Policy Environments and Household Inflation Expectations

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March 31, 2026

Abstract

We study how policy environments shape household inflation expectations and responses to information. Because households base consumption and saving decisions on expected inflation, misperceptions can distort intertemporal consumption choices. Using the first national survey of inflation expectations in China, combined with randomized information treatments and spatial variation in COVID-19 lockdown policies, we show that identical signals are processed differently across policy regimes. Households under lockdown respond more strongly to domestic policy communication, particularly official inflation targets, whereas households not in lockdown react more to adverse macroeconomic and pandemic news. Counterfactual exercises reveal asymmetric belief adjustments: entering lockdown leads to large upward revisions in inflation expectations, while exiting lockdown generates smaller downward revisions. We rationalize these patterns with a model of Bayesian updating with endogenous attention, in which lockdown status affects prior precision and the welfare cost of belief errors. The results demonstrate that policy regimes alter expectation formation by changing the effective precision and relevance of information.

JEL classification: E31, D83, D84
Keywords: expectation formation; inflation misperception, state-dependent updating; endogenous attention; policy communication

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1 Introduction

Macroeconomic expectations play a central role in the transmission of monetary policy, yet relatively little is known about how policy environments shape the way households form and update these expectations. Expectation errors can have real economic consequences: if households misperceive inflation, they may choose suboptimal savings and consumption decisions, leading to inefficient intertemporal allocation of resources. During periods of heightened uncertainty and restricted mobility, inflation can exhibit unusually high volatility. Households can experience these inflationary dynamics in markedly different ways depending on faced constraints, shocks, and policy interventions. While a growing literature shows that households revise inflation expectations in response to new information (Coibion et al. 2022; Coibion et al. 2023b), most existing evidence implicitly assumes that the mapping from information to beliefs is stable across states of the world.

This paper studies how expectation formation depends on policy environment. We show that households update beliefs in a state-dependent manner, with signal weights varying with constraints and conditions. Policy environments shape not only fundamentals but also the precision, salience, and credibility of information. Households subject to restrictive policies may face distinct price experiences from shortages, higher delivery costs, and the price salience of essential goods that elevate perceived inflation. Our study design isolates information processing conditional on these environments. The mechanisms we uncover are general and suggest that expectation formation depends on the interaction between information and the environment, implying that identical signals can generate different belief updates in contexts with changing constraints, policy regimes, or economic uncertainty.

We demonstrate that restrictive policies fundamentally alter how households process economic information using the first national expectations survey in China, the Survey of Household Inflation Expectations. The study leverages geographic variation in Chinese lockdown policies during the COVID-19 pandemic as a source of exogenous variation in household constraints. This setting provides a unique empirical environment to identify the causal impact of lockdown exposure on household expectations. Our findings suggest that policy environments shape expectation formation not only by changing economic fundamentals, but also by altering the precision and relevance of information.

Three key features distinguish this survey and setting. First, China experienced a nationwide lockdown episode in early 2020, but by 2022 lockdown policies were implemented locally rather than nationally, generating spatial variation in household lockdown exposure. This variation enables causal identification of how information treatments influence expectations under different policy conditions. 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, it is conducted in a large emerging market economy, contrasting the extensively documented studies based in developed economies and offering novel insights on emerging market contexts.

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-19 projections 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. We find that respondents 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 respondents 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 respondents react more to "bad news" about the economy or COVID-19 cases, likely due to heightened surprise or uncertainty during this crisis period. Therefore, lockdown raises the precision of policy signals and lowers the salience of bad news. Price salience does not alter this behavior.

Finally, we interpret our empirical findings through a model of Bayesian updating with endogenous attention by lockdown status. Lockdown status affects both prior precision and the welfare cost of misperceiving inflation. In the model, differences in belief updating arise endogenously from optimal information processing. A counterfactual lockdown exercise further shows that entering lockdown induces large upward revisions in inflation expectations, while exiting lockdown leads to smaller downward revisions, consistent with heightened uncertainty associated with restrictive policy environments.

This paper contributes to the literature that studies expectation formation using randomized information treatments. Prior research shows that households update inflation expectations in response to central bank communication and macroeconomic news, often in ways consistent with Bayesian learning (Armantier et al. 2016; D'Acunto et al. 2021; Coibion et al. 2022). A common implicit assumption in this literature is that responsiveness to information is stable across states of the world.

We challenge this invariance by showing that policy environments systematically alter how information is processed. Exploiting variation in lockdown exposure, we document that identical signals have different effects on expectations depending on whether households are subject to restrictive policy conditions. Lockdown status affects both the precision of prior beliefs and the effective weight assigned to policy versus adverse macroeconomic signals. Kuang et al. (2024) find that perceived political alignment with institutions affect how households process and weight policy communication.

Our findings also relate to research on disagreement and modality in inflation expectations (Mankiw et al. 2003; Adrian et al. 2021). While prior studies emphasize heterogeneous updating and multi-modal belief distributions, such as by homeowner status (Ahn et al. 2024), we show that policy communication interacts with environmental context to shape both the level and dispersion of expectations. Policy regimes therefore influence not only economic fundamentals but also the transmission of information.

To interpret these patterns, we develop a model of Bayesian updating with endogenous attention (Sims 2003; Maćkowiak and Wiederholt 2009; Matějka and McKay 2015). In the model, policy environments affect prior precision and the welfare cost of belief errors, generating state-dependent signal weights that map directly to the empirical estimates.

The paper proceeds as follows. Section 2 describes the design of the Survey of Household Inflation Expectations in China, including the sampling strategy, survey questions, and the randomized information treatments. Section 3 presents descriptive evidence on household inflation perceptions and expectations, examines the counterfactual relationship between lockdown status and expectations, and documents how information treatments affect the distribution of beliefs. Section 4 estimates the causal impact of the information treatments on inflation expectations and explores heterogeneity by lockdown status. Section 5 develops a model of Bayesian updating with endogenous attention to interpret the empirical findings and link the estimated treatment effects to differences in signal precision across policy environments. Section 6 concludes and discusses implications for expectation formation and policy communication.

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 collects rich demographic and economic data via WeChat, which is China's most widely used online platform (see the full questionnaire in Appendix L). In September 2022, 6,835 individuals were surveyed.

Our data cleaning procedure for our final sample is as follows. 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 an attention check question to identify any respondents rushing through the survey.[1] 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 individuals. 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.

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).

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-19 trends. Pre- and post-treatment questions

[1]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.

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.

enable us to identify treatment effects on expectations.

This survey was administered during a period when lockdown orders were implemented locally, not nationally. This geographic variation in individual lockdown status makes China a good case study to estimate the causal effects of lockdown status and enables 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. We find that lockdowns alter both work behavior and economic expectations.[2] Those in lockdown report reduced working hours and productivity.[3] These real economy effects are important for interpreting changes in expectations.

[2]Of those in lockdown, 55% report that they work from home (WFH) and the rest that they work at their usual workplace. Ideally, respondents 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.

[3]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.

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.

To ensure data quality in the survey, inflation expectations are elicited as a point estimate of expected inflation along with a measure of respondent uncertainty in that estimate. The inflation expectation questions in the survey are as follows:

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 above questions were straightforward for respondents to answer and provide 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.

Households in China tend to overestimate inflation. Actual annual CPI inflation was 2.8% in September 2022 and 0% in September 2023.[4] Table 2 shows that individuals perceive food inflation to be 5.45% and overall inflation to be 5.81% on average, while inflation expectations are elevated at 4.16%. There remains a sizable degree of overestimation even after accounting for potential measurement issues in annual CPI, as Cavallo (2024) shows that the official CPI underestimated the Covid inflation rate by 0.5-1 percentage points (pp) in several countries and Jiang et al. (2022) find that alternative online price indices in China exceed official CPI by 0.4 pp.[5] Respondents are generally certain in their expectations, with an average uncertainty score of 7 out of 10 (with 10 denoting extremely confident). Consistent with prior work (Dräger et al. 2016; Binder 2020), we document non-monotonic beliefs about

[4] Annual CPI inflation is calculated as the change in the CPI for a given month compared to the same month in the previous year.

[5] A concern in Cavallo (2024) is that the official CPI may understate the cost of living during the COVID-19 pandemic and lockdown due to basket mismeasurement, missing goods, and imputation procedures.

growth and inflation (Appendix B).

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

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

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.

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.[6] 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% versus 4.02%. Individuals in lockdown additionally have lower uncertainty in their inflation expectations than those not in lockdown.[7]

[6] 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%).

[7] 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.

3.2 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 individuals 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]? _____ %

Respondents update their expectations in response to both counterfactual scenarios. Approximately half of respondents 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 of individuals 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. Individuals 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 inflation expectation updates differs sharply across hypothetical lockdown scenarios. Respondents imagining being in lockdown revise their expectations upward by 9.1 pp on average, whereas those imagining no lockdown revise expectations downward by only 2.7 pp. Lockdown-induced inflation fears therefore dominate the relief associated with lifting restrictions, revealing a clear asymmetry in the scale of expectation adjustments.

Consistent with this pattern, inflation expectation elasticities with respect to lockdown status are substantially larger in the counterfactual setting. Table 3 Panel A reports average inflation expectations by actual and hypothetical lockdown status. While respondents currently in lockdown report expectations about 10% (0.42 pp) higher than those not in lockdown, expectations increase much more strongly when respondents imagine moving from no lockdown to lockdown. In the counterfactual, inflation expectations of respondents hypothetically in lockdown are 124% (5.10 pp) higher than those hypothetically not in lockdown.

