THE NEW CAUSAL MACROECONOMICS OF SURVEYS AND EXPERIMENTS

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This draft: October 30, 2025

Abstract: We discuss how Randomized Control Trials (RCTs) can be used to study the causal effects of expectations on the decisions of households, firms and other economic agents. Specifically, information provision in RCTs can create exogenous variation in the beliefs of survey participants and thus can address a key identification challenge that has plagued research efforts focused on understanding the role of expectations in shaping economic decisions. When linked to either external information on their actions or subsequent survey waves that measure their ex-post decisions, RCTs can provide clear causal identification of the passthrough from expectations to decisions. We review recent evidence using this strategy and discuss potential challenges associated with this approach.

JEL: E3, E4

Keywords: expectations, surveys, identification.

1. Introduction

The interplay between expectations and decisions is at the heart of every macroeconomic model in which most decisions are forward looking and depend on beliefs about the future. Indeed, how much to save, how to set prices, what technology to use, how to allocate investment across assets and many other decisions depend on what households, firms, traders, etc. predict about economic conditions in a day, a week, a month, a year, and so on. Despite this prominent feature, it has been challenging for researchers to actually quantify the extent to which expectations affect decisions as posited by theoretical models. The slow progress in this area reflects the fact that taking up this challenge requires measures of people's beliefs as well as a source of exogenous variation in those beliefs. While the increasing availability of survey data has made the former less of a constraint, it is not enough to measure expectations and decisions. For instance, a positive correlation between consumption and inflation expectations could reflect the intertemporal channel through which inflation expectations are predicted to affect consumer spending, but causation could also run in the opposite direction if, when consumers are spending more, they think others will do the same and the increase in demand will cause prices to rise more rapidly. The only way to break through this identification challenge is to find variation in inflation expectations that is unrelated to these other channels.

Randomized control trials (RCTs) offer a credible way to do so. The idea is to provide information to randomly selected survey participants that leads them to revise their inflation expectations relative to other households who do not receive this information. But because the choice of who to provide the information to is randomized, the selection of those who revise their beliefs is as well. Therefore, if those individuals who changed their beliefs due to this treatment also tend to change their subsequent spending in a clear way relative to the untreated, one can label the change in spending as being caused by the change in inflation expectations.

In this paper, we review recent papers that implement this approach to study how households' inflation expectations affect their decisions and discuss potential challenges that arise in the implementation of this RCT approach. One of the first studies to use this strategy in the context of inflation expectations is Coibion, Gorodnichenko and Weber (2022). Using information about inflation that was provided to randomly selected U.S. households, these authors were successful in creating large exogenous changes in the inflation expectations of randomly selected participants and link those changes to their subsequent spending decisions. They found that,

consistent with the intertemporal substitution channel, higher inflation expectations led households to persistently and significantly raise their spending on non-durables in subsequent months. However, the effects on durables goods purchases seemed to go in the opposite direction, a feature they speculated had to do with how households changed other expectations along with inflation.

A subsequent and recent paper by Georgarakos et al. (2024) tackles this possibility by separating changes in inflation expectations from changes in inflation uncertainty. Because high inflation tends to be more volatile inflation, it would be natural for households who expect higher inflation to also be more uncertain about future inflation, a feature that Georgarakos et al. (2024) confirm for European households. Higher uncertainty could induce households to postpone large durable goods purchases, as in Bloom (2009), so higher inflation expectations, to the extent that they are associated with higher inflation uncertainty, could have ambiguous overall effects on durable goods purchases. Through the use of multiple information treatments that generate separate variation in inflation expectations and inflation uncertainty, Georgarakos et al. (2024) show that this is precisely what happens: higher inflation uncertainty (holding expectations constant) tends to reduce the likelihood of subsequent durable goods purchases whereas higher inflation expectations (holding uncertainty constant) tends to increase it. The combined effect is dominated by the uncertainty channel, which explains why Coibion, Gorodnichenko and Weber (2022) found negative overall effects of inflation expectations on durable goods purchases.

In addition to consumer spending, Georgarakos et al. (2024) can assess how inflation expectations and uncertainty affect other margins of adjustment available to households. They report three key findings. First, higher inflation uncertainty leads households to adjust their financial portfolios away from (illiquid) retirement accounts and toward (very liquid) checking and savings accounts, while higher inflation expectations lead to the opposite behavior. Second, when households become more uncertain about future inflation, they expect to search more actively for work in coming months, whereas higher inflation expectations lead to reductions in job search intensity. Third, these changes in job search behavior are reflected in labor market outcomes, especially in the case of inflation uncertainty. As households become more uncertain about future inflation and search for work more actively, their probability of being unemployed declines in subsequent months as does their probability of being in part-time work, even as their likelihood of being out of the labor force declines. In short, higher inflation uncertainty leads to more workers (both employed and unemployed) moving into full-time employment.

Together, these results provide decisive causal evidence that consumers' beliefs about future inflation shape their decisions along several different margins. While this paper focuses on households, further research studying firms and other economic agents paints a similar picture. We view this new evidence as providing support for the use of RCTs in studying how expectations affect decisions. However, this approach faces a number of challenges to its widespread use. We review these challenges in the paper and discuss how they can be overcome. Doing so would allow macroeconomists to answer many new questions and potentially validate and quantify some of the most fundamental mechanisms at work in our models.

Furthermore, these results speak to important policy discussions, particularly about the use of communication to shape the expectations of households and firms. One potential implication is that policy communications, even if they are successful in changing expectations such as about inflation, may have effects that differ from those that might be expected from theoretical models if they induce indirect effects on decisions, such as by changing uncertainty. Similarly, policy pronouncements that emphasize the "data dependence" of future policy may help avoid tying the hands of policymakers but they may have negative effects on economic activity by increasing uncertainty about future inflation outcomes.

The paper is organized as follows. Section 2 describes the RCT approach and why it can address fundamental identification issues involving expectations and decisions of economic agents. Section 3 discusses recent evidence from RCTs on the effects of inflation expectations on households' decisions. Section 4 considers potential challenges facing RCTs in the future and potential limits to how they can be used, as well as some possible solutions to these challenges. Section 5 concludes by discussing some policy implications.

2. The RCT Strategy to Identifying the Causal Effects of Expectations on Decisions

How do we identify the effect on inflation expectations on the decisions of economic agents? In this section, we review some of the main challenges as well as how RCTs can help break through this identification challenge.

2.1 Challenges to Identification

Expectations of the future are omnipresent in macroeconomic models and the decisions that are embodied in them. Yet characterizing how expectations actually affect the decisions of agents is

challenging. There are two major issues. First, the measurement of expectations. Second, the endogeneity of expectations.

