Subjective Models of the Macroeconomy: Evidence From Experts and Representative Samples[*]

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We study people's subjective models of the macroeconomy and shed light on their attentional foundations. To do so, we measure beliefs about the effects of macroeconomic shocks on unemployment and inflation, providing respondents with identical information about the parameters of the shocks and previous realizations of macroeconomic variables. Within samples of both 6,500 US households and 1,500 experts, beliefs are widely dispersed, even about the directional effects of shocks, and there are large differences in average beliefs between households and experts. Part of this disagreement seems to arise from selective retrieval of different propagation channels of macroeconomic shocks. We confirm this mechanism causally by exogenously shifting households' attention to either supply-side or demand-side channels. Moreover, households with different personal experiences recall different propagation channels of the shocks, while experts tend to recall textbook models. Our findings offer a new perspective on the widely documented disagreement in macroeconomic expectations.

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1 Introduction

Individuals usually exhibit substantial disagreement in their expectations about macroeconomic outcomes. This holds true for consumers, firm managers, retail investors, and even professional forecasters (Coibion and Gorodnichenko, 2015a; Dovern et al., 2012; Giglio et al., 2021; Link et al., 2020; Mankiw et al., 2003). Disagreement in turn has major implications for the transmission of shocks and of fiscal and monetary policy (Angeletos and Lian, 2018; Ball et al., 2005; Paciello and Wiederholt, 2014). There are two broad views on what is driving disagreement in expectations. Disagreement is most commonly attributed to differences in information about the current state of the economy (Coibion and Gorodnichenko, 2012; Mankiw and Reis, 2002; Reis, 2006). According to such explanations, conditional on the same information set, economic agents make homogeneous predictions about the reaction of the economy to shocks. Alternatively, disagreement could be due to heterogeneity in subjective models, that is, the way agents think about the functioning of the economy (Angeletos et al., 2020; Bray and Savin, 1986; Marcet and Sargent, 1989; Molavi, 2019). Such heterogeneity generates disagreement in expectations even when all agents observe the same shock and have the same information about previous realizations of macroeconomic variables.

In this paper, we provide the first direct empirical evidence on people's subjective models of the macroeconomy and their origins. We propose that heterogeneity in subjective models is a consequence of selective recall of specific economic mechanisms, which differ across individuals and contexts. We use a new approach to measure people's subjective models, which we apply to samples of about 6,500 respondents representative of the US population and about 1,500 academic and non-academic experts. Our approach relies on vignettes in which respondents predict future unemployment and inflation under different hypothetical macroeconomic shocks. We focus on four different shocks that are among the most commonly studied in macroeconomics: an oil supply shock, a monetary policy shock, a government spending shock, and an income tax shock. The vignettes make sure that all respondents observe the shock, and provide information about the source of the shock and previous realizations of unemployment and inflation. This ensures comparable information sets across respondents and enables us to characterize heterogeneity in forecasts to the extent it arises from differences in subjective models.

For each vignette, we elicit the respondents' expectations about the unemployment rate and the inflation rate twice: first, under a hypothetical baseline scenario in which no shock occurs; second, under a hypothetical shock scenario in which the shock variable unexpectedly changes. In the oil price vignette, we tell our respondents that the oil price will be on average \$30 higher over the following 12 months. In the monetary policy vignette, the federal funds rate increases by 0.5 p.p. In the government spending vignette, the government announces a major new spending program on defense, while in the income tax vignette, the government increases income taxes by 1 p.p. for every US household for one year. To establish the exogeneity of the shocks, we tell respondents that the change in the oil price is due to problems with the local production technology in the Middle East, that the federal funds rate is increased even though the Fed does not change its assessment of economic conditions, and that government spending or taxes are increased without any changes in the government's assessment of national security or economic conditions. By taking the difference in the forecasts of unemployment and inflation between the shock scenario and the baseline scenario, we identify each respondent's beliefs about the effects of the shock, while taking out differences in baseline expectations across individuals.

We document five key results. Our first main result is that there is substantial heterogeneity in forecasts about the effects of macroeconomic shocks, among experts, among households, and between the two groups. For example, in the monetary policy vignette, 72% of experts predict an increase in unemployment in response to the rise in the federal funds rate, 12% expect no change, and the remaining 15% expect a decrease. Among households, 51% predict an increase in unemployment, 16% expect no change, and 33% expect a decrease. Similarly, there is strong heterogeneity in beliefs about the inflation response to interest rate hikes, with both increases and decreases being predicted by substantial fractions of households (57% vs. 30%) and experts (19% vs 72%). Across all vignettes, there is more disagreement among households than among experts. Average predictions of households and experts are often similar but differ substantially in three cases: Experts predict inflation to decrease in response to a hike in the federal funds rate, while households forecast an increase in inflation. Similarly, households predict inflation to increase in response to the income tax hike, while experts predict it to decrease. Finally, households predict a muted unemployment response to a government spending program, while experts predict a decrease. The high levels of disagreement in a setting where individuals have comparable information about past realizations of macroeconomic variables indicates an important role for heterogeneity in subjective models in expectation formation.

In a second step, we explore the origins of this heterogeneity. Specifically, we examine the possibility that individuals selectively retrieve specific propagation mechanisms of the shocks, while neglecting others. Selective memory has been shown to be important in shaping people's thoughts and behavior in various contexts (Bordalo et al., 2020a; Kahana, 2012; Tversky and Kahneman, 1973). In our setting, differences in associations across individuals and contexts could be a key driver of heterogeneity in forecasts. Based on an additional tailored survey, we provide direct evidence on this conjecture. We directly measure what comes to respondents' minds when they think about the shocks using a combination of unstructured textual responses as well as responses to more structured questions. Our second main finding is that the propagation channels that are on respondents' minds vary systematically within and between our samples of households and experts. Across vignettes, experts tend to recall channels that are central in textbook models, while households in many cases neglect these channels and think of channels that are conventionally seen as less important. For example, households are relatively more likely than experts to think of a "cost channel" in the context of the monetary policy shock, according to which firms pass on higher costs of borrowing to consumers in the form of higher prices. By contrast, experts are more likely to think of demand-side mechanisms, such as intertemporal substitution or an investment channel.

In a third step, we ask whether the propagation channels that are on top of respondents' minds are related to their predictions. Our third finding is that thoughts of the different propagation channels are significantly correlated with respondents' unemployment and inflation forecasts, in expected directions. Thoughts of different propagation channels also reconcile part of the differences in forecasts between experts and households.

In a fourth step, we provide proof-of-concept evidence that selective retrieval of specific propagation channels is a causal driver of households' forecasts of the effects of macroeconomic shocks. We conduct an additional experiment with a representative sample in which we use a priming intervention to exogenously shift households' attention to either supply-side or demand-side channels in the context of the monetary policy shock. Our fourth main result is that being primed on demand-side factors significantly increases respondents' retrieval of negative demand-side implications of an increase in the federal funds rate, and has a negative effect on respondents' predicted inflation response to the shock. The finding that drawing households' attention to a specific aspect of the shock changes their forecasts suggests that households' subjective models are not fixed. Instead, these models may be formed "on the fly", depending on the associations triggered by the context. This suggests that news or actual events in the economy may systematically affect which models people entertain. Rather than sticking to one particular model, economic agents retrieve specific memories when cued by events, which in turn shape the economic mechanisms they think of.

Finally, in a fifth step, we test the prediction of selective recall that differences in personal experiences in the memory database should be a key driver of differences in associations and forecasts. Our fifth main result confirms this prediction: households' personal experiences are correlated with selective recall of specific propagation mechanisms, which in turn is reflected in individuals' forecasts about the effects of macroeconomic shocks. For instance, under the government spending shock, which focuses on an increase in defense spending, previous employment by suppliers of the military is associated with a greater tendency to think of mechanisms related to increases in product demand and labor demand. This experience is also associated with a stronger predicted unemployment decrease. Furthermore, in the oil price vignette, having experienced the OPEC crisis in the 1970s is associated with significantly stronger retrieval of cost-push mechanisms, which is reflected in higher predicted unemployment and inflation responses.

Our findings offer a new perspective on the strong heterogeneity in macroeconomic expectations – one of the most well-documented empirical facts in the literature (Coibion and Gorodnichenko, 2012; Mankiw et al., 2003). Our results imply that, even if agents hold comparable information about previous realizations of macroeconomic variables, associative recall of different economic mechanisms generates heterogeneity in expectations. In this view, the subjective models individuals rely on are not fully stable, but depend on what is cued by the context and on individuals' past experiences. Incorporating associative recall into a macroeconomic model could thus be a fruitful avenue for future research.

The main contribution of our paper is to provide the first direct evidence on heterogeneity in subjective models of the macroeconomy and their origins. Our paper builds on previous work studying the relationships between beliefs about different macroeconomic variables. Carvalho and Nechio (2014), Dräger et al. (2016), and Kuchler and Zafar (2019) use observational data to examine how households' beliefs about unemployment, inflation and interest rates are correlated with each other. A series of papers have used information experiments to study households' beliefs about the autocorrelation of macroeconomic variables (Armantier et al., 2016; Armona et al., 2018; Cavallo et al., 2017; Fuster et al., 2020b). Other information experiments have studied how respondents update their expectations about one macroeconomic variable in response to information about a different macroeconomic variable (Coibion et al., 2019, 2018, 2020; Roth and Wohlfart, 2020). While the randomized provision of information in these experiments allows for causal identification, the interpretation is complicated by the fact that respondents' beliefs about the sources of changes in inflation or GDP growth are unrestricted. In contrast to previous literature, our approach directly measures households' beliefs about the causal effects of macroeconomic shocks on unemployment and inflation, controlling for information about previous realizations of macroeconomic variables and about the sources of the shocks.[1]

Our work relates to research on attention and memory in people's belief formation and decision-making (Bordalo et al., 2016, 2020a; Enke et al., 2020; Gabaix, 2019; Gennaioli and Shleifer, 2010; Graeber, 2021; Lacetera et al., 2012). Bordalo et al. (2020a) propose a model of choice in which a choice option cues recall of similar past experiences. We contribute to this literature by documenting what comes to people's mind when they think about a set of canonical macroeconomic shocks and by providing causal evidence on the role of associations in shaping the predictions that individuals make. This relates to work by Stantcheva (2020), who provides descriptive evidence on what people think about when they evaluate economic policies, such as estate taxation or health insurance. Our combination of unstructured text responses with priming interventions allows us to characterize how associations causally affect expectation formation.

We also contribute to the literature on the role of personal experiences in macroeconomic expectation formation (Kuchler and Zafar, 2019; Malmendier and Nagel, 2011,

[1] More generally, we contribute to a growing literature studying the formation of macroeconomic expectations of experts, households and firms, and the role of these expectations in economic and financial decisions (Acosta and Afrouzi, 2019; Afrouzi, 2019; Armantier et al., 2015; Bachmann et al., 2021, 2015; Binder and Rodrigue, 2018; Binder and Makridis, 2020; Bordalo et al., 2018, 2020b; Coibion and Gorodnichenko, 2012, 2015a,b; Fuster et al., 2012, 2010; Goldfayn-Frank and Wohlfart, 2020; Kamdar, 2019; Malmendier and Nagel, 2011, 2016; Roth et al., 2021; Vellekoop and Wiederholt, 2019).

2016; Malmendier et al., 2021). While the existing literature has focused on the reduced-form effects of experiences on unconditional expectations of macroeconomic variables, we study how experiences shape forecasts of these variables conditional on the occurrence of shocks. Moreover, our paper provides novel evidence on the link between personal experiences and selective recall of propagation channels, highlighting a potential attentional mechanism underlying experience effects.

Finally, the paper contributes to a small literature that investigates the views and beliefs of academic economists (e.g., Andre and Falk, 2021; DellaVigna and Pope, 2018; Gordon and Dahl, 2013; Sapienza and Zingales, 2013). We document how economists assess and think about four commonly studied macroeconomic shocks.

The rest of this paper is structured as follows. Section 2 provides an overview of the samples of households and experts, and the survey design. Section 3 presents our evidence on experts' and households' predictions in the different vignettes. Section 4 provides evidence on selective recall as a driver of heterogeneity in forecasts. Section 5 discusses the implications of our findings for understanding heterogeneity in survey data and for modeling the formation of macroeconomic expectations. Section 6 concludes.

2 Data and Design

2.1 Samples

Household survey For our main online survey, we collect a sample of about 2,200 respondents that is representative of the US population in terms of gender, age, region, total household income, and education. We collect the data in two waves. The first wave was launched in February and March 2019 in collaboration with the market research company Dynata, and the second wave was conducted in July 2019 with the survey company Lucid. Both online panel providers are commonly used in economics and social science research (Haaland et al., 2021). The pooled sample from Waves 1 and 2 closely matches the characteristics of the general population. For instance, 55% of our respondents are female, compared to 51% in the 2019 American Community Survey (ACS, see Appendix Table A.1). 32% of the respondents in our sample have at least a bachelor's degree, compared to 31% in the ACS. The median income in our sample is $62,500 compared to $65,712 in the ACS.

Expert survey In parallel to both household survey waves, we recruit two samples of approximately 1,100 experts in total. For the first wave, we invited economists who were authors or discussants at leading macroeconomic conferences.[2] In total, 180 experts completed the first wave of the survey. 83% of these experts are from academic institutions, while 16% work at policy institutions, such as the IMF and central banks (for more details, see Appendix Table A.2). For the second wave, we included our module in the World Economic Survey (WES) – a global survey of economic experts, run by the ifo Institute (Boumans and Garnitz, 2017). 908 experts participated in our module. 56% of these experts are from academia, 16% from policy institutions, 16% work at a bank or a private company, while the remaining 12% have another type of employer. 65% of the experts have a Ph.D., and they predominantly come from North America or Western Europe (50%) (for more details, see Appendix Table A.2). Table A.3 provides an overview of the different data sets used in the paper.

2.2 Structure of the Survey

Respondents to the household survey start by completing a series of demographic questions. Then, they receive brief non-technical definitions of the unemployment rate and the inflation rate to establish a common-ground definition of the two terms at the start of the survey, and are informed about the current values of these rates. In the subsequent main part of the survey, participants make predictions about unemployment and inflation under two hypothetical vignettes.[3] Finally, we collect data on some additional respondent characteristics. The expert survey consists of a subset of the household survey. After being introduced to the question format, experts directly proceed to the prediction task in two randomly selected vignettes. We do not include the definitions of inflation and unemployment, but still provide the experts with the most recent values of both variables.[4]

[2]For details on the conferences considered, see Appendix J. We also invited a few Ph.D. students, experts from several policy institutions, as well as several experts working in the broader areas of expectation formation and macroeconomic forecasting.

[3]A series of papers uses hypothetical vignettes to study belief formation in contexts such as human capital (Delavande and Zafar, 2019; Wiswall and Zafar, 2017) or consumption behavior (Christelis et al., 2019; Fuster et al., 2020a).

[4]The median household respondent spends about 14 minutes to complete the survey (10th percentile: 7-8 min, 90th percentile: 27-33 min, depending on the wave). The median expert in wave 1 needs 5 minutes to complete the shorter expert survey (10th percentile: 3 min, 90th percentile: 14 min). The survey completion rates are close to 80%. See Table A.4 for further details. Appendix Figure A.1 summarizes

2.3 Hypothetical Vignettes

To measure our respondents' beliefs about the effects of different macroeconomic shocks, we use hypothetical vignettes in which we introduce our respondents to different scenarios and ask them to predict future unemployment and inflation. This approach allows us to provide individuals with identical information about the source and the parameters of the shock. The vignettes focus on four different exogenous shocks, which are among the most commonly studied in macroeconomics: an oil supply shock, a government spending shock, a monetary policy shock, and a tax shock. This enables us to compare respondents' predictions with estimates from a rich macroeconomic literature. At the same time, these shocks have the advantage that they can be explained to individuals without an economics degree. Our participants are randomly assigned to make predictions for two out of four hypothetical vignettes, which are presented in random order.[5]

Each vignette follows the same structure (summarized in Appendix Figure A.1). All start with a short introduction that familiarizes respondents with the setting of the vignette. For example, in the income tax vignette, they are informed about the average US income tax rate and the amount that the median household currently pays in taxes on labor income. Then, respondents are presented with a *baseline scenario* in which they are asked to imagine that the variable of interest (e.g., income tax rates) does not change. We elicit people's expectations about the unemployment rate in 12 months and the inflation rate over the next 12 months under this scenario. Thereafter, respondents are asked to predict unemployment and inflation in a *shock scenario* in which an exogenous shock to the economy is introduced. Specifically, we randomize respondents into a rise-scenario with an increase in the shock variable (e.g., all income tax rates rise by 0.5 p.p.) and a fall-scenario with a decrease in the shock variable (e.g., all income tax rates fall by 0.5 p.p.). To simplify the exposition, we reverse all predictions for the fall-scenarios and analyze them together with predictions for the rise-scenario.[6] Our main outcome variable is respondents' beliefs about the effect of a shock, i.e., the difference in predictions between the shock and the baseline scenario. Eliciting beliefs under both a baseline and

the structure of both surveys. The full set of experimental instructions for Wave 1 and Wave 2 of the surveys can be found under the following link: https://osf.io/6mxaz/.

[5]In Wave 2 of the expert survey, it was not feasible to randomize the order of vignettes. Instead, the vignettes were ordered as follows: 1. income tax shock, 2. federal funds rate, 3. government spending shock, 4. oil supply shock. Respondents received two randomly selected vignettes.

[6]In appendix Section D.1, we compare predictions across the rise and fall scenarios. Asymmetries occur more often for households than for experts, but are mostly minor.

a shock scenario has two important methodological advantages: first, it decomposes and simplifies the prediction problem for households; second, divergent beliefs about baseline trends of the US economy that are present in both scenarios cancel out.

Respondents indicate the expected unemployment and inflation rates on two sliders that range from 0% to 10% for unemployment and from -2% to 8% for inflation. The default position of each slider is the value of the respective rate at the time of each survey. The sliders ease the task for our respondents and reduce noise and cognitive strain.[7] In what follows, we provide details on each of the four vignettes.

Oil supply shock In the introduction to the oil vignette, respondents learn about the current average price of one barrel of crude oil. Then, in the baseline scenario, our respondents are told to imagine that the average price of crude oil stays constant over the next 12 months. Thereafter, they are randomly assigned to either an "oil price rise scenario" or an "oil price fall scenario". Specifically, respondents in the "oil price rise scenario" receive the following instructions:

> Imagine the average price of crude oil unexpectedly rises due to problems with the local production technology in the Middle East. On average, the price will be $30 higher for the next 12 months than the current price. That is, the price will be on average $84 for the next 12 months.[8]

As is the case for all other vignettes, instructions for the fall-scenario are analogous to the rise-scenario.

Government spending shock This vignette first provides respondents with information on the size of yearly government spending in the US and its usual growth rate. In the baseline scenario, our respondents are told to imagine that federal government spending grows as usual over the next 12 months. In the rise-scenario, our respondents receive the following instructions:

> Imagine federal government spending unexpectedly grows to a larger extent than usual over the next 12 months due to a newly announced spending program on

[7] Finally, to account for potential order effects, we cross-randomize whether respondents first receive the question on the inflation rate or the question on the unemployment rate. For each participant, the order of the inflation and unemployment questions is identical across all scenarios.

[8] The last sentence of the vignette was not included in Wave 2.

> defense. In particular, total government spending grows by 2.4 p.p. more than the usual growth that took place in the previous years.
>
> The government announces: The change is temporary and occurs despite no changes in the government's assessment of national security or economic conditions. Moreover, federal taxes do not change in response to the spending program.

Monetary policy shock We familiarize respondents with the federal funds target rate and its current value. The baseline scenario asks our respondents to imagine that the Federal Open Market Committee announces that it will keep the federal funds target rate constant. In the subsequent rise-scenario, our respondents receive the following instructions:

> Imagine the federal funds target rate is unexpectedly 0.5 percentage points higher. That is, in its next meeting, the Federal Open Market Committee announces that it is raising the rate from 2.5% to 3%.
>
> Imagine the committee announces it does so with no changes in their assessment of the economic conditions.

Tax shock After a brief explanation of federal income taxes in the US, the baseline scenario tells our respondents to imagine that income tax rates stay constant for all US citizens over the next 12 months. The subsequent rise-scenario is described as follows:

> Imagine that income tax rates are unexpectedly 1 percentage point higher for all households in the US over the next 12 months. This means that the typical US household would pay about $400 more in taxes.
>
> The government announces: The tax change is temporary and occurs despite no changes in the government's assessment of the economic conditions. Moreover, government spending does not change in response to the tax increase.

Discussion of the design Our design allows us to interpret belief disagreement as arising from heterogeneity in respondents' subjective models of the economy. We measure a respondent's belief about the effects of a shock as the difference in the respondent's forecasts between the rise/fall and the baseline scenario. By focusing on the difference in forecasts across scenarios, we already control for differences in the baseline level of expected inflation or unemployment across respondents. This aspect of our design shuts down information frictions – the key alternative explanation for belief disagreement – to a large extent. Of course, holding different information about the state of the economy could still affect forecasts of the *effect* of a shock, even under the same subjective model. However, our design choice to provide individuals with identical information about past unemployment, inflation and the realization and parameters of the shock strongly mitigates this remaining concern. As a result, heterogeneity in forecasts across respondents should be due to heterogeneity in the way individuals think about the functioning of the economy – the subjective models they rely on.[9]

Since we work with a general population sample, we face a trade-off between the precision of the vignettes and the ease of understanding them. To avoid cognitive overload among respondents from the general population sample, we make the vignettes as simple to understand as possible. At the same time, we are careful to make clear that the shocks are exogenous to the US economy, which makes our estimates comparable to theoretical models and empirical evidence. For instance, we attribute the oil supply shock to changes in the local production technology in the Middle East. Similarly, in the interest rate scenario, we explicitly state that the change in interest rates occurs with no changes in the Fed's assessment of economic conditions. Moreover, we also fix people's beliefs about the duration of the shocks by clarifying that the changes in taxation and government spending only last for one year.[10] For the government spending and taxation shocks, we clarify that the temporary nature of the shock is common knowledge by using the wording "the government announces".

Furthermore, many of our design choices are motivated by common modeling assumptions in DSGE models and by empirical evidence from VARs in order to ensure comparability of our survey responses to these external benchmarks. For example, empirical evidence on government spending shocks often focuses on defense spending (e.g., Auer-

[9]Part of the heterogeneity in forecasts in our vignettes could reflect measurement error. However, much of our descriptive analysis in Section 3 focuses on directional predictions, for which measurement error should be strongly mitigated. In addition, in our analysis of the role of thoughts of different propagation channels in Section 4, forecasts are used as dependent variables, so (classical) measurement error should not bias coefficient estimates.

[10]We do not fix beliefs about the duration of the change in interest rates under the monetary policy shock, since the interest rate should react endogenously to changes in inflation and unemployment in response to the shock through the Taylor rule.

bach et al., 2020; Basso and Rachedi, 2019; Nakamura and Steinsson, 2014) as this type of spending does not affect the economy's productivity and does not directly redistribute resources across the income distribution.

Theoretical and empirical benchmarks We draw from seminal studies in the theoretical and empirical literature to obtain benchmark estimates for the inflation and unemployment responses to each shock.[11] These values broadly illustrate the view on the effects of shocks established in the literature and put respondents' estimates into context. For example, for the oil price shock, our empirical benchmark is derived from the VAR estimate of Blanchard and Galí (2010) for the Great Moderation period, while the theoretical benchmark is based on Bodenstein et al. (2011) and Balke and Brown (2018). The former paper models the US as a purely oil-importing country and the latter treats the US as both oil-producing and oil-importing. Naturally, given the always ongoing debates in the respective areas, these benchmarks neither represent "correct" values nor do they fully capture the degree of estimates across the entire literature on each topic. Appendix C provides details on the derivations of the benchmarks and lists the main studies that we consulted.

Differences between Waves 1 and 2 We introduce a couple of minor wording changes to the instructions of Wave 2 to confirm that the results are robust to these modifications. First, our main object of interest are individuals' beliefs about the effects of the shocks accounting for potential endogenous responses by policymakers. We, therefore, explicitly tell respondents in Wave 2 of both the household and the expert survey to account for potential responses of the government and the central bank when making the predictions. Second, to ensure that the respondents do not just interpret our questions as a test of their knowledge of economics, we tell them that we are interested in their own subjective views on what would actually happen under the different scenarios. Despite these differences in instructions across Waves 1 and 2, there are barely any differences in responses, neither in the household nor in the expert survey. We therefore focus on the pooled sample in our main analysis.

[11] We found no established benchmark estimate for the inflation response to the income tax shock.

3 Predicted Unemployment and Inflation Responses to Shocks

In this section, we present our results on experts' and households' forecasts of the effects of macroeconomic shocks. For each shock, we discuss the heterogeneity in predictions within the expert sample, within the household sample, and between both groups. Figure 1 presents the fractions of experts and households who predict a fall, no change, or rise of inflation and unemployment for each shock, respectively. We focus mostly on the qualitative directions of forecasts as those are less susceptible to extreme predictions.[12] Panel A of Figure 2 then presents the average quantitative predictions as well as the benchmark estimates from the empirical and theoretical literature. Panel B of Figure 2 displays the full distribution of the quantitative predictions in separate violin plots.

Oil price shock Experts mostly agree on the directional response of inflation to an exogenous increase in the oil price, with 84% of experts predicting an increase, 6% expecting no change, and 10% predicting a decrease. There is more disagreement about the unemployment response, with 65% predicting an increase, 16% forecasting no change, and 19% predicting a decrease. Disagreement among households is higher than among experts. Only 71% of households predict an increase in inflation, and only 62% expect an increase in unemployment.

Thus, our data suggest that both experts and households primarily hold the conventional view that an oil shock increases both inflation and unemployment, although this view is more pronounced among experts. In terms of quantitative predictions, both households and experts on average predict positive responses of inflation and unemployment to the oil price shock. The quantitative magnitudes of the average predicted responses are higher among households, but below the benchmarks from the empirical and theoretical literature.[13]

[12] Given the large sample size, even minor differences in households' and experts' directional predictions are statistically different ($p < 0.01$, χ^2-tests). Moreover, disagreement is always significantly larger among households than among experts (see Appendix Table A.5). We also confirm the robustness of our results in several checks. Appendix D.3 discusses order effects and the effect of incentives on predictions of households. Figure A.2 showcases the stability of the expert results in different subsamples of experts.

[13] Bordalo et al. (2020b) propose a framework to study over- and underreaction of individual and consensus forecasts to news.

Government spending shock For the government spending shock, Figure 1 displays similar levels of disagreement as in the oil vignette among experts, and much higher levels of disagreement among households. The majority of experts predict an increase in inflation (80%) and a decrease in unemployment (80%) in response to a government spending program. Among households, only 55% predict an increase in inflation, while 29% predict a decrease. For the unemployment rate, disagreement among households is even larger: Only 43% expect a decrease in unemployment in response to an increase in government spending, while 39% forecast higher unemployment.

The high level of disagreement about the unemployment response among households is reflected in a muted average predicted response close to zero (-0.03 p.p., see Figure 2), while experts on average predict a decrease in unemployment by 0.31 p.p. For inflation, households predict an average response of 0.20 p.p., while experts predict a response of 0.26 p.p. The average expert predictions are close to the benchmarks from the empirical and theoretical literature.

Interest rate shock We uncover substantial disagreement about the effect of an unexpected hike in the federal funds target rate – both within and between the samples of experts and households. 67% of experts predict a decrease in inflation in response to an unexpected interest rate hike and 22% predict an increase. 15% of experts think that the unemployment rate would decrease, whereas 72% predict an increase. Households' beliefs are more dispersed than those of experts. A majority of respondents believe that the inflation rate will increase in response to the interest rate hike (57%), while only 30% expect a decrease. 51% of households predict an increase in unemployment and 33% a decrease.

The differences in qualitative inflation predictions between households and experts are also reflected in their quantitative forecasts: While households on average predict an increase in inflation by 0.17 p.p., experts predict a decrease in inflation by 0.15 p.p.[14] Average predictions about unemployment have the same direction in the two samples but are more muted among households than among experts. Experts' average predictions are close to the empirical benchmarks for both unemployment and inflation.[15]

[14] In Section 4.7 we show that only a very small fraction of households seem to misperceive the interest rate hike as the Fed's endogenous reaction to a higher inflation outlook.

[15] These patterns also become apparent if we study the predictions of the joint response of inflation and unemployment (see appendix D.2.1). For instance, 55% of experts express the conventional view that

Tax shock For the tax shock, we find very similar patterns as for the monetary policy shock. While the view that tax hikes are inflationary is prevalent among households (51%), experts overwhelmingly predict a negative response of inflation (68%). The majority of both households (55%) and experts (69%) expect an increase in unemployment. Again, experts are on average close to the empirical and theoretical benchmarks.

Summary Taken together, our first main result can be summarized as follows:

Result 1. *There is substantial heterogeneity in forecasts of the effects of macroeconomic shocks, among experts and among households. Average predictions of households and experts are similar in many cases but differ substantially for the inflation response to monetary policy and income tax shocks as well as for the unemployment response to government spending shocks. Disagreement in forecasts in a setting where respondents have comparable information about past realizations of macroeconomic variables indicates an important role for heterogeneity in subjective models in expectation formation.*

4 The Role of Selective Recall

What drives the heterogeneity in unemployment and inflation forecasts within and between the household and expert samples? One possibility is that individuals selectively retrieve different propagation mechanisms of the shocks. Selective recall has been shown to be important in shaping people's thoughts and behavior in various contexts (Bordalo et al., 2020a; Kahana, 2012; Tversky and Kahneman, 1973). In our setting, experts may tend to think of textbook models, which account for the full general equilibrium effects of a shock. Households may selectively retrieve specific partial equilibrium effects and propagation channels, for instance driven by their personal experiences. Associations of propagation channels may be strongly context-dependent, as the same individual may recall different memories when confronted with different economic shocks. Moreover, the propagation channels that immediately come to households' minds may not necessarily coincide with the mechanisms that are most central to the transmission of a shock.

To shed light on the role of associations, we conduct additional surveys in which we directly measure respondents' thoughts while they make their predictions. We also

the interest rate shock increases unemployment and decreases inflation, compared to 11% of households.

implement an experiment that exogenously shifts households' attention to two different propagation mechanisms and allows for a causal analysis of the effect of selective recall of particular propagation channels. Finally, we shed light on the role of personal experiences as a source of households' associations.

4.1 Samples

Household sample (Wave 3) We recruit a sample of 2,126 respondents in February 2021 in collaboration with the survey company Lucid. Our sample is again broadly representative of the US population in terms of a set of basic demographic variables (see Table A.1).

Expert sample (Wave 3) We identify the email addresses of all economists who published in the top 20 economics journals on JEL code "E: Macroeconomics and Monetary Economics" in the years 2015-2019. We also invite experts from our Wave 1 expert survey and Ph.D. students from 22 leading research institutions (see Appendix J.2 for more details). The expert survey was run in March 2021, shortly after the household survey. In total, 375 experts completed our survey, of which 40% are Ph.D. students (see Appendix Table A.2).

4.2 Design

Our design closely follows the main experiment, with some important modifications tailored to measure the thoughts that underlie respondents' predictions. The baseline vignettes are identical to the main survey. However, instead of predicting the level of each rate twice, once in the baseline and once in the shock scenario, respondents directly predict *differences* in each rate between the shock and baseline scenario. This approach allows us to elicit what comes to respondents' minds when they think about the *effect* of a shock. To reduce the cognitive strain of respondents, they indicate their predictions on discrete scales, proceeding in steps of 0.25 p.p. from "1 (or more) p.p. lower" to "1 (or more) p.p. higher". We only collect data on rise-scenarios and each respondent completes only one vignette to keep the collection parsimonious.[16]

[16]We replicate our main results for both the directional and the quantitative predictions (see Appendix Figures A.3 and A.4). This highlights the robustness of our findings across time and to changes in the design, such as the prediction scales or the simultaneous measurement of thoughts.

Our main object of interest is measuring what people think about while making the prediction. We collect two complementary measures of respondents' associations. First, we ask respondents to tell us about their "main considerations in making the prediction" and about how they "come up with [their] prediction" in an open-text box. This open-response question is placed on the same page as the shock scenario, just below the inflation and unemployment predictions. Second, on the subsequent survey page, we present respondents with a structured list of seven to eight shock-specific propagation channels and ask them to indicate which of these channels – if any – they were thinking about when they made their predictions. For each vignette, we select propagation channels that play a key role in canonical models and channels that were frequently mentioned in open-text responses from pilot studies.[17] Because many propagation channels are only meaningful for a specific shock and to avoid mental overload among respondents, the structured questions focus on a different subset of propagation channels in each vignette. For instance, in the oil price vignette, these channels include a reduction in firms' labor demand due to higher production costs and a reduction in households' spending due to lower purchasing power, among others. In the case of the monetary policy vignette, the survey question includes a cost channel, an intertemporal substitution channel, a channel capturing changes in household spending due to changes in income, as well as several other channels. In several parts of our analysis, we focus on groups of those channels, such as negative supply-side mechanisms (e.g. higher production costs for firms) or negative demand-side mechanisms (e.g. reduced household spending due to lower purchasing power). Appendix E provides an overview of the full instructions used in the structured questions on propagation channels.

For ease of exposition, we focus mostly on the structured questions in our main analysis. These structured questions also offer several advantages compared to the open-text questions. First, the responses to the structured questions are straightforward to compare across respondents, while there is likely large variation in the way individuals respond to the open-text questions. Second, the structured questions allow us to measure thoughts of full, clearly defined propagation channels, while this is more difficult with the open-text responses, which are often not sufficiently nuanced. Third, the structured questions require less effort by the respondents, which may result in lower measurement error. Fi-

[17] The order of response options is randomized across individuals to address potential order effects.

nally, responses to the structured questions do not need to be categorized and interpreted before the analysis, which avoids judgment calls on the part of researchers.

One potential concern is that responses to the structured questions may be prone to ex-post rationalization of forecasts. To address this concern, we also make use of the open-text responses as an additional data source. These responses offer a unique lens into respondents' associations without priming them on any particular propagation channel that could be at play, and should therefore be more immune to ex-post rationalization. We use the open-text responses i) to validate responses to the structured questions, ii) to demonstrate the robustness of our findings, and iii) to capture additional features of thinking not covered by the structured questions (e.g., general equilibrium thinking, mentioning models, and perceived endogeneity of the shock).

COVID-19 pandemic At the time of the data collection, the coronavirus pandemic was still affecting the US economy. To avoid respondents' thoughts being captured by the COVID-19 pandemic, we ask them to assume that "it is the 1st of January 2025. The COVID-19 pandemic is over. The US economy has fully recovered and is back to 'business as usual'." In particular, we ask our respondents to assume that the inflation rate is at 1.8% and that the unemployment rate is at 3.6% on the 1st of January 2025, similar to our main data collection from February and July 2019.

4.3 Results: Propagation Mechanisms that Come to Mind

Figure 3 summarizes respondents' thoughts of propagation channels based on the structured questions. We first describe variation of thoughts within the household and within the expert sample, and then discuss differences between the two groups.

Heterogeneity within the household sample For each of the vignettes, there is a lot of heterogeneity in the thoughts that come to households' minds. Very few of the propagation channels are selected by more than half of the respondents.

How do households' thoughts vary across the different shocks? Supply-side mechanisms related to price increases or layoffs due to higher costs are most frequently mentioned under the oil vignette (about 50% for each). For the interest rate and the income tax shock, which are conventionally seen as demand-side shocks, smaller but still sizable fractions (between 30% and 40%) think of the different negative supply-side channels.

Moreover, many households indicate reductions in product demand due to lower purchasing power or job loss in the oil vignette (about 40% for each channel). By contrast, only 25% of households indicate increases in demand due to higher incomes in the government spending vignette, and only 31% and 27% indicate lower spending due to lower incomes or due to intertemporal substitution in the interest rate vignette, even though these shocks are commonly considered to be classical demand-side shocks.

These patterns are in line with households selectively retrieving specific mechanisms, where the types of mechanisms that are recalled depend on the context. Our evidence also suggests that in many cases households neglect mechanisms that may plausibly play a major role in reality, and that may be useful in forecasting responses of unemployment and inflation.

Heterogeneity within the expert sample We also observe substantial heterogeneity in the propagation channels experts think of within each of the vignettes. However, the within-vignette variation is smaller than among households, and experts' thoughts tend to be more concentrated in specific channels. This suggests that there is more agreement among experts about which propagation channels are important under each shock.