To formalize these patterns, we estimate differences in expectation revisions across counterfactual lockdown states. We consider three outcomes: (i) whether respondents revise their inflation forecasts relative to their prior expectation, (ii) whether the revision is upward

Table 3: Inflation expectations in the lockdown status counterfactual (cf)

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

Panel B: Regression Results			
	(1) Revision	(2) Upward revision	(3) $\Delta\pi^{cf}_{prior}$
Lockdown: Now (cf)	0.006	0.444***	10.073***
	(0.026)	(0.041)	(0.500)
N	4,294	1,731	1,671
Adj. R^2			0.217
Pseudo R^2	0.023	0.119	
Controls	Yes	Yes	Yes
Model	Probit	Probit	Huber

Note: Panel A shows the mean actual pre-treatment inflation expectations (π_{prior}) and counterfactual inflation expectations (π^{cf}_{prior}) by lockdown status. The standard deviation is reported in parentheses. Expectations are truncated at the 5 and 95 percentiles and use Huber (1964) robust weights. Panel B shows estimates of (1) the likelihood of actually revising expectations in the counterfactual, (2) the intensive margin likelihood of the revision being upward, and (3) the intensive margin change in pre-treatment expectations between the counterfactual and actual scenarios on lockdown status. Estimates in columns (1) and (2) are the average 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. All regressions use sampling weights, column (3) uses inflation expectations truncated at the 5 and 95 percentiles. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

conditional on revising, and (iii) the magnitude of the revision measured as the difference between counterfactual and prior expectations. Each outcome is regressed on a lockdown-status indicator and a common set of controls, including a quadratic polynomial in age and indicators for sex, college education, urban residence, and employment status. Column (1) of Table 3 Panel B shows little difference in the extensive margin of revision likelihood across lockdown scenarios. However, strong asymmetries emerge along the intensive margin: respondents imagining being in lockdown are 44.4 pp more likely to revise expectations upward relative to those imagining no lockdown. The magnitude of revisions increases by about 10.07 pp after controlling for respondent characteristics.[8] The similarity between

[8]This estimate is consistent with including geographic controls for the city or province of the respondent

this estimate and the raw difference in averages indicates that lockdown status, rather than demographic composition, drives most of the variation in revisions.

The results from this counterfactual exercise provide direct supporting evidence that individuals believe lockdowns themselves drive higher inflation expectations. Respondents therefore consciously link lockdown status and inflation beliefs.

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-19 cases in China. The specific treatment groups are as follows:

> *Group 1: Control group.*
> *Group 2 (Treatment 1): The probability of a recession in the United States over the next year is estimated to be about 40%.*
> *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 new 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-19 pandemic developments and lockdowns on household economic expectations.

3.4 Prior versus post-treatment expectations

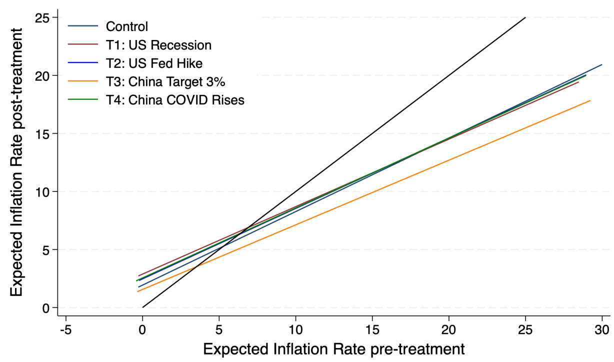
We ask respondents to report their inflation expectations before and after these treatments to study whether the receipt of new information influences how people view the economy. Posterior inflation expectations are elicited using identically worded questions as those used to measure prior expectations. We expect to find that individuals 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 1 displays the figures for the overall sample. We observe a slope of less than one for all treatment groups, even the control, which could

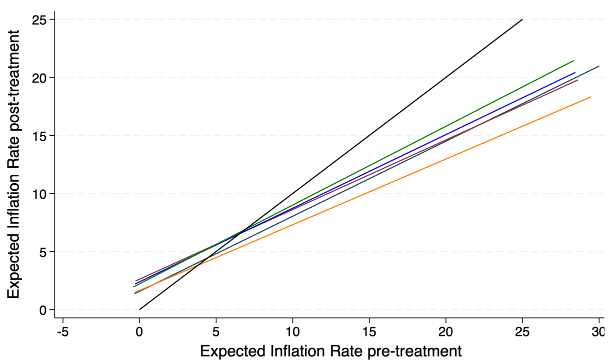
and geographically clustered standard errors.

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 Inflation Target treatment group has a particularly flatter slope compared to the control.

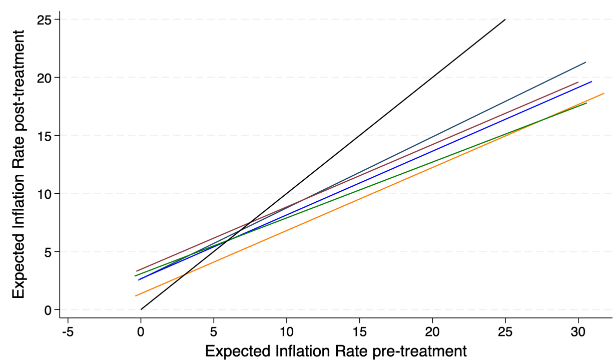
Figure 1: Binscatter plots of prior and post-treatment inflation expectations



(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 respondents, Figure (b) represents respondents not in lockdown, and Figure (c) represents respondents recently or currently in lockdown. The solid black line is the 45-degree line. Plots use sample weights.

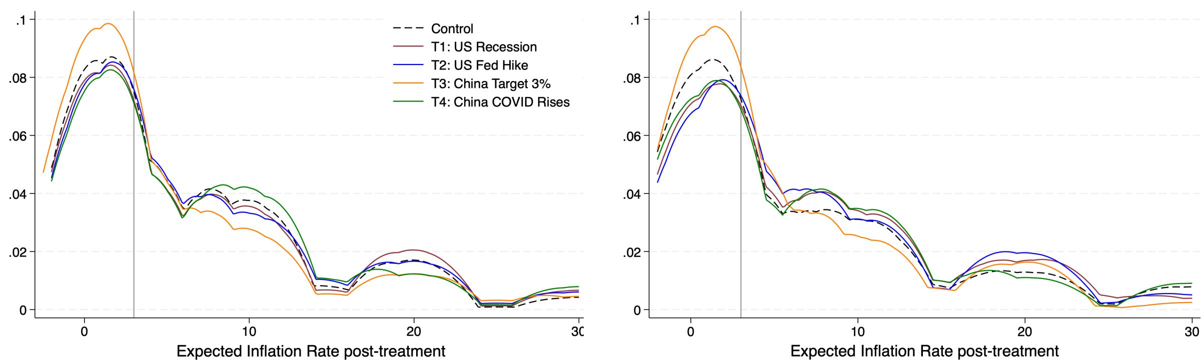
The relationship between prior and post-treatment inflation expectations varies by lockdown status. Figure 1b shows that individuals not in lockdown have a similar relationship to the general sample. In contrast, Figure 1c shows a much flatter slope, indicating that the information treatments reduce reliance on 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 individuals based on their lockdown status.[9]

[9] Appendix C contains binscatter plots showing the relationship between respondents' prior and posterior

3.5 The modality of inflation expectations

The distribution of inflation expectations changes following certain treatments. Figure 2a plots the distribution separately for each treatment group for respondents not in lockdown.[10] 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 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.

Figure 2: Distribution of post-treatment inflation expectations by lockdown status



(a) No lockdown

(b) Lockdown

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

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 2a 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 illustrates the power of targeted policy communication (Adrian et al. 2021).

The distribution of post-treatment inflation expectations differ by lockdown status. Figure 2b 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

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 individuals, plotted in Appendix C(a), is flatter for all groups compared to the overall sample since all individuals in this figure make revisions. The US Recession, China Inflation Target, and China COVID Rises treatment groups have particularly flatter slopes compared to the control.

[10]The distribution for respondents not in lockdown is similar to the overall sample (see Appendix Figure D.1).

to the control group.[11]

The distribution of respondent uncertainty also differs by lockdown status (see Appendix Figure D.2). There is no clear difference in uncertainty by treatment groups for individuals not in lockdown, or the overall sample. Respondents are relatively certain in their expectations, with the majority of ratings above a level 5 out of 10 (with 10 being extremely confident). However, individuals in lockdown are more certain about their expectations after receiving the China Inflation Target treatment. In lockdown, 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 (see Appendix Figure D.2c).

This distributional evidence highlights the role that targeted policy communication can play in shaping both the level and uncertainty of inflation expectations. The China Inflation Target 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. The effect for the overall sample and the intensive margin sample - respondents that revise their priors after treatment - is evaluated using a framework that is consistent with Bayesian updating following Coibion et al. (2022). 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 control. The vector of control variables, $\boldsymbol{X_j}$, 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

[11] Appendix Table D.1 reports summary statistics corresponding to the density plots in Figure 2. Across the full sample and subsamples by lockdown status, respondents receiving the China Inflation Target treatment exhibit lower mean and standard deviation of inflation expectations, alongside greater skewness and kurtosis, indicating a more asymmetric distribution. While the non-lockdown subsample closely mirrors the overall sample, respondents in lockdown show notably higher mean and dispersion when exposed to the US Recession, US Fed Hike, and China COVID Rises treatments. Non-parametric Kolmogorov–Smirnov tests confirm that the distribution of post-treatment expectations under the China Inflation Target treatment differs significantly from all other groups (Control vs. China Inflation Target: $p = 0.021$; all other pairwise comparisons: $p < 0.001$), with systematically lower expectation values.