The most direct approach to measuring expectations is to ask economic agents what they expect about the future. This is now commonly done in surveys of households, firms, financial market participants, etc. But in practice, many issues arise. First, surveys need to be representative and not based on convenience samples. This has proven to be a major challenge for surveys of firms, where getting randomly selected top executives of large firms to participate is often difficult. Second, the specifics of how expectations are measured can matter for the resulting measures of beliefs. Whether questions are formulated as point forecasts or distributions or whether questions are formulated in terms of prices or inflation, for example, can affect the answers provided by respondents. See De Bruin et al. (2011) and Armantier et al. (2013) for an extensive discussion of these points. Different surveys often take different approaches, occasionally leading to diverging patterns for measured expectations.

The second major challenge in identifying how expectations affect decisions is endogeneity: beliefs are not formed in a vacuum and are themselves a function of the economic environment. Suppose for example that we observe in the data that households who tend to expect higher inflation in the future also expect to consume more in the next month. One potential reason for this correlation could be the intertemporal substitution motive of the consumption Euler equation: if prices are expected to rise more rapidly in the future, households have an incentive to purchase more before those price increases take place. But causality could also run in the opposite direction. If households expect to increase their consumption (e.g. because their income is rising), then they might expect other households to do the same which, by increasing aggregate demand, could raise inflation in the future. So it is not enough to simply be able to measure the expectations of agents, one also needs to be able to identify exogenous variation in those beliefs to assess how changes in expectations pass through into decisions. While finding this type of variation in historical data has been very challenging, RCTs can provide a clear source of exogenous variation that allows for causal identification.

2.2 The RCT Approach

In principle, the RCT strategy is simple and follows several steps, presented in Figure 1. First, we need to measure the initial expectations of economic agents through a survey. These provide a measure of the "prior" beliefs of all survey participants. Second, a piece of information is provided

to a randomly selected subset of survey participants. This is the "information treatment" step, which serves to create the exogenous variation in beliefs of some agents. It is exogenous since participants are randomly assigned to either the control group (that receives no information) or the treatment group (that receives the information), making the subsequent change in beliefs orthogonal to all of the characteristics of participants. Haaland et al. (2023) provide an extensive review of how information treatments can be applied in surveys. Importantly, because of randomization, the two groups are identical in all respects but one: they have the same distributions of age, income, education, political preferences, etc. but one group receives information that we control while the other group does not. Third, we measure the ex-post beliefs and decisions of respondents. Measuring ex-post beliefs helps the researcher identify how well the information treatment worked in terms of creating exogenous variation in expectations of agents. Measuring ex-post decisions is essential to being able to characterize whether those changes in beliefs then impacted the economic decisions of the survey participants. Fourth, we track respondents over time to observe their choices. Decisions can be measured using external sources of information on the economic actions of the agents (when such data can be matched to the survey) or through self-reported decisions of the respondents measured through subsequent waves. In the absence of such measures, one can also use planned decisions measured in the same survey as the information treatment but asked after the treatment is applied. Roth and Wohlfart (2020) provide an excellent illustration of how this can be done in the context of how beliefs about the probability of a future recession affect planned household spending.

Conceptually, this approach is therefore very similar to the use of quasi-experimental variation in applied work (see Angrist and Pischke 2009). But whereas the latter relies on historical episodes which provide variation that is similar to an experiment, the RCT approach directly *creates* the exogeneity in beliefs via the information provided to randomly selected participants in the survey. As we describe in the next section, RCTs can sometimes serve as very powerful sources of variation in beliefs. However, in practice there are many challenges that can arise with this empirical strategy, and we will discuss some of these challenges and how they can potentially be addressed.

3. Recent Causal Evidence on the Effects of Inflation Expectations on Household Decisions

In this section, we review two papers that applied this RCT strategy to study how inflation expectations of households affect their economic decisions. Other studies have similar designs and thus our discussion applies more broadly to this emergent field.

3.1 Inflation Expectations and Consumer Spending

The first paper is Coibion, Gorodnichenko and Weber (2022, CGW henceforth). This paper uses households who participate in the Nielsen Homescan panel, which requires them to track their individual retail purchases. This data is commonly used to study household spending decisions using the scanner data. However, Nielsen also allows implementing surveys of households, which can then be linked to their subsequent spending decisions, and the surveys can include randomized information treatments, making this an ideal setting to utilize the RCT approach. Furthermore, because the size of the survey is very large (~20,000 respondents per survey wave), it allows for large numbers of participants in each treatment arm.

In 2018, CGW ran a survey of Nielsen households which applied the strategy described above. First, survey participants were asked to assign probabilities to different possible inflation outcomes, providing a measure of their initial inflation expectations. Then, survey participants were randomly assigned to either the control group or one of multiple information treatment groups. Three of these treatments are particularly relevant for us. One treatment group was provided with the most recent inflation statistic (close to 2%). A second treatment group was provided with the most recent SPF or FOMC 12-month ahead inflation forecast (again close to 2%). The third group was provided with the Federal Reserve's inflation target of 2%. Subsequently, survey participants were asked to provide a point forecast for inflation over the next 12 months, which provided a measure of their "posterior" beliefs. To give a sense of how simple information treatments can be, we list the treatments in CGW:

> Group 1: *Over the last twelve months, the inflation rate in the U.S. (as measured by the Consumer Price Index) was 2.3%.*
>
> Group 2: *The inflation target of the Federal Reserve is 2% per year.*
>
> Group 3: *The U.S. Federal Open Market Committee (which sets short-term interest rates) forecasts 1.9% inflation rate in 2018.*

Despite their simplicity, these treatments proved to be quite powerful in changing the inflation expectations of survey participants. To demonstrate this, Figure 2 presents a binscatter plot of households' prior inflation expectations against their posterior inflation expectations, broken down by each treatment arm. Consider first the control group. For this group, posteriors and priors are closely linked, and the slope of the regression line linking the two is close to one. This is what one would expect since these participants were not provided with any information, so their posterior

beliefs should be the same as their prior beliefs. However, because two different question formulations were used to measure prior and posterior beliefs (to minimize survey fatigue), the slope of the line is somewhat less than one due to attenuation bias.

For the three treatment groups on the other hand, the regression line linking posteriors and priors is flatter: respondents' posterior beliefs moved strongly in the direction of the provided information and away from their prior beliefs. This indicates that they placed a lot of weight on the new information. Had they chosen to dismiss the information, their posteriors would be close to their priors, as was the case for the control group. They could have dismissed the information if, for example, they already knew it or if they viewed it as non-credible or irrelevant. But instead, they responded very strongly to the information, leading to strong revisions in expectations toward the provided signal. Thus, the information treatment can be viewed as having been very successful in generating exogenous variation in the inflation expectations of survey participants.