The variation in experts' thoughts across vignettes largely reflects differences in how the shocks are typically viewed in textbooks. For instance, thoughts of negative supply-side channels associated with increases in production costs are most frequently stated in the oil price vignette (79% and 57% for price increases and reductions in labor demand due to higher costs, respectively). Experts think much less frequently of supply-side channels under the three demand-side shocks (ranging from 5% to 26% for different channels across the three vignettes).

Sizable fractions of experts indicate thoughts of demand reductions under the oil vignette due to lower purchasing power (41%) or job loss (33%), consistent with second-round effects in standard models. Under the three shocks conventionally seen as demand-side ones, even higher fractions select demand-side channels that are prominent in textbook models. For instance, 68% of experts think of a reduction in firms' investment expenditure in response to an interest rate hike, while 50% think of a reduction in household spending due to intertemporal substitution. 53% and 69% of experts indicate changes in household spending due to changes in incomes under the government spending vignette and the tax vignette, respectively.

Overall, the variation in experts' thoughts across vignettes suggests that many experts retrieve textbook models when they are confronted with the different macroeconomic shocks.[18]

Similarities and differences between households and experts We next compare households' and experts' associations under each of the shocks.

Households and experts think about similar propagation mechanisms in the context of the oil price vignette. In the other three vignettes, however, there are marked differences between households and experts in the propagation mechanisms respondents think about. Most importantly, compared to experts, households tend to attach lower relative importance to demand-side channels and higher relative importance to supply-side mechanisms in the interest rate and income tax vignettes. For instance, in the interest rate vignette, households choose the two supply-side mechanisms – higher costs leading firms to increase prices and to reduce labor demand – more often than any of the channels related to negative demand-side effects. The patterns are reversed among experts. Thus, many households seem to attribute an important role to a cost-channel in the transmission of monetary policy, where firms pass on higher borrowing costs to consumers in the form of higher prices (Barth and Ramey, 2002). Experts' views are much more closely aligned with the common textbook view that interest rate shocks primarily operate through reductions in product demand. To illustrate households' thoughts in the interest rate vignette, Table 1 provides example responses for households mentioning a cost channel or a demand channel in the open-text response. Similarly, under the income tax vignette, 35% of households indicate propagation channels according to which firms need to raise wages to compensate employees for the higher tax rate and pass the higher cost on to consumers in the structured question, while only 5% of experts think of such a channel.

Moreover, across all vignettes, sizable fractions of households (about 20% to 30%) indicate thoughts that firms react to reductions in demand by *increasing* prices to maintain

[18]Figure A.6 shows that thoughts of the different propagation channels are very similar across different subgroups in the expert sample. For instance, experts that are PhD students think of very similar channels as non-PhD student experts.

profit levels – a channel that has no role in standard models, and which is selected by almost none of the experts. Households' positive predicted inflation response to interest rate or income tax hikes – the most striking deviation from experts' forecasts – could thus be partially driven by i) relatively higher attention to supply-side factors, and ii) a different view on how firms adjust their prices in response to changes in product demand.

In the government spending shock, households select channels working through increases in product demand much less frequently than experts (between 25% and 33% among households compared to between 53% and 63% among experts). By contrast, households are almost twice as likely as experts to indicate *reductions* in household spending due to an increase in expected future taxes (29% vs 14%). Together, these patterns could explain households' more muted average prediction about the unemployment response to higher government spending.

Finally, we use the open-ended data to document that experts are more likely to account for general equilibrium effects in their forecasts than households based on two facts. First, 10% and 6% of experts refer to endogenous reactions of the central bank to the oil shock and to the government spending shock, respectively, in the open-text question (see Figure A.7). Virtually none of the households refer to reactions by the Fed to these shocks. Second, 22% of the experts explicitly refer to an economic model (such as the New-Keynesian model), compared to none of the households, suggesting that experts are more likely to think about the shocks through the lens of economic theories. These theories in turn account for general equilibrium effects of the shocks.[19]

Discussion Taken together, we find strong heterogeneity in the propagation mechanisms respondents think about, both within and between our samples of households and experts. The responses by experts suggest that many experts retrieve textbook models when making their forecasts. These models in turn account for general equilibrium effects of the shocks. Heterogeneity within the expert sample could, for instance, be driven by differences in academic backgrounds or fields of expertise.[20] Households frequently choose

[19]These findings are in line with participants' responses to a question about the approach they pursued in their forecasts. Figure A.5 shows that 88% of experts report that they drew on their knowledge of economics compared to only 29% of households. This is consistent with the notion that experts are more likely to think about the shocks through the lens of textbook models. In contrast to experts, households are relatively more likely to rely on their memories of past economic events and their gut feeling when making their predictions.

[20]Our surveys are not tailored to study the drivers of heterogeneity in associations within the expert sample due to space constraints.

channels that are less important in textbook models, and often neglect mechanisms that are commonly considered to be central. Their forecasting seems to be based on a patchwork of partial equilibrium responses that strongly differs across contexts and individuals. Households often do not account for second-round effects, such as policy responses, or disagree on their direction, such as for the pricing response of firms to changes in product demand. We explore the role of heterogeneous personal experiences as one driver of differences in associations within the household sample in Section 4.6 below.

Taking together the evidence presented above, our second main result is the following:

Result 2. *The propagation channels that are on top of respondents' minds vary systematically within and across our samples of households and experts. Experts tend to recall channels that are central in textbook models, while households in many cases neglect these channels and think of channels that are conventionally seen as less important.*

Robustness: Open-ended responses We also leverage responses to the open-text question eliciting participants' thoughts on the prediction screen to demonstrate the robustness of our findings to a different measurement technique. First, Appendix Figure A.7 highlights how frequently different word groups are mentioned in the open-ended question across vignettes and samples. While naturally the levels are not comparable between structured and unstructured data of thoughts, we replicate differences between households and experts in terms of the relative importance of different mechanisms. Second, in Online Appendix F, we develop a coding scheme to manually categorize open-ended responses into thoughts of different mechanisms. Each response is independently coded by two coders, with high inter-rater reliability. The hand-coded measures of thoughts are strongly correlated with our main measures based on the structured question (see Tables A.19 and A.20), and are similarly distributed across vignettes (see Figure A.11). These findings validate our measures based on the structured questions and mitigate concerns related to ex-post rationalization of forecasts in the structured questions.

4.4 Correlations between Associations and Predictions

Is heterogeneity in thoughts about propagation channels driving heterogeneity in inflation and unemployment forecasts? Table 2 shows that the propagation mechanisms selected in the structured question are strongly associated with inflation and unemployment forecasts in both the expert and the household sample across all four vignettes. For presentational convenience, we use dummies indicating whether a respondent selects at least one (positive/negative) demand-side or supply-side channel, respectively.[21]

Most of the correlational patterns uncovered in Table 2 go into the expected direction. For example, households thinking of negative supply-side propagation channels expect higher increases of inflation ($p < 0.01$) and unemployment ($p < 0.01$) in response to an oil price shock. Experts choosing supply-side propagation channels also expect higher increases in unemployment ($p < 0.01$) in response to oil price hikes, but do not expect higher levels of inflation. In the context of the government spending shock, we uncover robust negative correlations between choosing propagation channels related to positive demand-side shocks and expected changes in unemployment rates ($p < 0.01$). Among households, we also find a strong positive association between choosing channels related to crowding-out and predicted increases in inflation ($p < 0.01$) in response to a government spending increase, while for experts this association is more muted. For households, we document strong positive associations between choosing supply-related propagation mechanisms and predicted increases in inflation ($p < 0.01$) and unemployment ($p < 0.01$) in response to both an interest rate hike and an increase in income taxes, while for experts these patterns are less pronounced. For experts, on the other hand, we find that choosing demand-related mechanisms is associated with lower inflation ($p < 0.01$) and higher unemployment ($p < 0.01$) predictions in response to both an interest rate and an income tax hike.

Table 2 illustrates that, across shocks, dummies for thoughts about different propagation channels have significant explanatory power for forecasts. Regressing forecasts on dummies for all vignette-specific channels gives an R-squared between 6% and 21% for households, and between 10% and 44% for experts. These values are sizeable given the low R-squared often documented in studies of the determinants of survey expectations, such as individual characteristics or experiences (Das et al., 2020; Giglio et al., 2021; Kuchler and Zafar, 2019; Malmendier and Nagel, 2011). The actual explanatory power of associations is likely even larger than measured in our survey given i) the potential measurement error in associations, ii) the fact that we do not measure the perceived strength of the different channels, and iii) the possibility that we do not capture all relevant channels

[21] In Appendix F we demonstrate robustness of these correlations to using the hand-coded measures of thoughts based on the open-text data.

that respondents have on their minds.

Can differences in associations account for differences in average predictions between households and experts? Table 3 examines the extent to which the gap in predictions between experts and households can be explained by differences in responses to the structured question on propagation mechanisms. Our analysis zooms in on the three predictions for which the average gap between households and experts is most pronounced. Columns 1 and 2 show that the average differences in unemployment predictions in the government spending vignette are fully explained by differences in the selected propagation mechanisms. Columns 3 and 4 show that the propagation channels explain approximately one third of the gap in inflation predictions in the interest rate vignette. Finally, they explain about one third of the prediction gap in the tax vignette (Columns 5 and 6). Taking together the evidence presented above, our third main result is the following:

Result 3. *Thoughts of specific propagation channels are correlated with forecasts of the effects of macroeconomic shocks on inflation and unemployment in the expected directions, and account for part of the differences in forecasts between households and experts.*

One important caveat about our descriptive evidence is that omitted variables could be driving both thoughts of propagation channels and forecasts about unemployment and inflation. To provide evidence of a causal effect of thoughts and selective recall of propagation mechanisms, we conduct an additional experiment, which we discuss in the next subsection.

4.5 The Causal Effect of Associations

To shed light on the causal effects of selective retrieval of particular propagation mechanisms on households' inflation and unemployment forecasts, we conduct a simple experiment. We focus on beliefs about the effect of a federal funds rate hike on the inflation rate as this is one of the cases where predictions differ the most between households and experts.[22] Moreover, monetary policy innovations are the most studied type of shock in the theoretical and empirical literature. The experiment aims to provide a proof of concept that an exogenous shift in people's selective retrieval of propagation mechanisms can causally affect their beliefs about the effects of macroeconomic shocks. If an exogenous

[22] Given the nature of attention, focusing on one macroeconomic variable (inflation) gives us more control over the respondents' thoughts while they make their predictions.

change in attention to specific aspects of the prediction problem changes respondents' forecasts, this would suggest that individuals do not hold a "fixed" subjective model, but instead form their models "on the fly", depending on the associations triggered by the context.

Sample We conduct this experiment with a sample of 1,521 respondents provided by Lucid in February 2021 (Wave 4 of the household survey). Our sample is again broadly representative of the US population in terms of a set of basic demographic variables (see Table A.1).

Design Our design closely follows the descriptive survey on associations, except that it only focuses on inflation expectations and the interest rate vignette (see Figure A.1 for a visual summary). In the experiment, we randomize respondents into one of three treatments: Respondents in the "cost treatment" are asked two additional questions on firms' costs of doing business before making their inflation prediction. First, they are asked whether US firms face higher or lower costs of doing business when the federal funds rate rises. Second, they are asked to describe their main considerations in making their prediction about costs in an open-text box. In the "demand treatment", respondents are asked about the demand for firms' products before they forecast effects on inflation. First, they are asked whether firms face higher or lower demand for their goods and services when the federal funds rate rises. Second, as in the cost treatment, they describe their main considerations in making the prediction about demand in an open-ended question. Respondents in the "control treatment" do not receive any additional prompt before they make their inflation prediction. Respondents in all three groups report in an open-text box what considerations are on their mind while they make their inflation prediction.[23]

At the end of the survey, respondents in the control treatment are asked either the same two additional questions on costs ("cost control group") or the same two additional questions on demand ("demand control group"). This allows us to characterize heterogeneity in beliefs and to study whether the effects of our attention treatments depend on participants' beliefs about the direction of the effect of the federal funds rate hike on costs or demand.[24]

[23] Appendix Section G provides an overview of the prediction screens across all three treatment arms.

[24] For this analysis to be valid, beliefs about the directions in which costs and demand change need to be balanced between the treatment and control groups, which we confirm empirically.

The purpose of asking respondents to forecast the response of costs or demand to the shock before they make their inflation forecast is to exogenously draw their attention to different propagation channels of the interest rate shock. For instance, if households' forecasts of a positive inflation response to interest rate hikes are partially driven by relative inattention to demand-side compared to supply-side mechanisms, then our demand treatment should reduce respondents' inflation forecasts by increasing their retrieval of demand-side mechanisms. We believe that drawing respondents' attention to a particular mechanism by asking a question on the decision screen is a relatively subtle way of manipulating associations, which mitigates concerns about experimenter demand effects (de Quidt et al., 2018).

Results We leverage the text data in which respondents describe what is on their mind while making the inflation prediction to shed light on the "first-stage" effects of our treatments on selective retrieval of propagation mechanisms. Columns 1 and 2 of Table 4 present the effects of the treatments on the words that respondents use to describe their thoughts.[25] Respondents in the "cost treatment" arm are 8.6 p.p. ($p < 0.01$) more likely to use words related to firms' costs (control mean: 9.3%). The demand treatment increases the use of words related to demand by 7.7 p.p. ($p < 0.01$) – a 75% increase compared to the control group mean of 10.6%. There are no spillovers of the cost treatment on the use of demand-related words, or vice versa. The overall small fractions mentioning such words should be viewed in light of the unstructured nature of the open-text data. Taken together, our treatments seem to be successful in drawing respondents' attention to supply-side or demand-side mechanisms, respectively.

We next turn to the effects on respondents' inflation forecasts. Column 3 of Table 4 shows that while the cost prime increases inflation predictions insignificantly by 0.021 p.p. ($p = 0.50$), the demand prime significantly decreases inflation predictions by 0.057 p.p. ($p < 0.05$). The stronger response of inflation forecasts to the demand treatment could be due to the fact that many households already predict a positive inflation response by default, potentially due to higher attention to supply-side mechanisms. This could limit the scope for further increases in inflation forecasts.

[25] In Online Appendix F, we show similar patterns using measures of thoughts based on hand-coding of the open-text data. We do not use structured measures as those were not included in this data collection.

Despite the relatively large first-stage effects on word usage, the effects on inflation forecasts we uncover are relatively small in magnitude. There are at least three potential explanations. First, the effect of attention to changes in costs or product demand on inflation forecasts should depend on respondents' beliefs about the direction of changes in costs or product demand in response to the rate hike. If there is disagreement on the directions of these changes, this will attenuate the average effects of attention to costs or demand on inflation forecasts. Consistent with this conjecture, Table A.6 in the Online Appendix shows that the demand treatment decreases inflation forecasts by 0.10 p.p. ($p < 0.05$) among respondents expecting a decrease in demand, while it has no significant effect among those expecting an increase. Similarly, the cost treatment increases inflation predictions by 0.05 p.p. among respondents who expect an increase in costs ($p = 0.20$), while it decreases predictions by 0.15 p.p. among respondents who expect a decrease in costs ($p = 0.14$). Second, even among respondents with beliefs about changes in costs or changes in demand in the same direction, there could be disagreement about the direction of firms' pricing response to a given change in costs or demand. Indeed, as documented in Section 4.3, households seem to disagree about the direction in which firms adjust their prices in response to decreases in demand. Such disagreement implies that higher attention to demand or costs shifts different households' inflation forecasts in different directions, which may further attenuate the average effects on inflation forecasts. Third, inattention to the demand- or supply-side may only be part of the story, i.e. people could hold differential beliefs about the importance of demand- and supply-side channels in the transmission. Hence, even if respondents are made attentive to these channels, only part of them might think this is important for inflation.

Taking together the evidence presented above, our fourth main result is the following:

Result 4. *An exogenous shift in attention to demand-side factors has a negative causal effect on households' predicted inflation response to interest rate hikes. The fact that an exogenous change in retrieval of propagation mechanisms of shocks changes households' forecasts suggests that households may not form their expectations based on a fixed subjective model. Instead, individuals may form their subjective models "on the fly", in line with the associations that come to their minds depending on the context.*

This suggests that news or actual events in the economy may systematically affect which models people entertain. Rather than sticking to one particular model, economic agents retrieve specific memories when cued by events, which in turn shape the economic mechanisms they think of.

4.6 The Role of Experiences

A key open question is what determines households' recall of specific propagation channels when they think about macroeconomic shocks. Human memory is known to be associative, selective, and to draw on personal experiences (Bordalo et al., 2017; Enke et al., 2020; Kahana, 2012). Different personal experiences in the memory database should therefore be reflected in differences in associations and forecasts. In this subsection, we use an additional data collection on the government spending vignette among households (Wave 5) and data on the oil price vignette from Wave 3 of the household survey to shed light on this conjecture.

Experiences with the propagation channels of military spending In an additional data collection (Wave 5 of the household survey, n=486), we collect data on the government spending vignette using identical baseline instructions as in Wave 3.[26] In addition, we include two main sets of variables to gauge the role of personal experiences.

First, we ask respondents to assess their overall experience with the mechanisms that we listed in our structured question on propagation channels, such as an increase in household spending due to higher incomes (see Figure 3). Respondents rate the extent to which they themselves or their family and friends have been part of each mechanism on a five-point scale ranging from "no experiences" to "a lot of experiences". For the analysis, we compute two summary indices, namely the standardized sum of experiences with positive demand-side channels and a standardized version of experience with "crowding-out" channels. The two indices provide measures of respondents' cumulative first-hand and second-hand experiences with propagation channels.

Second, we also zoom in on a more specific experience by eliciting whether the respondent or anyone among their friends and family members has ever been employed by a company receiving contracts from the US military. This, in turn, allows us to capture one specific way in which a respondent could have direct personal experience with the

[26] Our respondents in this sample are on average somewhat older and more educated compared to our other data collections (see Table A.1).

demand-side mechanisms and, in particular, the potential labor market effects of military spending increases.

Panel A of Table 5 shows that respondents who indicate to have more experiences with positive demand-side mechanisms are more likely to choose demand channels ($p < 0.01$) and somewhat less likely to choose channels related to crowd-out ($p < 0.10$) in the structured question, and are more likely to mention words related to product demand ($p < 0.10$) and labor demand ($p < 0.10$) in the open-text question. Conversely, respondents who have more experiences with crowd-out channels are more likely to choose propagation channels related to crowd-out ($p < 0.01$) and less likely to choose channels related to demand ($p < 0.01$) in the structured question, and somewhat more likely to mention words related to costs ($p < 0.10$) and less likely to mention words related to labor demand ($p < 0.05$) in the open-text question. These differences in the propagation channels respondents think of are reflected in a more negative predicted unemployment response to the spending program among those with positive demand-side experiences ($p < 0.01$) and a more positive predicted unemployment response among those with crowd-out experiences ($p < 0.01$).

Panel B of Table 5 shows that respondents who were either personally employed by a company receiving contracts from the US military or have someone among their friends and family members who was employed by such a company are somewhat more likely to choose propagation channels related to demand in the structured question ($p < 0.10$), and are more likely to use words related to labor demand in the open-ended question ($p < 0.01$) when they make their forecasts. They also predict a stronger decrease in the unemployment rate in response to the increase in government spending ($p < 0.01$).[27]

Experiences with oil supply shocks To provide further evidence on the role of personal experiences, we leverage variation in whether respondents lived through the OPEC crisis in the 1970s – a singular and particularly memorable event. Building on prior work by Binder and Makridis (2020), we proxy personal experiences of the 1970s oil crisis with an indicator for whether the respondent was born before 1962 (teenagers by the late 1970s). Given that the oil price shocks of the 1970s are conventionally seen as supply-side shocks, we would expect respondents with personal experiences of the OPEC

[27]Table A.7 shows that we obtain similar results using alternative measures of personal employment experience with government suppliers.

crisis to be more likely to recall channels related to production cost increases.

Panel C of Table 5 shows that individuals born before 1962 are indeed more likely to choose propagation channels related to the supply-side ($p < 0.01$) and more likely to use words related to costs ($p < 0.05$) when making predictions in the oil vignette. Consistent with the associations on top of their mind, respondents who experienced the OPEC crisis predict stronger increases in unemployment and inflation ($p < 0.01$) (Panel C of Table 5).[28]

Our fifth and final result can be summarized as follows:

Result 5. *Personal experiences are correlated with selective recall of specific propagation mechanisms, which is reflected in individuals' beliefs about the effects of macroeconomic shocks.*

Personal experiences typically vary widely across individuals and are hence likely to be a key driver of heterogeneity in associations regarding macroeconomic shocks. At the same time, personal experiences are likely not the only source of households' associations. For instance, individuals could retrieve things they have recently heard in the news, recall things about economics they learned in college or school, or think of the immediate consequences of a shock for themselves.

Table A.8 uses responses to a question on which approaches households followed in making their forecasts (see Figure A.5) to examine how thoughts of different channels vary across different sources of associations. Households that use knowledge of economics in their predictions are more likely to have associations of channels that are important in textbook models, moving their thoughts closer to those of experts. Respondents whose predictions are shaped by their personal situations are more likely to think of demand-side channels, such as changes in household spending, across the different vignettes. Finally, retrieving macroeconomic experiences or things heard in the news is significantly associated with having more thoughts of both supply-side and demand-side channels in the different vignettes.

Future research could provide more systematic evidence on how personal experiences or media exposure trigger different associations across contexts. Such an exercise could be guided by a model of memory of own experiences that makes predictions on how

[28] In Online Appendix F, we show similar patterns for the effect of experiences on associations using measures of thoughts based on hand-coding of the open-text data.

experiences affect associations across contexts.

4.7 Other Drivers of Forecasts

In the previous subsections, we provided descriptive and causal evidence highlighting that selective recall of different propagation channels is driving heterogeneity in forecasts both between and within our samples of households and experts. In this subsection, we study a range of other factors that could be important for households' unemployment and inflation forecasts, and compare their quantitative importance to the role of thoughts about propagation channels.

Data In our Wave 3 data collection, we also collect rich data capturing (i) respondents' knowledge of different aspects of the economy, (ii) their beliefs about historical correlations of different macroeconomic variables, (iii) the extent to which they consider knowledge of how the economy works useful for making good economic decisions, (iv) their numeracy, and (v) a range of other background characteristics – all of which are described in further detail below and in Appendix H.

Specifications To ease presentation, we examine correlates of whether a prediction is benchmark-consistent, that is whether it is directionally aligned with the literature benchmarks, using data from Wave 3 of the household survey.[29] We pool unemployment and inflation forecasts for this exercise. Column 1 of Table 6 depicts bivariate regression coefficients for different potential determinants (coded as dummy variables, see table notes), while Column 2 shows multivariate regression coefficients. Each coefficient can be interpreted as the increase in probability that a forecast is benchmark-consistent. In the description of the results, we focus on the bivariate regressions, but the patterns are very similar for the multivariate ones.

Thoughts of propagation channels We start by assessing the role of associations. Table 6 corroborates our main finding that respondents' selective retrieval of propagation mechanisms affects predictions. When respondents report thinking about a propagation

[29] We have at least one theoretical or empirical benchmark in all cases except for the effects of income tax shocks on inflation. In this case, we rely on the conventional view of income tax shocks as demand-side shocks.

channel that is in line with the benchmark, they are 17 p.p. ($p < 0.01$) more likely to make a benchmark-consistent prediction.[30] This effect is sizable, given an overall fraction of benchmark-consistent predictions of 48%.

Perceived past correlations In Section 4.6, we showed that personal experiences are correlated with the associations respondents have on their mind when thinking about macroeconomic shocks. Here, we examine how a respondent's perception of the historical correlation between the shock variable (e.g., the oil price) and the prediction variable (e.g., inflation) is related to their forecasts (for details, see Appendix H.1). Table 6 highlights that respondents who perceive a correlation between the variables that is consistent with the benchmark are 18 p.p. ($p < 0.01$) more likely to make a benchmark-consistent prediction.[31] Thus, we document that perceived experienced joint movements of macroeconomic variables are related to households' forecasts of the effects of macroeconomic shocks – similar to the reduced-form relationship between average experienced realizations of macroeconomic variables and unconditional expectations of these variables documented by previous literature (Kuchler and Zafar, 2019; Malmendier and Nagel, 2011, 2016). This relationship could reflect a direct effect or could partially be driven by associative recall of specific propagation channels, in line with our evidence presented in Section 4.6.

Rational inattention We also examine whether individuals who consider it necessary to be knowledgeable about macroeconomic relationships to make good economic decisions are more likely to make benchmark-consistent forecasts, in line with a premise of rational inattention models (Maćkowiak and Wiederholt, 2015; Sims, 2003; for details see Appendix H.2). Table 6 shows that there is a small but statistically significant positive association of respondents' perceived importance of understanding the working of the economy with giving benchmark-consistent responses. The table also highlights that an objective measure of respondents' knowledge about the economy is significantly positively correlated with benchmark-consistent forecasts, but the coefficient estimate is compara-

[30] The explanatory variable is based on the structured question on propagation channels. Supply-side propagation channels are in line with the benchmarks in the oil price vignette, while demand-side propagation channels are in line with the benchmarks in the other three vignettes.

[31] One concern is that respondents may derive their estimates for historical correlations from their causal understanding of the economy as measured in the vignette forecasts. This could give rise to reverse causality, which would upward-bias the estimated coefficient.

tively small (see Appendix H.3 for details).

Other correlates of forecasts Moreover, we find a small but significant effect of cognitive ability as proxied by numeracy skills, which has been shown to be an important driver of inflation expectations (D'Acunto et al., 2021b). A wide set of basic demographics, such as education, age, income, and respondents' political affiliation, are at most weakly correlated with the tendency to make benchmark-consistent forecasts of unemployment and inflation.[32,33] Overall, thoughts of propagation channels seem to play a more important role than several other plausible drivers of respondents' forecasts.

Misperceived endogeneity All vignettes are carefully worded to make clear that the shocks are exogenous. However, there may still be a concern that respondents in the representative sample believe that the shock is endogenous and the result of changing economic conditions. This concern is particularly relevant for the monetary policy vignette since exogenous changes in the federal funds rate are atypical and might be particularly difficult to imagine for respondents. For instance, participants might believe that the higher interest rate indicates that the Fed is reacting to an expected rise in inflation and therefore predict higher inflation. However, the open-text data of Wave 3 suggest that only a small fraction of respondents misperceive the shocks as endogenous. We hand-code whether respondents erroneously mistake a shock as a signal for another change to the US economy. Across vignettes, only 1.5% of respondents falsely interpret a shock as endogenous. Even in the monetary policy vignette, the fraction is negligible (2.9%). Moreover, our main results are robust to excluding the relevant respondents.[34]

5 Implications

In this section, we discuss the broader implications of our findings for understanding macroeconomic expectation formation and for modeling choices.

[32] We also find no significant political heterogeneity in quantitative forecasts – not even in the government spending vignette (see Table A.9).

[33] In Appendix H.4, we discuss the potential of a simple affective heuristic to explain variation in making benchmark-consistent predictions across respondents.

[34] If respondents misperceive the interest rate change as endogenous, their predictions should be shaped by their beliefs about how the Fed endogenously responds to changes in inflation or unemployment. We measure these beliefs and show that they cannot explain the patterns in our data (Appendix H.5).

Understanding disagreement in expectations One of the most well-documented empirical facts on the macroeconomic expectations of households, firms, and experts is that there is a substantial amount of disagreement about the future development of the economy (Coibion and Gorodnichenko, 2012; Dovern et al., 2012; Giglio et al., 2021; Link et al., 2020; Mankiw et al., 2003). This evidence is at odds with traditional models of full information and rational expectations. There are two broad views on the origins of disagreement in macroeconomic expectations. The most prominent explanation for belief disagreement brought forward by the theoretical literature is that agents have different information on the current state of the economy, which may be driven by infrequent updating of information sets (Mankiw and Reis, 2002; Reis, 2006) or by noise in private signals about the economy (Sims, 2003; Woodford, 2003). According to such explanations, if agents have the same information sets, they fully agree on how the economy responds to shocks. In contrast to this view, we document strong heterogeneity in unemployment and inflation forecasts even in a setting where all individuals observe the same shock and hold similar information about current realizations of macroeconomic variables. This finding is more in line with the alternative view that dispersion in expectations is (partially) due to individuals relying on different subjective models of the economy (Andrade et al., 2016; Angeletos et al., 2020; Bray and Savin, 1986; Marcet and Sargent, 1989; Molavi, 2019). Accordingly, economic agents evaluate the same news about the economy through the lens of their own model. Since there is strong heterogeneity in these models, disagreement about the future arises even when agents have comparable information about current realizations of macroeconomic variables and shocks.

Relation to existing theories featuring disagreement about the model Can existing theories featuring disagreement about the model of the economy explain our findings? For instance, in theories of learning and model misspecification, agents may disagree about structural parameters of the economy, such as the persistence of inflation (Angeletos et al., 2020; Bhandari et al., 2019; Bray and Savin, 1986; Evans and Honkapohja, 2012; Marcet and Sargent, 1989; Milani, 2007; Molavi, 2019; Orphanides and Williams, 2005). In models of learning from experience (Malmendier and Nagel, 2016), individuals only use realizations of macroeconomic variables observed during their lifetimes to estimate the data-generating process, leading to disagreement in inflation expectations across cohorts even if everyone observes the same current realization. While heterogeneous beliefs about structural parameters from this literature find support in our results, these models cannot quantitatively account for the large heterogeneity in beliefs about the impact of the shocks we document, including disagreement even about the directional responses to shocks. More importantly, our priming evidence that changes in attention to different aspects of the problem affect forecasts is at odds with these models.[35]

Associative recall and subjective models Instead, our evidence is consistent with the idea that heterogeneity in macroeconomic expectations is partially due to associative recall of different propagation mechanisms of shocks (Bordalo et al., 2020a; Gennaioli and Shleifer, 2010). In this view, heterogeneity in the models individuals rely on is not fully stable, but depends on what is cued by the context and on individuals' past experiences. Given our evidence, we believe that incorporating associative recall could be a fruitful avenue for macroeconomic modeling.

While formulating a model of associative recall as a driver of heterogeneity in subjective models is beyond the scope of our paper, in Appendix I we compare the predictions of a canonical sticky-information model (Mankiw and Reis, 2002) with those of a basic framework that features heterogeneity in beliefs about the effects of macroeconomic shocks, being agnostic about the sources of heterogeneity in these beliefs. We calibrate both models to the empirical results from our vignettes and show that subjective models can produce either an under- or over-reaction of expectations relative to the true inflation response to shocks, and a rise in disagreement of comparable magnitude to that of the sticky-information model. However, unless some frictions in observation of shocks (i.e., sticky information) are assumed, the subjective models framework cannot explain empirical evidence on the persistence in forecast errors by Coibion and Gorodnichenko (2012). Hence, a subjective models approach does not fully substitute but rather complements information frictions.

[35] A literature in behavioral macroeconomics has proposed k-level thinking (Farhi and Werning, 2019), a lack of common knowledge (Angeletos and Lian, 2017), or myopia (Gabaix, 2020) in macroeconomic expectation formation to explain muted responses of output and consumption to shocks. These models mostly do not directly speak to disagreement in expectations. Moreover, in models of diagnostic expectations, disagreement arises from economic agents' use of the representativeness heuristic to learn from noisy private signals about the economy (Bordalo et al., 2018, 2020b). In our survey, we provide agents with identical information.

Disagreement in more natural settings How do our findings speak to disagreement in more natural settings? Our vignettes describe different hypothetical shocks with a small number of parameters, including previous realizations of the shock variable, unemployment and inflation, as well as the duration of the shock and the information structure. Real-world macroeconomic shocks likely feature a higher number of relevant parameters. Moreover, the simplifying common knowledge assumption about the duration of changes in government spending or taxes in our vignettes will rarely be fulfilled in the real world. These points suggest that disagreement about the effects of shocks in more natural settings, both among households and among experts, may be even larger than measured in our surveys.

6 Conclusion

Using samples of about 6,500 households representative of the US population and samples of about 1,500 experts, we use a new vignette-based approach to measure individuals' subjective models of the economy and investigate their attentional foundations. We document substantial disagreement, even about the directional effects of macroeconomic shocks, both within and between samples of households and experts, in a setting where individuals have similar information about previous realizations of macroeconomic variables. Part of this disagreement seems to be due to selective recall of different propagation mechanisms of the shocks. While experts tend to retrieve textbook models, households often neglect channels that are commonly viewed as central to the transmission of a shock. We confirm a causal role for selective retrieval of specific propagation channels by exogenously shifting households' attention to either supply-side or demand-side channels. Finally, we show that personal experiences are correlated with households' associations about specific propagation channels when they are confronted with the shocks. Our findings highlight selective recall as a new explanation for disagreement in macroeconomic expectations.

We believe that our approach of measuring beliefs about the effects of shocks can be applied to many other questions in macroeconomics. For example, it could be fruitful to apply our approach to other structural shocks that are commonly found to be quantitatively important, such as total factor productivity or sentiment shocks. In addition, we believe that our approach of measuring what is on top of people's mind while they make their predictions is a widely applicable tool that could help to better understand how associations drive belief formation.

Our findings also have several implications for policymakers.[36] First, in recent years policy institutions have made efforts to reach broader groups with their communication to increase the effectiveness of fiscal and monetary policy (Haldane and McMahon, 2018). Such efforts could be less fruitful if households disagree about the direction in which policy shocks affect macroeconomic outcomes. Second, our evidence suggests that the way a policy is communicated – for example, whether demand-side implications rather than supply-side implications are emphasized – could substantially alter its effect on individuals' expectations. Finally, our finding of substantial heterogeneity in households' beliefs about macroeconomic relationships implies a large degree of variation in the effectiveness of monetary policy and fiscal policy in shifting expectations and behavior for different subpopulations of interest.

[36] The role of macroeconomic expectations in households' spending decisions is still being debated in the literature. Some studies find a positive association of inflation expectations with consumption (D'Acunto et al., 2021a), while others document a muted (Bachmann et al., 2015; Galashin et al., 2021) or negative relationship (Coibion et al., 2019). The evidence on the role of expectations about aggregate unemployment and growth is more limited, but there is some evidence suggesting a role in households' spending decisions (Coibion et al., 2021; Roth and Wohlfart, 2020).

