *(go to Q69)*

68. Over the next 12 months, by how much your income will decrease?
    _____ %

69. Please confirm again whether you have a paid job now

    (a) Yes *(go to Q70)*
    (b) No *(go to End)*

70. How likely is it that you will lose your job over the next 12 months? Please give your answer on a scale from 1 (no chance of losing job) to 10 (certain to lose job)

    _____

We sincerely thank you for your time and cooperation.