This result—which has been replicated in subsequent work for other times, countries, and economic agents (e.g., Coibion et al. 2018b, Binder and Rodrigue 2018, Dräger et al. 2023, D'Acunto et al. 2024, Guglielminetti and Loberto 2024, Akarsu et al. 2024, Abberger et al. 2024¸ Jaeger et al. 2024)—is important in itself. Recall that standard macroeconomic models rely on full-information rational expectations (FIRE). This framework posits that economic agents should not change their beliefs (and hence their behavior) in response to treatments that provide publicly available information. This and similar RCTs unambiguously demonstrate that this fundamental prediction is inconsistent with the data. The fact that updating of beliefs is in line with Bayesian learning (i.e., beliefs are revised roughly proportionally towards the provided signals) suggests that economic agents are rational at least to some extent but they likely face information frictions, which corroborates earlier evidence based on observational data (Coibion et al. 2018a, Bachmann et al. 2022, Binder and Kamdar 2022, Weber et al. 2022, Dräger and Lamla 2024 for surveys of this literature). Information frictions can take a variety of forms such noisy information or sticky information and which form should become a workhorse approach remains to be determined (and RCTs can be highly instrumental in narrowing the set of empirically plausible models), but it is clear that some form of information frictions is needed to make macroeconomic models consistent with the empirical evidence. But does the change in beliefs translate into a different behavior?

To quantify the effect of inflation expectations on household spending, CGW ran the following regression:

$$\log(spend)_{i,t+h} = \beta E_i^{post}\pi + \theta E_i^{prior}\pi + \kappa \log(spend)_{i,t-1} + Controls_{it} + error_{i,t+h} \quad (1)$$

where ex-post spending is measured using Nielsen scanner-level reported spending of households on non-durable goods, $E_i^{post}\pi$ is the posterior inflation expectations of households and $E_i^{prior}\pi$ is the prior inflation expectations. To be clear, whether lagged (or planned) spending and other controls are included in specification (1) should not affect the consistency of estimated β, but these regressors can reduce the size of the error term and hence improve the precision of estimated β.

To identify the exogenous variation in inflation expectations, CGW use an IV strategy in which the first stage is given by:

$$E_i^{post}\pi = a + \sum_j b_j \times Treat_{i,j} + \sum_j \gamma_j \times Treat_{i,j} \times E_i^{pre}\pi + \psi \times E_i^{pre}\pi + error \quad (2)$$

where $Treat_{i,j}$ is an indicator variable equal to one if household *i* belongs to treatment group *j*. Since this specification includes the interaction of the treatment indicator with households' prior inflation expectations, it is effectively reproducing the regressions presented visually Figure 2.

We present the results of this regression from CGW in Table 1 for spending levels 3 months and 6 months after the information treatment. Note first that the F-statistics for the first stage are well above 100, indicating again that the information treatments provided a powerful source of exogenous variation in inflation expectations. Second, the estimated coefficient on inflation expectations is close to one, indicating that a one percentage point increase in inflation expectations is followed by a close to one percent increase in consumption over the next 3-6 months by U.S. households. Hence, this presents clear evidence of a large and persistent causal relationship running from the inflation expectations of households to their spending decisions.

CGW document two other notable results. First, when they use self-reported spending outcomes from subsequent survey waves rather than the Nielsen measures of spending, the estimates are much noisier, albeit still significantly different from zero. This is because self-reported spending measures incorporate recall error, rounding, and other sources of noise. As a result, it is more difficult to precisely estimate the effects of expectations on decisions with these self-reported spending measures. This illustrates the importance of being able to match the surveys with external sources of information on decisions, when possible.

Second, CGW find that when inflation expectations of households rise, they became less likely to engage in purchases of durable goods in subsequent periods, a finding at odds with the

intertemporal channel typically emphasized for inflation expectations. CGW speculate that this could reflect the fact that other expectations of households could be changing as well. For example, since higher inflation tends to be more volatile inflation, it could be that respondents who raise their inflation expectations also tend to increase their uncertainty about inflation. Because uncertainty tends to lead to "wait and see" effects on durable goods purchases (see e.g. Coibion et al. 2024), it could be that the response of durable goods purchases confounds these two different expectations channels. Because CGW did not measure inflation uncertainty after the treatments, they could not assess whether this channel was indeed at work. In a similar experiment applied to households in the Netherlands, Coibion et al. (2023) also find a negative effect of inflation expectations on consumer durables purchases. The next paper we discuss tackles this question directly and tries to separate out the effects of inflation expectations and uncertainty on household decisions.

3.2 Inflation Expectations, Uncertainty and Household Decisions

Since Okun (1971), it is a well-known empirical pattern that high inflation is volatile inflation. So changes in inflation expectations could well be associated with changes in inflation uncertainty. A recent paper by Georgarakos et al. (2024, GGCK henceforth) addresses this joint dynamic of inflation expectations and uncertainty directly and tries to separately identify their effects on the decisions of households.

To do so, GCCK use the European Central Bank's Consumer Expectations Survey (CES), a monthly survey of around 19,000 households in 11 European countries. In September 2023, GGCK added a special set of questions to the regular CES survey. One question asked respondents about what the lowest and highest inflation rates they considered likely were over the next 12 months, which provided an initial measure of inflation uncertainty as well as a measure of their average inflation expectation. Following CGW, they then implemented an information treatment, which was followed by another question that measured posterior inflation expectations and uncertainty. Specifically, following Altig et al. (2022), respondents were asked to provide three scenarios for inflation (low, medium and high) and then assign probabilities to each scenario. With these questions, GGCK could assess the effects of information treatments on both inflation expectations and uncertainty, which are highly correlated in the data (see Figure 3).

The information treatments were designed to generate differential variation in the first and second moments of respondents' inflation expectations. To do so, GGCK randomly assigned participants either to a control group or one of three treatment groups. One treatment group was told

about the average inflation forecast of professional forecasters. The second treatment group was instead told about the difference in inflation expectations between the most optimistic and the most pessimistic professional forecasters, which conveys uncertainty in the inflation outlook. The third group was provided with both pieces of information. The objective, following Coibion et al. (2024), was to generate independent movements in the first and second moments of households' beliefs about inflation, which would be necessary to identify their separate effects on household decisions.

Through follow-up waves of the survey, GGCK can assess how inflation expectations and uncertainty affect household decisions along a number of different margins. Their first set of results focus on household durable goods purchases, following CGW. The results for how inflation expectations and inflation uncertainty affect selected ex-post durable goods purchases from GGCK are shown in Table 2, with the estimation done in a similar manner as CGW, but now including both inflation expectations and uncertainty as RHS variables and instrumenting for both using the information treatments. Column (1) shows the main results of these regressions for one category of durable goods purchases (the results are similar for other categories) one month after the information treatment. They find a clear pattern: high inflation uncertainty is followed by a lower probability of households purchasing durable goods whereas higher inflation expectations are followed by a greater probability. The latter is the opposite of the finding in CGW and suggests that the strong positive correlation between expectations and uncertainty was responsible for the negative relationship between expectations and durable goods spending that they had found. Indeed, when GGCK only include inflation expectations as a right-hand side variable (column (2) of Table 2), they similarly find that inflation expectations appear to affect durable goods purchases negatively. But column (1) makes clear that this is because there are two effects are work. First, the direct effect of higher inflation expectations is to move durable goods purchases forward in time. Second, the indirect effect is that higher inflation expectations lead to more uncertainty about inflation, which tends to reduce durable goods purchases. The results in column (2) indicate that the indirect effect is stronger than the direct effect.