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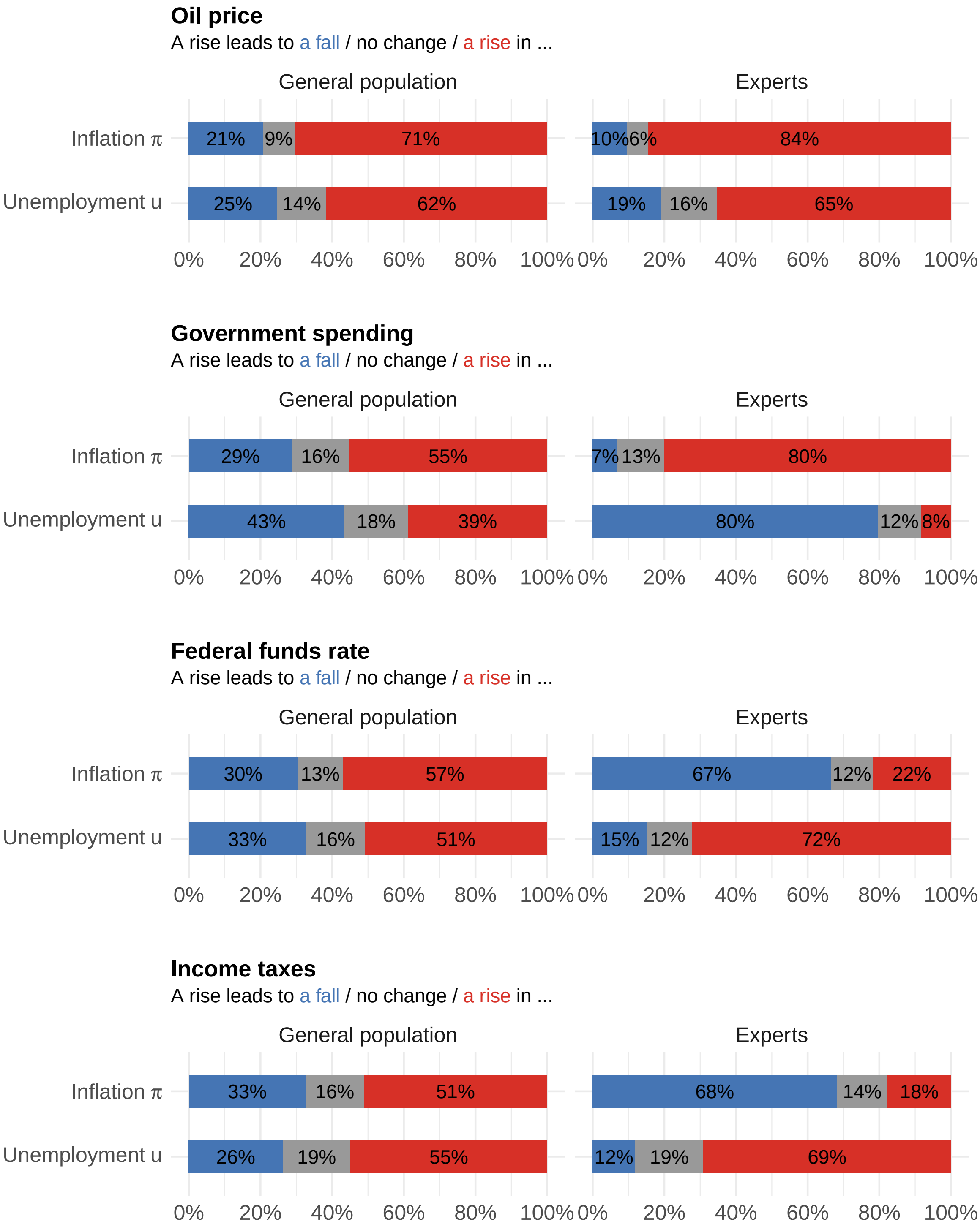
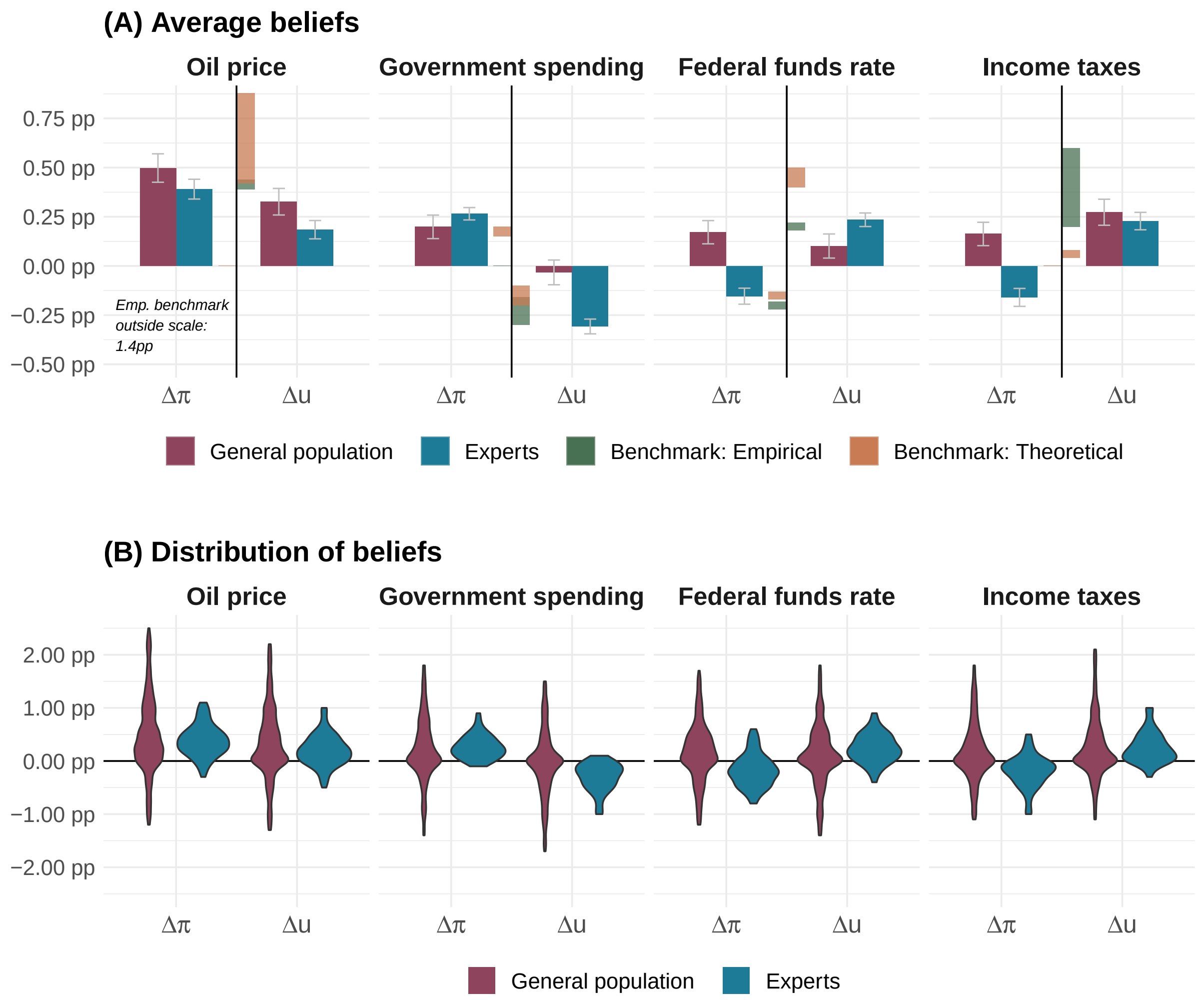
Main Figures

Figure 1: Forecasts of the directional effects of macroeconomic shocks



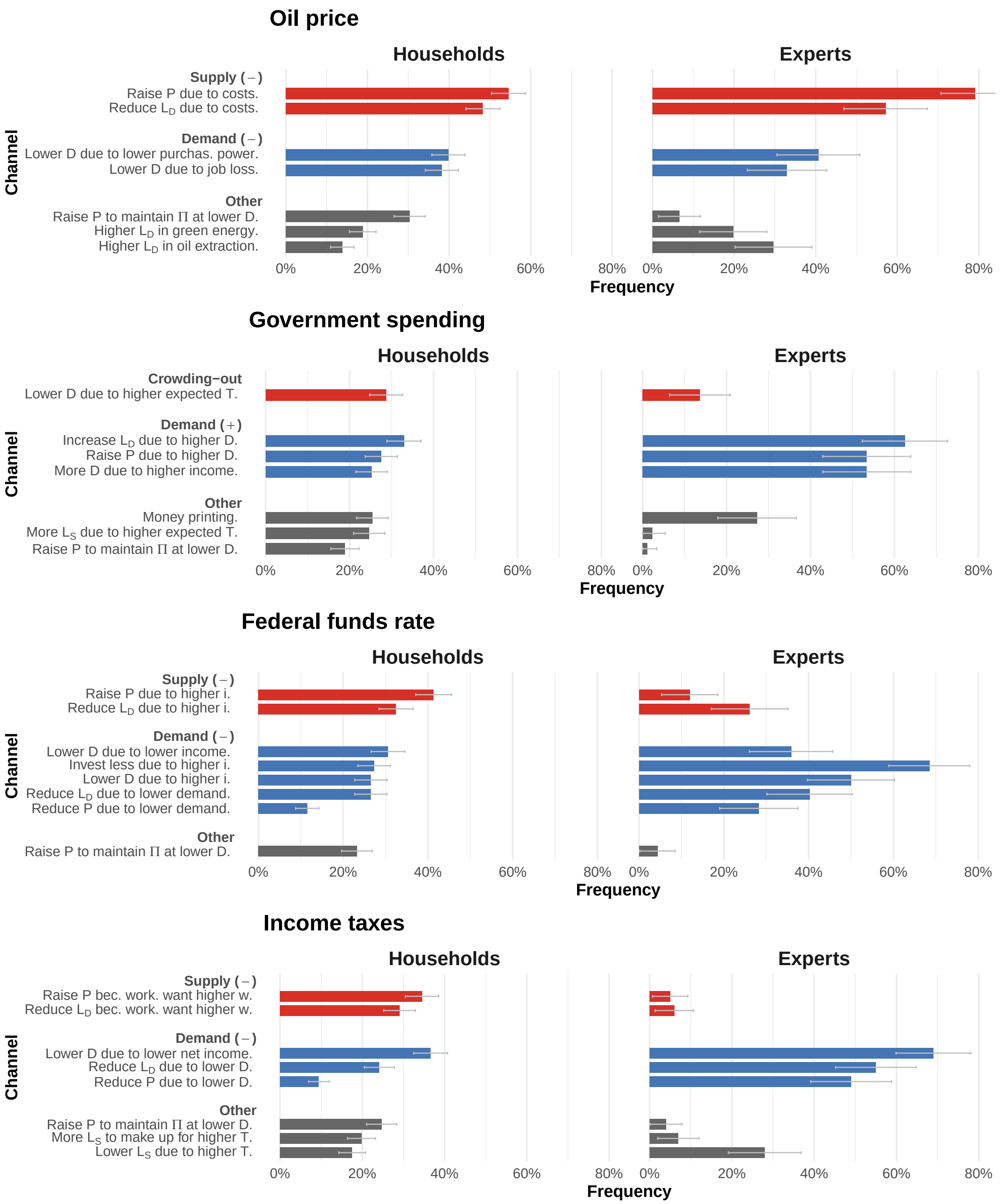
Notes: This figure presents the forecasts of the directional effects of macroeconomic shocks on the inflation rate and the unemployment rate, using Wave 1 and Wave 2 data. It compares the forecasts of the general population (left column) to those of experts (right column). Predictions in the fall scenarios are reversed to render them comparable to rise predictions.

Figure 2: Forecasts of the quantitative effects of macroeconomic shocks



Notes: Panel A displays the average forecasts of the effects of macroeconomic shocks on the inflation rate ($\Delta\pi$) and the unemployment rate (Δu), using Wave 1 and Wave 2 data. It compares responses in the representative sample (red bars) with those of experts (blue bars). Error bars present 95% confidence intervals, using robust standard errors. The green and yellow rectangles depict the range of benchmark estimates that we compile from the empirical and theoretical macroeconomic literature. Panel B plots the distribution of responses (with trimmed 5% tails), using kernel density estimators. Both panels pool forecasts for the "rise" and "fall" scenarios. Predictions in the fall scenarios are reversed to make them comparable to rise predictions.

Figure 3: Thoughts of propagation channels



Notes: This figure shows which propagation channels are on respondents' minds when they make their predictions, using Wave 3 data. Respondents can select the channels from a list. The results are displayed separately for each vignette and for households (left panel) and experts (right panel). Error bars display 95% confidence intervals. P abbreviates "firm prices", L_D "labor demand", D "product demand", Π "firm profits", T "taxes", i "interest rates", w "wages", and L_S "labor supply". The full wording of the channels is available in Appendix E.

Main Tables

Table 1: Associations in the federal funds rate vignette: Examples of households' open-text responses

Thoughts about a cost channel	Thoughts about demand-side channels
"If the cost to borrow funds goes up, then a business will have to pay more to pay back a loan. Thus, businesses will have to raise prices. This will result in inflation. A business may not be able to pay employees and have to let them go or a business will not be able to pay back the load and the business will fail. The employees will lose their jobs and raises unemployment"	"with change in fed funds rate upward, unemployment is likely to rise (as cost to business to borrow increases and invest less in expansion) and inflation should in theory be kept in check and even fall."
"I believe if the fed rate increases, the inflation rate will as well because companies will be paying more on their credit and they will pass that on to consumers. Do not think it will affect unemployment."	"Interest rates rising will increase the cost of investment. This will make companies lay people off. However, with higher interest rates, less money will be invested and it will cause inflation to fall."
"If the Fed rate is increased, the following usually happens –the cost of borrowing money for businesses increases –the business has to raise prices –there is usually a corresponding effect on the unemployment rate as employers find they have to cut staff to remain competitive "	"when the interest rate goes up I believe the unemployment rate goes up as well. Inflation will also hurt the job market. If people are not buying the jobs decrease."
"The higher federal funds rate causes the cost of borrowing to rise. As a result, prices are raised. And employment is lowered to cover cost of borrowing."	"the demand will decrease and the investment will be less then usual also saving will be increased"
"When the interest rate rises that would mean that it would cost more for companies to borrow money and so they would charge more for their products (inflation would go up) and they would not have money to expand and hire more people (unemployment would go up). I really don't know if the exact amounts of the inflation and unemployment rises would be the same as the % that the inflation rate rose but I thought maybe it would."	"With the target rate going up, money will become more expensive to borrow, consumer credit rates will rise. This will cause consumer demand to drop and possibly put people out of work"
"The cost of business goes up so business will try to raise prices to make a profit. Business will try to cut costs by employing fewer workers."	"when interest rates increase there is less spending no new jobs"
	"Interest rate hike will cause less overall spending slightly more unemployment and greater inflation as prices adjust to this rate hike."

Notes: This table displays examples for households' responses to the open-text question, focusing on the monetary policy vignette. The left-hand side focuses on responses explicitly referring to a cost channel and neglecting demand-side mechanisms. The right-hand side focuses on responses pointing to demand-side channels.

Table 2: Thoughts of propagation channels correlate with predictions

Oil price

	Households		Experts	
	$\Delta\pi$	Δu	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)
Supply (−)	0.343***	0.145***	−0.010	0.329***
	(0.047)	(0.046)	(0.081)	(0.063)
Demand (−)	0.069*	0.230***	0.174**	0.165**
	(0.040)	(0.041)	(0.077)	(0.076)
Constant	0.173***	0.090**	0.296***	−0.076*
	(0.044)	(0.042)	(0.065)	(0.046)
Observations	557	557	91	91
R^2	0.113	0.078	0.058	0.150
R^2 (all 7 channel indicators)	0.168	0.214	0.095	0.440

Government spending

	Households		Experts	
	$\Delta\pi$	Δu	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)
Crowding-out	0.140***	0.236***	−0.036	0.057
	(0.050)	(0.055)	(0.071)	(0.046)
Demand (+)	−0.067	−0.249***	0.076	−0.299***
	(0.045)	(0.047)	(0.076)	(0.057)
Constant	0.329***	0.080**	0.195***	0.009
	(0.038)	(0.037)	(0.067)	(0.051)
Observations	519	519	88	88
R^2	0.023	0.102	0.014	0.266
R^2 (all 7 channel indicators)	0.062	0.180	0.178	0.438

Table continued on next page.

Table 2 (continued): Thoughts of propagation channels correlate with predictions

Federal funds target rate

	Households		Experts	
	$\Delta\pi$	Δu	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)
Supply (–)	0.188***	0.142***	0.090	−0.094
	(0.041)	(0.044)	(0.075)	(0.063)
Demand (–)	−0.053	0.088**	−0.324***	0.340***
	(0.040)	(0.044)	(0.096)	(0.068)
Constant	0.229***	0.068*	0.068	−0.012
	(0.034)	(0.039)	(0.084)	(0.063)
Observations	520	520	92	92
R^2	0.041	0.032	0.175	0.199
R^2 (all 8 channel indicators)	0.088	0.068	0.167	0.206

Income taxes

	Households		Experts	
	$\Delta\pi$	Δu	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)
Supply (–)	0.217***	0.188***	0.018	0.004
	(0.041)	(0.044)	(0.074)	(0.074)
Demand (–)	0.024	0.054	−0.150***	0.212***
	(0.041)	(0.043)	(0.046)	(0.038)
Constant	0.254***	0.130***	−0.035	0.041
	(0.032)	(0.034)	(0.041)	(0.030)
Observations	530	530	100	100
R^2	0.053	0.039	0.095	0.169
R^2 (all 8 channel indicators)	0.128	0.129	0.375	0.277

Notes: This table shows data from Wave 3. It regresses the predicted inflation ($\Delta\pi$) and unemployment (Δu) changes on the propagation channels that were on respondents' minds while they made their predictions (see Figure 3). Each panel presents results for a different vignette. In each panel, Columns (1) and (2) present results for households, Columns (3) and (4) present results for experts. "Supply (–)" takes value 1 for respondents who choose a negative supply-side propagation channel. "Demand (–)" and "Demand (+)" take value 1 for respondents choosing a negative or positive demand-side propagation channel, respectively. In the government spending vignette, "Crowding-out" takes value 1 for respondents who select the channel that demand falls due to higher expected future taxes (see Figure 3 for more details). Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table 3: Thoughts of propagation channels account for differences between experts' and households' predictions

	Government spending Unemployment $\boldsymbol{\Delta u}$		**Federal funds rate** Inflation $\boldsymbol{\Delta \pi}$		**Income taxes** Inflation $\boldsymbol{\Delta \pi}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Expert	-0.215^{***}	-0.003	-0.462^{***}	-0.323^{***}	-0.517^{***}	-0.347^{***}
	(0.036)	(0.035)	(0.037)	(0.048)	(0.030)	(0.041)
Constant	0.013	0.040	0.297^{***}	0.207^{***}	0.368^{***}	0.248^{***}
	(0.025)	(0.035)	(0.020)	(0.030)	(0.021)	(0.030)
$\boldsymbol{p_F}$: Expert coeff. equal		**<0.001**		**<0.001**		**<0.001**
Channels	–	✓	–	✓	–	✓
Observations	608	607	614	612	631	630
R^2	0.020	0.203	0.127	0.199	0.152	0.258

Notes: This table uses data from Wave 3 of the expert and household surveys. It tests whether thoughts of different propagation channels (see Figure 3) can account for the differences in experts' and households' predicted inflation ($\Delta\pi$) and unemployment (Δu) changes. We consider the three cases for which large differences in experts' and households' predictions can be found: Unemployment in the government spending vignette (columns 1-2), inflation in the federal funds rate vignette (columns 3-4), and inflation in the income tax rate vignette (columns 5-6). "Expert" takes value 1 for respondents from the expert sample. Results in columns (2), (4), and (6) control for the selected propagation channels (7-8 indicators, depending on the vignette, see Figure 3 for all propagation channels). p-values result from an F-test of equality of the "Expert" coefficient with and without channel controls (estimated using seemingly unrelated regressions). * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table 4: Results of the priming study (households only)

	Word usage (open-text data)		Inflation prediction
	Cost-related words	Demand-related words	$\Delta\pi$
	(1)	(2)	(3)
Costs prime	0.086***	0.007	0.021
	(0.023)	(0.020)	(0.031)
Demand prime	−0.021	0.077***	−0.057**
	(0.017)	(0.023)	(0.029)
Constant	0.093***	0.106***	0.366***
	(0.010)	(0.011)	(0.017)
p: Costs = Demand	<0.001	0.007	0.028
Observations	1,521	1,521	1,521
R^2	0.017	0.010	0.004

Notes: This table presents results from the priming study which focuses on the interest rate vignette (Wave 4 of the household survey). "Costs prime" takes value 1 for respondents randomly assigned to be primed on the costs of production. "Demand prime" takes value 1 for respondents randomly assigned to be primed on product demand. Columns (1) and (2) show effects on word usage in the open-text responses, and Column (3) presents the effects on the inflation forecast. The variable "Cost-related words" takes value 1 for responses which include the word (stem) "cost". "Demand-related words" takes value 1 for responses which use the words or word stems "demand", "buy", "purchas", "invest", "spend", and "consum". $\Delta\pi$ denotes the perceived reaction of the inflation rate. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table 5: Households' experiences correlate with mechanism associations and forecasts

(A) Government spending: Experience with propagation channels (std. indices)

	Propagation channels		**Word usage** (open-text data)			**Predictions**	
	Crowding-out	Demand (+)	Costs	Demand	Labor	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exp. crowd.-out	0.093***	−0.081***	0.023*	−0.034	−0.050**	0.004	0.106***
	(0.026)	(0.026)	(0.012)	(0.025)	(0.025)	(0.026)	(0.029)
Exp. demand +	−0.046*	0.107***	0.003	0.044*	0.048*	0.038	−0.109***
	(0.026)	(0.026)	(0.014)	(0.025)	(0.026)	(0.025)	(0.030)
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	483	483	483	483	483	483	483
R^2	0.113	0.076	0.038	0.191	0.092	0.142	0.180

(B) Government spending: Ever worked for military supplier (self/friend, binary indicator)

	Propagation channels		**Word usage** (open-text data)			**Predictions**	
	Crowding-out	Demand (+)	Costs	Demand	Labor	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Yes	−0.010	0.081*	−0.005	0.036	0.121***	−0.024	−0.101**
	(0.043)	(0.046)	(0.020)	(0.043)	(0.042)	(0.045)	(0.049)
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	483	483	483	483	483	483	483
R^2	0.088	0.050	0.025	0.187	0.098	0.137	0.155

(C) Oil price: Experienced OPEC crisis (born before 1962, binary indicator)

	Propagation channels		**Word usage** (open-text data)			**Predictions**	
	Supply (–)	Demand (–)	Costs	Demand	Labor	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Yes	0.114***	0.036	0.100**	0.039	0.011	0.208***	0.202***
	(0.040)	(0.045)	(0.040)	(0.031)	(0.041)	(0.044)	(0.043)
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	521	521	521	521	521	521	521
R^2	0.064	0.040	0.053	0.020	0.026	0.080	0.074

Notes: This table presents results from Wave 3 (Panel C) and Wave 5 (Panel A and B) of the household survey. In Columns (1) and (2), it asks whether respondents who made experiences related to the vignettes think about different propagation mechanisms (binary indicators; see Figure 3). In Columns (3) to (5), it tests whether respondents with vignette-related experiences use different word (stems) in their open-text responses (binary indicators; "Costs": cost; "Demand": demand, buy, purchas, invest, spend, consum; "Labor": layoff, fire, hire, labor, work, job). In Columns (6) and (7), it tests whether they make different forecasts (inflation: $\Delta\pi$, unemployment: Δu). The right-hand-side experience variable varies across panels. In Panel A, "Experienced crowding-out" and "Experienced demand (+)" are standardized indices of self-rated experiences (familiarity) with crowding-out and positive demand-side channels, respectively. In Panel B, "Yes" is a binary dummy taking value 1 if respondents themselves or friends/family of them ever worked for a company that sells to the US military. In Panel C, "Yes" is a binary dummy taking value 1 if respondents were born before 1962, a proxy that they experienced the OPEC crisis. Control variables comprise age (except for Panel C), log income, inflation and unemployment forecasts in the baseline scenario, as well as binary indicators for gender, college education, being a Republican, having taken an economics course at the college level, and census regions. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table 6: Correlates of benchmark-consistent forecasts (households only)

	Indicator for benchmark-consistent prediction	
	Separate bivariate models	Multivariate model
	(1)	(2)
Consistent channel association	0.170***	0.143***
	(0.015)	(0.015)
Consistent perceived correlation	0.181***	0.157***
	(0.017)	(0.016)
Importance of model (1 if >median)	0.040***	0.015
	(0.015)	(0.015)
Knowledge (1 if >median)	0.077***	0.034**
	(0.015)	(0.015)
Numeracy (1 if >median)	0.062***	0.031**
	(0.015)	(0.014)
Female	−0.026*	−0.008
	(0.015)	(0.014)
Age (1 if >median)	0.057***	0.032**
	(0.015)	(0.014)
College degree	0.022	−0.001
	(0.015)	(0.015)
Income (1 if >median)	0.012	−0.001
	(0.016)	(0.016)
Republican	0.022	0.021
	(0.016)	(0.015)
Mean share of benchmark-consistent pred.	0.480	0.480
Fixed effects	Vignette ⊗ rate	Vignette ⊗ rate
Observations	3,860	3,860
R^2	–	0.237

Notes: This table presents results from Wave 3 of the household survey. It presents the effect of various binary covariates on the likelihood of making inflation or unemployment predictions (pooled) that are consistent with the benchmarks, i.e. directionally aligned with the empirical and theoretical literature benchmarks. Each coefficient can be interpreted as the increase in probability that a forecast is benchmark-consistent. Column (1) shows the results from separate bivariate regressions, while Column (2) shows the results from a multivariate model. "Consistent channel association" takes value 1 if the respondent chooses a channel that suggests a benchmark-consistent prediction (e.g. a negative demand-side channel for the federal funds rate vignette). Likewise, "Consistent perceived correlation" takes value 1 if respondents believe in a past correlation between the shock variable (e.g. oil price) and the target variable (e.g. inflation) that is in line with a benchmark-consistent prediction. "Importance of model" measures respondents' assessment of how important knowledge of the functioning of the economy is to them for making good economic decisions. "Knowledge" measures information about the current state of the economy. "Numeracy" is respondents' score on a numeracy test. "1 if >median" indicates that a variable is binarized and takes value 1 for respondents with an above-median value. We include fixed effects for each vignette-rate combination (e.g. oil-inflation). Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Online Appendix: Subjective Models of the Macroeconomy: Evidence from Experts and Representative Samples

Peter Andre[1] Carlo Pizzinelli[2]

Christopher Roth[3] Johannes Wohlfart[4]

Summary of the Online Appendix

Appendix A provides additional figures. Appendix B provides additional tables. Appendix C provides details on the empirical and theoretical literature used to derive the benchmarks for changes in unemployment and inflation in response to shocks. In Appendix D, we provide more detailed results on the household and expert predictions in Waves 1 and 2. In Appendix E, we provide screenshots of the questions on structured propagation channels for all four vignettes. In Appendix F, we demonstrate the robustness of our findings on thoughts of different propagation channels based on manual coding of the open-text responses from Waves 3-5. In Appendix G, we provide screenshots for the priming experiment. In Appendix H, we provide additional results on alternative mechanisms including perceived past correlations, the perceived importance of knowledge about the functioning of the economy, (objective) knowledge about the economy, and a simple affective heuristic. In Appendix I, we provide additional details on the quantitative exercise related to subjective models in inflation expectations. Finally, Appendix J provides additional details on the recruitment of the expert samples.

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A Additional Figures

Figure A.1: **Main survey** (Waves 1 and 2). Overview of the survey structure and the structure of the vignettes

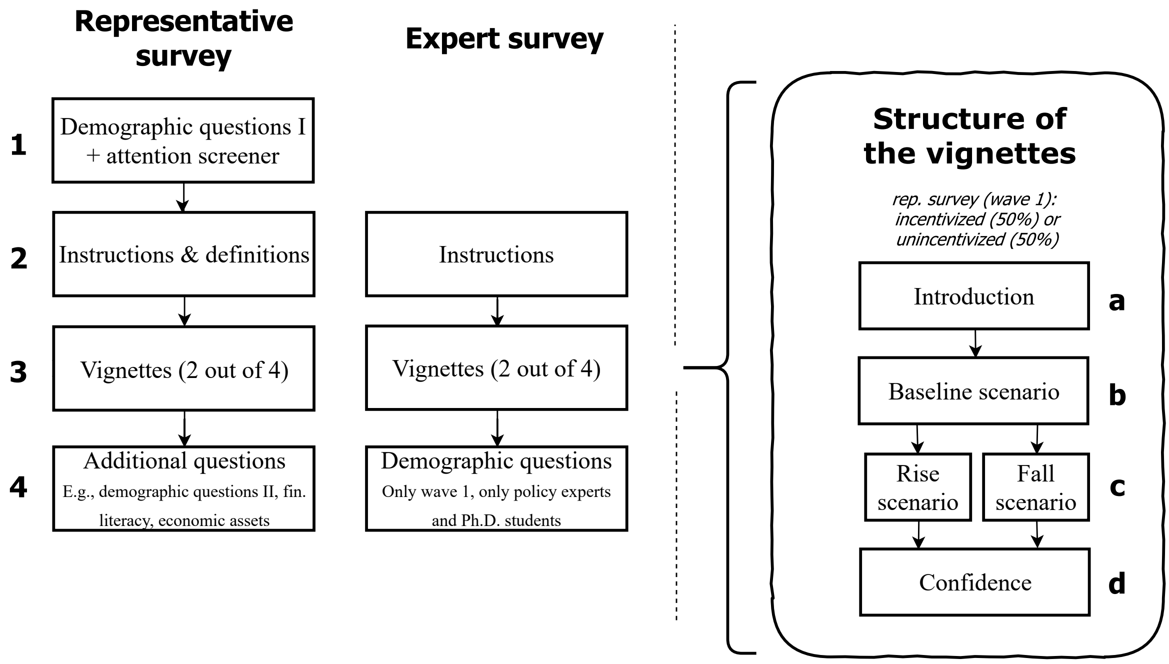


Figure A.1 (continued): **Associations survey** (Wave 3). Overview of the survey structure and the structure of the vignettes

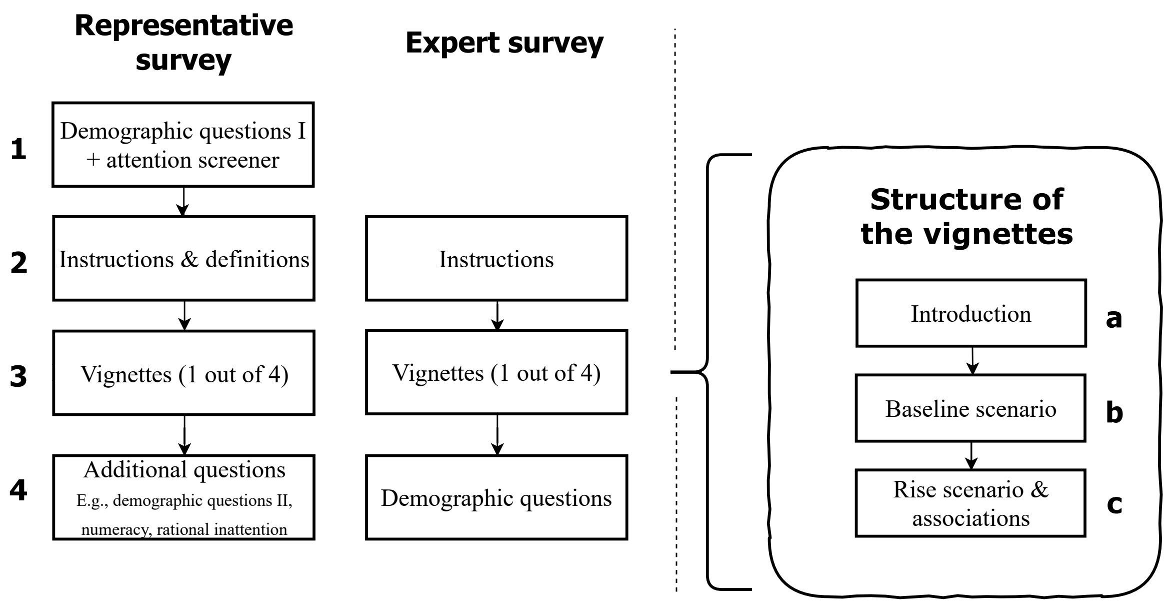


Figure A.1 (continued): **Priming study** (households only, Wave 4). Overview of the survey structure and the structure of the vignettes and treatments

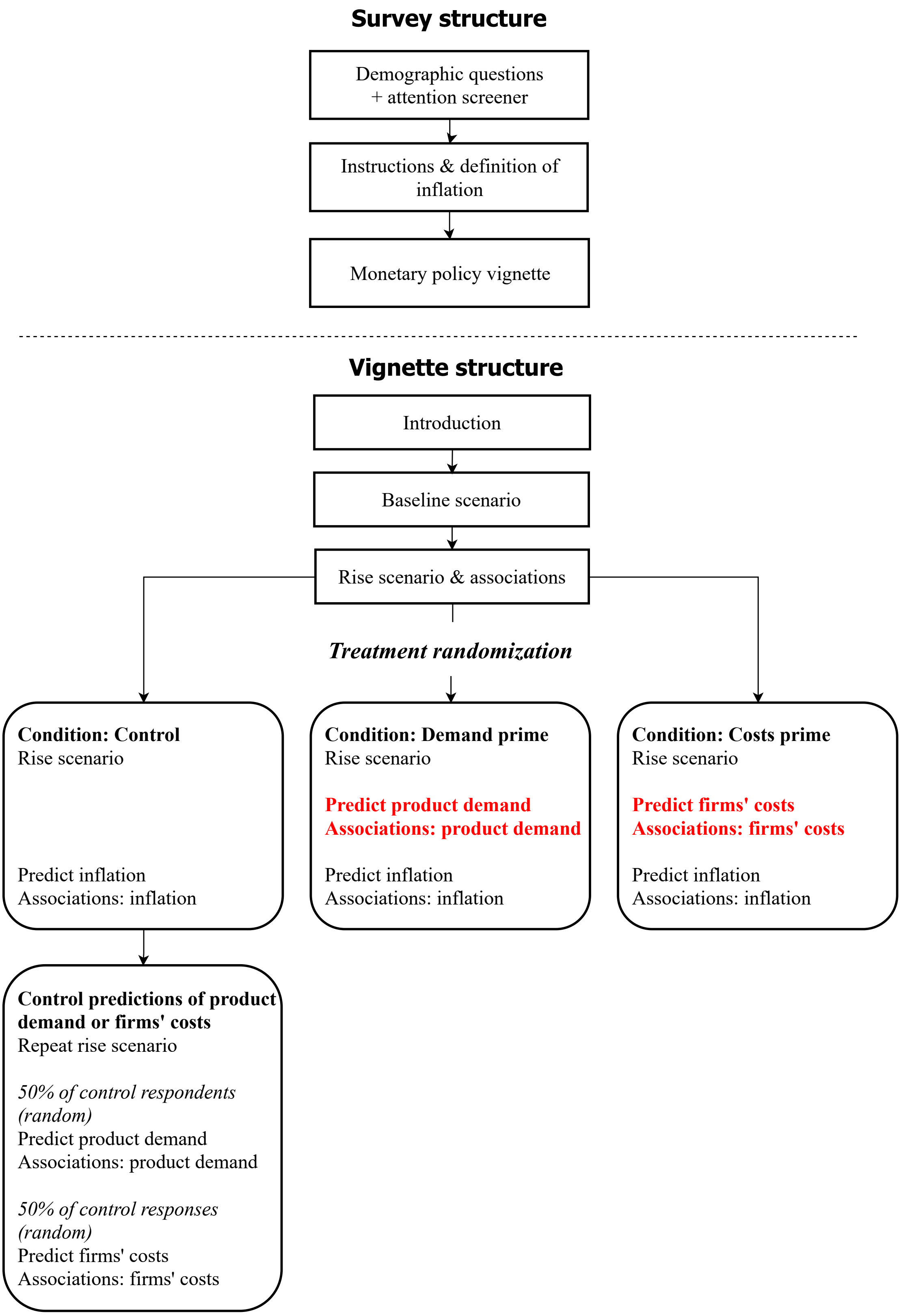


Figure A.1 (continued): **Experience survey** (households only, Wave 5). Overview of the survey structure and the structure of the vignettes