30%. Second, we present estimates of both OLS and Huber (1964) robust regressions that systematically control for outliers.[12]

We additionally evaluate the treatment effect for the extensive margin as a respondent's likelihood of updating expectations after an information treatment. The dependent variable $d\_\pi_{j,post}$ is a dummy indicating the respondent updated their inflation expectations and the remaining variables are as in equation (1). This likelihood is estimated using linear probability and probit models, following Dräger et al. (2024):

$$P(d\_\pi_{j,post} = 1|X) = \Phi(\alpha + \sum_{k=2}^{5} \beta_k T_{j,k} + \delta\pi_{j,prior} + \sum_{k=2}^{5} \gamma_k T_{j,k} \times \pi_{j,prior} + \boldsymbol{X_j \psi} + \nu_j) \quad (2)$$

Table 4 reports estimates of the treatment effect for the overall sample, extensive margin, and intensive margin. 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 individuals at the intensive 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.

Respondents 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 respondents 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 the public views domestic policy information as more influential than international or general news when forming their inflation expectations.

4.2 Lockdown heterogeneity

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):

$$\begin{aligned}\pi_{j,post} = \alpha + \sum_{k=2}^{5} \beta_k T_{j,k} + \delta\pi_{j,prior} + \sum_{k=2}^{5} \gamma_k T_{j,k} \times \pi_{j,prior} + \phi Lockdown_j \\ + \sum_{k=2}^{5} \zeta_k T_{j,k} \times Lockdown_j + \boldsymbol{X_j \psi} + \epsilon_j,\end{aligned} \quad (3)$$

[12] Huber (1964) robust regressions impose restrictions on the sample to control for outliers. Estimates of Huber (1964) robust regressions are thus conducted on a smaller sample than OLS regressions.

Table 4: 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	0.063	1.907***	1.163***
	(0.397)	(0.252)	(0.039)	(0.039)	(0.722)	(0.330)
USHike	0.524	0.099	0.049	0.049	0.378	0.335
	(0.409)	(0.224)	(0.039)	(0.039)	(0.757)	(0.303)
CTarget	-0.364	-0.295	0.049	0.049	-1.161*	-0.257
	(0.359)	(0.222)	(0.039)	(0.040)	(0.662)	(0.295)
CCOVID	0.654	0.335	0.033	0.033	1.237*	0.623*
	(0.419)	(0.258)	(0.040)	(0.040)	(0.737)	(0.341)
π_{prior}	0.631***	0.711***	0.009***	0.009***	0.332***	0.377***
	(0.040)	(0.026)	(0.003)	(0.003)	(0.054)	(0.025)
USRec $\times$ π_{prior}	-0.053	-0.020	-0.005	-0.005	-0.163**	-0.156***
	(0.059)	(0.040)	(0.004)	(0.004)	(0.076)	(0.037)
USHike $\times$ π_{prior}	-0.027	0.021	-0.005	-0.005	-0.017	-0.115***
	(0.058)	(0.035)	(0.004)	(0.004)	(0.079)	(0.038)
CTarget $\times$ π_{prior}	-0.080	-0.085**	-0.001	-0.000	-0.075	-0.230***
	(0.061)	(0.041)	(0.004)	(0.004)	(0.078)	(0.036)
CCOVID $\times$ π_{prior}	-0.034	-0.008	-0.005	-0.005	-0.110	-0.099**
	(0.065)	(0.039)	(0.004)	(0.004)	(0.084)	(0.038)
Constant	-1.511	-1.045	0.696***		0.072	0.808
	(1.060)	(0.730)	(0.102)		(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, with average marginal effects displayed for the Probit model. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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. Estimates for individuals recently or currently in lockdown have the same sign. We therefore pool these groups to increase statistical power and for ease of the discussion of results.[13] The effects for the extensive

[13]Potential measurement error may arise for individuals reporting that they were recently in lockdown. To

margin are estimated using linear probability and probit models as in equation (2) with the additional *Lockdown* interaction terms of equation (3).

Chinese households not in lockdown expect higher inflation from all "bad news" about the economy. Table 5 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.

The estimates in Table 5 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 individuals react more to "bad news" about the economy. Their higher inflation expectations following these treatments are likely due to heightened surprise or uncertainty.

Lockdown household post-treatment expectations converge more to the aggregate than those of non-lockdown households in response to information about the inflation target. Estimates in Table 5 column (1) show that respondents in lockdown receiving the China Inflation Target treatment report expectations that are 0.436 pp lower than those of treated respondents not in lockdown.[14] This difference is larger in the intensive margin, with estimates in column 5 indicating a difference of 1.318 pp. The fact that lockdown households react more than non-lockdown households to information on the target suggests greater trust in institutions to achieve lower inflation. Trust in institutions is likely higher among lockdown households due to greater exposure to strong government lockdown intervention during the pandemic, reducing their uncertainty and lowering inflation expectations.

Consistent with this stronger response, Appendix G examines whether lockdown households place different weights on their priors under Bayesian updating. Equation (1) is estimated for each sub-sample by lockdown status using Huber (1964) robust regressions. The results align with estimates in Table 5. Respondents in lockdown report higher prior expectations and significantly revise them downward following the CTarget information treatment. In contrast, non-lockdown households show no statistically significant response to this treatment.

To ensure that our findings of the differential treatment effects by lockdown status are not driven by geographic heterogeneity, we account for potential differences in pandemic severity and regional inflation across locations. We estimate alternative specifications with city or province fixed effects and geographically clustered standard errors. The results remain consistent.

address this concern, we re-estimate the specification excluding these respondents and show that the results remain consistent both qualitatively and quantitatively. Results are available upon request.

[14] 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 $-1.318 = 1.595 - 2.913$.

Table 5: 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	0.064	2.168***	1.022***
	(0.445)	(0.294)	(0.045)	(0.045)	(0.778)	(0.383)
USHike	0.926**	0.423	0.077*	0.076*	1.049	0.290
	(0.450)	(0.264)	(0.044)	(0.044)	(0.791)	(0.343)
CTarget	0.063	-0.069	0.049	0.049	-0.085	-0.164
	(0.421)	(0.264)	(0.045)	(0.045)	(0.761)	(0.355)
CCOVID	1.127**	0.497*	0.044	0.044	2.224***	0.688*
	(0.495)	(0.301)	(0.046)	(0.046)	(0.818)	(0.403)
π_{prior}	0.633***	0.712***	0.009***	0.009***	0.338***	0.378***
	(0.040)	(0.026)	(0.003)	(0.003)	(0.055)	(0.025)
USRec × π_{prior}	-0.055	-0.023	-0.005	-0.005	-0.170**	-0.156***
	(0.059)	(0.040)	(0.004)	(0.004)	(0.077)	(0.037)
USHike × π_{prior}	-0.029	0.019	-0.005	-0.005	-0.023	-0.120***
	(0.058)	(0.035)	(0.004)	(0.004)	(0.080)	(0.038)
CTarget × π_{prior}	-0.081	-0.087**	-0.001	-0.001	-0.082	-0.231***
	(0.062)	(0.041)	(0.004)	(0.004)	(0.079)	(0.036)
CCOVID × π_{prior}	-0.035	-0.010	-0.005	-0.005	-0.113	-0.100***
	(0.064)	(0.039)	(0.004)	(0.004)	(0.083)	(0.039)
Lockdown	0.844	0.546*	0.037	0.037	1.595*	-0.003
	(0.515)	(0.331)	(0.045)	(0.045)	(0.893)	(0.401)
USRec × Lockdown	-0.389	-0.295	-0.003	-0.003	-0.636	0.443
	(0.752)	(0.476)	(0.063)	(0.063)	(1.265)	(0.588)
USHike × Lockdown	-1.240*	-1.019**	-0.091	-0.091	-1.908	0.195
	(0.741)	(0.443)	(0.063)	(0.063)	(1.351)	(0.558)
CTarget × Lockdown	-1.280*	-0.690	0.001	0.000	-2.913**	-0.208
	(0.690)	(0.467)	(0.063)	(0.064)	(1.135)	(0.517)
CCOVID × Lockdown	-1.460*	-0.487	-0.033	-0.033	-2.880**	-0.137
	(0.786)	(0.475)	(0.064)	(0.064)	(1.318)	(0.595)
Constant	-1.883*	-1.266*	0.682***		-0.583	0.825
	(1.070)	(0.746)	(0.103)		(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 (3) 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 roles of the extensive and intensive margins for the overall average effects are estimated in Appendix E. We decompose the overall treatment effects into the contribution of each margin following Dräger et al. (2024). Consistent with the results above, the intensive margin accounts for the majority of variation in average posterior inflation expectations across treatments. We find no meaningful differences in these contributions by lockdown status. Accordingly, the remaining analysis focuses on the role of the intensive margin.