Column (3) of Table 2 focuses on the importance of the RCT for identification purposes. Specifically, it presents estimates of the same specification as in column (1) but using OLS instead of IV, in other words without taking advantage of the exogenous variation created by the treatments. In this case, we see that the coefficients estimated on the control group are small and generally insignificant. One cannot generally discern the effect of either inflation expectations or uncertainty on the durable goods purchases of households. This illustrates the key role played by the information

treatment in generating the exogenous variation in beliefs that is necessary to identify their effects on decisions. In short, without the RCT, there is no identification.

With respect to non-durable goods purchases, GGCK do not have access to external measures of spending as was the case for CGW and instead must rely on self-reported measures of ex-post spending. They find that the latter are too noisy to yield precise estimates of the effects of either inflation expectations or uncertainty on household purchases of non-durables and services. Given that one would expect that both the direct and indirect effects of inflation expectations were at work in the estimates of CGW for non-durables as well as durables, this suggests that the estimated effects found by CGW for non-durables should be thought of as a lower bound for the direct effect of inflation expectations on this type of spending.

In addition to spending decisions, GGCK could quantify other decisions taken by survey participants in the months following the information treatment, allowing them to characterize the effects of inflation expectations on different margins of adjustment available to households. One such margin is the composition of their financial portfolio. GGCK rely on two outcomes. One is a hypothetical question asking respondents how they would allocate an income windfall across different types of financial assets, immediately after the information treatment. The second outcome comes from the fact that respondents were asked to report the actual composition of their financial wealth across different asset types two months after the treatment.

Columns (4)-(7) of Table 2 present the estimated effects of inflation expectations and inflation uncertainty on the share of assets that households would either allocate a hypothetical financial windfall (columns (4)-(5)) or on their actual financial portfolio (column(6)-(7)). To save space here, we report results for two asset classes: current/saving accounts in banks and retirement accounts. The main result is that higher inflation uncertainty leads to a reallocation of the portfolio away from retirement assets (which are highly illiquid) and toward checking/savings accounts (which are highly liquid), whereas higher inflation expectations (i.e., the first moment) lead to the opposite pattern. Intuitively, withdrawing money from retirement accounts is difficult and costly, which makes these accounts less attractive in the face of higher uncertainty when one may need access to liquidity to cover unexpected spending. On the other hand, bank accounts offer poor protection from inflation as interest rates on current and saving deposits tend to be rather low, which makes bank accounts less attractive when expected inflation is high. In short, both inflation

expectations and uncertainty lead to clear and economically large portfolio reallocations by households that take place fairly rapidly.

Another margin of adjustment available to households is their labor supply and job search decisions. Because the CES asks questions about how intensively respondents search for work and track their employment status across waves, GGCK are also able to assess the effects of inflation expectations and uncertainty on these decisions in outcomes. The main finding is that higher uncertainty about inflation leads respondents to report that they plan to search more actively for work, whereas higher inflation expectations do the reverse. Consistent with this search behavior, unemployed respondents who become more uncertain about inflation raise the probability they will have a job in 3 months whereas unemployed respondents with higher inflation expectations view this outcome as less likely. For working respondents, those who become more uncertain about inflation view it as more likely that they will be searching for a new job over the next 3 months but not because they are more likely to be fired, which indicates that it will be a conscious decision to search harder while on the job, whereas the reverse is true when inflation expectations rise.

Does this changing search behavior affect employment outcomes? GGCK find that when respondents become more uncertain about inflation, they become less likely to be either unemployed or working part-time in subsequent months, but not through movements out of the labor force. Consistent with higher job search, the results instead suggest that high uncertainty about inflation induces workers to take on more work or move into full-time work. In contrast, there is little clear effect of higher inflation expectations on subsequent job outcomes. In short, households appear to use labor supply as a margin for adjustment to insure themselves against inflation risk.

Together, these results indicate that inflation expectations matter for the decisions of households, but that it is important to separate out the direct effects of these expectations from their indirect effects that operate through inflation uncertainty. Note that for policymaking, the total effect may be the more relevant statistic: if communication raises inflation expectations and uncertainty jointly, then the total effect will provide a good approximation to the likely effects on households' decisions. But for modeling purposes or whenever the channels can be separated via targeted communication, knowing the difference between the direct and indirect effects will be important. For example, a policy communication which raises inflation expectations while simultaneously reducing inflation uncertainty would be predicted to have a much larger effect on household decisions than one that did not control for the endogenous response of uncertainty to inflation

expectations. In a similar spirit, when central banks raise inflation expectations with the hope of stimulating spending on durable goods, one may obtain an opposite result: because households view high inflation as a bad state of the world, they can reduce rather than increase spending, so this type of policy can potentially backfire (Candia et al. 2020).

4. Other Challenges to RCT Identification

The potential need to separately identify the direct and indirect effect of a change in expectations arising from an RCT is one issue that can make the inference from this type of approach challenging. But it is not the only one. In this section, we briefly review a number of other challenges that can arise, as well as potential solutions to them, and refer the reader interested in more detailed discussions to Coibion and Gorodnichenko (2026).

A. Measurement of Expectations and Survey Implementation

While hugely informative, surveys are subject to a wide range of issues, from ensuring their representativeness to how questions are asked, in what order, etc., all of which can matter for the results. As a result, every concern that applies to surveys will be relevant for the RCT strategy that relies on surveys to measure expectations. However, because RCTs entail a comparison between treatment and control groups, any issue that affects the two groups equally (e.g. a bias induced by a question formulation) will effectively be differenced out. To the extent that one is also examining the change in expectations of one individual over time, this will also take out individual fixed effects. The result is that the RCT, by effectively delivering a difference-in-difference setting, mitigates some of the issues that are unavoidable in surveys. As a result, while some of the concerns commonly associated with surveys are still relevant, many are much less acute in this context.

Having said this, it is still important to word the questions and treatments in such a manner that survey participants understand what they are asked and what information is communicated to them. If the language is overloaded with technical terms and economics jargon, an average person may miss the point and even drop out from the survey. For example, most people would not be able to tell the difference between Personal Consumption Expenditure Deflator and the Consumer Price Index and therefore overly precise questions can generate confusion rather than decrease it.

It is also important to ensure that the elicited information measures the object that one wants to study. For example, if one is interested in measuring inflation expectations at the aggregate level (i.e., macro-level expectations), asking people to report their expectations for their

own wages or prices (i.e., micro-level expectations) does necessarily deliver the desired object. Indeed, various studies (e.g., Coibion et al. 2020a) document that micro- and macro-expectations can be poorly correlated.