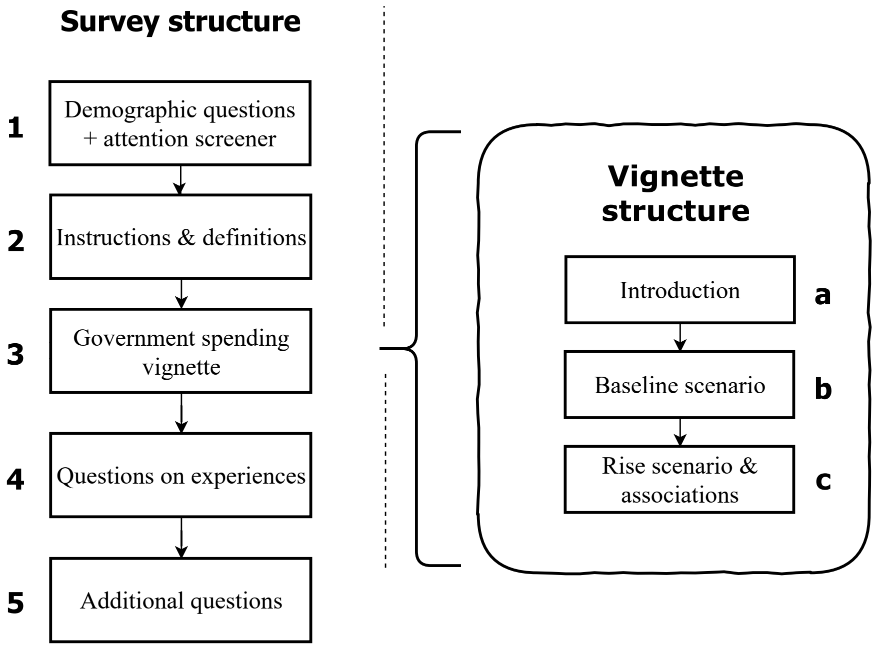
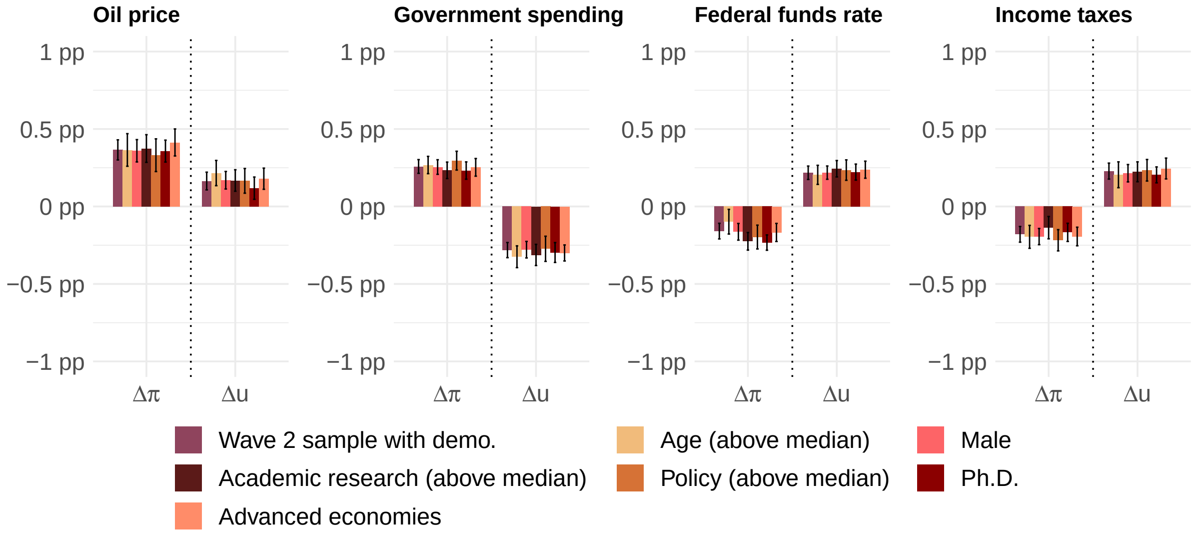
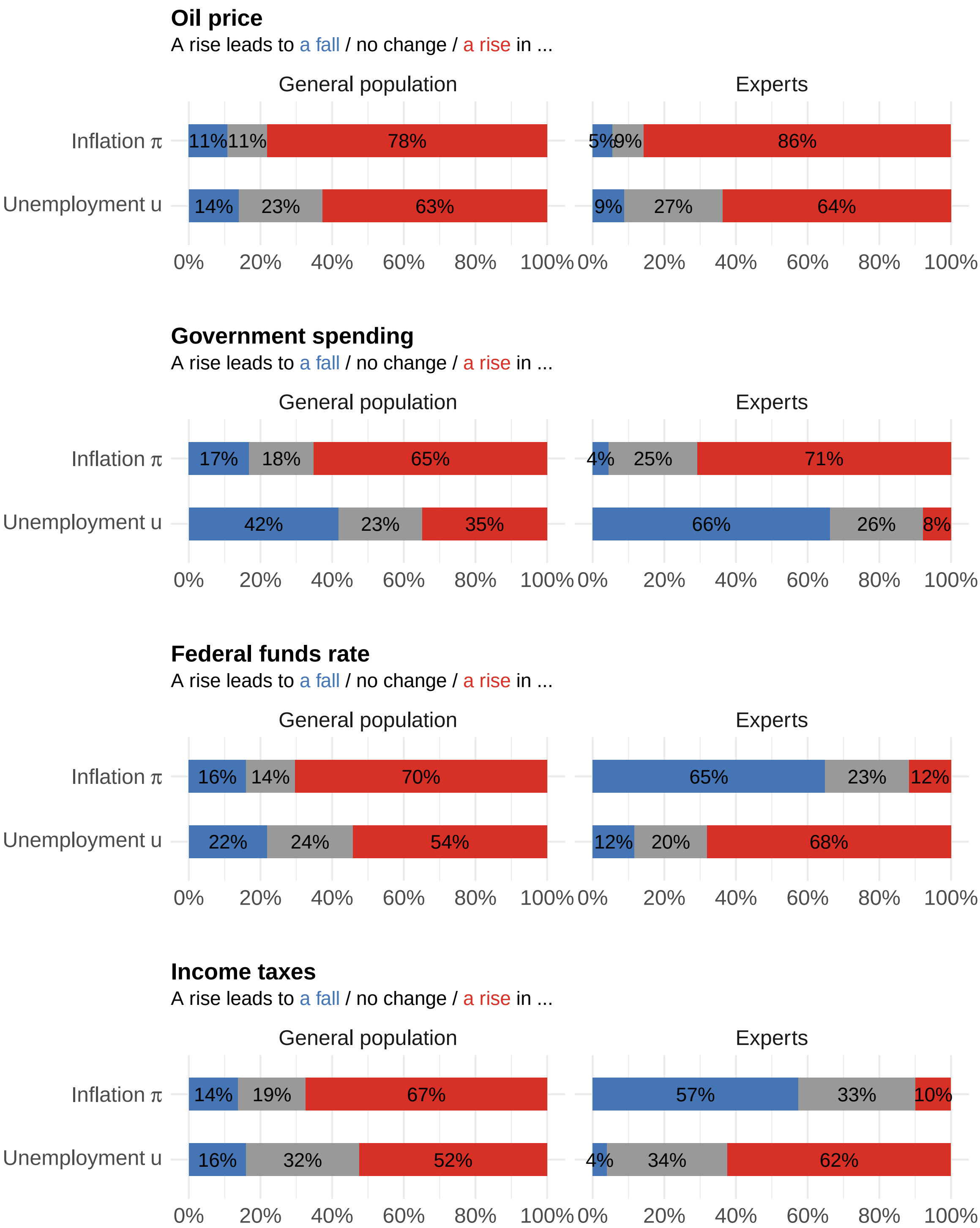


Figure A.2: Robustness of experts' forecasts across different subsamples



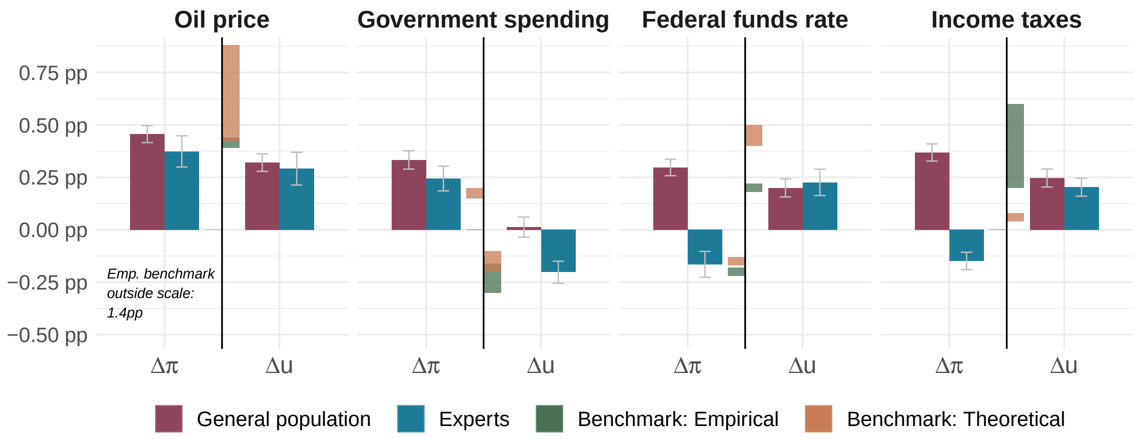
Notes: This figure shows the stability of expert forecasts across various subsamples of the expert Wave 2 sample. It repeats the main analysis for different subsamples and plots expected changes in the unemployment rate (Δu) and the inflation rate ($\Delta \pi$) for each of the different vignettes separately. Predictions in the fall scenarios are reversed to render them comparable to rise predictions. Error bars show the 95% confidence intervals. "Wave 2 sample with demo." denotes the full sample for which background data are available ($n = 596$). "Age (above-median)" contains only respondents with above-median age. "Male" contains only male respondents. "Academic research (ab.-median)" focuses on respondents that spend an above-median percentage of their working time on academic research, while "Policy (ab.-median)" restricts the sample to those who do an above-median amount of policy work. "Ph.D." contains only respondents with a Ph.D., and "Advanced economies" contains only respondents that are registered at the WES to make forecasts about an advanced economy (as classified by the IMF).

Figure A.3: Wave 3: Forecasts of the directional effects of macroeconomic shocks



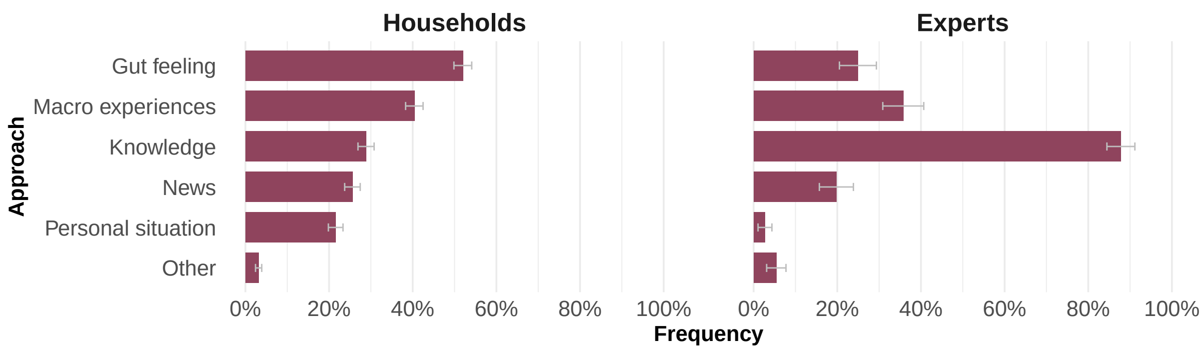
Notes: This figure presents the forecasts of the directional effects of macroeconomic shocks on the inflation rate and the unemployment rate, using Wave 3 data. It compares the forecasts of the general population (left column) to those of experts (right column). Predictions in the fall scenarios are reversed to render them comparable to rise predictions.

Figure A.4: Wave 3: Forecasts of the quantitative effects of macroeconomic shocks



Notes: This figure displays the average forecasts of the effects of macroeconomic shocks on the inflation rate ($\Delta\pi$) and the unemployment rate (Δu), using Wave 3 data. It compares responses in the representative sample (red bars) with those of experts (blue bars). Error bars present 95% confidence intervals, using robust standard errors. The green and yellow rectangles depict the range of benchmark estimates that we compile from the empirical and theoretical macroeconomic literature. The figure pools forecasts for the "rise" and "fall" scenarios. Predictions in the fall scenarios are reversed to render them comparable to rise predictions.

Figure A.5: Prediction approaches by households and experts



Notes: This figure presents the prediction approaches adopted by households and experts in Wave 3, averaged across all four vignettes. In a multiple response question, respondents report which factors they thought most about when making their predictions. Error bars display 95% confidence intervals. "Gut feeling" denotes respondents choosing "I simply responded based on my gut feeling." "Macro experiences": "My memories of economic events in the past." "Knowledge": "My knowledge of economics." "News": "Things I read or heard in the news." "Personal situation": "My personal economic situation today."

Figure A.6: Robustness of thoughts of propagation channels

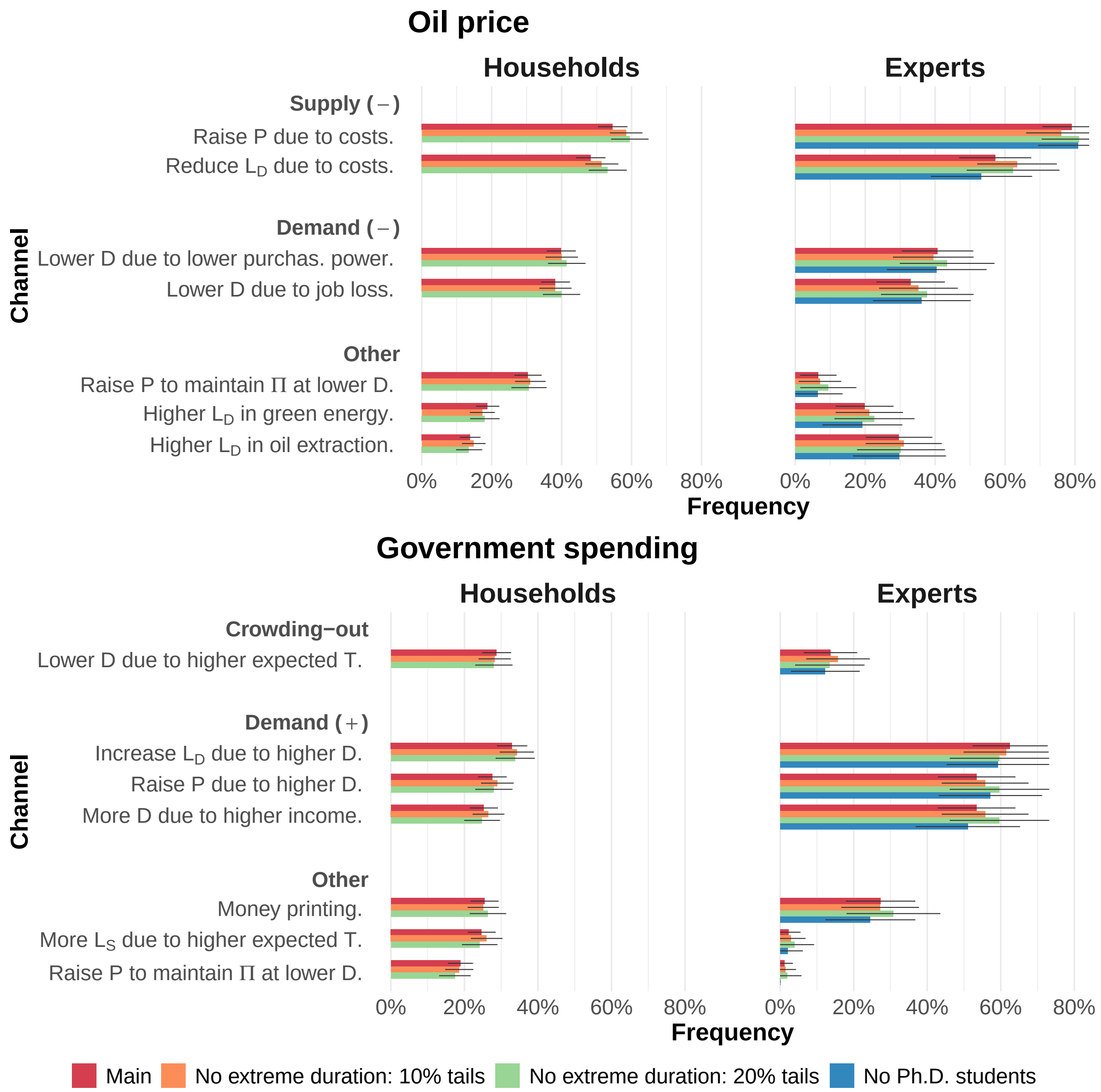


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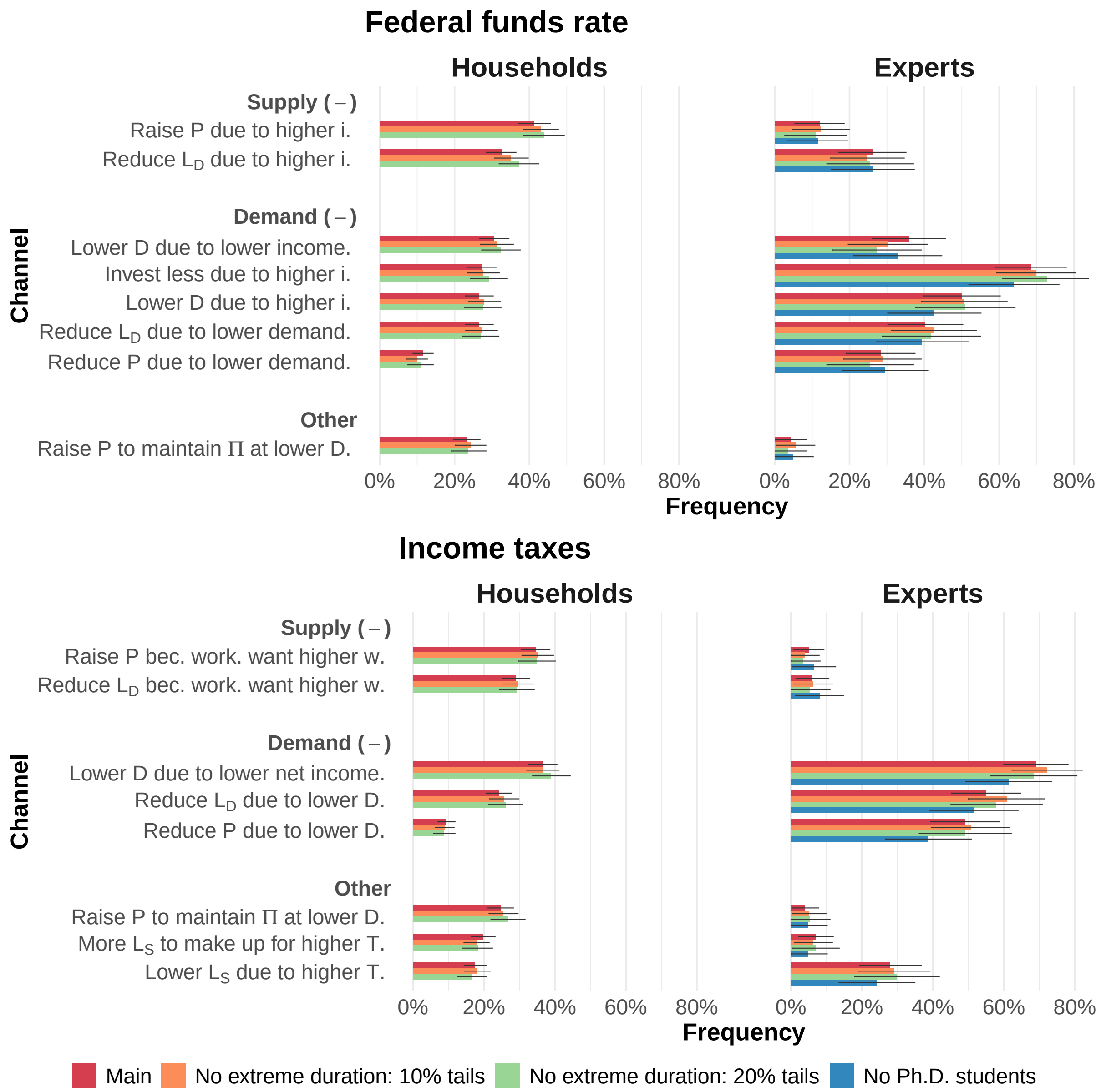
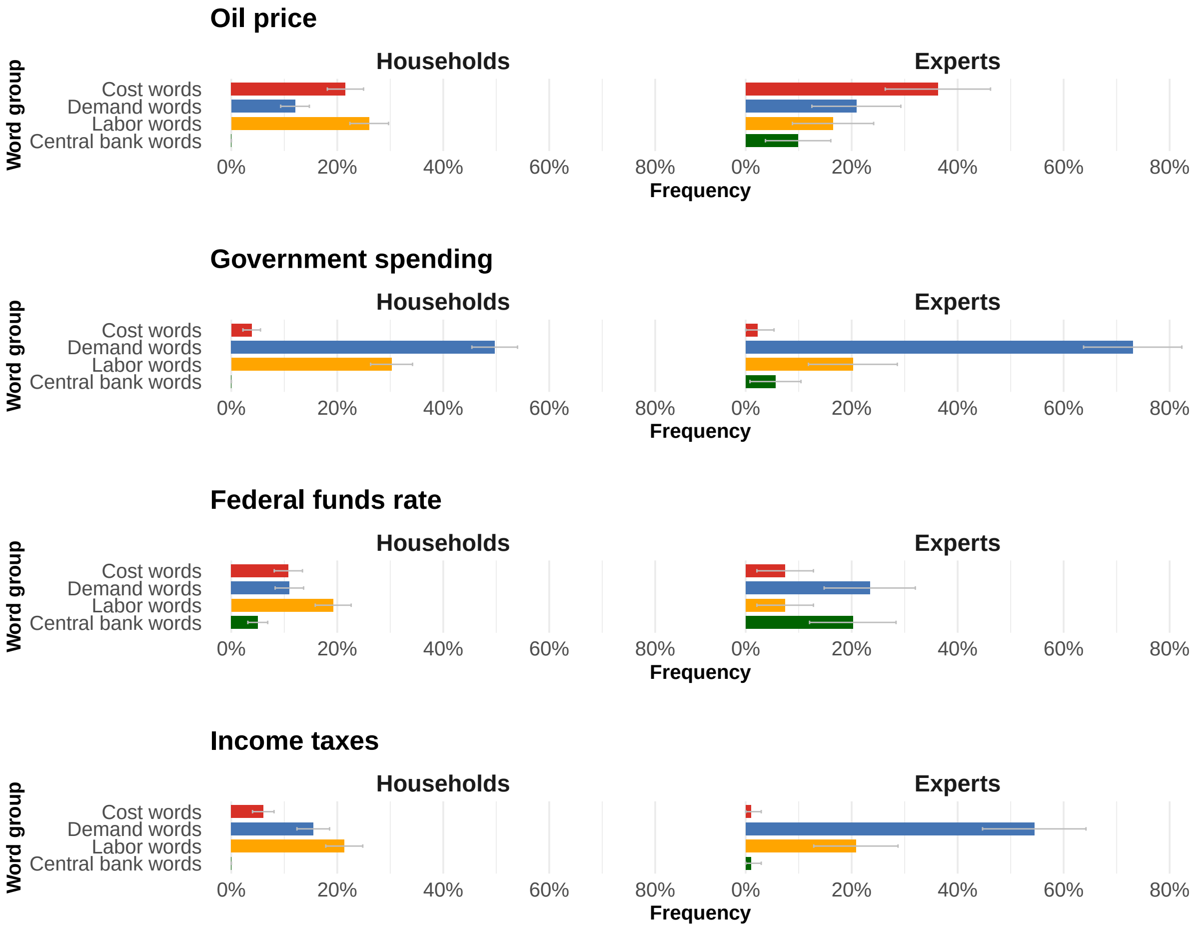
Figure A.6 (continued): Robustness of thoughts of propagation channels



Notes: This figure shows the robustness of the relevant propagation channels that respondents' have on their minds when they make their predictions, using Wave 3 data. Specifically, the figure presents the selected propagation channels for different subsamples. "Main" is the full sample. "No extreme duration: 10% tails" drops the 10% of respondents with the lowest and the 10% of respondents with the highest response duration. Analogously, "No extreme duration: 20% tails" drops both 20% tails of the response duration distribution. "No Ph.D. students" drops all graduate students from the expert sample. The results are displayed separately for each vignette and for households (left panel) and experts (right panel). Error bars display 95% confidence intervals. P abbreviates "firm prices", L_D "labor demand", D "product demand", Π "firm profits", T "taxes", i "interest rates", w "wages", and L_S "labor supply". The full wording of the channels is available in Appendix E.

Figure A.7: Word usage across vignettes (open-text data)



Notes: This figure shows the shares of households (left panel) and experts (right panel) mentioning words from three groups in their open-text response in Wave 3. Cost words include the word (stem) "cost". Demand words include the words or word stems "demand", "buy", "purchas", "invest", "spend", and "consum". Labor words include the words or word stems "layoff", "fire", "hire", "labor", "work", and "job". Central bank words include "monetary policy" and "fed* funds (target) rate". The error bars indicate 95% confidence intervals.

B Additional Tables

Table A.1: Summary statistics: Covariates in the general population samples

Variable	**ACS (2019)**	**Waves 1-2**	**Wave 3**	**Wave 4**	**Wave 5**
Gender					
Female	51%	55%	54%	56%	54%
Age					
18-34	30%	28%	27%	27%	18%
35-54	32%	39%	27%	33%	17%
55+	38%	33%	46%	40%	65%
Household net income					
Median income, in USD	65,712	62,500	62,500	62,500	62,500
Education					
Bachelor's degree or more	31%	32%	38%	46%	51%
Region					
Northeast	17%	21%	22%	22%	24%
Midwest	21%	22%	24%	22%	21%
South	38%	41%	36%	40%	36%
West	24%	16%	18%	16%	19%
Sample size	2,059,945	2,214	2,126	1,521	486

Notes: This table compares the distributions of individual characteristics in our different household waves with those in the American Community Survey (ACS) 2019.

Table A.2: Summary statistics: Covariates in the expert samples

Variable	Wave 1	Wave 2	Wave 3
Gender, age			
Female	26%	14%	17%
Age (median)		52	34
Institution			
Policy institution	16%	16%	11%
Academia	83%	56%	88%
Private sector	0%	16%	1%
Academic position (wave 1 and wave 3)			
Full professor	21%		19%
PhD student	18%		40%
Field of study (WES only)			
Economics		84%	
Business		7%	
Completed Ph.D.		65%	
Region of expertise (WES only)			
Western Europe		42%	
Eastern Europe		12%	
CIS		7%	
North America		8%	
Latin America		10%	
Africa		7%	
Middle East		2%	
Asia		10%	
Oceania		2%	
Sample size	180	908	375

Notes: This table provides an overview of the covariates in the expert sample. Different covariates were collected in the three waves. Demographic data are not available for all respondents.

Table A.3: Overview of data collections

Data collection	**Sample**	**Treatments arms**	**Mechanism questions**
Households Wave 1 (February/March 2019) (N=1,063)	Online panel in collaboration with Research Now	None	Beliefs about propagation mechanisms, financial literacy
Households Wave 2 (July 2019) (N=1,151)	Online panel in collaboration with Lucid	None	Good-bad heuristic, rational inattention, numeracy, beliefs about supply-side mechanisms, subjective interest rate rule
Households Wave 3 (February 2021) (N=2,126)	Online panel in collaboration with Lucid	None	Open-text mechanism associations, structured propagation channels, structured prediction approaches, good-bad heuristic, rational inattention, numeracy, perceived past correlations, knowledge
Households Wave 4 (February 2021) (N=1,521)	Online panel in collaboration with Lucid	Demand prime, cost prime and pure control group	None
Households Wave 5 (June 2021) (N=486)	Online panel in collaboration with Lucid	None	Open-text mechanism associations, structured propagation channels, structured prediction approaches, experiences
Experts Wave 1 (February/March 2019) (N=180)	Experts recruited via email invitation (for details see Section J)	None	None
Experts Wave 2 (July 2019) (N=908)	Experts recruited via the ifo World Economic Survey	None	None
Experts Wave 3 (February 2021) (N=375)	Experts recruited via email invitation (for details see Section J)	None	Open-text mechanism associations, structured propagation channels, structured prediction approaches

Table A.4: Response times

Survey	Wave	10%	25%	50%	75%	90%	Completion rate
Households	1	7m 3s	9m 56s	13m 46s	19m 28s	26m 57s	78%
	2	7m 38s	10m 27s	14m 36s	21m 51s	32m 48s	79%
	3	9m 4s	12m 35s	17m 37s	25m 47s	36m 22s	74%
	4	4m 0s	5m 52s	8m 52s	13m 38s	19m 42s	70%*
	5	7m 4s	10m 22s	15m 8s	23m 6s	31m 36s	68%
Experts	1	2m 44s	3m 50s	5m 21s	8m 11s	14m 2s	78%
	3	5m 12s	6m 55s	9m 14s	14m 18s	22m 53s	62%

*The completion rates vary only negligibly and insignificantly across treatments (control: 70%, costs prime: 67%, demand prime: 72%).

Notes: This table summarizes quantiles of the distribution of the response duration for all survey waves, except Wave 2 of the expert survey. In Wave 2 of the expert survey, collected via the World Economic Survey, we were not able to collect data on response duration. The last column additionally displays the survey completion rate. Households: the fraction of respondents passing the attention check who complete the survey. Experts: the fraction of respondents passing the general instructions who complete the survey.

Table A.5: Disagreement in perceived effects on inflation and unemployment

		Inflation $\Delta\pi$			**Unemployment Δu**		
Vignette	**Case**	$\sigma_{experts}$	$\sigma_{gen.\ pop.}$	p	$\sigma_{experts}$	$\sigma_{gen.\ pop.}$	p
Oil price	rise	0.28	0.74	<0.01	0.27	0.64	<0.01
	fall	0.32	0.71	<0.01	0.28	0.69	<0.01
Gov. spend.	rise	0.22	0.54	<0.01	0.27	0.61	<0.01
	fall	0.20	0.61	<0.01	0.24	0.63	<0.01
Fed. funds rate	rise	0.31	0.52	<0.01	0.27	0.55	<0.01
	fall	0.28	0.59	<0.01	0.25	0.63	<0.01
Inc. taxes	rise	0.29	0.52	<0.01	0.26	0.55	<0.01
	fall	0.25	0.58	<0.01	0.27	0.56	<0.01
Weighted mean		0.27	0.60		0.26	0.61	

Notes: This table reports data from Waves 1 and 2 of the household and expert surveys. It reports the standard deviations of predicted changes in inflation and unemployment in response to shocks for experts and for the general population, respectively, as well as p-values from a Levene's test of equality of variance (trimmed, median-based, bootstrapped) for each rise or fall scenario. For both the household and the expert sample, we exclude extreme predictions, namely both 5% tails of the distribution, to reduce the influence of outliers. The last row presents the average within-scenario standard deviation, weighted by the differential number of respondents across scenarios.

Table A.6: Heterogeneity of priming effects (households only)

Costs prime: Heterogeneous effects

	Word usage (open-text data)		**Inflation prediction**
	Cost-related words	Demand-related words	$\Delta\pi$
	(1)	(2)	(3)
Costs prime	0.065*	0.003	−0.147
	(0.037)	(0.041)	(0.101)
Costs prime × Costs rise	0.022	−0.009	0.193*
	(0.046)	(0.048)	(0.107)
Costs rise	0.109***	0.089***	0.138*
	(0.017)	(0.033)	(0.072)
Constant	0.000	0.040	0.245***
		(0.028)	(0.069)
Observations	761	761	761
R^2	0.029	0.008	0.032

Demand prime: Heterogeneous effects

	Word usage (open-text data)		**Inflation prediction**
	Cost-related words	Demand-related words	$\Delta\pi$
	(1)	(2)	(3)
Demand prime	−0.043	0.132***	−0.102**
	(0.033)	(0.038)	(0.049)
Demand prime × Demand rises	0.056	−0.084*	0.094
	(0.038)	(0.049)	(0.069)
Demand rises	−0.113***	−0.054*	−0.027
	(0.028)	(0.030)	(0.049)
Constant	0.143***	0.118***	0.378***
	(0.025)	(0.023)	(0.035)
Observations	760	760	760
R^2	0.028	0.040	0.007

Notes: This table presents results from the priming study which focuses on the interest rate vignette (Wave 4 of the household survey). "Costs prime" takes value 1 for respondents randomly assigned to be primed on the costs of production. "Costs rise" takes value 1 for respondents who think that firms' costs increase in response to an increase in the federal funds rate, and zero otherwise. "Demand prime" takes value 1 for respondents randomly assigned to be primed on product demand. "Demand rises" takes value 1 for respondents who think that the demand for firms' products increases in response to an increase in the federal funds rate, and zero otherwise. Columns (1) and (2) show effects on word usage in the open-text responses, and Column (3) presents the effects on the inflation forecast. The variable "Cost-related words" takes value 1 for responses which include the word (stem) "cost". "Demand-related words" takes value 1 for responses which use the words or word stems "demand", "buy", "purchas", "invest", "spend", and "consum". $\Delta\pi$ denotes the perceived reaction of the inflation rate. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table A.7: Robustness of experience analysis for government spending vignette (households only)

(A) *Respondent* worked for military supplier (binary indicator)

	Crowding-out	Demand (+)	Costs	Demand	Labor	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Yes	0.029	0.114**	−0.031	−0.022	0.063	−0.072	−0.155**
	(0.056)	(0.057)	(0.021)	(0.055)	(0.054)	(0.055)	(0.066)
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	483	483	483	483	483	483	483
R^2	0.088	0.051	0.028	0.186	0.084	0.139	0.158

(B) *Friend/family* of respondent worked for military supplier (binary indicator)

	Crowding-out	Demand (+)	Costs	Demand	Labor	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Yes	−0.009	0.063	0.003	0.047	0.127***	−0.040	−0.131***
	(0.044)	(0.047)	(0.020)	(0.044)	(0.043)	(0.046)	(0.049)
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	483	483	483	483	483	483	483
R^2	0.088	0.047	0.025	0.188	0.099	0.138	0.160

(C) Ever worked for *government* supplier (self/friend, binary indicator)

	Crowding-out	Demand (+)	Costs	Demand	Labor	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Yes	−0.005	0.077	0.002	0.044	0.141***	−0.057	−0.132***
	(0.045)	(0.048)	(0.022)	(0.045)	(0.044)	(0.045)	(0.051)
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	483	483	483	483	483	483	483
R^2	0.088	0.049	0.025	0.188	0.103	0.139	0.159

Notes: This table presents results from Wave 5 of the household survey. In Columns (1) and (2), it asks whether respondents who made experiences related to the vignettes think about different propagation mechanisms (binary indicators; see Figure 3). In Columns (3) to (5), it tests whether respondents with vignette-related experiences use different word (stems) in their open-text responses (binary indicators; "Costs": cost; "Demand": demand, buy, purchas, invest, spend, consum; "Labor": layoff, fire, hire, labor, work, job). In Columns (6) and (7), it tests whether they make different forecasts (inflation: $\Delta\pi$, unemployment: Δu). The right-hand-side experience variable varies across panels. In Panel A, "Yes" is a binary dummy taking value 1 if respondents *themselves* ever worked for a company that sells to the US military. In Panel B, "Yes" is a binary dummy taking value 1 if respondents' *friends/family* ever worked for a company that sells to the US military. In Panel C, "Yes" is a binary dummy taking value 1 if respondents themselves or friends/family of them ever worker for a company that sells to the US *government.* Control variables comprise age, log income, inflation and unemployment forecasts in the baseline scenario, as well as binary indicators for gender, college education, being a Republican, having taken an economics course at the college level, and census regions. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table A.8: Relationship between prediction approaches and thoughts of propagation channels for households

	Propagation channels in different vignettes							
	Oil price		**Government spending**		**Federal funds rate**		**Income taxes**	
	Supply (–)	Demand (–)	Crowd.-out	Demand (+)	Supply (–)	Demand (–)	Supply (–)	Demand (–)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
News	0.007	0.121**	0.081*	0.102**	0.135***	0.113**	0.189***	0.069
	(0.044)	(0.048)	(0.048)	(0.050)	(0.052)	(0.047)	(0.052)	(0.052)
Knowledge	0.119***	0.026	−0.031	0.098*	0.030	0.160***	0.090	0.199***
	(0.045)	(0.050)	(0.048)	(0.051)	(0.053)	(0.049)	(0.055)	(0.054)
Personal sit.	0.054	0.236***	0.138***	0.077	0.057	0.161***	0.070	0.199***
	(0.047)	(0.050)	(0.052)	(0.053)	(0.060)	(0.051)	(0.052)	(0.052)
Macro exp.	0.192***	0.164***	0.055	0.012	0.209***	0.177***	0.219***	0.152***
	(0.041)	(0.046)	(0.044)	(0.048)	(0.048)	(0.045)	(0.047)	(0.048)
Gut feeling	0.074*	0.062	0.109**	0.010	0.068	0.101**	−0.005	0.051
	(0.043)	(0.047)	(0.048)	(0.051)	(0.051)	(0.050)	(0.048)	(0.048)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	521	521	492	492	477	477	490	490
R^2	0.111	0.119	0.077	0.110	0.089	0.134	0.147	0.120

Notes: This table shows data from the household survey of Wave 3. It regresses the propagation channels that are on respondents' minds while they make their predictions (see Figure 3) on respondents' prediction approaches (see Figure A.5). Each column presents results for a different propagation channel: "Supply (–)" takes value 1 for respondents who choose a negative supply-side propagation channel. "Demand (–)" and "Demand (+)" takes value 1 for respondents choosing a negative or positive demand-side propagation channel, respectively. In the government spending vignette, "Crowding-out" takes value 1 for respondents who select the channel that demand falls due to higher expected future taxes. The explanatory variables are binary and defined as follows: "News" denotes respondents choosing "Things I read or heard in the news." "Knowledge": "My knowledge of economics." "Personal situation": "My personal economic situation today." "Macro experiences": "My memories of economic events in the past." "Gut feeling": "I simply responded based on my gut feeling." Control variables comprise age, log income, inflation and unemployment forecasts in the baseline scenario, as well as binary indicators for gender, college education, being a Republican, having taken an economics course at the college level, and census regions. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table A.9: Households: Political heterogeneity in forecasts

	oil price		gov. spending		fed. funds rate		income taxes	
	$\Delta\pi$	Δu	$\Delta\pi$	Δu	$\Delta\pi$	Δu	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Democrat	−0.014	0.018	−0.086	0.026	0.072	0.020	−0.018	−0.019
	(0.076)	(0.069)	(0.065)	(0.067)	(0.063)	(0.064)	(0.063)	(0.071)
Constant	0.503***	0.319***	0.232***	−0.043	0.144***	0.094**	0.170***	0.280***
	(0.046)	(0.046)	(0.036)	(0.040)	(0.038)	(0.040)	(0.038)	(0.041)
Joint F-test does not detect a significant effect of Democrat.								
p = 0.891								
Observations	1,099	1,099	1,085	1,085	1,123	1,123	1,121	1,121
R^2	0.000	0.000	0.002	0.000	0.001	0.000	0.000	0.000

Notes: This table reports data from Waves 1 and 2 of the representative general population sample. It provides an overview of political heterogeneity in the predicted changes in inflation ($\Delta\pi$) and unemployment (Δu) for each of the different vignettes separately. The joint F-test results from Seemingly Unrelated Regressions (SUR) with respondent-level clustered standard errors and tests for an overall zero effect of *Democrat*. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

C Details on the Derivation of the Theoretical and Empirical Benchmarks

We compile a set of quantitative benchmarks for each shock from the theoretical and empirical macroeconomic literature. This enables us to compare the forecasts of experts and the general population with how the macroeconomic literature conventionally assesses the effect of each shock on inflation and unemployment.