We additionally find that lockdown not only affects the treatment response, but also weakens respondent anchoring to salient price experiences. Individuals in lockdown rely less on their priors than those not in lockdown when forming post-treatment inflation expectations. In Appendix F, we compare estimates of the impact of prior inflation expectations with the impacts of past inflation experiences and expectations of food prices on post-treatment inflation expectations. Respondents place a weight that is approximately twice larger on prior food inflation expectations than overall inflation expectations. While lockdown individuals report relatively higher food inflation expectations, they rely less on this prior following receipt of the treatment. In contrast, non-lockdown respondents exhibit a stronger persistence of prior food inflation beliefs, suggesting a higher degree of expectation rigidity. Lockdown thus weakens the link between prior food inflation expectations and post-treatment overall inflation expectations.

4.3 Information environments and expectations

Lockdown status substantially reshapes how individuals 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 individuals in lockdown have higher inflation expectations and stronger responsiveness to policy-target signals. These patterns suggest that lockdown conditions 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 people more actively responded to policy news.

The effect of lockdowns on macroeconomics expectations is not uniform across countries. Our findings contrast 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 in China, 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 with endogenous attention

This section develops a stylized model of expectation formation that rationalizes the empirical heterogeneity in household responses to information treatments by lockdown status. Its purpose is to discipline the interpretation of the estimated belief-updating coefficients in the empirical analysis.

5.1 A two-period framework

Time consists of two periods, $t = 1, 2$. Households care about consumption in both periods and face uncertainty about next-period inflation π. Each household is indexed by lockdown status $L \in \{0, 1\}$, where $L = 1$ denotes being currently or recently under lockdown.

The timing of the model is as follows. At the beginning of period 1, households enter with a prior belief about next-period inflation. They then observe an information signal and choose how much attention to allocate to that signal when forming expectations. Based on the resulting posterior belief about inflation, households choose consumption c_1 and savings a_1. In period 2, inflation is realized and determines the real value of nominal resources and thus realized consumption.

Households enter period 1 with a Gaussian prior over inflation:

$$\pi \sim N(\mu_p, \sigma_p^2(L)), \tag{4}$$

where the prior variance depends on lockdown status.[15] Consistent with the survey evidence, we assume

$$\sigma_p^2(1) < \sigma_p^2(0), \tag{5}$$

so that households under lockdown hold more precise prior beliefs.

Households may receive one of two types of information signals: (i) a policy signal s_{pol}, which directly concerns inflation (e.g., an inflation target), or (ii) a bad-news signal s_{bad}, which captures adverse macroeconomic or pandemic developments. Signals take the form

$$s_j = \pi + \varepsilon_j, \qquad \varepsilon_j \sim N(0, \sigma_{s,j}^2), \qquad j \in \{pol, bad\}. \tag{6}$$

Rather than assuming that households fully process the signal, we allow them to allocate limited attention to it. Posterior beliefs therefore take the linear form

$$E[\pi | s_j] = (1 - \omega_j)\mu_p + \omega_j s_j, \tag{7}$$

where $\omega_j \in [0, 1]$ denotes the weight assigned to signal j.

After forming expectations about inflation, households choose consumption and savings subject to

$$c_1 + a_1 = y_1, \tag{8}$$

[15] The relationship between lockdown status and inflation expectations implied by the model continues to hold if the prior mean depends on lockdown status. In Appendix I, we allow both the prior mean and variance to depend on lockdown status in our model. The main text assumes that only the prior variance varies with lockdown status for simplicity.

and next-period nominal resources

$$\bar{y} = y_2 + (1+i)a_1. \tag{9}$$

In period 2, realized inflation determines the real value of these resources:

$$c_2 = \frac{\bar{y}}{1+\pi_2}. \tag{10}$$

This structure makes clear the channel through which inflation misperceptions affect welfare. Households choose savings a_1 based on their expected inflation π^e. If inflation expectations are incorrect, households choose a suboptimal level of savings, which in turn leads to an inefficient level of real consumption c_2 once inflation is realized. Thus, inflation misperceptions affect welfare through the intertemporal consumption-savings decision.

Allocating attention to information is costly. We assume a convex attention cost

$$C(\omega_j) = \frac{\kappa}{2}\omega_j^2, \tag{11}$$

where $\kappa > 0$ captures the marginal cost of processing information. Households choose the attention weight ω_j jointly with their consumption-savings decisions to maximize expected utility

$$\max_{c_1, a_1, \omega_j} \frac{c_1^{1-\sigma}}{1-\sigma} + \beta E\left[\frac{c_2^{1-\sigma}}{1-\sigma}\right] - \frac{\kappa}{2}\omega_j^2. \tag{12}$$

This formulation follows the rational inattention literature (Sims 2003; Maćkowiak and Wiederholt 2009; Matějka and McKay 2015), in which agents optimally choose how intensively to process information. When $\kappa = 0$, information processing is costless and the optimal weight on the signal collapses to the standard Bayesian weight determined by prior and signal variances. When $\kappa > 0$, households optimally place less weight on signals than the full-information Bayesian benchmark because attention is costly.

The first-order condition for ω_j equates the marginal cost of attention to the expected marginal benefit from improved inflation forecasts:

$$\kappa\omega_j^* = \beta\mathbb{E}\left[u'(c_2)\frac{\partial c_2}{\partial \pi_{post}}(s_j - \mu_p)\right]$$

The signal weight therefore increases as the higher changes in inflation expectations impact household welfare. Two forces govern optimal attention: (i) belief sensitivity: the optimal weight ω_j^* increases in the marginal cost of misperceiving inflation:

$$\frac{\partial c_2}{\partial \pi_{post}} = -\frac{\bar{y}}{(1+\pi_{post})^2} < 0,$$

implying that misperceiving inflation has real consumption consequences. (ii) Uncertainty and convexity: under CRRA preferences, marginal utility is convex in consumption. By the Rothschild and Stiglitz (1970) theorem, greater uncertainty raises expected marginal utility. Thus, signals that increase consumption risk are more valuable when beliefs are less precise.

We now show that lockdown status generates asymmetric attention to policy versus bad news.

Proposition 1 (Policy signal attention) *If* $\sigma_p^2(1) < \sigma_p^2(0)$*, then* $\omega_{pol}^*(1) > \omega_{pol}^*(0)$*.*

The policy signal directly shifts inflation beliefs. When priors are precise (low σ_p^2), posterior beliefs have higher curvature in utility terms: small belief errors translate into larger welfare losses. As a result, the marginal value of processing inflation-target information is higher for lockdown households.

Proposition 2 (Bad-news signal attention) *If households differ only in prior variance and preferences are CRRA, then* $\omega_{bad}^*(1) < \omega_{bad}^*(0)$*.*

Bad-news signals increase perceived downside risk to consumption rather than directly anchoring inflation beliefs. With convex marginal utility, households with more uncertain priors place greater value on information about adverse states. Non-lockdown households, who face higher belief uncertainty, therefore optimally allocate more attention to bad news.

Together, Propositions 1-2 imply:

$$\omega_{pol}^*(1) > \omega_{bad}^*(1), \qquad \omega_{pol}^*(0) < \omega_{bad}^*(0),$$

matching the empirical ordering of treatment effects.

5.2 Mapping empirical estimates to structural parameters

We next map the 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: $\pi_i^{post} = \alpha + \delta\,\pi_i^{prior} + \sum_k \gamma_k T_{ik} \times \pi_i^{prior} + \varepsilon_i$. Under linear-Gaussian updating, the empirical weight on new information equals:

$$\omega_k(L) = 1 - \big(\delta(L) + \gamma_k(L)\big)$$

Hence, estimated interaction terms directly identify endogenous signal weights. Relative signal precision can be recovered as:

$$\frac{\lambda_{pol}(L)}{\lambda_{bad}(L)} = \frac{\omega_{pol}(L)}{1-\omega_{pol}(L)} \Big/ \frac{\omega_{bad}(L)}{1-\omega_{bad}(L)} \tag{13}$$

This mapping allows the empirical results to be interpreted as differences in effective signal credibility by lockdown status, rather than reduced-form behavioral heterogeneity.

We use our survey to calculate the ratio of the relative precision of signals in equation (13) between lockdown and non-lockdown respondents. Equation (1) is estimated for households by lockdown status with Huber robust regressions (see Appendix G). 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 signal 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, on average. Table 6 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 6: 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 (13). Estimates are from Huber robust regressions with output in Appendix G.

To sum up, the model delivers three implications consistent with the data: (1) Lockdown households respond more strongly to policy-based information; (2) Non-lockdown households react more to adverse macroeconomic news; and (3) Policy signals reduce posterior uncertainty more for lockdown households.[16] Importantly, these patterns arise endogenously from differences in prior precision and optimal attention, without imposing signal-specific behavioral assumptions.

The counterfactual lockdown exercise in Section 3.2 is also consistent with the model. In the framework above, lockdown status affects not only prior precision but also the perceived inflation environment through supply disruptions and price salience. Moving from a non-lockdown to a lockdown state introduces an additional inflation wedge, leading households to revise expectations upward. Exiting lockdown removes this wedge but leaves residual uncertainty, generating smaller downward revisions. This asymmetry arises naturally from convex marginal utility and higher uncertainty associated with lockdown environments, without invoking behavioral assumptions. A formal treatment is provided in Appendix I.