B. Where Can You Run an RCT?

Another concern is that there are few settings in which this strategy can be implemented. Many of the existing surveys (e.g. Michigan Survey of Consumers) do not allow researchers to introduce information experiments in the survey. And the cost of running one's own survey may be prohibitive for many researchers. If there are no settings in which a researcher can implement the method, what good is it to have this new tool? This is a legitimate concern and expanding the range of settings where researchers can run RCTs would help improve the robustness of this type of estimate and ensure more external validity. It is worth noting that the number of surveys in which RCTs can be implemented, in conjunction with survey research teams, is expanding. Furthermore, while some surveys do not allow for information treatments, they do allow for the addition of hypothetical questions which can target the same kind of question, as we discuss further below. Some surveys permit researchers to experiment on outgoing or retired cohorts (e.g., Pfajfar and Winkler 2025). Finally, online surveys are another affordable option for researchers interested in the beliefs of ordinary households or even low- and mid-level managers (e.g., McClure et al. 2025).

C. Successful Information Treatments

A necessary condition for the strategy to correctly identify how beliefs affect decisions is that the first stage must be successful: the information treatment must create sufficient exogenous variation in expectations. The ones described in CGW and GGCK worked very well, but this will not always be the case. Information treatments that involve beliefs that are first-order concern for agents will tend to be less successful, since agents will be more informed about these topics in the first place. Indeed, even the same information treatments may have different effects over time or in different places depending on the incentives agents have to be informed about the topic. For example, while CGW find large treatment effects on the inflation expectations of households in 2018, the same information treatments had much smaller effects in 2022, when inflation was high (Weber et al. 2025), reflecting the fact that U.S. households became more informed about inflation during the

inflation spike. So researchers must take care to choose information treatments and expectations that are likely to be responsive, which may limit the scope of topics that can be studied with this approach.

Another important dimension is whether the control group should be passive (no provision of information) or active ("placebo" information is provided). Roth and Wohlfart (2020) is a nice example of the latter where the treatment group is provided with a high estimate of recession probability while the control group is provided with a low estimate. Which approach to use depends on the context (see Haaland et al. 2023 and Coibion and Gorodnichenko 2026 for discussions). For instance, an active control group can help address survey/experiment demand effects where respondents may feel obliged to give responses that are desirable to the person who runs a survey or experiment. On the other hand, an active control group is not appropriate if one is interested in studying how provision of information in itself changes the beliefs.

Finally, information may be provided in various forms. For instance, a treatment may focus on reporting a statistic (quantitative information) or a narrative (qualitative information) relevant for a given belief. A key advantage of the former is that one can easily map signals into beliefs such as expected inflation, unemployment, etc. But many decisions naturally rely on stories, explanations, etc. and so the latter is better suited for understanding *how* people reason. Andre et al. (2024) illustrates the power of this approach. By informing random subsets of respondents about potential explanations for post-COVID19 inflation (in principle these could cover many rationalizations such as an energy crisis, pent-up demand, monetary policy, or the Russian full-scale invasion of Ukraine), they can establish how respondents' narratives and numeric forecasts are shaped by exposure to various causal accounts for economic events.

D. Measurement of Outcomes

As already illustrated in CGW, how outcomes are measured can be important. The ideal scenario is for surveys to be matched to external sources of information such as administrative data that provide precise measures of the decisions taken by agents, as is possible in the Nielsen Homescan data. But this is not always feasible. There are two options that can be used when external data is unavailable. One is to rely on subsequent survey waves and to ask respondents about their decisions in those subsequent periods. CGW show, for example, that self-reported measures of spending line up closely with actual spending levels on average. However, it can take a large number of observations to estimate this average precisely. This is because self-reported data will

include rounding by respondents, recall error, and other forms of measurement error. As a result, it may be more difficult to establish clear causal links between expectations and decisions than would be the case with better data on outcomes. One potential solution is to use surveys with large numbers of respondents, which can help improve precision and statistical power. A second solution is to focus on outcomes that are less susceptible to measurement and recall error, for example the extensive margin of whether a durable good was purchased as opposed to the intensive margin of how much was spent on durable goods. Third, there is scope for matching more surveys to external sources of information, as in Caplin et al. (2023), Ropele et al. (2024), and Coibion et al. (2020b). This option is particularly attractive because it reduces the cost (one does not need to run another survey), the data are collected naturally and potentially at high frequencies (one does not need to disrupt the lives of survey subjects), attrition rates are lower (one does not need to rely on subject availability to participate in another survey). To be clear, external data don't have to be from government sources. Private providers (e.g., credit card companies, financial aggregators) or even publicly posted data (e.g., prices from the internet) could be useful resources in this context too.

E. External Validity

One concern that often arises with RCTs is whether the results would generalize to another time period or another setting, i.e. the external validity of the study. This is an important issue which can ultimately only be addressed by repeating RCTs in many different contexts. The replication of studies with new experiments is therefore particularly important for this line of work. But it is also important to recall that, to the extent that estimated parameters are often reduced-form coefficients rather than structural parameters, one should not necessarily expect them to be the same in different contexts. Understanding the mapping from estimated coefficients in RCTs to underlying structural relationships is important to identifying which results would be expected to hold in different situations and which would be expected to vary. This is another reason why it can be useful to separately identify direct and indirect effects of changes in expectations, since their combined effects are unlikely to map easily into structural parameters whereas direct effects may have a more natural structural interpretation. Consistent with this, Candia et al. (2024) argues that the total response of durable consumption to inflation expectations should vary depending on the inflation environment and provides evidence that this is indeed the case.

F. Mapping to theory

RCTs provide clean, credible identification but the interpretation of the estimated effects may be nontrivial. To illustrate the challenges of mapping empirical estimates to theory, we will use Werning (2022) who studies theoretically how inflation expectations π^e are connected to actual inflation π. Under fairly general conditions, Werning shows that $\pi = \frac{1-\lambda}{1-\rho\lambda}\pi^e + (1-\lambda)a$ where λ is the frequency of price adjustment (as in Calvo (1983)), ρ is the discount factor, and a summarizes all forces unrelated to inflation (e.g., the real marginal cost). When we do an experiment, we hope to change π^e and hold everything else constant. But the passthrough we estimate in practice may look as follows:

$$\underbrace{\frac{d\pi}{d\pi^e}}_{\substack{RCT \\ (total)}} = \underbrace{\left(\frac{1-\lambda}{1-\rho\lambda}\right)}_{direct} + \underbrace{(1-\lambda)\frac{\partial a}{\partial \pi^e}}_{\substack{\text{indirect} \\ \text{(Other expectations)}}} \quad (3)$$

Intuitively, we provide respondents with information aiming to alter inflation expectations, but respondents can change beliefs about other variables too. As a result, behaviour may change not only due to changes in inflation expectations but also due to other expectations (so called cross-learning). Hence, coefficient β in specification (1) estimates the total derivative rather than the direct effect.