The references for the empirical benchmarks are chosen from frequently cited papers reporting results that are generally referred to as conventional and/or seminal. The majority of these studies apply Vector Auto-Regression (VAR) models. For the theoretical benchmarks, when possible, we consider as an immediate benchmark the most comparable shock in a model that is widely accepted as a standard medium-size New Keynesian DSGE model such as Smets and Wouters (2007) and Galí et al. (2011).

To ensure comparability between the size of shocks in the literature and the vignettes, we first calculate the relative size of the shock in each paper relative to the corresponding shock in the vignettes and rescale appropriately. Since most papers focus on output as the main variable of real activity, we translate the responses into changes in the unemployment rate using Okun's Law using a coefficient of -0.4, based on Ball et al. (2017), which implies a 0.4 p.p. rise in unemployment associated to a 1% fall in output over the course of a year.

In each case, the following five key steps are involved: 1) identifying the size of the shock in the source paper(s), 2) identifying the size of the response of the variables of interest in the source paper(s), 3) determining the size of the shock in the vignettes, 4) rescaling the shocks from the source papers to be of the same size as those from the vignettes, 5) translating output changes into unemployment changes when needed.

Below, we describe the derivation of benchmarks for each vignette. Δy indicates a percent fall in output over four quarters, and $\Delta\pi$ and Δu are the respective four-quarter changes of inflation and the unemployment rate in p.p.[5] All calculations contain a small degree of approximation.

[5]In the case of government and tax shocks in the model of Galí et al. (2011), the responses of output and unemployment exhibited very low persistence, likely due to the specification of the shock process itself. We, therefore, opted for using the average change over four quarters rather than the change in the fourth quarter only.

Oil price Blanchard and Galí (2010) show that since 1984, a date conventionally considered as the beginning of the Great Moderation, the response of the US economy to oil price fluctuations has become milder. We thus derive our benchmark from the authors' post-1984 VAR results. As shown in Table A.10, the benchmark unemployment rate change for an oil price rise of \$30 is 0.4 to 0.45 p.p. For inflation, we derive an empirical benchmark rise of 1.25 to 1.5 p.p.

We choose two papers as theoretical references: Bodenstein et al. (2011) and Balke and Brown (2018). Both papers model the effect of shocks to oil supply outside the US. While the former paper models the US as a purely oil-importing country, the latter treats the US as both oil-producing and oil-importing, providing us with a theoretical benchmark effect ranging from 0.35 to 0.8 p.p. (see Table A.10). Neither of these papers studies the impact of oil supply shocks on domestic inflation.

Oil price - Empirical Source: Blanchard and Galí (2010), Figure 1, Panel B (i.e. post-84). 1) Shock is 10% change in price. 2) $\Delta y = -0.2$, $\Delta\pi = 0.25$. 3) Size of shock in vignette 55% (Wave 2) or 56% (Wave 1) so we approximately multiply the original shocks by 5.5. 4) $\Delta y = -1.1$, $\Delta\pi = 1.4$. 5) Okun's Law: $\Delta u = 0.425$.

Oil price - Theory Source: Bodenstein et al. (2011), Figure 2. 1) Shock is an 8% change in price 2) $\Delta y = -0.15$. 3) Size of shock in vignette 55% (Wave 2) 56% (Wave 1) so we approximately multiply the original shocks by 7. 4) $\Delta y = -1.05$ 5) Okun's Law: $\Delta u = 0.42$.

Source: Balke and Brown (2018), Figure 3. 1) Shock is 2.5% change in price 2) $\Delta y = -0.1$. 3) Size of shock in vignette 55% (Wave 2) 56% (Wave 1) so we approximately multiply the original shocks by 22. 4) $\Delta y = -2.2$ 5) Okun's Law: $\Delta u = 0.88$.

Government spending Regarding government spending, the growing body of studies focusing narrowly on defense spending shocks (Auerbach et al., 2020; Basso and Rachedi, 2019; Nakamura and Steinsson, 2014) would in theory constitute the optimal comparison for the vignette. However, these studies compute fiscal multipliers at the local level (e.g., metro area or state), which are not necessarily applicable to the national level. We therefore refer to studies that examine the impact of spending at the national level and that utilize the same methodologies (i.e., VAR models) as the papers we consider for the other shocks. For the effect of government spending increases on unemployment, we compute an empirical reference range of -0.1 to -0.2 p.p. (Auerbach and Gorodnichenko, 2012; Blanchard and Perotti, 2002; Ramey, 2011). No results are available for the effect on inflation. On the theoretical side, we interpret the exogenous spending shock in Smets and Wouters (2007) and Galí et al. (2011) as a government spending shock. A third source is the government spending shock in Zubairy (2014).[6] The theoretical reference range of values for the change in unemployment after a rise in spending of 0.5% of GDP, reported in Table A.10, is between -0.1 to -0.2 p.p., while the benchmark rise in inflation is 0.15 to 0.2 p.p.

Government spending - Empirical Source: Blanchard and Perotti (2002), Ramey (2011) and sources therein, Auerbach and Gorodnichenko (2012). 1) Shock is 1% of GDP 2) $\Delta y = 0.8$ to 1.5. 3) Size of shock in vignette is 2.4% of 4.2 trillion of government spending. US 2018 GDP is 20.89 trillion according to the Bureau of Economic Analysis, so the shock is about 2.4% of 20% of GDP, which is 0.5% of GDP. So we divide the original shock by 2. 4) $\Delta y = 0.4$ to 0.75. 5) Okun's Law: $\Delta u = -0.16$ to -0.3.

Government spending - Theory Source: Galí et al. (2011), Figure 3. 1) Size of shock is 0.47, with exogenous spending formulated in percent of output, so it can be interpreted as 0.5% of GDP. 2) $\Delta u = -0.1$, $\Delta \pi = 0.2$. 3) The shock in the vignette is very similar in size, so there is no need to scale it. 4) $\Delta u = -0.1$, $\Delta \pi = 0.2$.

Source: Smets and Wouters (2007), Figure 2. 1) Size of shock is 0.5, with exogenous spending formulated in percent of output, so it can be interpreted as 0.5% of GDP. 2) $\Delta y = 0.3$, $\Delta \pi = 0.15$. 3) The shock in the vignette is very similar in size, so there is no need to scale it. 4) $\Delta y = 0.3$, $\Delta \pi = 0.15$. 5) Okun's Law: $\Delta u = -0.12$.

Source: Zubairy (2014), Table 2. 1) Size of shock is 1% of GDP. 2) $\Delta y = 1$. 3) Divide by 2 to make it comparable to the vignette. 4) $\Delta y = 0.5$. 5) Okun's Law: $\Delta u = -0.2$.

Monetary policy Arias et al. (2019) gives an empirical benchmark effect of 0.2 p.p. on unemployment and 0.2 p.p. on inflation for our federal funds rate rise by 50 basis points. This is largely in line with a large and consistent body of VAR evidence since the

[6] Note that we do not use this paper as a benchmark for the response of inflation. Although inflation dynamics resulting from fiscal policy are embedded in the model, they are not discussed in detail by the author.

late 1990's (Bernanke and Mihov, 1998; Bernanke et al., 2005; Christiano et al., 1999; Primiceri, 2005; Romer and Romer, 2004; Stock and Watson, 2001; Uhlig, 2005). As a theoretical reference, we again use Smets and Wouters (2007) and Galí et al. (2011) and arrive at a benchmark of 0.4 to 0.5 p.p. for unemployment and a benchmark of -0.15 p.p. for inflation.

Monetary policy - Empirical Source: Arias et al. (2019) Figure 5 (i.e. estimation on full post-WWII sample, imposing a zero restriction on the systematic response of monetary policy to commodity prices). 1) Shock size is 0.25 p.p. 2) $\Delta y = -0.25$, $\Delta\pi = -0.1$. 3) To make the shock comparable to the vignette, we multiply by 2. 4) $\Delta y = -0.5$, $\Delta\pi = -0.2$. 5) Okun's Law: $\Delta u = 0.2$.

Monetary policy - Theory Source: Galí et al. (2011), Figure 3. 1) Size of shock is 0.15 p.p. 2) $\Delta u = -0.15$, $\Delta\pi = -0.05$. 3) We approximately multiply by 3.3 to make it comparable to the vignette. 4) $\Delta u = 0.5$, $\Delta\pi = -0.16$.

Source: Smets and Wouters (2007), Figure 2. 1) Size of shock is 0.175. 2) $\Delta y = -0.35$, $\Delta\pi = -0.05$. 3) We approximately multiply by 3 to make it comparable to the vignette. 4) $\Delta y = -1$, $\Delta\pi = -0.15$. 5) Okun's Law: $\Delta u = 0.4$.

Income tax rate The empirical benchmark for the unemployment change in response to the increase in the income tax rate by 1 p.p. on average ranges between 0.2 and 0.6 p.p. (Blanchard and Perotti, 2002; Favero and Giavazzi, 2012; Mertens and Ravn, 2012, 2014; Perotti, 2012; Romer and Romer, 2010). To our knowledge, the only paper modeling the impact of labor income tax rate fluctuations in a New Keynesian model is Zubairy (2014). For the theoretical benchmark of the effect on unemployment, we derive a value of 0.06.[7]

Tax rate change - Empirical Source: Blanchard and Perotti (2002), Romer and Romer (2010), Favero and Giavazzi (2012), Mertens and Ravn (2012, 2014), and Perotti (2012). 1) Shock size is a 1% of GDP increase in tax revenue. 2) Range of empirical output multipliers at 4 to 6 quarters is 1 to 3% of GDP. 3) The shock size in the vignette

[7]Once again, we do not use this paper as a benchmark for the response of inflation. Although inflation dynamics resulting from fiscal policy are embedded in the model, they are not discussed in detail by the author.

is approximately 0.5% of GDP. So we divide by 2 to make the shock comparable to the vignette. 4) $\Delta y = 0.5$ to 1.5. 5) Okun's Law: 0.2 to 0.6.

Tax rate change - Theory Source: Zubairy (2014), Table 2. 1) Size of shock is 1% of GDP. 2) $\Delta y = 0.32$. 3) Divide by 2 to make it comparable to the vignette. 4) $\Delta y = 0.15$. 5) Okun's Law: $\Delta u = -0.06$.

Table A.10: Benchmarks for the sign and size of the effects of different shocks

Shock		**Unemployment Response**		**Inflation Response**	
		Sign	Value (p.p.)	Sign	Value (p.p.)
Oil price rise	Theory	+	0.42 to 0.88		
(55% higher price)	Empirical	+	0.42	+	1.4
Government spending rise	Theory	−	−0.1 to −0.2	+	0.15 to 0.2
(2.4% higher growth rate)	Empirical	−	−0.16 to −0.3		
Interest rate rise	Theory	+	0.4 to 0.5	−	−0.15
(0.5 b.p. higher rate)	Empirical	+	0.2	−	−0.2
Tax rate rise	Theory	+	0.06		
(1 p.p. higher rates)	Empirical	+	0.2 to 0.6		

Notes: The table reports the benchmarks for changes in the unemployment rate and the inflation rate four quarters after the respective shock from the theoretical and empirical literature. The values are adjusted to be comparable to the size of the shocks in our survey. Empty fields indicate that – to the best of our knowledge – there is no robust and rigorous evidence on the effect of a given shock on the respective outcome variable of interest.

D Additional Results on Inflation and Unemployment Forecasts

In this Appendix, we provide more detailed results on the household and expert predictions, mostly based on data from Waves 1 and 2.

D.1 Predictions by Direction of the Shock

While we pooled the responses from the rise and (reverse-coded) fall scenarios in the main text, in this section, we present the expert and household predictions separately by the rise and fall scenarios. For brevity, we focus on differences in average (absolute) forecasts about inflation and unemployment between rise and fall scenarios. Both rise scenarios and fall scenarios feature considerable amounts of heterogeneity. As in our baseline analysis, we characterize beliefs about the effects of macroeconomic shocks pooling responses from Waves 1 and 2 as we do not find any qualitative differences in predictions across waves.

D.1.1 Expert Predictions

Oil supply shock Experts predict an increase in unemployment of 0.24 p.p. and a rise in inflation of 0.45 p.p. in the scenario where the oil price increases by $30 (Columns 1 and 2 in Table A.11, Panel A). In the scenario in which the oil price decreases by $30, they predict that the unemployment rate would be lower by 0.13 p.p. and that the inflation rate would be lower by 0.33 p.p. The table reveals that the absolute values of the predictions for the rise and fall scenarios are not statistically distinguishable.

Government spending shock Experts predict a 0.31 p.p. lower unemployment rate and a 0.30 p.p. higher inflation rate in the rise-scenario (Columns 3 and 4 in Table A.11, Panel A). In the fall scenario, they predict that the unemployment rate would be higher by 0.30 p.p. and that the inflation rate would be lower by 0.22 p.p. The absolute value of the unemployment and inflation predictions are not statistically distinguishable between the rise and fall scenarios.

Interest rate shock Our experts predict that unemployment would be higher by 0.29 p.p., while inflation would be lower by 0.15 p.p. in response to an unexpected increase in the interest rate. In the fall scenario, experts predict that unemployment would be lower by 0.19 p.p., and that inflation would be higher by 0.16 p.p. While the absolute value of inflation forecasts is almost identical between rise and fall scenarios, the magnitude of unemployment forecasts is significantly different ($p < 0.05$).

Tax shock On average, experts predict a 0.22 p.p. higher unemployment rate and a 0.11 p.p. lower inflation rate under the rise-scenario (Columns 7 and 8 in Table A.11, Panel A). For the fall-scenario, experts predict a 0.24 p.p. lower unemployment rate and a 0.21 p.p. higher inflation rate. The absolute values of predictions from the rise and fall scenarios are fairly similar and not statistically distinguishable from each other.

Summary Taken together, experts on average perceive no strong asymmetry between the effects of increases or decreases of the different shock variables.

D.1.2 Household Predictions

We continue with the forecasts from the general population, which are displayed in Panel B of Table A.11.

Oil supply shock Households on average predict the unemployment rate to be 0.45 p.p. higher and the inflation rate to be 0.67 p.p. higher in the scenario where the oil price rises by $30. In the oil price fall-scenario, they expect the unemployment rate to be 0.21 p.p. lower and the inflation rate to be 0.33 p.p. lower. Households predict a significantly larger response of inflation and unemployment (in absolute values) in the rise scenario compared to the fall scenario ($p < 0.05$).

Government spending shock Households believe that inflation will be 0.26 p.p. lower in response to an exogenous reduction in government spending, and that it would be higher by 0.13 p.p. in response to an increase in government spending. Households predict a significantly larger response of inflation (in absolute values) in the fall scenario compared to the rise scenario ($p < 0.05$), but similar magnitudes for unemployment. Households on average think that unemployment neither responds to increases nor decreases in government spending.

Interest rate shock Respondents think that unemployment would be 0.17 p.p. higher in response to a rise in interest rates. However, they expect unemployment to remain unchanged in response to a decrease in interest rates. Respondents expect a 0.15 p.p. *lower* inflation rate in response to a fall in the federal funds target rate and a 0.19 p.p. *higher* inflation rate in response to a rise. While the responses to the rise and fall scenario are fairly symmetric for inflation rate predictions, they are statistically different for unemployment ($p < 0.05$).

Tax shock Respondents think higher taxes would lead to a 0.30 p.p. higher unemployment rate, and that lower taxes would result in a 0.25 p.p. lower unemployment rate. Moreover, they predict that a tax hike would result in a 0.21 p.p. higher inflation rate, while they forecast a 0.12 p.p. lower inflation rate in response to a tax cut. The absolute values of predictions from the rise and fall scenarios are not statistically distinguishable from each other.

Summary Taken together, different from the expert forecasts, we find some evidence of asymmetry in households' predicted responses of inflation and unemployment between the rise and the fall scenarios.

Table A.11: Inflation and unemployment forecasts by direction of the shocks

(A) Experts

	Oil price		Government spending		Federal funds rate		Income taxes	
	$\Delta\pi$	Δu	$\Delta\pi$	Δu	$\Delta\pi$	Δu	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fall	−0.327***	−0.130***	−0.224***	0.303***	0.155***	−0.188***	0.209***	−0.235***
	(0.042)	(0.037)	(0.024)	(0.026)	(0.027)	(0.025)	(0.031)	(0.028)
Rise	0.449***	0.235***	0.299***	−0.311***	−0.152***	0.289***	−0.107***	0.221***
	(0.030)	(0.030)	(0.021)	(0.028)	(0.033)	(0.025)	(0.035)	(0.036)
p-values from additional tests								
Fall≠Rise	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
|Fall|≠|Rise|	0.018	0.028	0.019	0.837	0.953	0.004	0.028	0.772
Observations	482	481	474	475	517	513	515	521
R^2	0.333	0.120	0.373	0.352	0.096	0.270	0.093	0.164

(B) General Population

	Oil price		Government spending		Federal funds rate		Income taxes	
	$\Delta\pi$	Δu	$\Delta\pi$	Δu	$\Delta\pi$	Δu	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fall	−0.331***	−0.210***	−0.261***	0.042	−0.150***	−0.028	−0.122***	−0.250***
	(0.050)	(0.049)	(0.045)	(0.045)	(0.048)	(0.045)	(0.043)	(0.051)
Rise	0.667***	0.445***	0.135***	−0.023	0.193***	0.174***	0.206***	0.298***
	(0.053)	(0.047)	(0.041)	(0.046)	(0.037)	(0.043)	(0.043)	(0.044)
p-values from additional tests								
Fall≠Rise	<0.001	<0.001	<0.001	0.310	<0.001	0.001	<0.001	<0.001
|Fall|≠|Rise|	<0.001	0.001	0.038	0.762	0.481	0.019	0.171	0.471
Fall: (A)≠(B)	0.954	0.192	0.467	<0.001	<0.001	0.002	<0.001	0.794
Rise: (A)≠(B)	<0.001	<0.001	<0.001	<0.001	<0.001	0.020	<0.001	0.180
Observations	1,099	1,099	1,085	1,085	1,123	1,123	1,121	1,121
R^2	0.159	0.085	0.042	0.001	0.029	0.014	0.027	0.056

Notes: This table compares beliefs about the quantitative effects of the different macroeconomic shocks across the fall and rise scenarios for experts (Panel A) and for households (Panel B). "Fall" takes value 1 for the predictions in the fall scenario, and "Rise" takes value 1 for the rise scenario. $\Delta\pi$ denotes the predicted change in the inflation rate compared to the baseline scenario. Δu denotes the predicted change in the unemployment rate compared to the baseline scenario. Additionally, p-values from the following tests are reported: tests whether there is a difference between rise and fall predictions (Fall≠Rise), tests whether there is a difference in the absolute size of rise and fall predictions (|Fall|≠|Rise|), tests whether there is a difference in fall predictions between experts and the general population (Fall: (A)≠(B)), and tests whether the rise predictions differ between experts and households (Rise: (A)≠(B)). Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

D.2 Predictions about Joint Movement of Inflation and Unemployment

In the main text, we focus on forecasts about inflation and unemployment separately. In this subsection, we examine households' and experts' forecasts of the joint response of inflation and unemployment to macroeconomic shocks.

D.2.1 Predicted Co-movement (Waves 1 and 2)

To describe households' and experts' predicted co-movement, we focus on our main data collection in Waves 1 and 2, and pool predictions under the rise scenario with (reversed) predictions under the fall scenario. Throughout this section, we divide forecasts into five categories: i) inflation and unemployment both decrease; ii) inflation falls, while unemployment increases; iii) inflation rises, while unemployment falls; iv) both increase; v) other, which includes all cases where one variable is predicted to stay constant. In our discussion we focus on categories i)-iv), and treat category v) as residual. The fractions predicting joint movement in different directions are displayed in Figure A.8.

Oil supply shock Among households, a view that both inflation and unemployment increase in response to oil supply shocks is most prevalent (49% of responses). Fractions between 9% and 13% predict both to fall or movement in opposite directions.

Among experts, a majority (59%) predict both unemployment and inflation to increase, while 15% predict inflation to increase and unemployment to fall. Only very small fractions predict co-movement featuring a decrease in inflation.

Government spending shock We find strong heterogeneity in households' beliefs about the co-movement of inflation and unemployment in response to government spending shocks. Fractions between 17% and 26% predict both variables to fall, inflation to rise and unemployment to fall, or both variables to rise, while 8% forecast a fall in inflation and a rise in unemployment.

Strikingly, experts' views on the joint response of unemployment and inflation are much more homogeneous. 68% of experts view the government spending shock as a demand-side shock featuring an increase in inflation and a fall in unemployment, while only 6% predict both variables to rise, and almost no expert predicts both variables to fall or unemployment to increase and inflation to decrease.

Interest rate shock Households disagree strongly on the co-movement of unemployment and inflation in response to monetary policy shocks. A view that both variables will increase is most prevalent (36%), while fractions between 11% and 17% predict both variables to fall or movement in opposite directions.

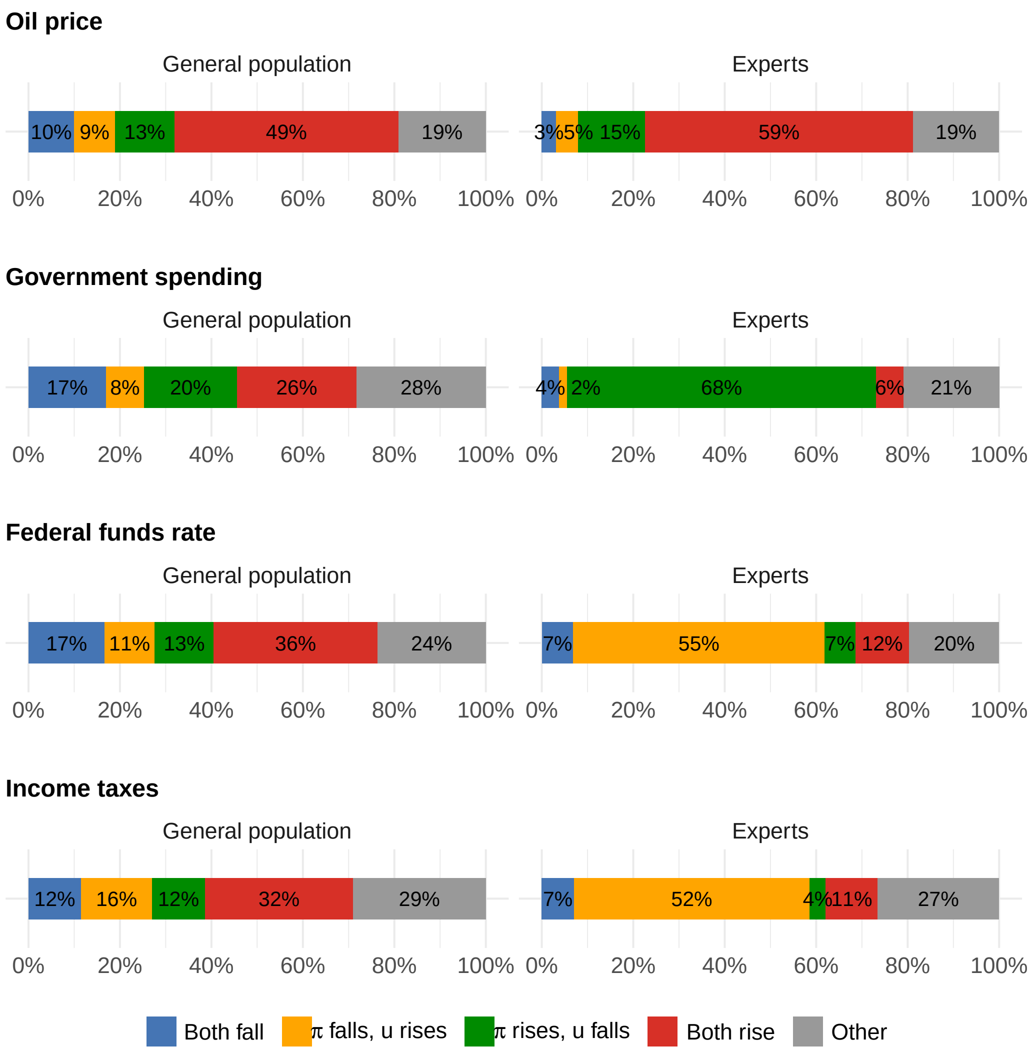
Experts agree much more on the joint response, with a majority of 55% taking the common view that an interest rate hike increases unemployment and decreases inflation. Fractions of 7% and 12% predict inflation to rise and unemployment to fall or both to rise, respectively, while only 7% predict both to fall.

Tax shock Households' beliefs about co-movement under the tax shock are very similar as under the interest rate shock, with a view that both variables will increase being most prevalent (32%).

Similarly, a majority (52%) of experts view a tax hike as increasing unemployment and decreasing inflation, while only fractions between 4% and 11% predict both variables to move but in different ways than predicted by the most common view in the literature.

Summary Taken together, these results highlight that there is strong disagreement among households about the joint response of inflation and unemployment to aggregate shocks, with majorities of households predicting co-movement different to literature benchmarks under all shocks. In contrast, heterogeneity in expert predictions is almost exclusively driven by making a forecast in line with theory benchmarks vs falling into the "other" category, where one variable is predicted to stay constant.

Figure A.8: Forecasts of the joint movement of inflation and unemployment in response to macroeconomic shocks



Notes: This figure presents the forecasts of the joint movement of inflation and unemployment in response to macroeconomic shocks measured in Waves 1 and 2. Directional predictions in the fall scenarios are reversed to render them comparable to rise predictions. It compares the forecasts of the general population (left column) to those of experts (right column).

D.2.2 Associations and predicted co-movement (Wave 3)

We also use our data from Wave 3 of the household survey to study the correlation of thoughts about propagation mechanisms with forecasts of the co-movement of unemployment and inflation. We focus on correlations of thoughts with a dummy indicating a predicted co-movement in line with literature benchmarks. For the household survey, Table A.12 shows correlations of forecasts with thoughts about propagation channels elicited under the structured survey questions. In the context of the oil price vignette, thoughts about propagation channels featuring reductions in demand or supply are strongly positively associated with predicting a benchmark-consistent co-movement. In the context of the government spending vignette, thoughts about channels indicating reductions in demand are negatively related to forecasting benchmark-consistent co-movement, while thoughts about channels featuring demand increases are positively related. In the context of the interest rate vignette, supply-side propagation channels are negatively related to predicting a benchmark-consistent co-movement, while demand-side propagation mechanisms are positively related. In the context of the income tax vignette, structured propagation channels related to a negative demand shock are positively associated with predicting a benchmark-consistent co-movement.

Table A.13 repeats the analysis for the expert survey of Wave 3. The results show that experts who think of propagation channels that are conventionally featured in macroeconomic models are more likely to forecast a co-movement of inflation and unemployment that is in line with the benchmarks from the literature.

Table A.12: Households: Thoughts of propagation channels correlate with benchmark-consistent co-movement of unemployment and inflation predictions

	Indicator: Both π and u prediction in line with benchmarks			
	Oil price	Government spending	Federal funds target rate	Income taxes
	(1)	(2)	(3)	(4)
Oil: Supply (–)	0.270***			
	(0.045)			
Oil: Demand (–)	0.201***			
	(0.041)			
Gov.: Crowding-out		−0.094**		
		(0.037)		
Gov.: Demand (+)		0.188***		
		(0.036)		
Fed.: Supply (–)			−0.065***	
			(0.024)	
Fed.: Demand (–)			0.080***	
			(0.022)	
Tax: Supply (–)				−0.013
				(0.019)
Tax: Demand (–)				0.059***
				(0.019)
Constant	0.259***	0.167***	0.058***	0.029**
	(0.039)	(0.028)	(0.018)	(0.013)
Observations	557	519	520	530
R^2	0.116	0.066	0.030	0.018

Notes: This table presents results from wave 3 of the household survey. The outcome variable is a dummy which takes value 1 if the directions of both the inflation and the unemployment forecast are consistent with the literature benchmarks. “Supply (–)” takes value 1 for respondents who choose a negative supply-side propagation channel in the structured question. “Demand (–)” and “Demand (+)” take value 1 for respondents choosing a negative or positive demand-side propagation mechanism in the structured survey question, respectively. “Crowding-out” takes value 1 for respondents who select the channel that demand falls due to higher expected future taxes.

Table A.13: Experts: Thoughts of propagation channels correlate with benchmark-consistent co-movement of unemployment and inflation predictions

	Indicator: Both π and u prediction in line with benchmarks			
	Oil price	Government spending	Federal funds target rate	Income taxes
	(1)	(2)	(3)	(4)
Oil: Supply (–)	0.460***			
	(0.098)			
Oil: Demand (–)	0.280***			
	(0.099)			
Gov.: Crowding-out		−0.063		
		(0.146)		
Gov.: Demand (+)		0.553***		
		(0.095)		
Fed.: Supply (–)			−0.116	
			(0.106)	
Fed.: Demand (–)			0.478***	
			(0.104)	
Tax: Supply (–)				0.137
				(0.154)
Tax: Demand (–)				0.381***
				(0.098)
Constant	−0.010	0.139*	0.186**	0.138*
	(0.072)	(0.075)	(0.092)	(0.082)
Observations	91	88	92	100
R^2	0.198	0.227	0.142	0.102

Notes: This table presents results from wave 3 of the expert survey. The outcome variable is a dummy which takes value 1 if the directions of both the inflation and the unemployment forecast are consistent with the literature benchmarks. “Supply (–)” takes value 1 for respondents who choose a negative supply-side propagation channel in the structured question. “Demand (–)” and “Demand (+)” take value 1 for respondents choosing a negative or positive demand-side propagation mechanism in the structured survey question, respectively. “Crowding-out” takes value 1 for respondents who select the channel that demand falls due to higher expected future taxes.

D.3 Robustness

Robustness to incentives To examine the role of effort and attention in responses to the hypothetical vignettes, we provide a random subset of respondents with monetary incentives in Wave 1 of the household survey. We inform these respondents that we asked experts the same questions and that for one randomly selected case they can earn an additional \$0.50 if their response is at most 0.2 p.p. away from the average expert response. This amount corresponds to approximately one third of the show-up fee. Of course, this incentivizes households to state their second-order beliefs about experts' beliefs, which might differ from the households' own beliefs. To address this concern, we also measure the perceived objectivity and accuracy of experts.

Incentives moderately increase the fraction of benchmark-consistent predictions of inflation by 4 p.p. (Table A.14 Column 1), while the predictions regarding unemployment are completely unaffected (Column 2). In a joint test, no effect of incentives on consistency of predictions with the benchmarks can be detected (Column 4), even though incentivized respondents spend roughly 40 seconds longer in the vignettes – a 25% increase in response time (Column 6). The effect of incentives does not significantly vary with a measure of trust in experts (Panel B of Table A.14).

Table A.14: Households: Robustness: Incentive effects

Panel A: Incentives

	$\Delta\pi$✓	Δu✓	both✓	all✓	time instructions	time vignettes
	(1)	(2)	(3)	(4)	(5)	(6)
Incentives	0.044**	−0.000	0.038**	0.022	−0.537	38.589***
	(0.022)	(0.023)	(0.019)	(0.016)	(10.361)	(13.236)
Constant	0.447***	0.508***	0.216***	0.477***	112.689***	165.001***
	(0.015)	(0.017)	(0.013)	(0.011)	(9.261)	(6.490)
Observations	1,063	1,063	1,063	1,063	1,063	1,063
R^2	0.004	0.000	0.004	0.002	0.000	0.008

Panel B: Incentives crossed with subjective perception of expert accuracy

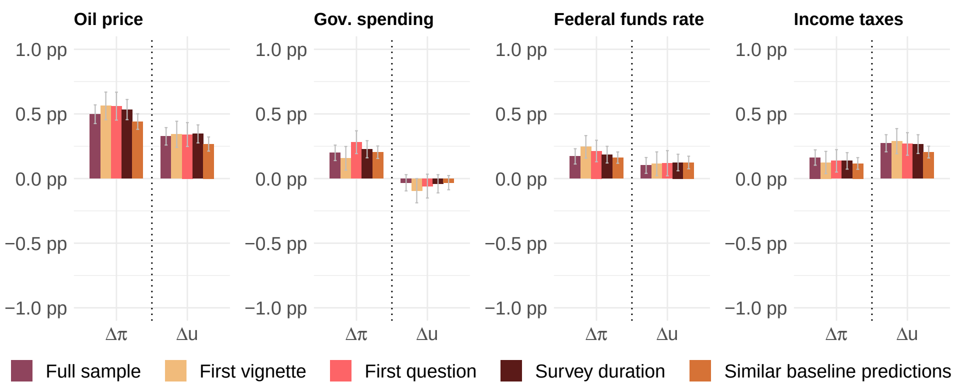
	$\Delta\pi$✓	Δu✓	both✓	all ✓	time instructions	time vignettes
	(1)	(2)	(3)	(4)	(5)	(6)
Incentives	0.040*	0.001	0.038**	0.020	−1.128	38.692***
	(0.022)	(0.023)	(0.019)	(0.016)	(10.555)	(13.029)
Experts acc.	0.006	−0.015	0.012	−0.005	7.261	5.663
	(0.015)	(0.017)	(0.013)	(0.012)	(7.068)	(4.976)
Incent. × Exp. acc.	−0.017	−0.007	−0.029	−0.012	0.246	7.697
	(0.022)	(0.024)	(0.018)	(0.017)	(9.717)	(17.501)
Constant	0.449***	0.506***	0.217***	0.477***	113.222***	165.118***
	(0.015)	(0.017)	(0.013)	(0.011)	(9.502)	(6.577)
Observations	1,049	1,049	1,049	1,049	1,049	1,049
R^2	0.004	0.003	0.006	0.003	0.002	0.010

Notes: This table provides an overview of the effect of monetary incentives on the response behavior of the general population in Wave 1. A forecast is classified as benchmark-consistent if it follows the same qualitative direction as literature benchmark. Panel A displays the effect on the benchmark-consistency of forecasts and response times. *Incentives* constitutes a binary variable that takes value 1 for incentivized respondents. For each individual, $\Delta\pi$✓measures the fraction of benchmark-consistent inflation forecasts (out of two), Δu✓the fraction of benchmark-consistent unemployment forecasts (out of two), *both*✓the fraction of vignettes in which both forecasts are benchmark-consistent (out of two), and *all*✓the overall fraction of benchmark-consistent forecasts (out of four). Thus, the coefficients can be interpreted as the effect of incentives on the probability of a benchmark-consistent forecast. Columns 5 and 6 show effects on the time spent reading the instructions and the total time spent on the vignettes. Panel B examines heterogeneity according to the respondents' perceived accuracy of experts (*Experts acc.*, standardized) to rule out that incentives might be ineffective merely because expert forecasts are perceived as inaccurate. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Order effects To account for potential order effects, we randomize both the order of vignettes as well as the order in which unemployment and inflation forecasts are elicited. Figure A.9 shows average quantitative forecasts in the vignettes for households pooling across Waves 1 and 2, separately for (i) all forecasts, (ii) forecasts under the first vignette faced by each respondent, (iii) forecasts for the first variable (either unemployment or inflation) in both vignettes faced by a respondent. The figure highlights that the responses are very similar, indicating a limited relevance of order effects.

Attention to the survey Figure A.9 also displays forecasts separately (iv) for a restricted sample excluding respondents in the upper and lower 10% tails of the survey time distribution, and (v) for a restricted sample excluding the 20% of respondents with the largest absolute difference in predictions in the baseline scenarios across the two vignettes to which they responded.[8] Our figure highlights very similar patterns for those two different samples, suggesting that a lack of attention to the survey does not account for the patterns observed in the household sample.