6 Conclusion

Macroeconomic expectations and policy communications vary by economic environment. Understanding household beliefs under environments of heightened uncertainty 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-

[16] We confirm that policy signals reduce posterior uncertainty more for lockdown groups in our RCT survey. In Appendix H, we estimate an ordered logit model of post-treatment confidence in inflation expectations on prior confidence, treatment indicators, lockdown status, the interaction of prior confidence and treatments, the interaction of lockdown status and treatments, and a vector of controls. We find that information treatments reduce respondent overconfidence by compressing the distribution of confidence from a high to middle confidence level. Only the effect of the CTarget differs by lockdown status, with this policy treatment increasing the probability of high confidence in lockdown. This response suggests that targeted policy communication can increase confidence among engaged consumers in high-uncertainty environments.

experimental setting in the first national survey on macroeconomic expectations in China: the Survey of Household Inflation Expectations.

This paper shows that lockdown status affects household inflation expectations and their responses to information. Because households make consumption and savings decisions based on their inflation expectations, misperceptions of inflation can distort intertemporal consumption choices and generate welfare losses. We provide causal evidence that identical information is processed differently depending on whether households are subject to restrictive policy regimes. Lockdown amplifies the credibility of domestic inflation policy communication and dampens the influence of bad news. This result extends to respondents with varying reliance on alternative measures of inflation. We interpret these findings through a model of Bayesian updating with endogenous attention, in which lockdown status affects optimal information processing. While our focus is expectation formation, we document in Appendix J that inflation expectations causally affect planned spending decisions.

There is potential for expectation surveys to inform both monetary policy design and communication strategies in periods of heightened uncertainty and crisis. Our findings highlight that expectation formation is state-dependent, as the interaction between information and the policy environment shapes how signals are interpreted. In environments with changing constraints, policy regimes, or economic uncertainty, identical information can generate different belief updates across households. Consistent with this, we show that the effectiveness of monetary policy communication varies by context, with official signals more effective at anchoring expectations under restrictive or uncertain conditions. These results underscore the importance of accounting for policy environment when designing communication strategies. Regular household inflation expectation surveys, particularly in China, would support improved policy design and enable deeper analysis of expectation formation and information transmission in emerging markets.

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Online Appendix:

Policy Environments and Household Inflation Expectations

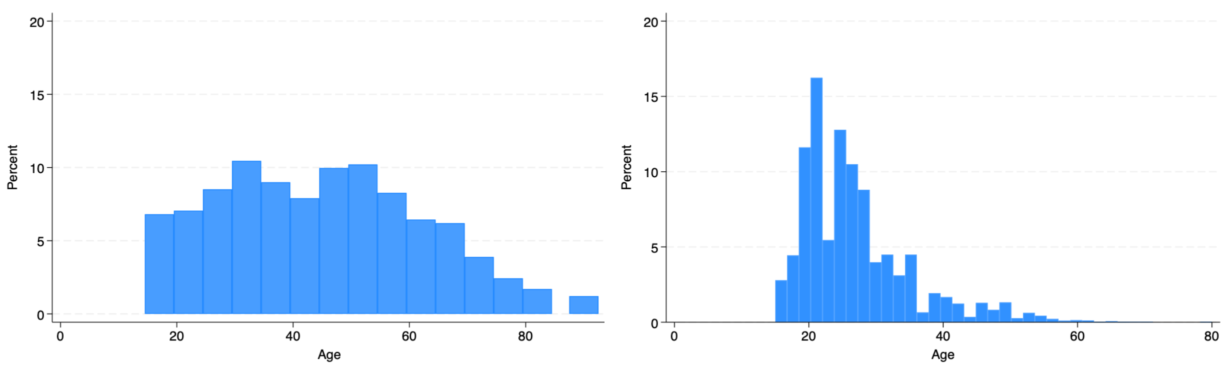
By Zhiyong Fan, Aina Puig, and Xuguang Simon Sheng

A Survey match of the population age distribution

One of our objectives when sampling individuals was to align the surveyed sample with the 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 individuals 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 as shown in Figure A.1a. In contrast, the average age of respondents in our surveys is 27. As shown in Figure A.1b, our survey samples a larger proportion of younger individuals compared to the national age distribution.

Figure A.1: Age distribution in population versus survey



(a) China population (b) Survey

Note: These figures show the age distributions (15+) of the population in China from the 2020 UN Economic and Social Commission for Asia and the Pacific (a), and our survey (b).

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. The threshold weight is age 25 to ensure enough observations in each bin to conduct our analysis. A higher age threshold, such as at age 30 or 35, assigns a large weight to the few older-age individuals sampled. Estimates become skewed 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). When collecting macroeconomic expectations in emerging market economies, it may be optimal to design surveys both online and on-site to ensure the collection of responses from these demographic groups. 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.

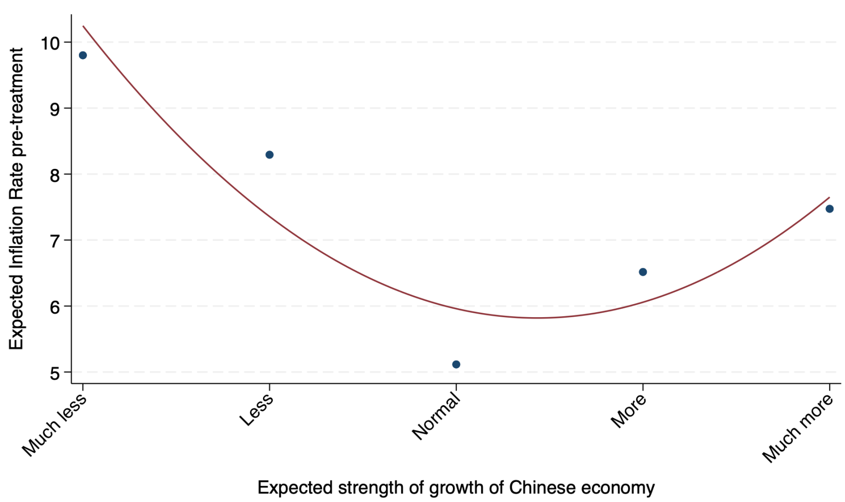
B Relationship between expectations of inflation and economic growth

Individuals 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 this theory. Dräger et al. (2016) find that expectations become less consistent with this 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 economic growth.[17] Figure B.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 of demand. This inconsistency likely reflects the differential treatment of the pandemic as a demand or supply shock.

Figure B.1: Expectations of inflation versus economic growth



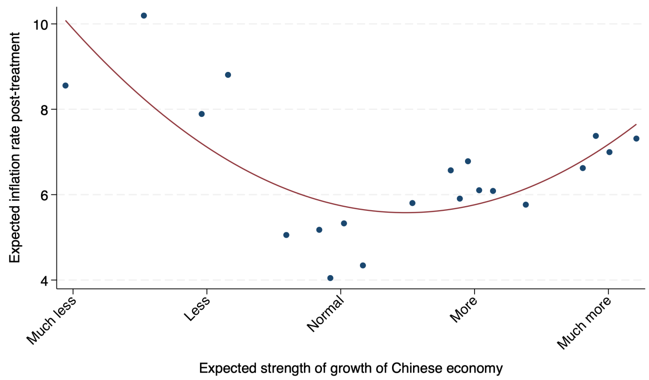
Note: This figure shows a binscatter plot of expectations of inflation pre-treatment and economic growth. Expectations of growth are elicited in reference to normal growth: for example, "much less" is presented to respondents as "much less strongly than normal". Plot uses sample weights.

We test several mechanisms for the V-shape relationship. Figure B.2 shows that the V-shape relationship holds when controlling for household characteristics such as age, sex,

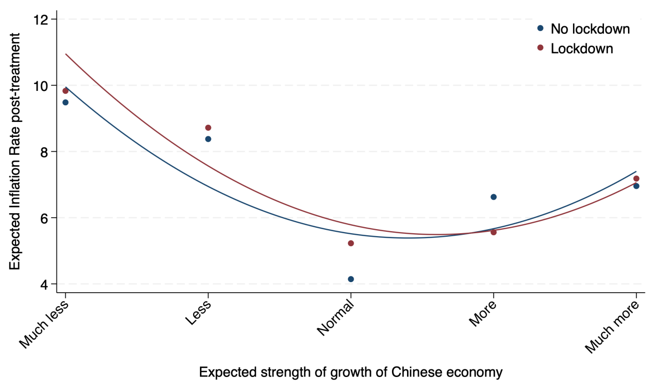
[17]The shape is consistent if plotting post-treatment, rather than prior, inflation expectations.

college education, urban residence, and employment. We also do not find a difference in this relationship between respondent lockdown status or information treatment.