As we discussed earlier, this is not necessarily a problem for policymakers as they would like to know whether a given policy works and how much stimulus one needs to apply to achieve a target. On other hand, we usually want to know the different mechanisms and channels at work and so we need to separate direct and indirect effects. This is doable but requires more effort. For example, one may need to measure other expectations (e.g., expected unemployment rate) to gauge how these expectations respond to information treatments. One may also need additional treatments aiming to create independent variation in a in specification (3) to isolate the indirect effect. We already demonstrated how this can work when we studied the effects of inflation uncertainty: recall that we had multiple treatments to create independent variations in the first and second moments of inflation expectations.

Because expectations are so diverse and affect so many different choices through multiple channels, we obviously need much more future research to systematically measure the impact and importance of these underlying mechanisms. Theory can offer a guide as to what forces and mechanisms are at play and hence make empirical work more focused. We anticipate high returns from merging the credibility of RCTs with the rigor and discipline of theoretical models.

G. Alternatives to RCTs

Despite the growing availability of surveys that allow for RCTs, it remains true that access to these surveys is limited and the cost of running one's own survey can be prohibitive. Ideally, one would like to have complementary approaches that are more easily accessible. One such approach is the use of hypothetical scenarios, as discussed in detail in Colarieti et al. (2024) and Andre et al. (2024). The idea is to ask survey respondents what they would do if they held different beliefs. For example, to measure behavioural responses to changes in uncertainty, one may ask the following question:

> *Please think about the ways in which uncertainty about changes in prices in general in the country you currently live in may (or may not) affect your decisions.*
>
> *If* ***uncertainty about changes in prices in general [increases/decreases]****, I would like to…*
>
> with answers being [Yes/No], [increase/same/decrease] or (percent) change for margin X.

In principle, this can provide a direct estimate of the passthrough coefficient that would be estimated through an RCT. But unlike having to do the full RCT, a hypothetical question does not require different treatment arms (and therefore can be done in smaller surveys), does not require external information on decisions or follow-up waves (so it can be implemented in a single wave), and can be phrased in such a way as to either allow for or exclude indirect effects of expectations. This approach has been used extensively in the New York Fed's Survey of Consumer Expectations, which does not allow for information treatments but can incorporate occasional additional questions that are framed as hypotheticals (e.g. Armantier et al. 2022). As documented in Colarieti et al. (2024), Kumar et al. (2024), and Coibion et al. (2024), available comparisons of RCTs and hypotheticals is supportive of the notion that they tend to yield similar results. For example, when we ask firms how changes in macroeconomic uncertainty would affect their prices, employment, investment, etc., we find that their responses to this hypothetical question qualitatively line up with the actual pricing behaviour in an RCT covering the same set of firms. However, it remains to be established how generally this is the case and what circumstances might cause the two to yield different results. Despite this uncertainty, we view the use of hypotheticals as complementary to RCTs since they aim to estimate similar passthroughs, can shed light on mechanisms (see e.g. Jiang et al. 2024), and can be implemented in a much more tractable and cost-effective manner.

H. Partial versus General Equilibrium

A final concern worth emphasizing is that coefficients from RCTs like the ones described here at best identify partial equilibrium responses of agents to a change in beliefs, which may differ significantly from general equilibrium outcomes. With a few notable exceptions (e.g., Egger et al. 2023), the latter cannot be assessed directly from RCTs. Instead, moving from partial equilibrium estimates to general equilibrium predictions requires a model and a mapping from the RCT estimates into such a model. One example of this is provided in Ropele et al. (2024), who use RCT estimates of how inflation expectations affect firms' employment and investment decisions to study the general equilibrium costs of misallocation induced by inflation. But this is more the exception than the rule: there would be much value added from seeing more research on how to reconcile RCT estimates of expectations passthrough into decisions with theoretical models that allow us to speak to general equilibrium outcomes.

E. Ethical consideration

Information treatments are a powerful tool but care must be taken to ensure that subjects do not get hurt while participating in experiments. This is why Internal Review Boards (IRB) are essential to have an independent look at survey/experiment designs to verify that a given study presents only minimal risks. While the procedures and rules may seem overwhelming, the basic tenet is simple: do not harm! As a simple test of whether a given treatment is potentially problematic or not, ask yourself if you would give this information treatment to a family member or a friend. If in doubt, you are likely in dangerous territory, and you should rethink your experiment. In practice, this means that treating subjecting with confusing/misleading information, fake news, and the like is problematic. On the other hand, providing subjects with publicly available information (e.g., past inflation, current unemployment rate, a forecast from the central bank) is generally harmless as such information is already in public domain and no subject is excluded from having access to it.

F. Artificial Intelligence (AI)

The rapidly developing AI capabilities have already affected the field of surveys, experiments, etc. For example, appropriately trained AI can effectively replace the human interviewers, who tend to be expensive, and thus allow researchers to run larger high-quality surveys with open-ended questions and to process huge amounts of unstructured text (see Haaland et al. 2025). One can also

use AI to create artificial personas who mimic the population (Wu et al. 2025) or a specific group (Hansen et al. 2025) in their beliefs and actions. As a result, one can use these personas to pilot surveys, pre-test treatments, recreate data when human responses are not available (e.g., construct a measure of information expectations for the Michigan Survey of Expectations before the survey started to collect these data), construct time series at higher frequencies, or cover topics that are uncomfortable, tiresome, or otherwise challenging for human respondents. Of course, such exercises should be (periodically) validated with human responses but the cost of running surveys and experiments—the main hurdle for the field—can be reduced dramatically.

5. Conclusion and Policy Implications

With RCTs providing clear exogenous variation in the expectations of households, recent research has been able to credibly characterize in unprecedented detail the different ways in which these expectations affect households' decisions. In parallel, other papers have used similar strategies to study how inflation expectations affect the decisions of firms, while another line of research has utilized the same type of method to quantify the passthrough of different expectations into the decisions of firms and households. Indeed, the emergent literature using RCTs to shed new light on questions often studied by macroeconomists has covered exchange rate expectations (e.g., Delgado et al. 2024), housing price expectations (e.g., Armona et al. 2018, Chopra et al. 2025, Bottan and Perez-Truglia 2025), financial asset price expectations (Beutel and Weber 2023, Weber et al. 2023, Gorodnichenko and Yin 2024) and other expectations. For macroeconomists, this line of research is providing new evidence on just how expectations affect the decisions of agents, a question which has long been outside the scope of clear causal empirical tests.

For policymakers, the results should also be of interest not only in terms of improving the comprehension of policy messages (see e.g., Haldane and McMahon 2018, Bholat et al. 2019, Kryvtsov and Petersen 2021, D'Acunto et al. 2021) but also in shaping economic outcomes. Since policy communication often aims to directly affect the beliefs of economic agents, understanding how these beliefs pass through into decisions is important. In this respect, the total effects estimated in papers like Coibion, Gorodnichenko and Weber (2022) speak directly to how communications that change inflation expectations are likely to affect decisions. But understanding direct and indirect effects may be important for policymakers as well. For example, communication that can change expectations without changing uncertainty or vice versa may have more powerful economic

consequences when first and second moments tend to have offsetting effects, as found in Coibion et al. (2024). Communication that actively uses both dimensions can be even more powerful, e.g. by simultaneously raising inflation expectations and reducing inflation uncertainty. Because of the strength of the unconditional correlation between first and second moments, doing so may not be easy and may require different communication styles, but the economic potential of this type of more targeted communication should make the notion worth considering. We anticipate that RCTs can offer tremendous opportunities to sharpen policy communication and make it more impactful.