Figure A.9: Households: Procedural robustness of quantitative beliefs



Notes: This figure provides an overview of procedural robustness checks that repeat the main analysis for different sub-samples of households from Waves 1 and 2. It pools beliefs for the "rise" and "fall" scenario. Predictions in the fall scenarios are reversed to render them comparable to rise predictions. Error bars show 95% confidence intervals using robust standard errors. Δu denotes the expected change in the unemployment rate compared to the baseline scenario. $\Delta\pi$ denotes the expected change in the inflation rate compared to the baseline scenario. "Full sample" denotes the full sample and, thus, replicates the results of the main Figure 2. "First vignette" contains only the responses to the first vignette, while "First question" focuses only on responses to the first forecast question (in both vignettes). "Survey duration" excludes both 10% tails in the survey duration distribution, and "Similar baseline prediction" excludes the 20% respondents with the largest absolute difference in baseline predictions across the two vignettes they responded to.

[8]Given that the baseline scenarios ask respondents to assume no change in the shock variable of interest, large differences in predictions between the two baseline scenarios each respondent faced could indicate inattention or random response behavior.

E Structured Question on Propagation Channels

The order of items is randomized across participants, except for *None of the above* which is always the last response option.

Oil vignette

How did you come up with your predictions?

The following statements describe different thoughts you might have had on your mind while making your predictions for the alternative scenario. **Did you have any of these thoughts on your mind?** Please tick all that you had on your mind.

- ☐ Due to lower incomes or job loss, households cut back on their spending.
- ☐ Businesses face lower demand for their products, so they increase their product prices to keep profits at the same level.
- ☐ The higher cost of oil makes it more attractive to use alternative energy sources and energy-saving technologies, which leads to job creation.
- ☐ To make up for the higher cost of production, businesses reduce their workforce.
- ☐ Because higher product prices lower their purchasing power, households cut back on their spending.
- ☐ To make up for the higher cost of production, businesses increase product prices.
- ☐ The US oil extraction industry profits from the higher oil price, which leads to job creation.
- ☐ *None of the above.*

Government spending vignette

How did you come up with your predictions?

The following statements describe different thoughts you might have had on your mind while making your predictions for the alternative scenario. **Did you have any of these thoughts on your mind?** Please tick all that you had on your mind.

- ☐ Because of higher incomes, households increase their spending.
- ☐ Because there is more demand for their products, businesses increase their product prices.
- ☐ Businesses face lower demand for their products, so they increase their product prices to keep profits at the same level.
- ☐ Households expect to pay higher taxes in the future, which may be needed to pay back the new government debt. Therefore, households work more.
- ☐ Households expect to pay higher taxes in the future, which may be needed to pay back the new government debt. Therefore, households cut back on their spending.
- ☐ Because there is more demand for their products, businesses increase their workforce.
- ☐ To help the government finance the additional spending, the central bank prints money.
- ☐ *None of the above.*

Interest rate vignette

How did you come up with your predictions?

The following statements describe different thoughts you might have had on your mind while making your predictions for the alternative scenario. **Did you have any of these thoughts on your mind?** Please tick all that you had on your mind.

- ☐ Because there is less demand for their products, businesses reduce their workforce.
- ☐ Businesses face lower demand for their products, so they increase their product prices to keep profits at the same level.
- ☐ To make up for the higher cost of borrowing, businesses reduce their workforce.
- ☐ Because there is less demand for their products, businesses reduce their product prices.
- ☐ Because higher interest rates make it more attractive to save and less attractive to borrow, households cut back on their spending.
- ☐ Due to the higher cost of borrowing, businesses pursue fewer investment projects.
- ☐ To make up for the higher cost of borrowing, businesses increase product prices.
- ☐ Because of lower incomes or job loss, households cut back on their spending.
- ☐ *None of the above.*

Taxation vignette

How did you come up with your predictions?

The following statements describe different thoughts you might have had on your mind while making your predictions for the alternative scenario. **Did you have any of these thoughts on your mind?** Please tick all that you had on your mind.

- ☐ Because workers demand higher wages to make up for the higher income taxes, businesses reduce their workforce.
- ☐ Because workers demand higher wages to make up for the higher income taxes, businesses increase their product prices.
- ☐ Because there is less demand for their products, businesses reduce their product prices.
- ☐ Because of lower disposable incomes, households cut back on their spending.
- ☐ Because higher taxes make it less attractive to work, households work less.
- ☐ Because there is less demand for their products, businesses reduce their workforce.
- ☐ Businesses face lower demand for their products, so they increase their product prices to keep profits at the same level.
- ☐ To make up for their reduced disposable incomes, households work more.
- ☐ *None of the above.*

F Robustness to Using Hand-coded Measures of Thoughts Based on Open-text Responses

In Wave 3 of our household and expert surveys, we elicit respondents' thoughts while they are forecasting the changes in unemployment and inflation in response to hypothetical shocks using an open-text question on the forecast survey screen. Specifically, we ask respondents to "tell us how [they] come up with their prediction" and about "[their] main considerations in making the prediction". In this appendix section, we demonstrate robustness of our findings on thoughts about different propagation channels presented in Section 4 to using alternative measures of thoughts based on hand-coding of the open-text responses.

F.1 Response Types

Coding scheme We first classify the open-ended text responses into broad response type categories. We use the following categories: i) "Mechanism", including all responses mentioning thoughts related to economic propagation mechanisms of the shocks; ii) "Model", including all responses mentioning a specific economic theory or model (only done by experts); iii) "Guess", indicating responses that express uncertainty or explicitly mention that the forecast is a guess; iv) "Politics", which includes general political or normative statements; v) "Historical", including reference to how things "typically" evolve or how things have evolved in the past; vi) "Misunderstanding", denoting whether respondents misunderstood features of the vignette; vii) "Restates prediction", indicating whether the open-text response repeats or summarizes the provided forecasts of unemployment and inflation; viii) "Endogenous shock", indicating whether respondents mention that e.g. changes in interest rates are the Fed's response to other developments in the economy; ix) "Other", which is a residual category for responses not falling into any of the other categories (e.g. including statements about general trends in the economy not specifically related to the shocks). We allow each response to fall into more than one category. Table A.15 provides an overview of the different categories, including example responses falling into each category.

Inter-rater reliability Each open-text response is independently coded by two reviewers.[9,10] This allows us to estimate the inter-rater reliability, i.e. the degree of agreement among independent raters. We observe a high inter-rater reliability for the response type classification: For 77% of the assigned codes, both reviewers agree.

Results The results are shown in Figure A.10. By far the largest fraction of open-text responses among both households and experts are classified as "mechanism associations", i.e. thoughts related to economic propagation mechanisms, such as changes in consumer spending or the hiring decisions of firms. 39% of households express thoughts about propagation mechanisms, while 79% of experts do so. In addition, 22% of experts explicitly refer to an economic model (such as the New-Keynesian model), compared to none of the households. These patterns suggest that experts are more likely than households to think about the shocks through the lens of economic theories. In contrast, households are more likely to comment on general political issues (10%), such as which political party is in power. Almost none of the experts do so. Likewise, 13% of households indicate that their prediction is based, at least in part, on a guess, compared to only 7% of experts. References to economic events from the past are equally frequent among households and experts (4% and 6%, respectively), and only few responses reveal that participants misunderstand features of the vignette or perceive the macroeconomic shocks as endogenous. Finally, 29% of household responses fall into a residual category, which e.g. captures general statements about the economy, compared to 6% among experts. Thus, we find overall similar patterns as based on our structured question of what approach respondents used in their predictions (see Figure A.5).

[9]For training purposes, about 50 responses of each vignette were coded independently by four coders. The coding of these responses was subsequently discussed. We do not use these responses to estimate the inter-rater reliability.

[10]In Wave 4 (priming study), each response is coded by only one reviewer.

Table A.15: Response type categories

Category	Explanation	Examples
Mechanism	Mentions (part of the) propagation mechanisms of the shock.	"I think people will cutback on expenses." "Banks will be more reluctant to borrow more money, which leads to charging people more interest, which will decrease their economic activity. When businesses have less ability to take out loans, they may hire less people." "An increase in oil prices will cause increases in costs of delivery, driving, heating and production. It would also increase the price of goods derived from oil such as plastics and fertilizers."
Model	Makes reference to a specific economic theory or model. *Occurs only among experts.*	"I am thinking of a textbook NK model of an economy at a steady state experiencing a nominal interest rate shock. Quantitatively, I expect relatively small effects but I do not have much confidence in the actual magnitudes." "transmission via Phillips curve" "The classic AD/AS model is still my reference point for these questions, and in that model this is an aggregate supply shock, raising prices and lowering output through a rise in the costs of production. The increase of 30% is substantial, but the US economy is relatively insulated from oil price fluctuations in the current economy, so I chose relatively small movements in both inflation and unemployment."
Guess	States that response was a guess or indicates uncertainty or low confidence in response.	"I just took a guess." "I don't know anything about any of this stuff. I'm just making guesses. It's not at all easy to understand or speculate about." "I'm not an economist nor do I follow economic trends so these really are wild guesses. It depends on who is in office and how the rest of the world is doing."
Politics	Makes a political statement or talks about what policymakers should do.	"This pandemic has turned this world upside down, due to the Non responce from the former President, it will take forever to get back to even a new normal" "The government should take measures to reduce unemployment" "The effects of a Biden presidency will be disastrous."

Notes: See next page.

Table A.15 (continued): Response type categories

Category	**Explanation**	**Examples**
Historical	Mentions how things have evolved in the past or how things typically evolve.	"Any time government spending goes up so does every thing else. Unemployment also tends to go up." "i based on the situation presented to me. i also thought about how it has happened in the past" "what i have seen in the past"
Misunderstanding	Gives a response that indicates misunderstanding of or unwillingness to accept key features of the vignette.	"In the alternative scenario the Federal Target Rate rises and there is no change in economic condition." "The above states that everything would remain the same so I don't believe anything would change with the tax rate" "Even when the government announces that a rate increase is temporary, it never is. The government is so far in debt right now that the only way they can raise more money to service that debt is to inflate the taxes paid by workers."
Re-states prediction	Repeats (part of) the forecasts about unemployment and inflation.	"The unemployment rate wouldn't rise but the inflation rate may rise slightly" "I believe that if the interest rate goes up, so will the inflation rate."
Endogenous shock	Misunderstood the exogenous shocks as happening in response to other events, i.e. as being endogenous.	"The main consideration in my predictions is due to the economy must be doing well in order to have the income tax rate increase. In order to achieve this unemployment must be low. People's income must have jump too." "The federal reserve doesn't change rates just to do so. There has to be a reason. Given that I expect unemployment and or the inflation rate to be a little higher than expected."

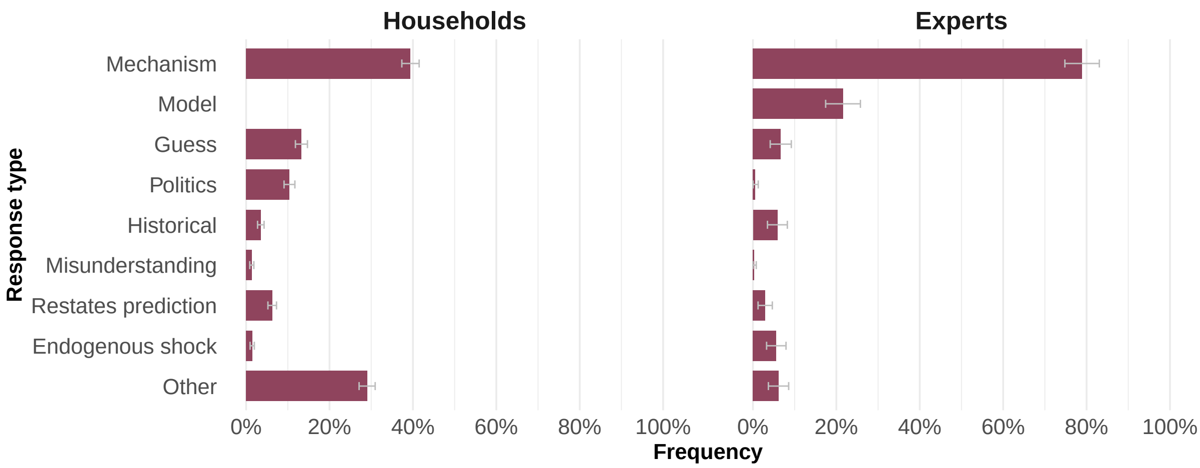
Notes: See next page.

Table A.15 (continued): Response type categories

Category	Explanation	Examples
Other	Residual category.	"the unemployment rate will be high" "I would assume that supply and demand will start to return once the pandemic is largely controlled" "Unless they're going to make more jobs, its going to raise "

Notes: This table provides details and examples on the response types into which we classify responses to the open-text question. Each response is allowed to fall into more than one category. The examples (except for the "model" category) are based on the household sample, given that there is much more heterogeneity in relevant response categories among households than among experts.

Figure A.10: Manually coded "response types" in the open-text data



Notes: This figure presents the manually-coded "response type" classification (open-text data) of households' and experts' responses in Wave 3, averaged across all four vignettes. Error bars display 95% confidence intervals. "Mechanism": Respondent mentions an economic mechanism through which the shock could affect the economy. "Model": Response explicitly mentions an economic model. "Guess": Respondent indicates that they made a guess. "Politics": Political issues and statements. "Historical": Reference to historical events or data. "Misunderstanding": Misunderstanding of vignette instructions. "Restates prediction": Restatement of prediction in the open-ended text. "Endogenous shock": Respondents who misperceive the exogenous shock as endogenous. "Other": Residual category.

F.2 Mechanism Associations

Next, we zoom in on those 39% of responses describing elements of a propagation mechanism (i.e. all responses falling into the "Mechanism" category).

F.2.1 Coding Scheme

Variable codes For each response in the "Mechanism" category, we hand-code which specific elements of a propagation mechanism are mentioned. For example, a respondent might mention that firms' costs of borrowing increase, or that households cut back on their spending. We use the following coding scheme: i) We identify variables that are mentioned by the respondent, e.g. "costs borrowing firms" or "labor demand". For many variables, we have a general form (e.g. "demand") and a more specific form (e.g. "demand households") to accommodate different levels of detail given in the open-text responses. ii) When applicable, we code the direction of the change the respondent mentions for this variable ("+" for an increase, "–" for a decrease, "o" for no change; no extension if no direction is mentioned). In addition, we include a range of codes not referring to any specific variable but indicating why a respondent thinks that a shock has no major effect (e.g. "minor" if respondents argue that the shock is too small in size to have any effect). Table A.16 presents all codes we use to classify elements of propagation channels. Table A.18 displays examples of assigned variable codes for selected mechanism responses.

Aggregation into broader mechanisms Finally, we classify the most commonly mentioned elements of propagation channels into broader classes of mechanism associations. For each of our vignettes, we identify the most prevalent mechanism associations. For example, in the case of the interest rate vignette the most common mechanism associations concern 1) increases in firms' costs, 2) reductions in product demand, and 3) a reduction in labor demand. For instance, if a respondent mentions that firms face higher costs of borrowing or "pass on" higher costs to the consumer, this falls under 1) increases in firms' costs, while 2) reductions in product demand subsume decreases in households' spending or lower investment by firms. If a respondent mentions that firms fire workers or that there are fewer job opportunities, we code this as 3) a reduction in firms' labor demand. Other elements of propagation mechanisms are mentioned less frequently and remain unassigned. For experts, we also subsume some responses coded as "model", since they clearly refer to one of the specific broader mechanisms: "supply shock", "demand shock", and "multiplier". Table A.17 describes how the different elements of mechanism associations are aggregated into broader vignette-specific mechanisms. Table A.18 provides examples for the coding of mechanism responses, including both the specific codes and the aggregate categories that are assigned to the example responses.

Table A.16: Mechanism associations: Variable codes

Code	**Explanation**
Economic variables:	
borrowing borrowing firms borrowing household borrowing government	Amount borrowed (debt) by different groups, or amount lent by banks to these groups
costs costs firms costs household	costs: Costs faced by different groups other than borrowing costs. costs firms: Production costs, including costs of input goods, wages paid; "Firms need to cover"; "firms need to make up for it", ... costs household: Costs of subsistence goods, e.g. heating, gasoline, ...
costs borrowing costs borrowing firms costs borrowing household costs borrowing banks costs borrowing government	Borrowing rates and/or access to credit faced by different groups.
demand demand firms demand household demand government	Demand for goods, spending, consumption, ...
expected inflation expected unemployment	Expectations of future realizations of macroeconomic variables as propagation mechanisms.
firm prices	Firms' decisions about pricing.
government taxes government finances	government taxes: Tax revenue collected by the government. government finances: Residual category referring to unspecified improvements or deterioration in the government's budget.
growth	GDP growth, overall growth of the economy.
housing housing demand housing supply	Quantity of housing demanded, supplied, or unspecified whether demand or supply is meant.
income	Household income, wages received, purchasing power.
interest interest household	General interest rate category if agent not specified or if not specified whether households' rates on borrowing vs saving are meant.
investment	Investment (expenditure) of firms.
labor demand labor supply labor	labor demand: "Job creation", firm's/government's demand for employees, "Job opportunities". labor supply: Changes in households' desired work hours. labor: Residual category for cases where it is unclear whether the respondent is thinking about labor demand or supply, e.g. "more people work".

Notes: See next page.

Table A.16 (continued): Mechanism associations: Variable codes (continued)

Code	**Explanation**
Economic variables (continued):	
money	Overall amount of money in circulation, money printing by the central bank.
policy rate	Target rate, central bank rate, policy rate, federal funds rate.
prices stock prices house	Asset prices, ”the stock market”.
production	Firms’ production / supply of goods and services
profit	Firms’ profits or profit margin, including firms facing pressure to take actions to keep the profit margin at a certain level.
saving	Amount saved by households.
saving rate	Interest rate earned on savings.
Other codes:	
crowd-out	Crowd-out of other types of demand due to increased government spending e.g. on defense, including crowd-out of other types of government spending.
domestic	Only relevant for the oil price shock. Highlights responses indicating that the domestic oil industry will benefit from the shock/buffer the shock.
green	Only relevant for the oil price shock. Highlights responses indicating that the economy is less dependent on oil than historically due to growing importance of new energy sources.
lag	Shock is perceived to only affect the economy with a lag.
minor	Shock is perceived as too small to have a pronounced effect on the economy.
sector-specific	Shock is perceived to have a small effect because it only affects a certain sector.
state-dependence	Impact of the shock is perceived to depend on initial conditions of the economy.
temporary	Shock is perceived to have no major effect because it is only temporary.

Notes: This table provides details on the definition of variables for the hand-coding of the open-text responses classified as “mechanism” responses. There is no limit on the number of variables that can be used for the coding of each individual response.

Table A.17: Mechanism associations: Aggregated

Aggregate category	**Variable codes**
	Oil price shock
Firms' costs (+)	costs firms +, firm prices +, supply shock –*
Product demand (–)	costs household +, demand –, demand household –, income –
Labor demand (–)	labor demand –
Oil dependency (–)	domestic, green
	Government spending shock
Crowding out	borrowing government +, costs firms +, crowd-out, government finances –, government taxes +, labor demand –
Product demand (+)	demand +, demand household +, demand shock +*, income +, money +, multiplier*
Labor demand (+)	labor demand +
	Interest rate shock
Firms' costs (+)	costs borrowing firms +, costs firms +, firm prices +
Product demand (–)	costs borrowing household +, costs household +, demand –, demand household –, demand shock –*, income –, investment –, money –
Labor demand (–)	labor demand –
	Income tax shock
Firms' costs (+)	costs firms +, firm prices +
Product demand (–)	costs household +, demand –, demand household –, income –
Labor demand (–)	labor demand –

Notes: This table shows how specific variable codes were aggregated into broader mechanism categories across the four vignettes. *References to economic models occur only in expert responses.

Table A.18: Mechanism associations: Coding examples

Text response	**Mechanism code(s)**	**Aggregated code(s)**
Households:		
(Oil price shock) "Unemployment will go up, because business will not be able to afford the increase in oil costs that go with it. Inflation will rise, since so many products are oil based, or use oil in some way, transportation etc."	costs firms +	*Firms' costs (+)*
(Government spending shock) "The government will be spending more money, which means the public has less money, I believe. I'm not exactly sure how it works, but that's my prediction as an uninformed citizen."	crowd-out, income -	*Crowding out*
(Government spending shock) "Defense spending leads to higher inflation. Higher government spending that's not really driving income-generation. The impact of unemployment depends on what they're spending on - are we making more weapons/planes that require more workers. Not sure"	income o, labor demand, sector-specific	None
(Interest rate shock) "with change in fed funds rate upward, unemployment is likely to rise (as cost to business to borrow increases and invest less in expansion) and inflation should in theory be kept in check and even fall."	costs borrowing firms +, investment -	*Firms' costs (+), Product demand (–)*
(Interest rate shock) "The rate of federal funds affects banks which in turn affects spending/inflation"	costs borrowing banks, demand	None
(Interest rate shock) "If the money that corporations borrow costs them more, they will charge more accordingly. If the merchandise costs businesses more, they will compensate by raising prices and by eliminating business expenses which means job termination raising the unemployment rate."	costs borrowing firms +, firm prices +, labor demand -	*Firms' costs (+), Labor demand (–)*
(Income tax shock) "The income tax increase would decrease disposable income by $400 per household, thus decreasing spending. Plus, an increase in the income tax rate can lower inflation. However, in this scenario the 1% increase does not seem high enough to affect unemployment or inflation significantly in the short-term."	demand household -, income -, lag, minor	*Product demand (–)*
(Income tax shock) "I believe that the unemployment rate will increase as people will be looking for higher paying jobs. They will need higher paying jobs to off set the increase of taxes."	costs firms +, costs household +, labor supply -	*Firms' costs (+), Product demand (–)*

Notes: See next page.

Table A.18 (continued): Mechanism associations: Coding examples

Text response	**Mechanism code(s)**	**Aggregated code(s)**
Experts:		
(Oil price shock) "I see it as a (near)-stagflation scenario: - production costs rise pushing inflation up - unemployment is constant or marginally higher - the Fed does not intervene because it has to balance two objectives (control inflation and support employment) and it knows that monetary expansions are ineffective against aggregate supply shocks"	costs firms +, policy rate o, supply shock -	*Firms' costs (+)*
(Oil price shock) "Negative supply shocks are contractionary and inflationary, since they raise firms' marginal costs. I don't know exactly what the pass-through of oil prices is, but it seems reasonable to expect a moderate pass-through over a short period of time, also given the muted effects of oil price movements of the last decade."	costs firms +, firm prices +, supply shock -	*Firms' costs (+)*
(Government spending shock) "In the short term, the government spending will create more jobs, which decreases u. It can't go down by much though because it's already at the natural rate/ very low. Inflation increases because the government consumption has to come from somewhere and it is likely that it's financed with bonds/seigniorage/ some form of money creation that will raise prices."	demand +, government finances -, labor demand +, money +, state-dependence	*Crowding out*, *Product demand (+)*, *Labor demand (+)*
(Government spending shock) "Inflation will increase because people have more income and will consume more. Unemployment will decrease because more government spending can finance more employment in the economy."	demand household +, income +, labor demand +	*Product demand (+)*, *Labor demand (+)*
(Interest rate shock) "With higher interest rates, consumption and investment will be typically lower and moved to the future. "	demand household -, investment -	*Product demand (–)*
(Income tax shock) "The tax change is temporary, so should affect non-liquidity constrained households too much. However, some households at the constraint will spend less, which underlies my projection for slightly higher unemployment (and slightly lower inflation)."	demand household -, temporary	*Product demand (–)*
(Income tax shock) "households will decrease working hours but if no other change takes place they should borrow to smooth out the negative shock so that the shock should not affect inflation as it is temporary. For unemployment, I would expect a fall in labor hours/employment because of the temporal shift in labor supply, so a slight fall in unemployment should occur, for me here the substitution effect is higher than the income effect, as the shock is pretty temporary. As workers will not want to break the employment relationship temporarily I expect the fall to be small"	borrowing household +, labor supply -, temporary	None

Notes: This table provides selected examples for how responses to the open-text question included in Wave 3 falling under the mechanism category are coded and which broader, more aggregated mechanisms are assigned. Wave 3 only contained rise scenarios, so all examples refer to scenarios where the shock variable of interest increases.

Inter-rater reliability We observe a high inter-rater reliability for the aggregated mechanism associations among households. In 95% of cases, the two coders independently agree whether or not a specific mechanism association should be assigned to the response. The inter-rater reliability is only slightly lower for expert responses (92%). If we restrict attention to cases where at least one coder detects a "mechanism" response, the inter-rater-reliability of mechanism associations is still very high (88% and 91% for households and experts respectively).

F.2.2 Validation of Structured Measures of Thoughts

Table A.19 shows that the structured measures of thoughts and the hand-coded mechanism associations based on the open-ended data are mostly strongly and statistically significantly correlated in the expected directions under the different vignettes. For instance, indicating a negative supply-side channel under the structured question in the oil vignette increases the likelihood of mentioning an increase in firms' cost in the open-text data by 26 p.p. Selecting negative demand-side channels in the structured question under the income tax vignette increases the likelihood of mentioning decreases in product demand by 17.9 p.p. The coefficients are naturally smaller than one because i) there is no one-to-one correspondence between the hand-coded mechanism associations and the more nuanced channels in the structured questions, and ii) both structured and open-ended data likely contain measurement error.

Table A.20 shows similar results for experts.

Table A.19: Households: Structured propagation channels predict manually-coded open-text data

Panel A

	Oil price			Government spending		
	Firms' costs (+)	Product D (–)	Labor D (–)	Crowding-out	Product D (+)	Labor D (+)
	(1)	(2)	(3)	(4)	(5)	(6)
Supply (–)	0.260***	0.144***	0.219***			
	(0.028)	(0.031)	(0.025)			
Demand (–)	0.018	0.145***	0.038			
	(0.034)	(0.032)	(0.032)			
Crowding-out				0.111***	−0.073***	−0.132***
				(0.035)	(0.023)	(0.029)
Demand (+)				−0.139***	0.119***	0.237***
				(0.029)	(0.025)	(0.031)
Constant	0.024	0.019	0.002	0.165***	0.066***	0.105***
	(0.018)	(0.023)	(0.017)	(0.026)	(0.017)	(0.020)
Observations	557	557	557	519	519	519
R^2	0.083	0.067	0.072	0.081	0.054	0.127

Panel B

	Federal funds rate			Income tax rates		
	Firms' costs (+)	Product D (–)	Labor D (–)	Firms' costs (+)	Product D (–)	Labor D (–)
	(1)	(2)	(3)	(4)	(5)	(6)
Supply (–)	0.163***	0.057**	0.157***			
	(0.026)	(0.026)	(0.028)			
Demand (–)	−0.029	0.044*	0.045			
	(0.028)	(0.026)	(0.028)			
Supply (–)				0.067***	−0.019	0.055**
				(0.022)	(0.032)	(0.027)
Demand (–)				0.015	0.179***	0.086***
				(0.021)	(0.032)	(0.027)
Constant	0.036**	0.044**	0.018	0.025*	0.090***	0.038**
	(0.016)	(0.020)	(0.018)	(0.013)	(0.021)	(0.015)
Observations	520	520	520	530	530	530
R^2	0.067	0.016	0.064	0.020	0.056	0.029

Notes: This table presents data from Wave 3 of the household survey. It regresses the manually-coded mechanism associations that respondents mention in their open-text response on the selected propagation channels in the structured question (see Figure 3). *Explanatory variable, propagation channels, structured question*: "Supply (–)" takes value 1 for respondents who choose a negative supply-side propagation channel in the structured question. "Demand (–)" and "Demand (+)" take value 1 for respondents choosing the negative or positive demand-side propagation mechanism in the structured question respectively. "Crowding-out" takes value 1 for respondents who select the channel that demand falls due to higher expected future taxes. *Outcome variable, manually-coded mechanism associations, open-text data*: "Firm's costs (+)" takes value 1 for respondents who mention an increase in firms' costs. "Product D (–)" takes value 1 for respondents who mention a decrease in product demand. Likewise, "Labor D (+)" represents an increase in labor demand, "Labor D (–)" a decrease in labor demand, "Crowding-out" the negative effects of increases in government spending, and "Product D (+)" an increase in product demand. See appendix Section F for further details on the coding of the open-text data which varies across vignettes. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table A.20: Experts: Structured propagation channels predict manually-coded open-text data

Panel A

	Oil price			**Government spending**		
	Firms' costs (+)	Product D (–)	Labor D (–)	Crowding-out	Product D (+)	Labor D (+)
	(1)	(2)	(3)	(4)	(5)	(6)
Supply (–)	0.539***	0.022	0.188***			
	(0.060)	(0.088)	(0.047)			
Demand (–)	0.031	0.044	0.010			
	(0.100)	(0.065)	(0.079)			
Crowding-out				0.295*	0.022	0.127
				(0.151)	(0.155)	(0.144)
Demand (+)				−0.051	0.225*	0.182**
				(0.096)	(0.116)	(0.071)
Constant	−0.010	0.069	−0.003	0.168*	0.272***	0.040
	(0.034)	(0.089)	(0.026)	(0.086)	(0.097)	(0.046)
Observations	91	91	91	88	88	88
R^2	0.137	0.006	0.030	0.071	0.039	0.059

Panel B

	Federal funds rate			**Income tax rates**		
	Firms' costs (+)	Product D (–)	Labor D (–)	Firms' costs (+)	Product D (–)	Labor D (–)
	(1)	(2)	(3)	(4)	(5)	(6)
Supply (–)	0.033	0.077	0.036			
	(0.063)	(0.103)	(0.073)			
Demand (–)	0.019	0.336***	0.114***			
	(0.062)	(0.059)	(0.039)			
Supply (–)				0.191	−0.033	−0.095**
				(0.131)	(0.119)	(0.040)
Demand (–)				−0.027	0.622***	−0.019
				(0.038)	(0.083)	(0.069)
Constant	0.050	−0.013	−0.006	0.044	0.090	0.103
	(0.057)	(0.018)	(0.012)	(0.028)	(0.068)	(0.064)
Observations	92	92	92	100	100	100
R^2	0.005	0.102	0.030	0.089	0.292	0.009

Notes: This table presents data from Wave 3 of the expert survey. It regresses the manually-coded mechanism associations that respondents mention in their open-text response on the selected propagation channels in the structured question (see Figure 3). *Explanatory variable, propagation channels, structured question*: "Supply (–)" takes value 1 for respondents who choose a negative supply-side propagation channel in the structured question. "Demand (–)" and "Demand (+)" take value 1 for respondents choosing the negative or positive demand-side propagation mechanism in the structured question respectively. "Crowding-out" takes value 1 for respondents who select the channel that demand falls due to higher expected future taxes. *Outcome variable, manually-coded mechanism associations, open-text data*: "Firm's costs (+)" takes value 1 for respondents who mention an increase in firms' costs. "Product D (–)" takes value 1 for respondents who mention a decrease in product demand. Likewise, "Labor D (+)" represents an increase in labor demand, "Labor D (–)" a decrease in labor demand, "Crowding-out" the negative effects of increases in government spending, and "Product D (+)" an increase in product demand. See appendix Section F for further details on the coding of the open-text data which varies across vignettes. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

F.2.3 Hand-coded Mechanism Associations Across Vignettes

We first demonstrate robustness of our descriptive evidence on variation in thoughts of propagation channels across vignettes and samples presented in Section 4.3. Figure A.11 shows the fractions of respondents mentioning different aggregated mechanism associations, while Figure A.12 displays the results for the more detailed mechanism codes. We focus our discussion on the aggregated mechanism codes.

Heterogeneity within the household sample The left column of Figure A.11 presents the fractions of households mentioning different mechanisms across the four vignettes. Overall, smaller fractions of households mention the different mechanisms than in the structured data. This should be seen in light of the fact that only 39% of households provide a response that we classify as "mechanism response".

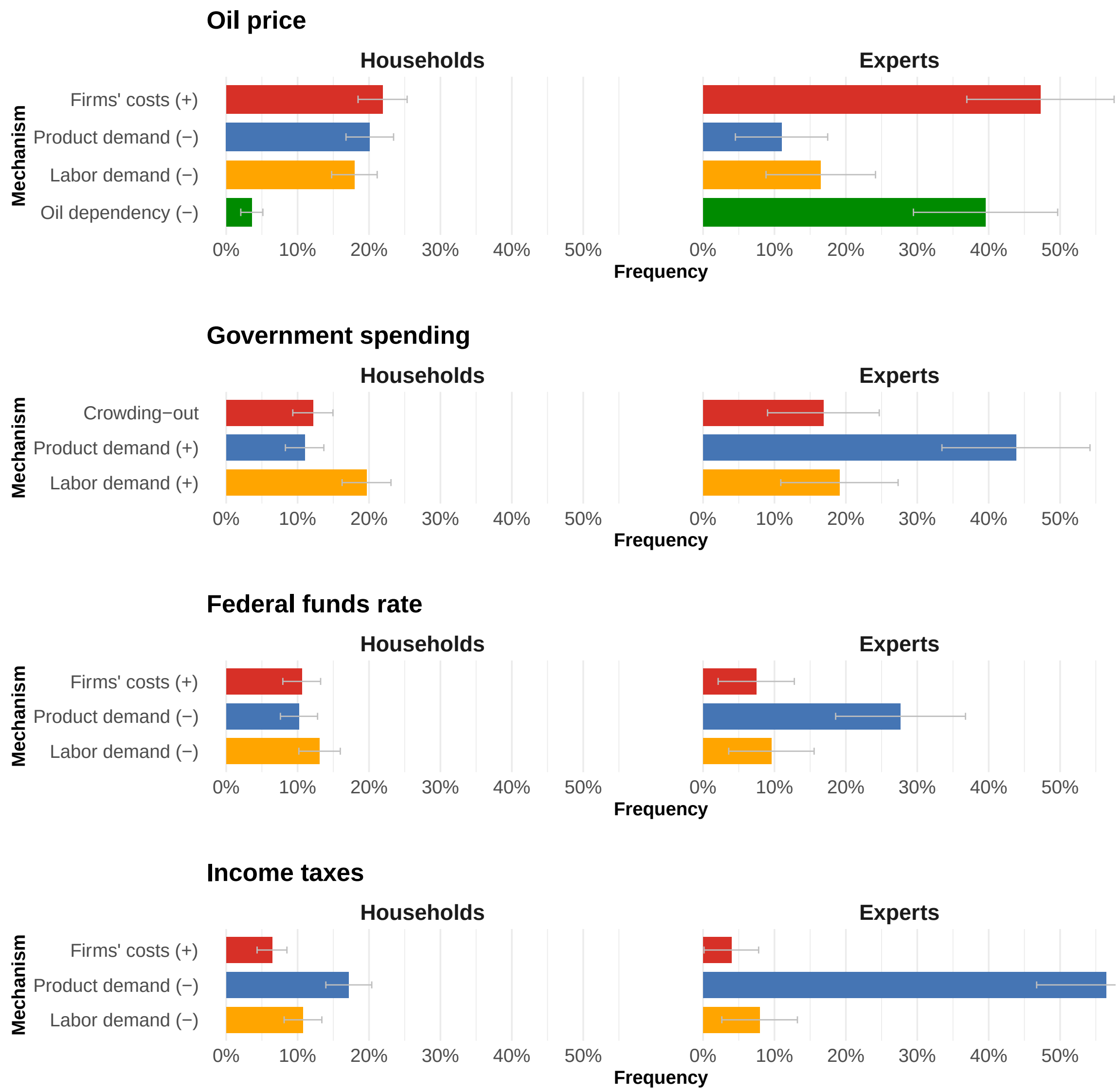
How do households' thoughts vary across the different shocks? Similarly as in our results based on the structured data, increases in firms' costs are most frequently mentioned under the oil price vignette (22%), but are still quite common in both the income tax vignette (6%) and the monetary policy vignette (11%). Similarly, the product demand channel is most commonly mentioned in the oil price vignette (20%), and less frequently in the income tax vignette, the government spending and interest rate vignette, even though these shocks are conventionally viewed as demand-side shocks. The labor demand channel is most commonly mentioned in the government spending vignette (20%), but also frequently mentioned in the oil price vignette (18%) as well as the interest rate and income tax vignettes (13% and 11%, respectively). Taken together, the hand-coded mechanism associations provide a similar picture as the structured measures of thoughts: households think of different propagation channels depending on the context, but the variation across contexts is not fully aligned with textbook models.