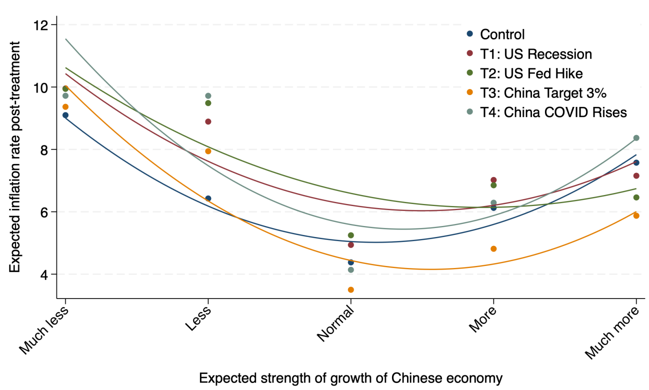
Figure B.2: Expectations of inflation versus economic growth by subgroups



(a) Controls



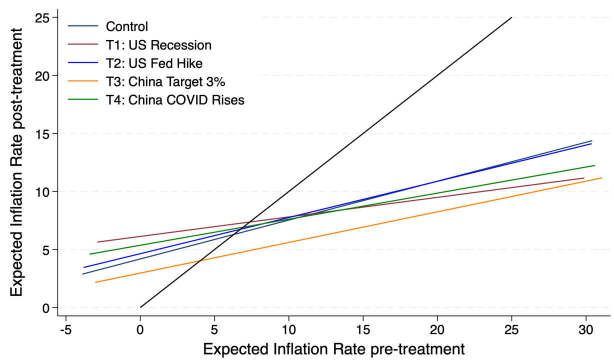
(b) Lockdown



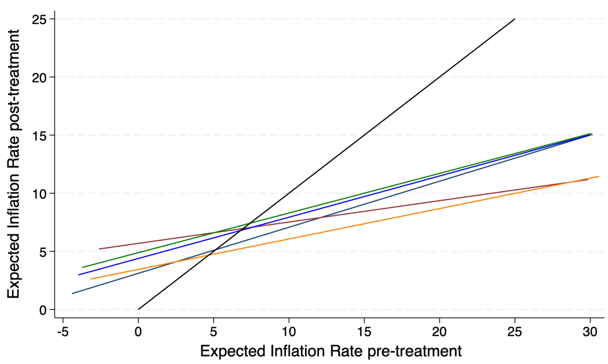
(c) Treatment

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.

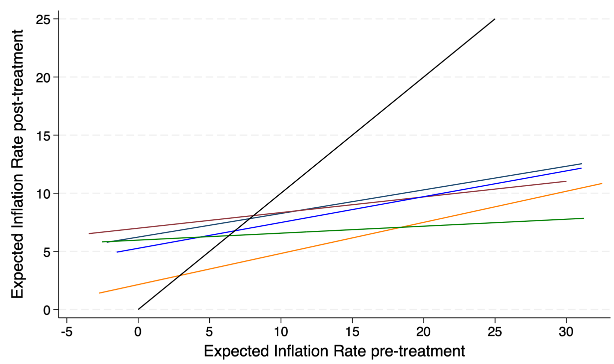
C Intensive margin binscatter plots of prior and post-treatment inflation expectations



(a) All



(b) No lockdown

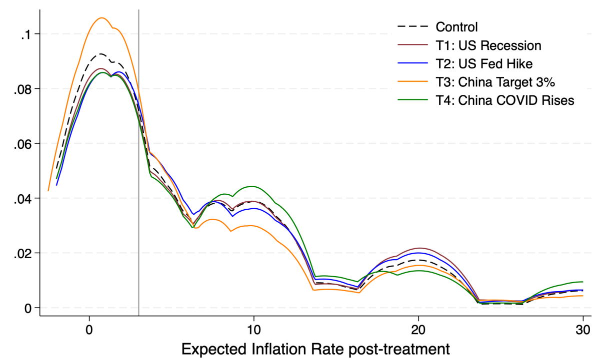


(c) Lockdown

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 respondents, Figure (b) represents respondents not in lockdown, and Figure (c) represents respondents recently or currently in lockdown. The solid black line is the 45-degree line. Plots use sample weights.

D Distribution statistics of post-treatment inflation expectations

Figure D.1: Distribution of post-treatment inflation expectations



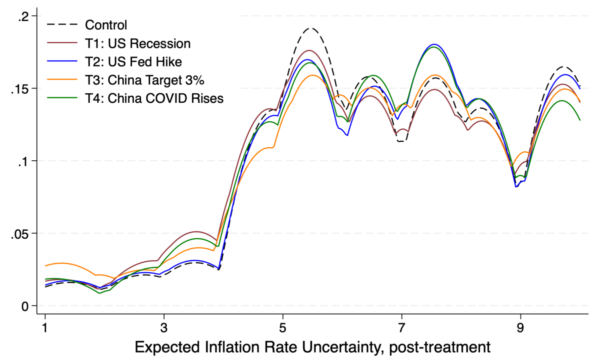
Note: This figure shows the kernel densities of post-treatment inflation expectations by treatment group. Vertical grey line is at 3%. Plots use sample weights.

Table D.1: Statistics of post-treatment inflation expectations

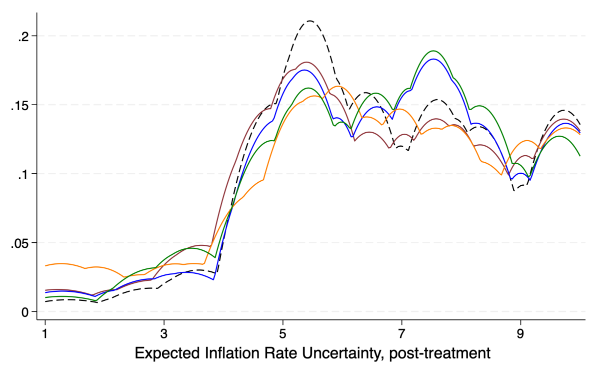
	Mean	SD	Kurtosis	Skewness
All sample				
Control	3.74	4.52	5.34	1.42
T1: US Recession	4.02	4.80	5.87	1.51
T2: US Fed Hike	3.83	4.34	5.46	1.39
T3: China Target 3%	3.24	4.21	6.42	1.65
T4: China COVID Rises	4.20	4.81	4.72	1.26
No lockdown				
Control	3.31	4.04	5.69	1.48
T1: US Recession	3.37	4.25	7.42	1.75
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.

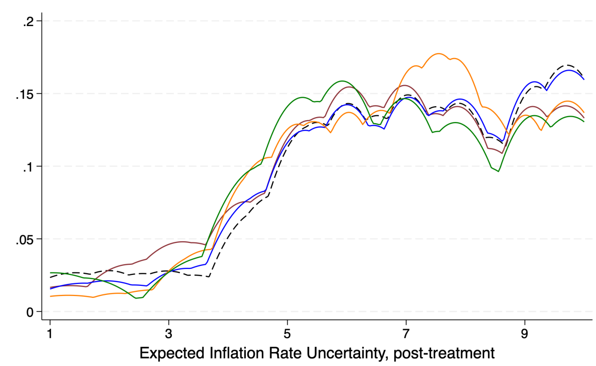
Figure D.2: Distribution of post-treatment inflation expectation uncertainty



(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.

E Decomposition of the overall treatment effect into the extensive and intensive margin

We follow Dräger et al. (2024) in decomposing the overall treatment effects into the contribution of the extensive and intensive margin using our RCT cross-sectional data. The cross-sectional decomposition is computed in the following way:

$$\pi_{i,post} = fr_i \cdot \pi^{ch}_{i,post} + (1 - fr_i) \cdot \pi^{nch}_{i,post},$$

where $\pi_{i,post}$ is the average posterior inflation expectation in treatment group i and fr_i is the fraction of households who update expectations in treatment i. $\pi^{ch}_{i,post}$ represents the average expectation of those who update their expectations in treatment i and $\pi^{nch}_{i,post}$ is the average inflation expectation of those who do not update their expectations in treatment i. The cross-sectional differences in the average inflation expectations are further decomposed to changes in the intensive and extensive margins by taking a first-order approximation around the average inflation expectations in this survey experiment ($\overline{\pi}$):

$$\pi_{i,post} - \overline{\pi} = \underbrace{(fr_i - \overline{fr})\left(\overline{\pi^{ch}_{post}} - \overline{\pi^{nch}_{post}}\right)}_{\text{extensive}} + \underbrace{(\pi^{ch}_{i,post} - \overline{\pi^{ch}_{post}})\overline{fr} + (\pi^{nch}_{i,post} - \overline{\pi^{nch}_{post}})(1 - \overline{fr})}_{\text{intensive}} + O_i,$$

where O_i is the residual and variables with the upper bar represent averages across all treatments, following Dräger et al. (2024). We decompose the cross sectional variation in the level of average inflation expectations for the overall sample and separately for each subsample by lockdown status.

The decomposition estimates in Table E.1 suggest that most of the variation in average posterior inflation expectations across treatments is driven by the intensive margin. In the overall sample, the intensive margin accounts for over 80% of average expectations across the four treated groups. Similar patterns emerge in the sub-samples by lockdown status, as shown in Panels B and C of Table E.1.

Table E.1: Cross sectional variation in the level of average inflation expectations

	Treatment Group				
	Control	USRec	USHike	CTarget	CCOVID
Panel A: Overall Sample					
$\pi_{i,post}$	3.74	4.02	3.83	3.24	4.20
$\pi_{i,post} - \overline{\pi}$	-0.05	0.23	0.04	-0.55	0.41
IM contr.	-0.00	0.22	0.07	-0.57	0.36
EM contr.	-0.02	0.00	-0.00	0.03	-0.01
Panel B: No Lockdown					
$\pi_{i,post}$	3.81	3.87	3.66	3.10	4.15
$\pi_{i,post} - \overline{\pi}$	0.10	0.16	-0.04	-0.61	0.44
IM contr.	0.11	0.14	0.02	-0.66	0.42
EM contr.	-0.02	0.01	0.01	0.02	-0.02
Panel C: Lockdown					
$\pi_{i,post}$	3.59	4.31	4.20	3.50	4.31
$\pi_{i,post} - \overline{\pi}$	-0.37	0.35	0.24	-0.46	0.35
IM contr.	-0.23	0.39	0.20	-0.37	0.23
EM contr.	-0.02	0.00	-0.02	0.04	0.00

Note: This table shows estimates calculated using Huber (1964) robust and sampling weights with inflation expectations truncated at the 5th and 95th percentiles. IM stands for intensive margin and EM for extensive margin. 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. $\pi_{i,post} - \overline{\pi}$ is the difference in average expectations in treatment group i and the average expectations in this RCT (for the overall sample in panel A and by lockdown status in panels B and C).