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Table 1. The Effects of Inflation Expectations on Household Non-Durable Goods Spending

	Dependent variable: Actual log spending	
	3 months after treatment	6 months after treatment
	(1)	(2)
Posterior inflation expectations	0.950***	0.864**
	(0.286)	(0.336)
Observations	13,170	13,132
1st stage F-stat	134.8	128.1

Notes: The table is taken from Coibion, Gorodnichenko and Weber (2022) and reports the effect of inflation expectations on household spending on non-durables measured in Nielsen Homescan panel using the IV strategy described in section 3.1.

Table 2. The Effect of Inflation Expectations and Uncertainty on Purchases of Durable Goods and Portfolio Allocation for Selected Asset Classes.

	Purchases of home appliances, furniture or electronic items (incl. gadgets), actual response one month after treatment, extensive margin			Selected portfolio shares, hypothetical response		Selected portfolio shares, actual allocation two months after treatment	
				Curr./Saving account	Retirement account	Curr./Saving account	Retirement account
	IV	IV	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)		(5)	(6)
Posterior mean	4.812***	-1.695***	-0.014	-2.346	1.039*	-4.894***	1.833*
	(1.369)	(0.400)	(0.332)	(1.642)	(0.595)	(1.723)	(1.073)
100×log(Posterior uncertainty)	-0.230***		3.383**	0.173***	-0.065***	0.233***	-0.076*
	(0.057)		(1.645)	(0.066)	(0.025)	(0.071)	(0.044)
Observations	11,506	8,652	2,638	13,601	13,601	9,121	9,121
R-squared	-0.041	0.04	0.080	0.05	0.02	0.02	-0.05
1st stage F-stat (mean)	113.8	200.1		143.9	143.9	101.1	101.1
1st stage F-stat (uncert)	99.29			122.5	122.5	91.79	91.79
KP Wald test	9.532			12.78	12.78	11.30	11.30

Notes: This table is based on the results reported in Georgarakos et al. (2024). The table reports estimated coefficients on posterior beliefs about inflation. Panel C includes the control group and the specification does not include pre-treatment beliefs. The dependent variable in columns (1)-(3) takes values 0 (no purchase) and 100 (a purchase is made). Portfolio shares are from 0 to 100. Households can allocate portfolios across cash, current/saving accounts, stocks, mutual funds, retirement accounts, bonds, crypto assets, and other. The shares sum up to 100. The table shows results only for current/saving accounts and retirement accounts. Heteroskedasticity robust standard errors are reported in parentheses. ***, **, * denote statistical significance at 1, 5 and 10 percent levels.

Figure 1. Design of a RCT with information provision.