Heterogeneity within the expert sample The right column of Figure A.11 presents the fractions of experts mentioning different mechanisms across the four vignettes. The figure highlights that there is a lot of variation in the mechanisms that come to experts' minds across vignettes. Firms' costs are very frequently mentioned in the oil price vignette (47%), and much less frequently in the interest rate vignette (7%) and the income tax vignette (4%). Similarly, there is substantial variation in how frequently the product demand channel is mentioned across vignettes. While a very large fraction of experts mention the product demand channel in the income tax and government spending vignettes (56% and 44%, respectively), smaller fractions mention this mechanism in the federal funds rate and oil price vignettes (28% and 11%, respectively). Finally, there is somewhat less variation across vignettes in the labor demand associations. While labor demand is somewhat more frequently mentioned in the oil price and government spending vignettes (16% and 19%, respectively), it is less frequently mentioned in the interest rate and income tax vignettes (10% and 8%, respectively). Taken together, the data on hand-coded mechanism associations confirm the findings from the structured measures of thoughts: the variation in experts' associations across contexts suggests that experts retrieve textbook models when thinking about macroeconomic shocks.

Similarities and differences between households and experts The hand-coded data on mechanism associations reveal striking differences between households and experts in terms of mechanism associations that come to their minds.[11] While in the context of the oil price vignette the differences in the relative importance of mechanisms between the household and expert samples are more muted, differences are quite striking in all other three vignettes. Experts are relatively more likely to think of mechanism associations related to product demand compared to households. Conversely, households are relatively more likely to think of mechanism associations related to either crowd-out or increases in firms' costs compared to experts. The hand-coded data on mechanism associations thus paint a very similar picture as the structured data on mechanism associations.

[11] Since the fraction of respondents mentioning any mechanism is much larger among experts compared to households, we focus our description of results not on the importance of levels but instead on differences in the relative importance that households and experts attach to different mechanisms.

Figure A.11: Mechanism associations across vignettes (open-text question)



Coding

Oil price

Firms' costs (+): costs firms +, firm prices +, supply shock –*

Product demand (–): costs household +, demand –, demand household –, income –

Labor demand (–): labor demand –

Oil dependency (–): domestic, green

Federal funds rate

Firms' costs (+): costs borrowing firms +, costs firms +, firm prices +

Product demand (–): costs borrowing household +, costs household +, demand –, demand household –, demand shock –*, income –, investment –, money –

Labor demand (–): labor demand –

Government spending

Crowding out: borrowing government +, costs firms +, crowd-out, government finances –, government taxes +, labor demand –

Product demand (+): demand +, demand household +, demand shock +*, income +, money +, multiplier*

Labor demand (+): labor demand +

Income taxes

Firms' costs (+): costs firms +, firm prices +

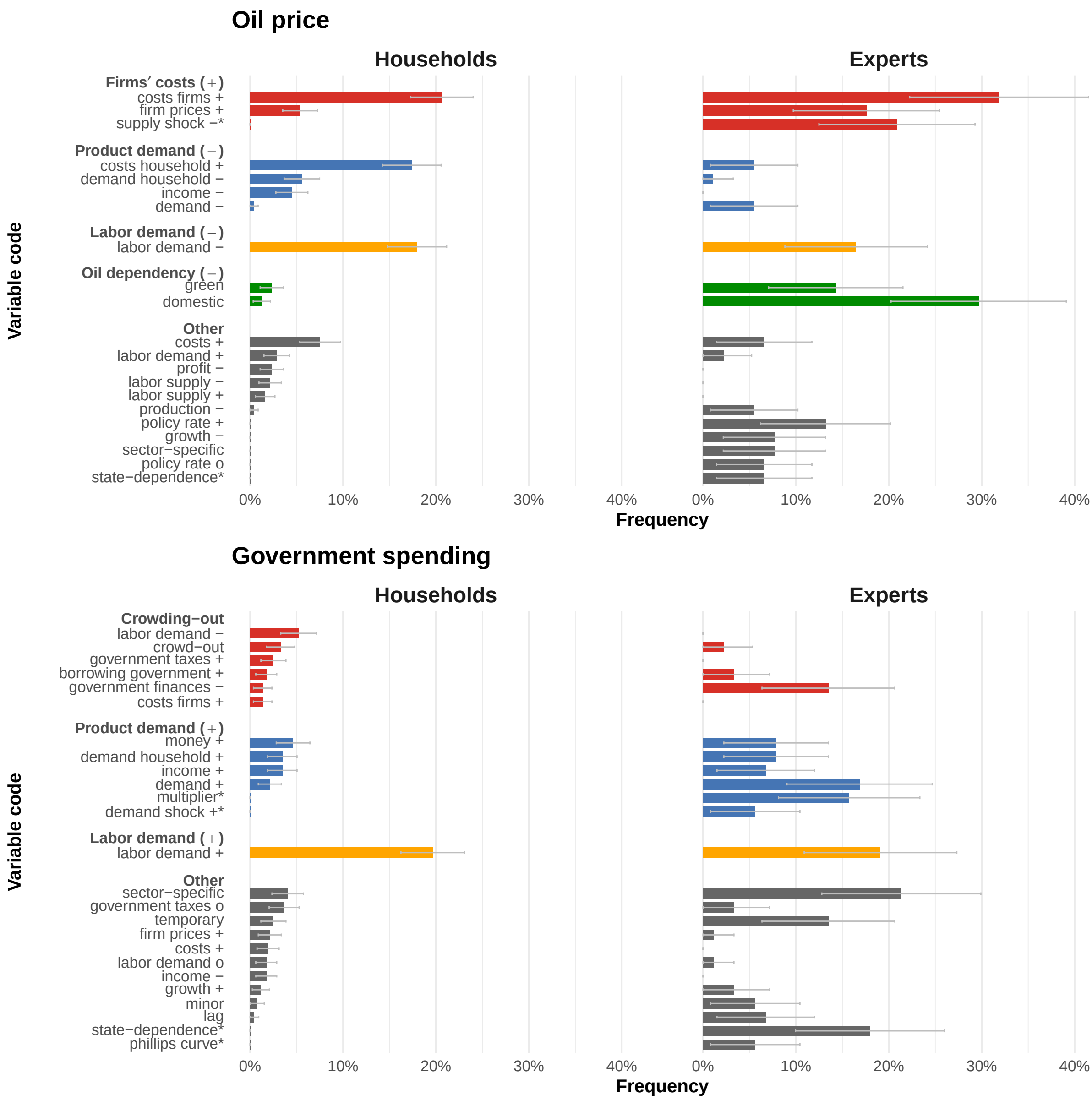
Product demand (–): costs household +, demand –, demand household –, income –

Labor demand (–): labor demand –

*References to economic models occur only in expert responses.

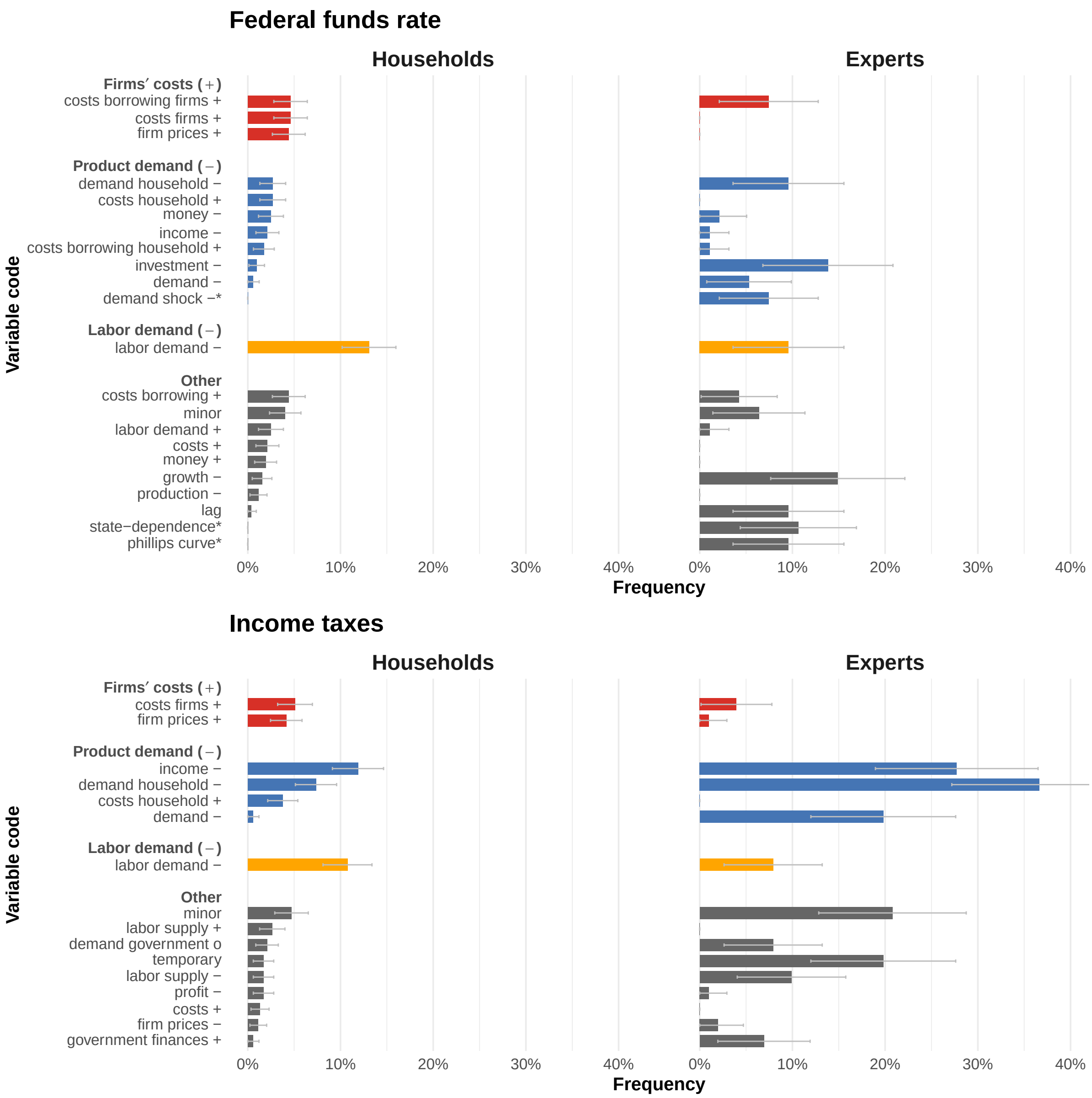
Notes: This figure shows the shares of households (left panel) and of experts (right panel) mentioning various mechanisms in their open responses in Wave 3. The responses are manually reviewed and assigned to various variable codes, which are then grouped into different mechanisms (see "Coding" panel). The results are displayed for each vignette. Error bars display 95% confidence intervals.

Figure A.12: Mechanism associations across vignettes (open-text data)



Notes: See next page.

Figure A.12 (continued): Mechanism associations across vignettes (open-text data)



Notes: This figure shows the shares of households (left panel) and experts (right panel) mentioning various mechanisms in their open-text response in Wave 3. The responses are manually reviewed and assigned to various variable codes which are then grouped into different mechanisms (bold labels). Only variable codes that are mentioned by at least 1% of households or 5% of experts are displayed. The error bars indicate 95% confidence intervals.

Correlations between associations and predictions Table A.21 documents correlations between the hand-coded mechanism associations and forecasts in the household sample. Households mentioning decreases in product demand and decreases in labor demand expect a larger increase in unemployment in response to the oil price shock. Moreover, mentioning a decreasing oil dependency of the US economy is associated with lower inflation and unemployment increases in response to an increase in oil prices. Crowd-out associations are robustly associated with larger increases in inflation and unemployment in response to an increase in government spending. Moreover, mentioning increases in labor demand is robustly associated with predicting larger decreases in the unemployment rate in response to government spending increases. While mechanism associations do not robustly correlate with predictions about the inflation response in the interest rate vignette, they do strongly correlate with unemployment predictions. Households mentioning decreases in product demand, and decreases in labor demand predict a larger increase in unemployment in response to an interest rate hike. Households that mention increases in firms' costs and decreases in labor demand predict higher increases in inflation in response to income tax hikes. Households that mention decreases in labor demand also predict higher increases in unemployment in response to income tax hikes. Taken together, similarly as based on the structured data of thoughts (shown in Table 2), thoughts of the different propagation channels are mostly significantly associated with households' forecasts of inflation and unemployment responses to the different shocks in the expected directions.

Table A.22 reports an analogous analysis for Wave 3 of the expert survey. The thoughts of experts correlate with their forecasts in directions suggested by conventional macroeconomic models. For instance, experts who think of a rise of product demand in the government vignette predict higher inflation but lower unemployment. Likewise, experts who think of a fall in product demand in the income tax vignette predict lower inflation and higher unemployment.

Table A.21: Households: Relationship between manually-coded mechanism associations (open-text data) and predictions

Oil price

	Inflation $\Delta\pi$		Unemployment Δu	
	(1)	(2)	(3)	(4)
Firms' costs (+)	0.126***	0.043	0.002	0.033
	(0.048)	(0.055)	(0.045)	(0.052)
Product dem. (–)	0.158***	0.056	0.119**	0.156***
	(0.048)	(0.054)	(0.047)	(0.054)
Labor demand (–)	0.148***	0.084	0.292***	0.315***
	(0.053)	(0.055)	(0.049)	(0.052)
Oil depend. (–)	−0.222*	−0.386***	−0.304**	−0.245*
	(0.117)	(0.126)	(0.120)	(0.128)
Any mech.		0.207***		−0.075
		(0.060)		(0.062)
Constant	0.378***	0.339***	0.254***	0.268***
	(0.026)	(0.029)	(0.027)	(0.030)
Observations	557	557	557	557
R^2	0.086	0.104	0.091	0.094

Government spending

	Inflation $\Delta\pi$		Unemployment Δu	
	(1)	(2)	(3)	(4)
Crowding-out	0.245***	0.225***	0.260***	0.364***
	(0.059)	(0.073)	(0.069)	(0.080)
Product dem. (+)	0.138**	0.128*	−0.100*	−0.051
	(0.064)	(0.071)	(0.051)	(0.054)
Labor dem. (+)	−0.042	−0.060	−0.479***	−0.387***
	(0.054)	(0.066)	(0.045)	(0.060)
Any mech.		0.026		−0.132**
		(0.066)		(0.064)
Constant	0.296***	0.292***	0.086***	0.105***
	(0.028)	(0.031)	(0.030)	(0.033)
Observations	519	519	519	519
R^2	0.031	0.031	0.170	0.174

Notes: See next page.

Table A.21 (continued): Households: Relationship between manually-coded mechanism associations (open-text data) and predictions

Federal funds target rate

	Inflation $\Delta\pi$		Unemployment Δu	
	(1)	(2)	(3)	(4)
Firms' costs (+)	0.081	0.074	0.083	0.126*
	(0.067)	(0.072)	(0.065)	(0.071)
Product dem. (–)	−0.019	−0.029	0.149**	0.213***
	(0.072)	(0.077)	(0.067)	(0.073)
Labor demand (–)	0.042	0.034	0.247***	0.298***
	(0.065)	(0.069)	(0.064)	(0.071)
Any mech.		0.018		−0.115*
		(0.056)		(0.061)
Constant	0.285***	0.282***	0.143***	0.164***
	(0.023)	(0.025)	(0.024)	(0.027)
Observations	520	520	520	520
R^2	0.006	0.006	0.057	0.064

Income taxes

	Inflation $\Delta\pi$		Unemployment Δu	
	(1)	(2)	(3)	(4)
Firms' costs (+)	0.273***	0.309***	−0.025	0.037
	(0.070)	(0.073)	(0.096)	(0.096)
Product dem. (–)	−0.088	−0.019	−0.027	0.091
	(0.055)	(0.062)	(0.052)	(0.060)
Labor demand (–)	0.140**	0.183***	0.236***	0.311***
	(0.063)	(0.068)	(0.073)	(0.075)
Any mech.		−0.107**		−0.183***
		(0.054)		(0.051)
Constant	0.351***	0.371***	0.228***	0.261***
	(0.024)	(0.027)	(0.025)	(0.029)
Observations	530	530	530	530
R^2	0.035	0.041	0.019	0.035

Notes: This table shows data from Wave 3 of the household survey. It regresses the predicted inflation changes ($\Delta\pi$) and unemployment changes (Δu) on the manually-coded mechanism associations that respondents mention in their open-text response. "Firm's costs (+)" takes value 1 for respondents who mention an increase in firms' costs. "Product dem. (–)" takes value 1 for respondents who mention a decrease in product demand. Likewise, "Labor demand (–)" represents a decrease in labor demand. "Oil depend." a decrease in the US economy's dependency on oil, "Crowding-out" the negative effects of increases in government spending, and "Product dem. (+)" an increase in product demand. "Any mech." takes value 1 if the response mentions at least one economic mechanism through which the shock could affect the economy. See appendix Section F for further details on the coding of the open-text data which varies across vignettes. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table A.22: Experts: Relationship between manually-coded mechanism associations (open-text data) and predictions

Oil price

	Inflation $\Delta\pi$		Unemployment Δu	
	(1)	(2)	(3)	(4)
Firms' costs (+)	0.157**	0.125*	0.032	0.019
	(0.076)	(0.067)	(0.075)	(0.076)
Product dem. (–)	−0.080	−0.089	−0.134	−0.138
	(0.111)	(0.109)	(0.170)	(0.172)
Labor demand (–)	0.093	0.083	0.323***	0.318***
	(0.092)	(0.092)	(0.105)	(0.107)
Oil depend. (–)	−0.056	−0.094	−0.286***	−0.301***
	(0.074)	(0.067)	(0.072)	(0.076)
Any mech.		0.148		0.061
		(0.193)		(0.163)
Constant	0.315***	0.219	0.351***	0.311**
	(0.084)	(0.186)	(0.078)	(0.147)
Observations	91	91	91	91
R^2	0.072	0.087	0.239	0.241

Government spending

	Inflation $\Delta\pi$		Unemployment Δu	
	(1)	(2)	(3)	(4)
Crowding-out	−0.023	−0.041	0.043	0.054
	(0.094)	(0.092)	(0.071)	(0.071)
Product dem. (+)	0.150**	0.134**	−0.137**	−0.128**
	(0.060)	(0.057)	(0.057)	(0.057)
Labor dem. (+)	−0.004	−0.023	−0.085	−0.074
	(0.047)	(0.048)	(0.056)	(0.056)
Any mech.		0.108		−0.062
		(0.109)		(0.091)
Constant	0.183***	0.106	−0.133***	−0.089
	(0.045)	(0.105)	(0.036)	(0.084)
Observations	89	89	89	89
R^2	0.067	0.084	0.102	0.109

Notes: See next page.

Table A.22 (continued): Experts: Relationship between manually-coded mechanism associations (open-text data) and predictions

Federal funds target rate

	Inflation $\Delta\pi$		Unemployment Δu	
	(1)	(2)	(3)	(4)
Firms' costs (+)	−0.021	0.009	−0.040	−0.077
	(0.138)	(0.140)	(0.160)	(0.159)
Product dem. (–)	−0.133**	−0.097	0.112*	0.067
	(0.053)	(0.059)	(0.058)	(0.063)
Labor demand (–)	0.019	0.040	0.135	0.109
	(0.126)	(0.124)	(0.098)	(0.102)
Any mech.		−0.103		0.126*
		(0.071)		(0.071)
Constant	−0.128***	−0.088*	0.185***	0.136***
	(0.041)	(0.051)	(0.041)	(0.050)
Observations	94	94	94	94
R^2	0.037	0.060	0.053	0.085

Income taxes

	Inflation $\Delta\pi$		Unemployment Δu	
	(1)	(2)	(3)	(4)
Firms' costs (+)	0.210*	0.178	0.255**	0.277**
	(0.115)	(0.117)	(0.115)	(0.117)
Product dem. (–)	−0.149***	−0.180***	0.136***	0.158***
	(0.040)	(0.044)	(0.043)	(0.046)
Labor demand (–)	0.153**	0.148**	−0.052	−0.049
	(0.063)	(0.065)	(0.075)	(0.075)
Any mech.		0.141**		−0.096
		(0.065)		(0.076)
Constant	−0.085***	−0.194***	0.120***	0.194***
	(0.032)	(0.054)	(0.033)	(0.067)
Observations	101	101	101	101
R^2	0.198	0.229	0.113	0.126

Notes: This table shows data from Wave 3 of the expert survey. It regresses the predicted inflation changes ($\Delta\pi$) and unemployment changes (Δu) on the manually-coded mechanism associations that respondents mention in their open-text response. "Firm's costs (+)" takes value 1 for respondents who mention an increase in firms' costs. "Product dem. (–)" takes value 1 for respondents who mention a decrease in product demand. Likewise, "Labor demand (–)" represents a decrease in labor demand. "Oil depend." a decrease in the US economy's dependency on oil, "Crowding-out" the negative effects of increases in government spending, and "Product dem. (+)" an increase in product demand. "Any mech." takes value 1 if the response mentions at least one economic mechanism through which the shock could affect the economy. See appendix Section F for further details on the coding of the open-text data which varies across vignettes. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

F.2.4 Effects of Priming Exercise on Hand-coded Mechanism Associations

In this section, we discuss the effects of the priming treatment on hand-coded mechanism associations. Table A.23 shows that respondents whose attention is directed towards costs are 6.3 p.p. more likely to mention associations related to increases in firms' costs ($p < 0.01$), compared to a control mean of 7.3 percent. They are also 3 percentage points less likely to mention associations related to decreases in product demand ($p < 0.05$), compared to a control mean of 8.3 percent. Respondents in the "demand prime condition" are 4.1 p.p. more likely to mention associations related to decreases in product demand. The differences in the likelihood of mentioning increases in firms' costs and decreases in product demand are significantly different across the costs prime and demand prime conditions ($p = 0.01$ and $p < 0.01$, respectively). Thus, our results based on the hand-coded mechanism associations are consistent with the findings based on the word-counting exercise presented in Table 4. This gives us further reassurance that our treatments successfully shifted attention to the cost or the demand side of the propagation of the shock.

Table A.23: Effects of priming study on manually-coded mechanism associations (open-text data)

	Mechanism associations (open-text data)		**Inflation prediction**
	Firms' costs (+)	Product demand (–)	$\Delta\pi$
	(1)	(2)	(3)
Costs prime	0.063***	−0.030**	0.021
	(0.020)	(0.015)	(0.031)
Demand prime	−0.008	0.041**	−0.057**
	(0.016)	(0.019)	(0.029)
Constant	0.073***	0.083***	0.366***
	(0.009)	(0.010)	(0.017)
***p*: Costs = Demand**	**0.001**	**<0.001**	**0.028**
Observations	1,521	1,521	1,521
R^2	0.010	0.008	0.004

Notes: This table presents results from the priming study which focuses on the interest rate vignette (Wave 4 of the household survey). "Costs prime" takes value 1 for respondents randomly assigned to be primed on the costs of production. "Demand prime" takes value 1 for respondents randomly assigned to be primed on product demand. As before (see Figure A.11), "Firms' costs (+)" takes value 1 for respondents who mention increases in firms' borrowing costs, firms' costs, or firms' prices. "Product demand (–)" takes value 1 for respondents who mention increases in costs of borrowing for households, increases in the costs of households more generally, decreases in the demand of households or their income, or a decrease in firms' investments. $\Delta\pi$ denotes the perceived reaction of the inflation rate. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

F.2.5 Effects of Experiences on Hand-coded Mechanism Associations

In this section, we show correlations between experiences and thoughts as measured with hand-coded mechanism associations. Panel A of Table A.24 shows that respondents who indicate to have more experiences with positive demand side-mechanisms are more likely to mention increases in labor demand in the open-text question ($p < 0.05$) under the government spending shock. Conversely, respondents who have more experiences with crowd-out channels are more likely to mention mechanism associations related to crowding-out effects ($p < 0.05$), and are less likely to indicate increases in product demand ($p < 0.01$) or labor demand ($p < 0.01$).

Panel B of Table A.24 shows that respondents who were either personally employed by a company receiving contracts from the US military or have someone among their friends and family members who was employed by such a company think more about mechanisms related to increases in labor demand when they make their forecasts of the effects of government spending shocks ($p < 0.05$).

Panel C of Table A.24 shows that individuals born before 1962 are more likely to think of increases in production costs ($p < 0.10$) and decreases in product demand ($p < 0.05$) when making predictions under the oil vignette.

These results based on the hand-coded mechanism associations are consistent with the results from the word-counting exercise and the structured questions on thoughts presented in Table 5. This gives us further reassurance that experiences are significantly associated with the thoughts that come to respondents' minds.

Table A.24: Households' experiences correlate with manually-coded mechanism associations (open-text data)

(A) Government spending: Experience with propagation channels (std. indices)

	Mechanisms associations (open-text data)			**Predictions**	
	Crowding-out	Prod. demand (+)	Labor demand (+)	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)	(5)
Exp. crowding-out	0.043**	−0.045***	−0.056***	0.004	0.106***
	(0.018)	(0.017)	(0.021)	(0.026)	(0.029)
Exp. prod. demand (+)	0.018	0.021	0.050**	0.038	−0.109***
	(0.016)	(0.017)	(0.021)	(0.025)	(0.030)
Controls	✓	✓	✓	✓	✓
Observations	483	483	483	483	483
R^2	0.093	0.074	0.164	0.142	0.180

(B) Government spending: Ever worked for military supplier (self/friend, binary indicator)

	Crowding-out	Prod. demand (+)	Labor demand (+)	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)	(5)
Yes	−0.011	0.017	0.081**	−0.024	−0.101**
	(0.031)	(0.027)	(0.035)	(0.045)	(0.049)
Controls	✓	✓	✓	✓	✓
Observations	483	483	483	483	483
R^2	0.069	0.059	0.159	0.137	0.155

(C) Oil price: Experienced OPEC crisis (born before 1962, binary indicator)

	Firms' costs (+)	Prod. demand (–)	Labor demand (–)	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)	(5)
Yes	0.074*	0.075**	0.079**	0.208***	0.202***
	(0.039)	(0.037)	(0.038)	(0.044)	(0.043)
Controls	✓	✓	✓	✓	✓
Observations	521	521	521	521	521
R^2	0.066	0.072	0.041	0.080	0.074

Notes: This table presents results from Wave 3 (Panel C) and Wave 5 (Panel A and B) of the household survey. It asks whether respondents who made experiences related to the vignettes have different manually-coded mechanism associations (columns 1-3, open-text data) and make different forecasts (inflation: $\Delta\pi$, unemployment: Δu; columns 4-5). The right-hand-side experience variable varies across panels. In Panel A, "Experienced crowding-out" and "Experienced product demand (+)" are standardized indices of self-reported experiences with crowding-out and positive demand-side channels, respectively. In Panel B, "Yes" is a binary dummy taking value 1 if respondents themselves or friends/family of them ever worked for a company that sells to the US military. In Panel C, "Yes" is a binary dummy taking value 1 if respondents were born before 1962, a proxy that they experienced the OPEC crisis. Control variables comprise age (except for Panel C), log income, inflation and unemployment forecasts in the baseline scenario, as well as binary indicators for gender, college education, being a Republican, having taken an economics course at the college level, and census regions. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

G Key Screenshots for Priming Experiment

Demand prime

Step 1: Prediction of demand for firms' goods and services

Think about the demand for products and services that US firms face. Please complete the following sentence.

In the alternative scenario (federal funds rate rises), US firms face ________ than in the baseline scenario (federal funds rate constant).

Your thoughts in step 1

What are your main considerations in making the above prediction?

Please respond in 2-3 sentences.

Step 2: Prediction of inflation

Think about the US inflation rate over the 12 months from January to December 2025. Please complete the following sentence.

In the alternative scenario (federal funds rate rises), the inflation rate will be approximately ________ than in the baseline scenario (federal funds rate constant).

Your thoughts in step 2

Above, you predict how the change in the alternative scenario affects the US inflation. Please tell us how you come up with your predictions.

What are your main considerations in making the predictions in step 2?

Please respond in 2-3 sentences.

Cost prime

Step 1: Prediction of firms' costs

Think about the costs of doing business that US firms face. Please complete the following sentence.

In the alternative scenario (federal funds rate rises), US firms face _______ than in the baseline scenario (federal funds rate constant).

Your thoughts in step 1

What are your main considerations in making the above prediction?

Please respond in 2-3 sentences.

Step 2: Prediction of inflation

Think about the US inflation rate over the 12 months from January to December 2025. Please complete the following sentence.

In the alternative scenario (federal funds rate rises), the inflation rate will be approximately _______ than in the baseline scenario (federal funds rate constant).

Your thoughts in step 2

Above, you predict how the change in the alternative scenario affects the US inflation. Please tell us how you come up with your predictions.

What are your main considerations in making the predictions <u>in step 2</u>?

Please respond in 2-3 sentences.

Control

Prediction of inflation

Think about the US inflation rate over the 12 months from January to December 2025.
Please complete the following sentence.

In the alternative scenario (federal funds rate rises), the inflation rate will be approximately ________ than in the baseline scenario (federal funds rate constant).

Your thoughts

Above, you predict how the change in the alternative scenario affects the US inflation rate.
Please tell us how you come up with your prediction.
What are your main considerations in making the prediction?
Please respond in 2-3 sentences.

Only for control group: Demand and cost question

Important!

On the next page, your task is to predict how the change between the baseline and the alternative scenario affects another aspect of the US economy and to write down **what considerations you have on your mind** while you make your prediction.

Therefore, while you read the scenario description and think about its consequences for the US economy, please **pay special attention to what comes to your mind**. Of course, there are no right or wrong answers. Just write down your thoughts. Your response is very valuable for this research project.

Please take your time to respond carefully.

Federal funds target rate

Please think about the following two hypothetical scenarios once more.

Compare the alternative scenario to the baseline scenario where the federal funds rate stays constant.

Reminder: Please assume it is the 1st of January 2025. The COVID-19 pandemic is over. The US economy has fully recovered and is back to "business as usual".

Baseline scenario: Federal funds target rate stays constant

Imagine the **federal funds target rate** stays **constant**. That is, in its first meeting in 2025, the Federal Open Market Committee announces that it will keep the interest rate constant at 2.5%.

The committee announces it does so with no changes in their assessment of the economic conditions.

Alternative scenario: Federal funds target rate rises

Imagine the **federal funds target rate** is unexpectedly **0.5 percentage points higher**. That is, in its first meeting in 2025, the Federal Open Market Committee announces that it is raising the interest rate from 2.5% to 3%.

The committee announces it does so with no changes in their assessment of the economic conditions.

Demand: control (same page)

Prediction of demand for firms' goods and services

Think about the demand for products and services that US firms face. Please complete the following sentence.

In the alternative scenario (federal funds rate rises), US firms face _______ than in the baseline scenario (federal funds rate constant).

Your thoughts

What are your main considerations in making the above prediction?

Please respond in 2-3 sentences.

Cost: control (same page)

Prediction of firms' costs

Think about the costs of doing business that US firms face. Please complete the following sentence.

In the alternative scenario (federal funds rate rises), US firms face _______ than in the baseline scenario (federal funds rate constant).

Your thoughts

What are your main considerations in making the above prediction?

Please respond in 2-3 sentences.

H Alternative Explanations

H.1 Perceived Past Correlations

In this subsection, we provide additional details on our measurement of households' perceived past correlations of macroeconomic variables (used in Section 4.7), and the role of these beliefs in inflation and unemployment forecasts under the different shocks.

Measurement We elicit respondents' perceived past correlations in two ways. A random half of our respondents report their perceived correlations of past *changes* in macroeconomic variables. We first tell these participants that "we have analyzed data about the development of the US economy in the last 50 years (1969-2019). We studied which economic outcomes tend to move in the same direction, which tend to move in opposite directions, and which move independently of each other. Consider for example the average unemployment rate and the inflation rate. We calculated the share of years in which these outcomes (i) moved in the same direction, i.e. both rise or both fall, and (ii) moved in opposite directions, i.e. one rises, but the other one falls. The two variables moved independently of each other if they moved in the same direction 50% of the time and moved in opposite directions 50% of the time." We then ask our respondents to consider two variables (e.g. the oil price and the unemployment rate) and ask them what percent of the time these two variables moved (i) in the same direction and (ii) in opposite directions over the last 50 years.

The other half of our respondents report their beliefs about the correlation of levels of macroeconomic variables in the past, using a survey question with qualitative response categories.

Role in forecasts by shock In Section 4.7, we show that perceived past correlations of shock variable and outcome variable of interest are strongly correlated with households' forecasts in the vignettes, where we pool forecasts i) across inflation and unemployment, ii) across shocks, and iii) across the two ways of eliciting past correlations. We now study the role of perceived past correlations separately for forecasts of each outcome under each shock and for each elicitation method.

As shown in Table A.25, the perceived past correlations between inflation and the shock variables are strongly associated with respondents' forecasts. These patterns hold across vignettes and both for perceived correlation of levels and changes. Our findings hold for forecasts of both the unemployment rate and the inflation rate. This evidence is purely correlational and should be interpreted cautiously, as it could be confounded by omitted variables or reverse causality, as explained in the main text.

Table A.25: Households: Perceived past correlations

Inflation $\Delta\pi$

	Pooled		Oil price		Gov. spend.		Fed. funds rate		Inc. taxes	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Past corr.	0.139***	0.147***	0.184***	0.241***	0.071	0.131**	0.130*	0.077**	0.148**	0.177***
	(0.035)	(0.024)	(0.069)	(0.061)	(0.070)	(0.051)	(0.074)	(0.038)	(0.062)	(0.049)
Type	Changes	Levels	Changes	Levels	Changes	Levels	Changes	Levels	Changes	Levels
Vignette	All	All	Oil	Oil	Gov.	Gov.	Fed.	Fed.	Tax	Tax
Vig. FE	✓	✓	–	–	–	–	–	–	–	–
Obs.	1,026	1,059	285	265	245	264	229	280	267	250
R^2	0.027	0.060	0.031	0.083	0.004	0.025	0.016	0.016	0.022	0.060

Unemployment Δu

	Pooled		Oil price		Gov. spend.		Fed. funds rate		Income taxes	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Past corr.	0.066*	0.209***	0.139*	0.219***	0.061	0.314***	0.018	0.152***	0.032	0.133***
	(0.038)	(0.022)	(0.073)	(0.050)	(0.096)	(0.043)	(0.080)	(0.037)	(0.062)	(0.048)
Type	Changes	Levels	Changes	Levels	Changes	Levels	Changes	Levels	Changes	Levels
Vignette	All	All	Oil	Oil	Gov.	Gov.	Fed.	Fed.	Tax	Tax
Vig. FE	✓	✓	–	–	–	–	–	–	–	–
Obs.	1,026	1,059	285	265	245	264	229	280	267	250
R^2	0.062	0.117	0.015	0.077	0.002	0.181	0.000	0.057	0.001	0.030

Notes: This table presents results from Wave 3 of the household survey. Two measures of past perceived correlations ("Past corr.") are used. Changes: "Past corr." ranges from -1 (the two variables always move in opposite directions) to 1 (the two variables always move in the same direction). Levels: "Past corr." takes either value -1, 0 or 1, where 1 means that respondents think that the two variables are positively correlated, -1 means that respondents think that the two variables are negatively correlated and 0 means that respondents think that the two variables are uncorrelated. $\Delta\pi$ denotes the expected difference in inflation between the rise scenario and the baseline scenario. Δu denotes the expected difference in unemployment between the rise scenario and the baseline scenario. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

H.2 Perceived Importance of Knowledge About the Functioning of the Economy

In Section 4.7, we also examine whether individuals who consider it necessary to be knowledgeable about macroeconomic relationships to make good economic decisions are more likely to make benchmark-consistent forecasts, in line with a premise of rational inattention models (Maćkowiak and Wiederholt, 2015; Sims, 2003). In Wave 3 of the household survey, we ask how useful respondents consider it to have knowledge about different issues for making good economic decisions. Among others, we ask this question for "knowledge about how the US economy works" and e.g. "knowledge about how income tax rates affect the US economy". In the second case, the question varies depending on the vignette a respondent is assigned to. We construct our index of the perceived usefulness of understanding the functioning of the economy as the average of a participant's responses to the questions on these two issues.

H.3 Objective Measure of Knowledge About the Economy

We measure households' knowledge about the economy through questions on beliefs about the current and the 2019 unemployment rate, and beliefs about inflation over the previous 12 months, as well as questions on self-reported acquisition of information about unemployment and inflation over the last three months. For the quantitative beliefs we calculate deviations from the true values. We z-score deviations from the true values for the beliefs and the responses to the qualitative questions on information acquisition using the means and standard deviations of the variables. We construct our index of economic knowledge as the average over the resulting variables.