F Salient prices and the reliance on priors by lockdown status

In this section, we study the salience of prices on inflation expectations. We estimate the effect of each alternative inflation measure (past inflation or food inflation) 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. Table F.1 shows 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.

Respondents weight their perceived inflation less than their prior expectations when reporting their post-treatment expectations. Table F.1 displays estimates of weights on priors that are approximately five times larger than perceived inflation in the overall sample, but weights that are similar in size for the intensive margin. We also find that individuals 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:

$$\begin{aligned}\pi_{j,post} = \alpha &+ \sum_{k=2}^{5} \beta_k T_{j,k} + \delta \pi_j + \sum_{k=2}^{5} \gamma_k T_{j,k} \times \pi_j + \phi Lockdown_j + \lambda \pi_j \times Lockdown_j \\ &+ \sum_{k=2}^{5} \zeta_k T_{j,k} \times Lockdown_j + \sum_{k=2}^{5} \Delta_k T_{j,k} \times Lockdown_j \times \pi_j + \boldsymbol{X_j \psi} + \epsilon_j,\end{aligned} \tag{14}$$

where π is prior inflation expectations π_{prior}, prior food inflation expectations π^{food}_{prior}, perceived inflation π_{pcvd}, or perceived food inflation π^{food}_{pcvd}. 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 F.2 reports the estimated coefficients on the triple interaction term in equation (14) for each pre-treatment inflation measure (Table F.3 contains full regression estimates using the π_{prior} measure). 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 F.2 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

Table F.1: 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

a stronger persistence of prior food inflation beliefs. This pattern complements estimates in Table F.1 showing higher reliance on food than overall economy inflation expectations.

Table F.2: Treatment effects on inflation expectations by inflation measure and lockdown status

	Post-treatment inflation expectations							
	π_{prior}		π_{prior}^{food}		π_{pcvd}		π_{pcvd}^{food}	
	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 $\times$ L $\times$ 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 $\times$ L $\times$ 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 $\times$ L $\times$ 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 $\times$ L $\times$ 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 (14), 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_{prior}^{food}, π_{pcvd}, π_{pcvd}^{food}). See Table F.3 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F.3: 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	0.071	2.534***	2.363***
	(0.430)	(0.302)	(0.048)	(0.048)	(0.787)	(0.728)
USHike	0.815*	0.092	0.094*	0.093**	1.229	0.799
	(0.442)	(0.269)	(0.048)	(0.047)	(0.805)	(0.678)
CTarget	0.100	-0.279	0.039	0.039	0.402	0.199
	(0.414)	(0.268)	(0.048)	(0.048)	(0.804)	(0.708)
CCOVID	0.698	0.388	0.050	0.050	1.869**	1.674**
	(0.443)	(0.313)	(0.050)	(0.050)	(0.821)	(0.752)
π_{prior}	0.644***	0.690***	0.010***	0.010***	0.394***	0.394***
	(0.041)	(0.030)	(0.003)	(0.003)	(0.057)	(0.052)
USRec × π_{prior}	-0.049	-0.003	-0.006	-0.006	-0.210**	-0.206***
	(0.065)	(0.047)	(0.005)	(0.005)	(0.084)	(0.078)
USHike × π_{prior}	-0.013	0.075*	-0.007	-0.007	-0.037	-0.013
	(0.064)	(0.041)	(0.004)	(0.005)	(0.090)	(0.081)
CTarget × π_{prior}	-0.086	-0.048	0.001	0.001	-0.139	-0.155*
	(0.073)	(0.050)	(0.005)	(0.005)	(0.095)	(0.084)
CCOVID × π_{prior}	0.029	0.008	-0.006	-0.006	-0.056	-0.067
	(0.062)	(0.047)	(0.005)	(0.005)	(0.089)	(0.077)
Lockdown	1.085*	0.118	0.048	0.048	3.086***	2.681***
	(0.626)	(0.357)	(0.058)	(0.058)	(1.144)	(1.003)
USRec × Lockdown	-0.238	0.127	-0.026	-0.027	-1.794	-1.586
	(0.930)	(0.552)	(0.082)	(0.082)	(1.631)	(1.450)
USHike × Lockdown	-0.860	0.079	-0.145*	-0.146*	-2.349	-2.451*
	(0.965)	(0.488)	(0.082)	(0.082)	(1.823)	(1.318)
CTarget × Lockdown	-1.380*	-0.029	0.034	0.033	-4.447***	-3.786***
	(0.798)	(0.479)	(0.083)	(0.083)	(1.391)	(1.220)
CCOVID × Lockdown	-0.241	-0.128	-0.050	-0.050	-2.153	-2.015
	(0.954)	(0.552)	(0.085)	(0.085)	(1.630)	(1.381)
Lockdown × π_{prior}	-0.037	0.081	-0.002	-0.002	-0.194	-0.178
	(0.100)	(0.058)	(0.006)	(0.006)	(0.128)	(0.118)
USRec × π_{prior} × Lockdown	-0.023	-0.079	0.004	0.004	0.147	0.141
	(0.139)	(0.088)	(0.008)	(0.008)	(0.173)	(0.160)
USHike × π_{prior} × Lockdown	-0.048	-0.192**	0.008	0.008	0.067	0.063
	(0.134)	(0.078)	(0.008)	(0.008)	(0.178)	(0.155)
CTarget × π_{prior} × Lockdown	0.016	-0.125	-0.005	-0.005	0.200	0.184
	(0.138)	(0.086)	(0.008)	(0.008)	(0.168)	(0.153)
CCOVID × π_{prior} × Lockdown	-0.162	-0.070	0.002	0.002	-0.085	-0.083
	(0.147)	(0.084)	(0.008)	(0.008)	(0.171)	(0.152)
Constant	-1.938*	-1.098	0.680***		-1.071	0.135
	(1.059)	(0.742)	(0.104)		(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 (14) 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

G Treatment effects on inflation expectations by lockdown status subsample

	Post-treatment inflation expectations of households	
	Non-lockdown	Lockdown
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 $\times$ π_{prior}	-0.003	-0.092
	(0.047)	(0.074)
USHike $\times$ π_{prior}	0.074*	-0.115*
	(0.041)	(0.066)
CTarget $\times$ π_{prior}	-0.047	-0.181***
	(0.050)	(0.070)
CCOVID $\times$ 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

H Treatment effects on confidence in expectations

We estimate the treatment effects on respondent confidence in inflation expectations as follows:

$$P(conf_{j,post} \leq m|X) = F(\alpha + \sum_{k=2}^{5} \beta_k T_{j,k} + \delta conf_{j,prior} + \sum_{k=2}^{5} \gamma_k T_{j,k} \times conf_{j,prior} + \phi Lockdown_j + \sum_{k=2}^{5} \zeta_k T_{j,k} \times Lockdown_j + \boldsymbol{X_j \psi} + u_j), \tag{15}$$

where $conf$ is respondent j confidence in their inflation expectation point estimate for m ordered categories; and other variables follow equation (1). The coefficients γ_k measure the treatment effects on confidence and ζ_k indicate differential posterior confidence by lockdown status. The main specification is an ordered logistic model, although estimates of the same specification estimated via OLS are also presented for robustness.

Confidence, which is elicited on a 10-point Likert scale in the survey, is categorized into three categories for facility of presentation. Our model estimates are consistent with using the 10-point scale confidence measures. The three categories are: low (1-4), medium (5-7), and high confidence (8-10). As the sample averages in Table 2 show, respondents are highly confident in their expectations. Approximately 10% of the sample reports confidence below a 5 out of 10.

The average marginal effects in columns 1, 3, and 5 of Table H.1 show that information treatments compress the distribution of confidence toward the middle category. This pattern is consistent with a reduction in overconfidence, whereby the average respondent revises downward from high to medium confidence categories following treatment. The USRec, USHike, and CCOVID treatments shift confidence similarly regardless of lockdown status.

The effect of CTarget differs by lockdown status (Table H.1, columns 2, 4, 6). Among lockdown respondents, CTarget increases the probability of high confidence by 5.1 pp in the full sample and 14.6 pp in the intensive margin, with corresponding reductions in medium and low confidence. OLS estimates mirror this pattern, increasing the confidence index by 0.076 and 0.217 points, respectively. These estimates suggest that targeted policy communication operates differently in high-uncertainty environments, increasing confidence among engaged respondents rather than correcting overconfidence.