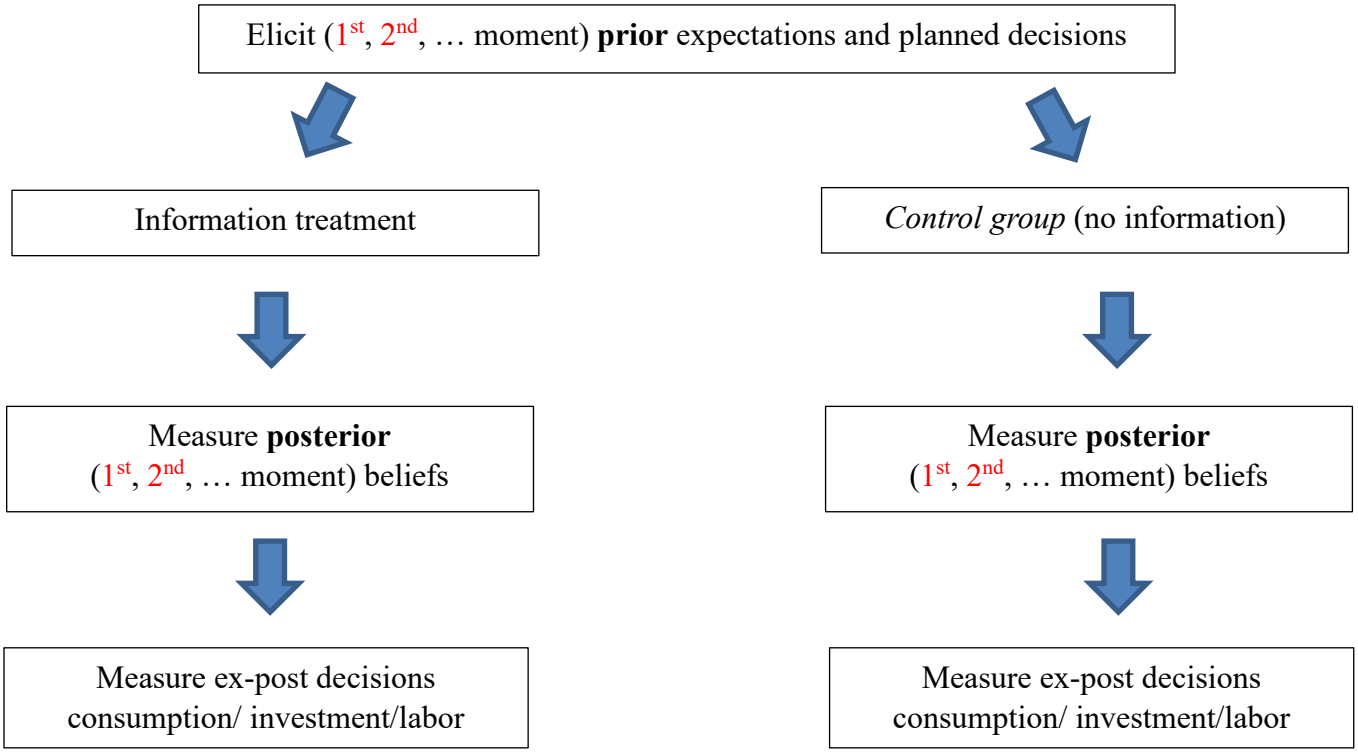
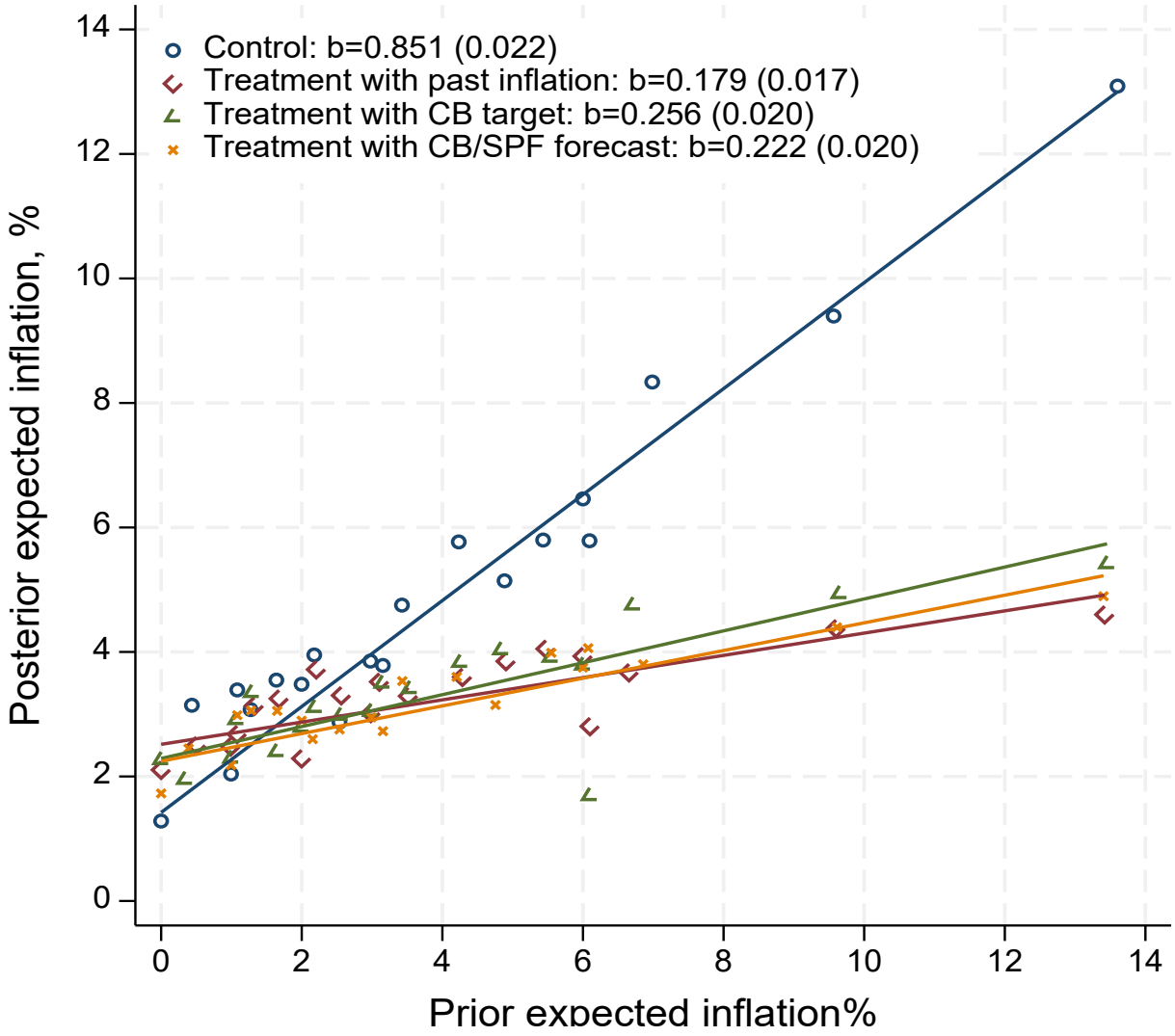
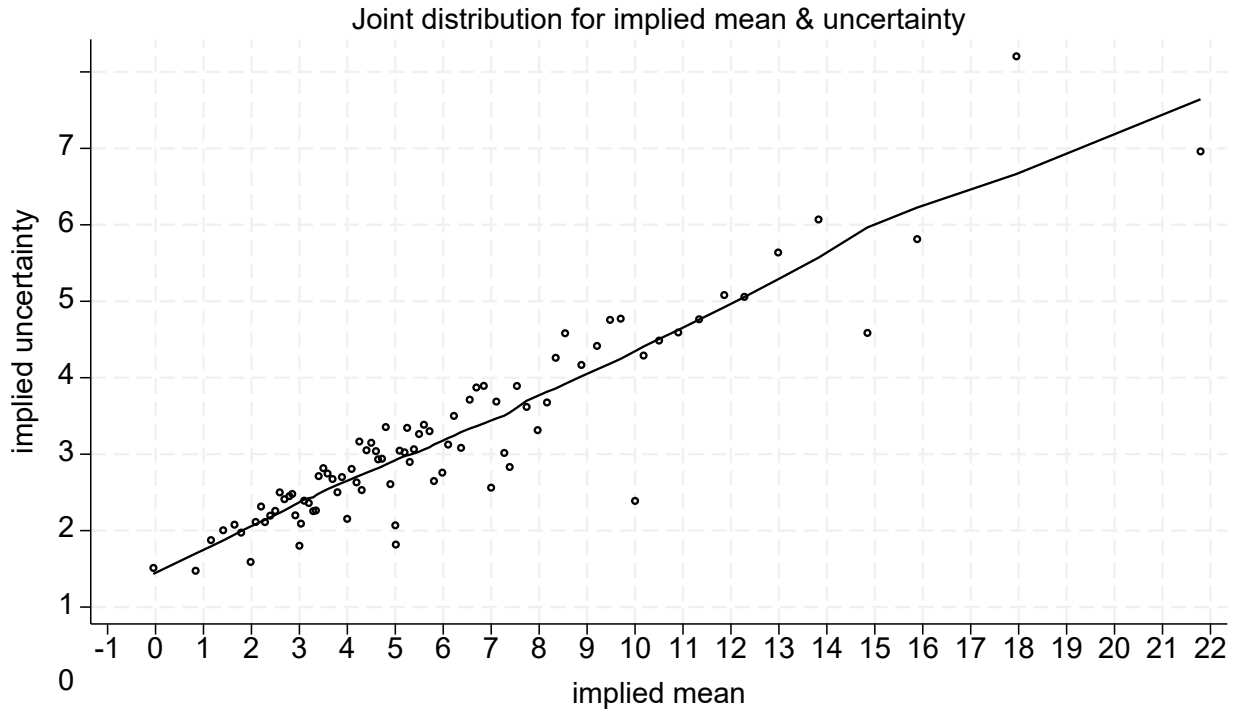


Figure 2. Effect of Information Treatments on Expectations in Coibion, Gorodnichenko and Weber (2022)



Notes: This figure presents results from Coibion, Gorodnichenko and Weber (2022). It is a binscatter plot of households' prior inflation expectations against their posterior inflation expectations for different groups of respondents based on which treatment arm they were randomly assigned to. The "control" group was not provided with any information. Other participants in the figure were either provided with the most recent inflation statistic at the time (close to 2%), the most recent SPF or FOMC 12-month ahead inflation forecast (close to 2%) or the Federal Reserve's inflation target (of 2%).

Figure 3. The Correlation of Inflation Expectations and Inflation Uncertainty



Notes: This figure is taken from Georgarakos et al. (2024) and plots the correlation between the inflation expectations and inflation uncertainty of European households in the ECB's CES in September 2023.