H.4 Good-bad Heuristic

Research from psychology suggests that individuals revert to simple heuristics in complex decision environments in which there is a lot of uncertainty (Gigerenzer and Todd, 1999). In light of this evidence, we consider whether a simple heuristic, namely that good things only lead to good things and bad things only lead to bad things, can explain the heterogeneity in predictions in the representative sample. We refer to this as the good-bad heuristic (GBH). It postulates that households perceiving two variables as both good or both bad (symmetric affective evaluation) are more likely to predict a positive co-movement between them, while predicting a movement in opposing directions if they perceive one variable as good and the other one as bad (asymmetric affective evaluation). Our evidence is related to evidence from psychology studying understanding of the macroeconomy using student samples where a similar idea has been discussed under the label "good-begets-good heuristic" (Leiser and Aroch, 2009; Leiser and Krill, 2017). It also relates to theoretical work in economics (Kamdar, 2019).

To test this hypothesis, we measure whether respondents consider higher values of the four shock variables, unemployment, and inflation as good or bad for the US economy and for their own household. Households can respond on two 7-point scales, ranging from very bad (-3) to very good (3). For each variable, we average the evaluations for the US economy and their own households. Then, we derive the directional prediction that follows from the GBH for each forecast. If a respondent evaluates the two variables underlying a forecast (e.g. government spending and inflation) symmetrically (asymmetrically), the GBH implies a predicted change of the outcome variable in the same (opposite) direction as the change in the shock variable. For example, if a respondent perceives both higher government spending and higher inflation as bad, the GBH predicts that she expects that inflation will increase in response to an exogenous increase in government spending. If a respondent perceives higher government spending as good but higher inflation as bad, the GBH predicts that she expects that inflation will decrease in response to an exogenous increase in government spending. If at least one variable is evaluated neutrally (neither good nor bad), no change is predicted. Finally, we construct a dummy that takes value 1 whenever the predicted change suggested by the GBH is in line with the literature benchmarks, that is, whenever following the GBH would result in making a benchmark-consistent forecast. This dummy is used in our analyses.

We uncover a fairly large explanatory power of the good-bad heuristic. On average, forecast consistency with benchmarks increases by 14 p.p. when the GBH makes a benchmark-consistent prediction (Table A.26).

One potential concern with the GBH evidence, however, is that respondents' forecasts in the vignettes might be driving their affective encoding of the different variables. We somewhat mitigate this concern in Wave 3 of the data collection by moving the questions on affective evaluations of different variables to the very end of the survey. Nonetheless, future work could randomize the order of the questions on affective evaluations and the vignettes to deal with this concern. To provide causal evidence on the GBH, future work could try to manipulate the affective encoding of different variables, for example, by providing individuals with personal payoffs associated with the rise or fall of macroeconomic variables.

Table A.26: Households: Good-bad-heuristic: Predictors of benchmark-consistent forecasts

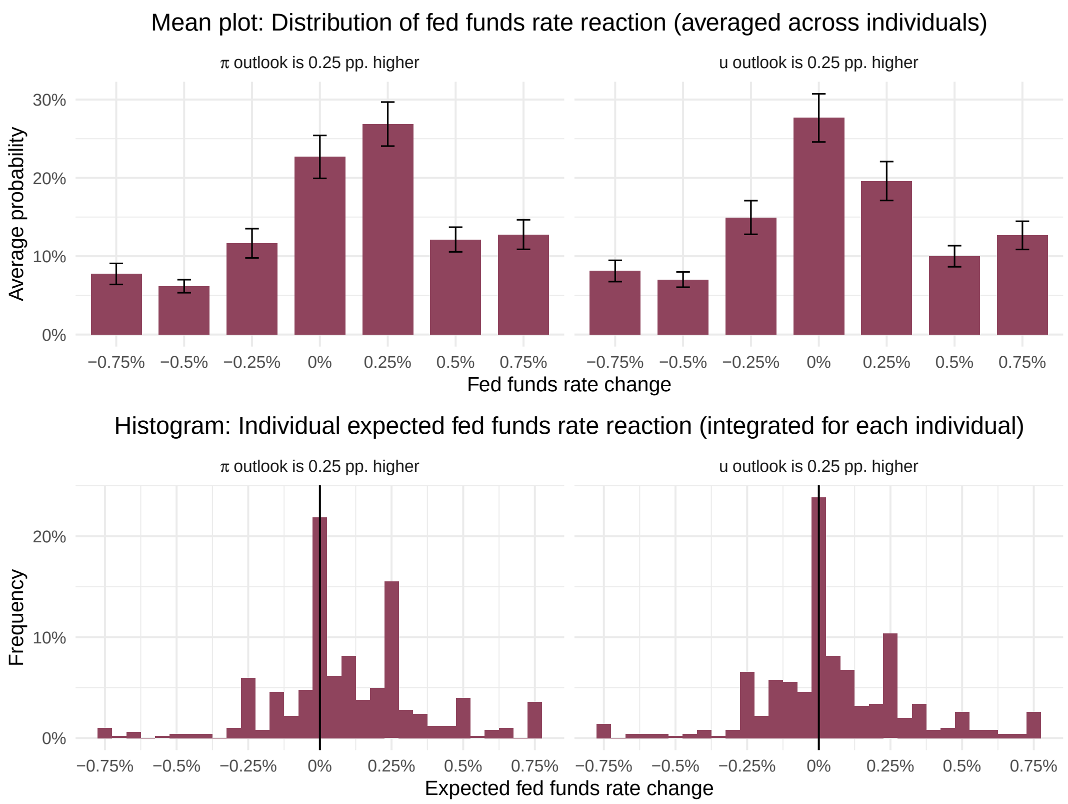
	Indicator for benchmark-consistent prediction	
	Separate bivariate models	Multivariate model
	(1)	(2)
Consistent Good-Bad-Heur.	0.138***	0.102***
	(0.019)	(0.019)
Consistent channel association	0.172***	0.141***
	(0.015)	(0.015)
Consistent perceived correlation	0.181***	0.149***
	(0.017)	(0.016)
Importance of model (1 if >median)	0.042***	0.014
	(0.015)	(0.015)
Knowledge (1 if >median)	0.077***	0.031**
	(0.015)	(0.015)
Numeracy (1 if >median)	0.062***	0.027*
	(0.015)	(0.014)
Female	−0.026*	−0.007
	(0.015)	(0.014)
Age (1 if >median)	0.058***	0.028*
	(0.015)	(0.015)
College degree	0.022	−0.004
	(0.015)	(0.015)
Income (1 if >median)	0.012	0.000
	(0.016)	(0.016)
Republican	0.021	0.018
	(0.016)	(0.015)
Mean share of benchmark-consistent pred.	0.480	0.480
Fixed effects	Vignette ⊗ rate	Vignette ⊗ rate
Observations	3,844	3,844
R^2	–	0.245

Notes: This table presents results from Wave 3 of the household survey. It presents the effect of various binary covariates on the likelihood of making inflation or unemployment predictions (pooled) that are consistent with the benchmarks, i.e. directionally aligned with the literature benchmark. Each coefficient can be interpreted as the increase in probability that a forecast is benchmark-consistent. Column (1) shows the results from separate bivariate regressions, while Column (2) shows the results from a multivariate model. "Consistent Good-Bad-Heur." takes value 1 if the good-bad-heuristic is directionally aligned with a benchmark-consistent prediction. "Consistent channel association" takes value 1 if the respondent chooses a channel (structured question) that suggests a benchmark-consistent prediction (e.g. a negative demand-side channel for the federal funds rate vignette). Likewise, "Consistent perceived correlation" takes value 1 if respondents believe in a past correlation between the shock variable (e.g. oil price) and the target variable (e.g. inflation) that is in line with a benchmark-consistent prediction. "Importance of model" measures respondents' assessment of how important knowledge of the functioning of the economy is to them for making good economic decisions. "Knowledge" measures information about the current state of the economy. "Numeracy" is respondents' score on a numeracy test. "1 if >median" indicates that a variable is binarized and takes value 1 for respondents with an above-median value. We include fixed effects for each vignette-rate combination (e.g. oil-inflation). Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

H.5 Misperceived Endogeneity in the Interest Rate Vignette

In Wave 2 of the household survey we conduct an additional quantitative robustness check against the possibility that respondents misperceive the monetary policy shock as the Fed's endogenous response to a change in its outlook for inflation. We elicit subjective beliefs about how the Fed usually adjusts interest rates to an unexpected increase in the outlook for (i) inflation and (ii) unemployment. For inflation, we ask our respondents to "imagine that the FOMC changes their outlook for inflation over the next 12 months due to data revisions, while there is no change in the outlook for unemployment. Specifically, the Fed believes that the inflation rate will be 0.25 p.p. higher than their initial estimate." We provide similar instructions for the change in the outlook for unemployment. Thereafter, we measure respondents' beliefs about how the Fed would adjust the federal funds rate. Figure A.13 shows that there is substantial heterogeneity in beliefs on how the Fed would adjust interest rates. If our results were driven by respondents attributing a higher fed funds rate to a change in the Fed's outlook for inflation, we would expect stronger predicted increases in inflation among those respondents who believe that the Fed reacts more strongly to a higher outlook for inflation. However, there is no significant heterogeneity along this dimension and, if anything, the patterns go in the opposite direction of what would be predicted by this potential confound (see Table A.27). Likewise, we can rule out that respondents interpret the interest rate change as a signal that the FOMC changed its unemployment outlook.

Figure A.13: Households: Descriptive statistics for the subjective interest rate rules



Notes: This figure analyzes the distribution of responses to the subjective interest rate rule questions in Wave 2 of the household survey. Respondents are asked to estimate the likelihood of different federal funds target rate changes in response to a 0.25 pp. increase in the Fed's outlook for the inflation rate or the unemployment rate. For each possible federal funds target rate reaction, the "Mean plot" summarizes the average probability assigned to this event (averaged across individuals), with 95% confidence intervals. The histogram plots the distribution of individual-level expected changes in the federal funds target rate in response to increases in the Fed's outlook for inflation or unemployment (integrated for each individual).

Table A.27: Households: Misperceived endogeneity of interest rate shock

Panel A: Binary monetary policy reaction

	fed. funds rate			
	$\Delta\pi$	Δu	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)
$1(\alpha > 0)$	−0.104		−0.088	0.055
	(0.099)		(0.099)	(0.097)
$1(\beta > 0)$		−0.098	−0.059	−0.113
		(0.092)	(0.097)	(0.095)
Constant	0.259***	0.152**	0.279***	0.126
	(0.076)	(0.064)	(0.087)	(0.079)
Observations	503	503	503	503
R^2	0.002	0.002	0.003	0.003

Panel B: Expected monetary policy reaction

	fed. funds rate			
	$\Delta\pi$	Δu	$\Delta\pi$	Δu
	(1)	(2)	(3)	(4)
$\alpha/4$	−0.332		−0.304	−0.143
	(0.211)		(0.201)	(0.188)
$\beta/4$		−0.068	−0.079	−0.015
		(0.188)	(0.204)	(0.188)
Constant	0.232***	0.107**	0.234***	0.119**
	(0.053)	(0.047)	(0.054)	(0.050)
Observations	503	503	503	503
R^2	0.006	0.000	0.007	0.001

Notes: This table reports regressions that test for a misperception of the interest rate shock as an endogenous reaction of the Fed to a changed outlook in inflation or unemployment, using Wave 2 household data. α denotes the perceived coefficient on π^e in the Fed's linear forward-looking interest rate rule, and β denotes the perceived coefficient on u^e. Δu denotes the predicted change in the unemployment rate compared to the baseline scenario. $\Delta\pi$ denotes the predicted change in the inflation rate compared to the baseline scenario. Panel A regresses both variables on $1(\alpha > 0)$ – a dummy taking value 1 if the respondent believes that the Fed would increase the federal funds target rate in response to an unexpected increase in the outlook for future inflation – and $1(\beta > 0)$ – a dummy taking value 1 if the respondent believes that the Fed would increase the federal funds target rate in response to an unexpected increase in the outlook for future unemployment. Panel B uses α and β which are the respondents' estimates of the coefficients in the forward-looking interest rate rule. They are divided by 4 because the inflation and unemployment outlook change by 0.25 p.p. (rather than 1 pp.) in the survey questions. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

I Subjective Models in Inflation Expectations: A Simple Framework

In this section, we present a simple framework to include subjective models of the propagation of shocks into the formation of inflation expectations. Without loss of generality, the same example is applicable to other macroeconomic variables. We consider how the resulting dynamics compare to those of the sticky-information model of Mankiw and Reis (2002). In particular, we discuss whether the framework can produce three empirical features of inflation expectations:

1. The cross-sectional average of inflation expectations across individuals under-reacts to a shock compared to actual inflation;
2. The sluggish response to a shock of the average expectation implies that forecast errors for inflation of period $T > t_0$ are correlated between periods t_0 and $T-1$;
3. Disagreement (i.e., the cross-sectional dispersion among individuals in expectations) increases in response to a shock.

Model Assume that inflation follows an AR(1) process:

$$\pi_t = \rho\pi_{t-1} + \omega_t \tag{1}$$

End-of-period inflation π_t is not observed at the beginning of period t, when agents fully observe past end-of-period inflation π_{t-1} and the beginning-of-period shock ω_t. However, while the true inflation process remains (1), agents hold different beliefs on the impact of the shock, such that they derive different expectations of π_t. Specifically an individual i receives a draw of the coefficient α such that:

$$\mathbb{E}_t^\alpha \pi_t = \pi_{t|t}^\alpha = \rho\pi_{t-1} + \alpha\omega_t, \tag{2}$$

$$\alpha \sim N(\mu_\alpha, \sigma_\alpha^2) \tag{3}$$

Note that α can be below 0, implying that an agent thinks that the shock affects the economy with opposite sign.

The individual expectation of inflation h periods ahead at the beginning of period t is

$$\begin{aligned}
\mathbb{E}_t^{\alpha}\pi_{t+h} &= \mathbb{E}_t\big(\rho^{h+1}\pi_{t-1} + \alpha\rho^h\omega_t + \sum_{k=0}^{h-1}\rho^{h-k}\omega_{t+h-k}\big) \\
&= \rho^{h+1}\pi_{t-1} + \alpha\rho^h\omega_t
\end{aligned}$$

The cross-sectional average of expectations for inflation h periods ahead, in period t is

$$\begin{aligned}
\overline{\pi_{t+h|t}} = \overline{\mathbb{E}}(\pi_{t+h|t}(\alpha)) &= \int \mathbb{E}_t^{\alpha}\pi_{t+h} \ \mathrm{d}F(\alpha) \\
&= \int \big(\rho^{h+1}\pi_{t-1} + \alpha\rho^h\omega_t\big) \ \mathrm{d}F(\alpha) \\
&=\rho^{h+1}\pi_{t-1} + \mu_\alpha\rho^h\omega_t
\end{aligned}$$

If $\mu_\alpha = 1$, the cross-sectional average across individuals is unbiased. If $\mu_\alpha < 1$, the cross-sectional average of inflation expectations under-reacts to a shock, which would be consistent with one of the empirical facts established by the literature mentioned above.

Disagreement is defined as the cross-sectional variance in the expectations:

$$\begin{aligned}
\mathbb{V}_t\pi_{t+h} &= \int \big(\mathbb{E}_t^{\alpha}\pi_{t+h} - \overline{\pi}_{t+h|t}\big)^2 \mathrm{d}F(\alpha) \\
&= \int \big(\rho^{h+1}\pi_{t-1} + \alpha\rho^h\omega_t - \rho^{h+1}\pi_{t-1} - \mu_\alpha\rho^h\omega_t\big)^2 \mathrm{d}F(\alpha) \\
&= \int \big(\alpha - \mu_\alpha\big)^2\big(\rho^h\omega_t\big)^2 \mathrm{d}F(\alpha) \\
&=\big(\rho^h\omega_t\big)^2\sigma_\alpha^2
\end{aligned}$$

Since disagreement is a function of the squared value of ω_t, it follows that disagreement rises with the absolute size of shocks, independently of their sign.

In the context of our empirical results, the model could be generalized to include multiple observed shocks ω_t^j, where j represents the nature of the shock, e.g., an oil, monetary policy, tax, or government spending shock. Moreover, each agent would have a draw of α^j corresponding to the shock j and capturing beliefs on the propagation of the specific shock. In the exercise we carry out below, we use the survey results to calibrate the parameters μ_α and σ_α for the oil shock and the interest rate shock. We then discuss how the computed response of inflation expectations and disagreement compares to that ensuing under the assumption of sticky information.

Comparison with sticky-information assumption As a benchmark for comparison we consider the sticky-information inflation expectations model of Mankiw and Reis (2002), as described in Coibion and Gorodnichenko (2012). The key assumption of the model is that, although agents form expectations according to (1), in each period t they observe the true inflation π_t with probability $(1-\lambda)$, where $0 < \lambda < 1$. Hence, a shock ω_t is gradually incorporated into expectations as more and more agents observe the new level of inflation over time. We refer the readers to Coibion and Gorodnichenko (2012) for a more detailed discussion of this model.

Responses of expectations and disagreement to shocks To compare the two models quantitatively, we compute the response of inflation expectations and disagreement to a shock ω_t starting from a steady state of $\pi_s = 0$ for $s < t_0$.

We parametrize the process of inflation by estimating an AR(1) equation on US inflation between 1960 and 2019 at quarterly frequency, which yields an estimate for ρ of 0.9.[12] For the size of the true shock ω_t we use the theoretical benchmarks that we derived for the discussion of our empirical results (see Appendix C for details).

For each shock, the values of μ_α and σ_α are derived from the survey results. μ_α is computed as the ratio of the average predicted change among household to the benchmark for the impact of the shock, while σ_α is the ratio of the standard deviation of the change predicted by households to the benchmark.[13]

For the sticky-information expectations, we set $\lambda = 0.75$, consistent with the findings by Carroll (2003) for non-expert households. This value implies that, on average, agents update their expectations for inflation once a year (i.e., every four quarters).

For the oil price (top panels) and interest rate (bottom panel) shocks, Figure A.14 reports the response of (i) the true inflation process, as it would also be elicited by full-information rational expectations (black triangles), (ii) the subjective-models expec-

[12]For inflation we use the annualized growth rate in the urban CPI downloaded from the FRED Database of the Federal Reserve of St. Louis.

[13]For the oil price shock, the values are $\mu_\alpha = 0.34$ and $\sigma_\alpha = 0.52$. For the interest rate shock, $\mu_\alpha = -0.93$ and $\sigma_\alpha = 3.12$

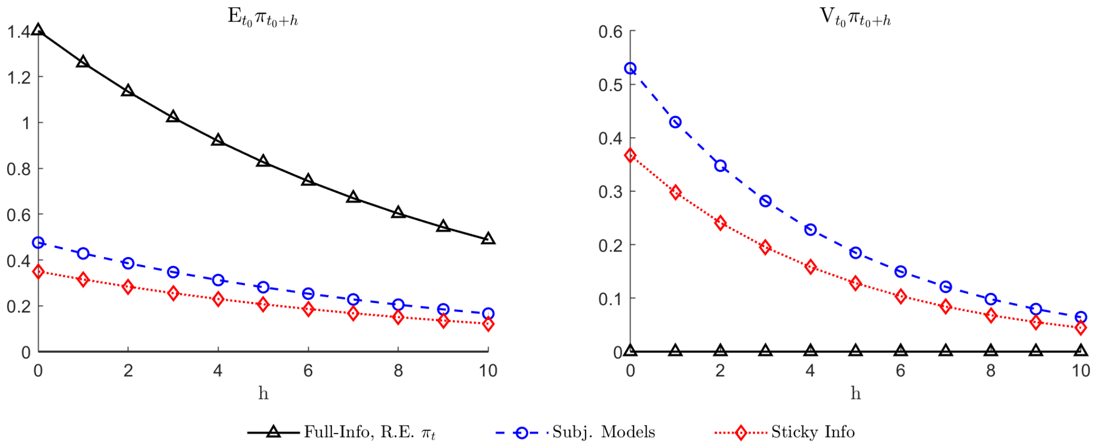
tations (blue circles), and (iii) the sticky-information expectations (red diamonds). The left panels report the change in the expectations at time t_0 of inflation for times $t_0 + h$. The right panels report the change in disagreement at time t_0 with respect to expectations for π_{t_0+h}. In the oil price shock, the subjective models specification produces an average expected inflation and disagreement that are approximately 25 to 35 percent larger than the sticky-information one. For the interest rate shock, the average expectation under subjective models is close in magnitude to the true shock but has the opposite sign compared to both the true inflation response and the sticky-information model. This is consistent with our baseline results showing that on average households expect inflation to rise after a tightening of monetary policy. Moreover, the large level of disagreement across households on the effect of monetary policy, as elicited in our survey, entails a rise in disagreement over expected inflation under the subjective models specification that is many times larger than for the sticky-information model (bottom right panel).

Persistence of expectations The previous figures focused on the contemporaneous response of average expected inflation and disagreement over a forecast horizon. However, a key empirical regularity of average inflation expectations, as discussed by Coibion and Gorodnichenko (2012), is the persistence in forecast errors for inflation at a given time T. In other words, $\pi_T - \overline{\pi}_{T|t}$ and $\pi_T - \overline{\pi}_{T|t+1}$ are positively correlated. The sticky-information model captures this feature because information on new shocks is only acquired by a fraction of agents in each period. In contrast, the subjective-models specification by itself does not produce any persistence in forecast errors under the assumption that past inflation is perfectly observed at time t, implying a fully updated information set up to the beginning of the period.

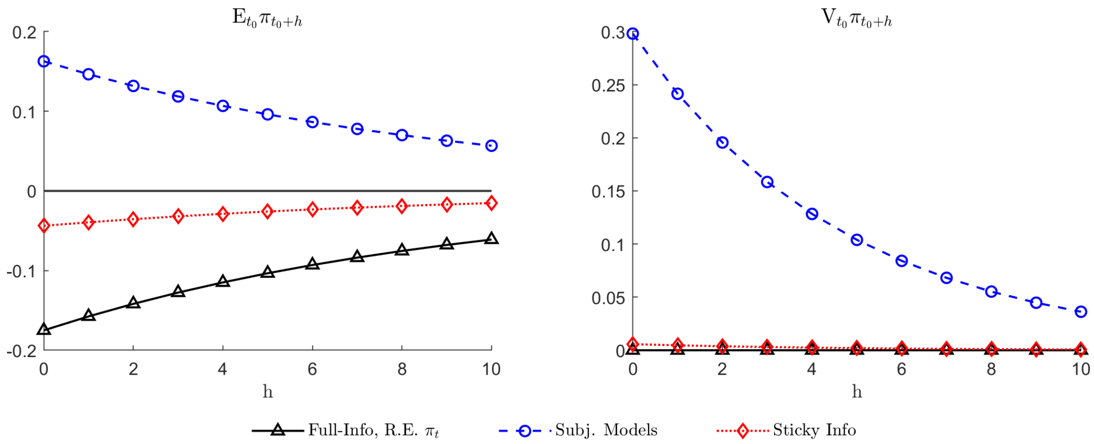
Combining sticky information and subjective models While our survey does not speak to the persistence of forecast errors, for illustrative purposes, below we discuss the behavior of forecast errors and disagreement over time in response to a shock – rather than just in the concurrent period. As an example we use the parametrization of the oil vignette. Moreover, to ease the comparison, we consider a third specification of expectations that combines sticky information and subjective models. In this set-up, at time t a fraction $1-\lambda$ of agents fully observes past inflation π_{t-1} and the current shock ω_t. This extra specification provides an indication of how some degree of information friction

Figure A.14: Responses of inflation expectations and disagreement to an exogenous shock under alternative specifications of expectations formation

(a) Oil price shock



(b) Interest rate shock



Notes: The panels report the response of the cross-sectional average and variance of inflation expectations at time t_0 over the forecasting horizon $t + h$, to a one-standard deviation shock to the true inflation process, where $h = 0, ..., 10$. The black triangles plot the response for the true inflation process, also consistent with a full-information rational-expectations model. The blue circles plot the response under the subjective-models specification. The red diamonds report the response under the sticky-information specification. See the main text in Appendix I for more details. The size of the shock is based on the empirical benchmarks used in the main text for the analysis of the results (see Appendix C for more details).

can be added to the subjective models assumption to replicate the empirical persistence in forecast errors.

The cross-sectional average of expectations of this specification is:

$$\overline{\pi_{t+h|t}}^{SI+SM} = (1-\lambda)\sum_{k=0}^{\infty}\lambda^k(\rho^{k+h+1}\pi_{t-k-1} + \mu_\alpha\rho^{k+h}\omega_{t-k}) = (1-\lambda)\sum_{k=0}^{\infty}\lambda^k\overline{\pi_{t+h|t}}^{SM},$$

where the superscript SM represents the subjective-models expectation and the superscript $SI{+}SM$ represents the joint sticky-information and subjective models specification. Disagreement is as follows:

$$\mathbb{V}_t^{SI+SM}\pi_{t+h} = (1-\lambda)\sum_{k=0}^{\infty}\lambda^k\Big(\mathbb{V}_t^{SM}\pi_{t+h} + (\overline{\pi_{t+h|t-k}}^{SM} - \overline{\pi_{t+h|t}}^{SM+SI})^2\Big).$$

For illustrative purposes, we examine the dynamics of the $SI + SM$ model using two alternative values of λ. The first is $\lambda^{SI+SM} = 0.75$, equal to the value used in the pure sticky-information model from Carroll (2003). The second is a calibrated value of λ^{SI+SM} such that the initial reaction of inflation expectations to the shock is equal to that of the sticky-information model. Based on the other parameter values used for the previous exercise, the resulting value is $\lambda^{SI+SM} = 0.265$.

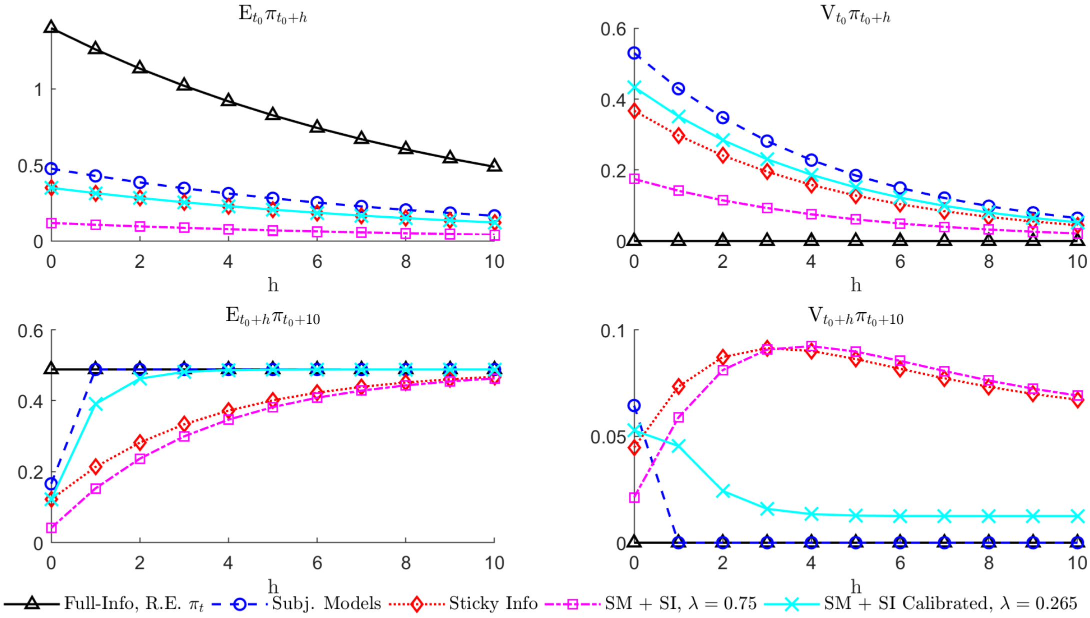
Figure A.15 reports the results of the exercise. The top panels are the same as in Figure A.14 except for the addition of the $SI + SM$ specifications (magenta squares for the baseline specification with $\lambda^{SI+SM} = \lambda = 0.75$ and light blue X's for the alternative calibrated $\lambda^{SI+SM} = 0.265$). In the top left panel, the response of average expectations under the baseline $SI + SM$ specification is more muted than both the subjective models and the sticky-information specifications by virtue of the parameter choice. Intuitively, in the first period the only response of expectations comes from the fraction $1 - \lambda < 1$ of agents observing the shock, whose average update of expectation is a multiple $\mu_\alpha < 1$ of the true shock. Hence, the two behavioral features of expectations compound each other in a multiplicative way. The average expectations in the alternative, calibrated $SI + SM$ model entirely overlap those of the sticky-information model. By construction, matching the response in period t_0 implies the same level of persistence in forecast across the two specifications also at longer time horizons. Intuitively, the addition of subjective models to sticky-information implies that the same level of under-reaction to a shock can be obtained with a lower level of information friction (0.265 instead of 0.75 in this case).

The response of disagreement in period t_0 under the baseline $SI+SM$ specification is also more muted than those of the two constituent models. While this result is dependent on parameter choices, and the fact that $\mu_\alpha < 1$ for the oil vignette, it intuitively derives from the fact that both specifications mute the true response of inflation: Disagreement is limited when fewer agents observe any new information that can lead to heterogeneous expectations or when they under-react to it. When re-calibrating the λ^{SI+SM} parameter, however, disagreement rises closer to the level of the subjective models specification since a larger fraction of agents noisily observe the shock.

The bottom panels of Figure A.15 report the response of expectations and disagreement at time $t_0 + h$ with respect to a fixed time in the future, in this case $t_0 + 10$. The subjective models specification assumes that after period t_0 all agents perfectly observe past inflation. Hence, average expectations converge to the true expected inflation and disagreement disappears after one period (left panel). Meanwhile, under sticky information, average expectations converge slowly, leading to the correlation in forecast errors, and disagreement has a hump-shaped response. In this case, $\mu_\alpha < 1$ implies that the baseline $SI + SM$ specification increases the lag in the convergence of average expectations compared to the sticky-information model. Meanwhile, the variance of expectations in the combined model maintains a path similar to the sticky-information model (right panel), as the inability to perfectly observe past realizations of inflation is the main driver of the persistence in disagreement. Having a lower degree of information frictions, the alternative, calibrated $SI + SM$ specification features a persistence in expectations and disagreement between that of the sticky-information model and the absence of persistence of the subjective models specification.

Take-aways from the combined model. This exercise shows that, in the case when $\mu_\alpha < 1$, the combination of subjective models and sticky information generates dynamics of expectations that compound the effect of the two models with respect to the immediate reaction of expectations to a shock but that more closely resemble those of the sticky information model in terms of persistence in expectations and disagreement over time. Moreover, adding heterogeneity in beliefs about the model of the economy implies that the sluggish response of inflation expectations to a shock need not be driven entirely by

Figure A.15: Responses of inflation expectations and disagreement to the oil price shock under alternative expectations formation models at time t_0 and a time $t_0 + h$



Notes: The panels report the response of the cross-sectional average and the variance of inflation expectations to a one-standard deviation shock to the true inflation process. The top panels focus on the path of expectations in period t_0, when the shock realizes, for the time horizon $t + h$, $h = 0, ..., 10$. The bottom panels focus on the expectations in period $t + h$, $h = 0, ..., 10$ for inflation at time $T = 10$. The black triangles plot the response for the true inflation process, also consistent with a full-information rational-expectations model. The blue circles plot the response under the subjective-models specification. The red diamonds report the response under the sticky-information specification. The magenta squares plot the specification combining sticky information and subjective models. The light blue X's report the specification combining sticky information and subjective models with the parameter λ calibrated to match the inflation expectation response of the sticky-information model. See the main text in Appendix I for more details. The size of the shock is based on the empirical benchmarks used in the main text for the analysis of the results (see Appendix C for more details).

information stickiness. It is hence possible that empirical estimates of the frequency at which agents update their information, if solely recovered from the time-series properties of average expectations, may over-estimate or under-estimate the level of information stickiness if subjective models are not accounted for. In the case of the oil shock, we find that information stickiness may be over-estimated. However, given that the parameters of the subjective models specification are dependent on the specific vignette, the result may differ for other shocks. In cases where the average expectation among respondents is larger than the true reaction of inflation (i.e., $\mu_\alpha > 1$), information stickiness would be under-estimated. Finally, in cases where agents update their beliefs in the wrong direction, such as in the interest rate vignette, the interaction of subjective models and information frictions is likely more complicated.

J Details on Expert Surveys

J.1 Wave 1

We compiled a list of participants of the following conferences:

- SITE Macroeconomics of Uncertainty and Volatility (2018, 2017, 2016)
- SITE Macroeconomics and Inequality (2018)
- Cowles Macro Conference (2018, 2017, 2016)
- NBER Annual Conference on Macroeconomics (2018, 2017, 2016)
- ifo Conference on "Macroeconomics and Survey Data" (2018, 2017, 2016)
- Venice Summer Institute on Expectation Formation (2018)
- Workshop on Subjective Expectations NY Fed (2016)

We also recruited a sample of graduate students in macroeconomics from the following institutions:

- University of Bonn
- Goethe University Frankfurt
- University of Oxford

Finally, we also recruited a sample of economists from the following policy institutions:

- The Federal Reserve Board, Washington D.C.
- The International Monetary Fund, Washington D.C.
- Bank for International Settlements, Basel
- Deutsche Bundesbank, Frankfurt
- European Central Bank, Frankfurt
- ifo centre, Munich

Below is a list of the institutions that our experts (from Wave 1) have as one of their main institutions: Kellogg School of Management, Northwestern University, University of Cologne, Haverford College, University of Minnesota, Ross School of Business, University of Michigan, Federal Reserve Bank of Boston, University of Amsterdam, Boston University, Questrom School of Business, Federal Reserve Bank of St. Louis, Goethe University Frankfurt, LMU Munich, University of Notre Dame, University of California San Diego, University of Oxford, Temple University, International Monetary Fund, University of Toronto, Carleton University, Yale University, Federal Reserve Board, University of Copenhagen, University of Bologna, Georgia Institute of Technology Atlanta, Statistics Norway, Deutsche Bundesbank, Frankfurt School of Finance & Management, Johns Hopkins University, Baltimore, Brandeis University, Federal Reserve Bank of Cleveland, Bank of England, MIT Sloan School of Management, Rand Corporation, University of Copenhagen, International Monetary Fund, Swiss National Bank, Boston College, University of Reading, UNC Kenan-Flagler Business School, Bonn Graduate School of Economics, Institute for Employment Research Friedrich-Alexander University (FAU) Erlangen-Nuremberg, College of Business Clemson University, ifo Institute Munich, Stockholm University, Banque de France, University of Nantes, Uppsala University, World Bank, University of St.Gallen, Austrian Institute of Economic Research, Copenhagen Business School, Federal Reserve Bank of Minneapolis, NYU Stern School of Busines, University of Bonn, Mannheim University, University of Manchester, University College London, University of Lausanne, Arizona State University, University of Birmingham, Federal Reserve Bank of Chicago, European Central Bank, Bank for International Settlements, Basel, University of Maryland, Amsterdam School of Economics, Columbia University, Christian Albrechts University at Kiel, Princeton University, Stockholm School of Economics, University of Chicago Booth School of Business, University of Warwick, Leibniz University Hannover, University of Heidelberg, University of Copenhagen, Northwestern University, New York University, Federal Reserve Bank of Minneapolis, Indiana University, Karlsruhe Institute of Technology.

J.2 Wave 3

We identify the email addresses of all economists who published in the top 20 economics journals on JEL code "E: Macroeconomics and Monetary Economics" in the years 2015-

2019. We consider the following journals: Journal of Political Economy, Quarterly Journal of Economics, Econometrica, Review of Economic Studies, American Economic Review, Journal of Economic Literature, Journal of Economic Perspectives, Journal of the European Economic Association, Journal of Financial Economics, Review of Financial Studies, Journal of Finance, Review of Economics and Statistics, International Economic Review, Journal of Monetary Economics, Review of Economic Dynamics, Economic Journal, American Economic Journal: Macroeconomics, American Economic Journal: Applied Economics, Journal of Economic Growth, and Brookings Papers an Economic Activity.

We also identify students from the top ten European and the top ten US economics departments according to the Shanghai 2020 ranking. The departments in the US are: Harvard, MIT, UChicago, Northwestern, Yale, Princeton, Berkeley, Stanford, Colombia, NYU. The departments in Europe are: LSE, Oxford, Cambridge, UCL, Toulouse, Warwick, Rotterdam, Bocconi, Zurich, Oslo.

We also invited PhD students from Bonn and Copenhagen (where two of the authors are based) as well as all respondents we reached out to in Wave 1 of our expert survey.

We sent a link to our study to all of these economists by email. We did not send any reminders. In total, we contacted 4,367 economists. 375 economists responded to our survey, corresponding to a response rate of 8.6%.

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