Table H.1: Treatment Effects on Posterior Confidence

	OLogit: P(Low)		OLogit: P(Med)		OLogit: P(High)		OLS
	Avg.	T × L	Avg.	T × L	Avg.	T × L	T × L
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Overall Sample							
USRec	-0.003	0.008	0.029**	0.009	-0.027**	-0.017	-0.029
	(0.010)	(0.014)	(0.014)	(0.013)	(0.013)	(0.027)	(0.042)
USHike	-0.011	-0.014	0.046***	-0.011	-0.035***	0.025	0.037
	(0.012)	(0.015)	(0.015)	(0.013)	(0.013)	(0.028)	(0.045)
CTarget	0.008	-0.021	0.031**	-0.030*	-0.039***	0.051*	0.076*
	(0.010)	(0.014)	(0.015)	(0.016)	(0.015)	(0.029)	(0.045)
CCOVID	-0.001	0.006	0.039***	0.008	-0.037***	-0.014	-0.032
	(0.011)	(0.015)	(0.015)	(0.014)	(0.014)	(0.028)	(0.044)
Panel B: Intensive Margin							
USRec	-0.001	0.007	0.077**	0.008	-0.076**	-0.015	-0.028
	(0.022)	(0.035)	(0.031)	(0.034)	(0.035)	(0.069)	(0.105)
USHike	-0.000	-0.019	0.105***	-0.018	-0.105***	0.037	0.040
	(0.025)	(0.038)	(0.030)	(0.035)	(0.033)	(0.073)	(0.113)
CTarget	0.015	-0.069*	0.071**	-0.077*	-0.085**	0.146**	0.217*
	(0.025)	(0.037)	(0.032)	(0.039)	(0.036)	(0.074)	(0.111)
CCOVID	-0.016	0.010	0.095***	0.011	-0.080**	-0.021	-0.045
	(0.026)	(0.038)	(0.032)	(0.038)	(0.037)	(0.076)	(0.116)

Note: This table shows estimates of the treatment groups in equation (15). 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. Columns (1)–(6) report average marginal effects from the ordered logit model on the probability of low, medium, and high confidence for treatments relative to the control group. Avg. columns report the treatment effect relative to the control averaged across lockdown conditions. T×L columns report the treatment group and lockdown status interaction term. Column (7) reports the estimate of the treatment group and lockdown interaction term from the OLS model. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

I Lockdown counterfactual and belief revisions in the two-period model

This appendix provides a formal interpretation of the counterfactual lockdown exercise in Section 3.2. Asymmetric belief revisions under hypothetical changes in lockdown status arise naturally within the framework of endogenous attention developed in Section 5, without introducing additional behavioral assumptions.

We model inflation as

$$\pi = \bar{\pi} + \Delta(L) + \eta,$$

where $\bar{\pi}$ denotes long-run trend inflation, $\Delta(L)$ is a lockdown-specific inflation wedge, and $\eta \sim \mathcal{N}(0, \sigma_\eta^2)$ is an idiosyncratic shock. Lockdown status is represented by $L \in \{0, 1\}$, where $L = 1$ denotes being currently or recently under lockdown. The lockdown-specific inflation wedge captures perceived supply disruptions, price salience, and policy-induced frictions associated with lockdown environments. Without loss of generality, we normalize the wedge to be relative to the non-lockdown state. Specifically, we assume

$$\Delta(1) > 0, \qquad \Delta(0) = 0,$$

to match our empirical finding that prior inflation expectations are higher under lockdown. We also assume that households are uncertain about the magnitude of $\Delta(L)$.

Households hold beliefs

$$\pi \mid L \sim \mathcal{N}(\mu_p(L), \sigma_p^2(L)),$$

with

$$\mu_p(L) = \bar{\pi} + \mathbb{E}[\Delta(L)], \qquad \sigma_p^2(1) < \sigma_p^2(0),$$

consistent with the empirical finding that lockdown households report greater confidence in their inflation expectations.

In the counterfactual exercise, households are asked to assess inflation expectations under a hypothetical lockdown status. Let L' represent the hypothetical lockdown, where $L' \neq L$. This induces a belief transition rather than an information signal update. The counterfactual mean belief satisfies

$$\mu_p(L') = \mu_p(L) + \big(\mathbb{E}[\Delta(L')] - \mathbb{E}[\Delta(L)]\big).$$

Since $\Delta(1) > \Delta(0)$, households revising beliefs from $L = 0$ to $L' = 1$ increase expected inflation, while those revising from $L = 1$ to $L' = 0$ decrease expected inflation. This matches the direction of revisions documented in Section 3.2.

To account for the asymmetry in revision magnitudes, we allow uncertainty about the lockdown wedge to differ by state:

$$\mathrm{Var}(\Delta \mid L = 1) > \mathrm{Var}(\Delta \mid L = 0).$$

Entering lockdown introduces an additional source of uncertainty related to policy duration, enforcement, and supply-chain disruptions. Exiting lockdown removes the mean wedge but leaves residual uncertainty.

Under CRRA preferences, marginal utility is convex in consumption. By standard results on convex order (Rothschild and Stiglitz 1970), higher uncertainty raises expected marginal utility, increasing the welfare cost of misperceiving inflation. As a result, upward revisions when moving into lockdown are larger in magnitude than downward revisions when moving out of lockdown:

$$\mathbb{E}[\Delta\pi^{cf} \mid L = 0 \to 1] > \left|\mathbb{E}[\Delta\pi^{cf} \mid L = 1 \to 0]\right|.$$

This mechanism explains the asymmetric counterfactual revisions observed in the data without invoking loss aversion, ambiguity aversion, or non-Bayesian updating.

Households revise beliefs whenever the expected welfare loss from misperceiving inflation exceeds the attention cost associated with reconsidering beliefs. Because the difference $|\Delta(1) - \Delta(0)|$ is large, a majority of households optimally revise expectations under hypothetical changes in lockdown status. This accounts for the high revision rates documented in Section 3.2.

The counterfactual lockdown results reinforce the main mechanism of the paper. Lockdown policies affect inflation expectations not only by changing economic conditions, but also by altering the perceived inflation environment and associated uncertainty. These effects interact with endogenous attention and convex marginal utility to generate large and asymmetric belief revisions when policy environments change.

J The causal effects of inflation expectations on planned spending and employment by lockdown status

In this section, we test whether inflation expectations causally affect planned spending, saving, and employment outcomes by policy environment. Following the model's purchasing-power channel, we expect higher inflation expectations leads to lower real spending. We also examine heterogeneity by lockdown status to assess whether the mapping from inflation expectations to spending decisions varies across economic environments.

Inflation expectations are of policy relevance due to their impact on household spending and employment outcomes. In our survey, respondents are asked their expectations of spending on durable goods, typical monthly spending, income, and job loss. 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 estimate the causal effects of inflation expectations on planned spending and employment expectations using instrumental variable regressions. The random assignment of information treatments is used to identify exogenous variation in inflation expectations following Coibion et al. (2023a). In the first stage, the planned spending or employment outcome P is regressed on inflation expectations and controls using a similar specification as equation (3):

$$P_{j,post} = \alpha_1+\phi_1\pi_{j,post}+\phi_2\Delta\pi_{j,pcvdf}+\phi_3\pi_{j,prior}+\phi_4 Lockdown_j+\phi_5 Lockdown_j\times\pi_{j,post}+\boldsymbol{\zeta_j}\boldsymbol{\psi}+\epsilon_j, \tag{16}$$

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:

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

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

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. The interactions of treatment and lockdown groups are included as instruments due to our Table 5 findings that inflation expectations differ by lockdown status. 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.

We find that higher inflation expectations influence household spending.[18] Table J.1 Panel A shows that higher inflation expectations increase expected typical monthly spending but reduce planned durable purchases. The increase in monthly spending reflects higher anticipated expenditure as expected prices rise. Table J.1 Panel B shows that an increase in inflation expectations causes respondents to significantly reduce planned house, car, TV, and refrigerator purchases. This decline in durables is consistent with the model setup in which higher inflation lowers real consumption.

Lockdown status affects spending levels but does not substantially alter the marginal effect of inflation expectations. Respondents in lockdown are more likely to decrease their saving compared to those not in lockdown.[19] However, the interaction between lockdown and post-treatment inflation expectations is generally insignificant, indicating that the negative durable response to inflation expectations is broadly similar across environments. Inflation expectations do not significantly affect income or job-loss expectations, although lockdown individuals report higher perceived job-loss risk (Panel A Column 5).

[18] Appendix K shows consistent estimates for the overall sample.

[19] Appendix K shows that lockdown respondents are more likely to plan to purchase home-related durable goods, such as computers and TVs.

Table J.1: 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 J). 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

K The causal effects of inflation expectations on planned spending and employment

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 (3):

$$P_{j,post} = \alpha_1 + \phi_1 \pi_{j,post} + \phi_2 \Delta\pi_{j,pcvdf} + \phi_3 \pi_{j,prior} + \phi_4 Lockdown_j + \boldsymbol{\zeta_j \psi} + \epsilon_j, \tag{17}$$

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 5 findings of differing inflation expectations by household lockdown status. The estimates are presented in Tables K.1 and K.2.

Table K.1: 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 (17) 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 K.2: 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 (17) 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

L 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)

Part B: Views on changes in price level in the past 12 months

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 <u>fewer hours per week</u> would you say you worked during the lockdown compared to before the lockdown?
_____ hours per week *(go to Q39)*

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

39. How many hours <u>per day</u> 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 fewer hours per week 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 more hours per week 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 per day 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.