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The Effect of Macroeconomic Uncertainty on Household Spending†

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We use randomized treatments that provide different types of information about the first and/or second moments of future economic growth to generate exogenous changes in the perceived macroeconomic uncertainty of treated households. The effects on their spending decisions relative to an untreated control group are measured in follow-up surveys. Our results indicate that, after taking into account first moments, higher macroeconomic uncertainty induces households to significantly and persistently reduce their total monthly spending in subsequent months. Changes in spending are broad based across spending categories and apply to larger durable good purchases as well. (*JEL* D12, D81, D84, E21, E23, G51)

Volatility, according to some measures, has been over five times as high over the past six months as it was in the first half of 2007. The resulting uncertainty has almost surely contributed to a decline in spending.
—CEA Chair, Christina Romer (2009)

"Almost surely." The idea that high uncertainty induces households to spend less and firms to reduce their investment and employment is intuitive and consistent with many theoretical models. It is also omnipresent in policymakers' discussions of the economy, particularly during times of crisis. Yet, as emphasized in Bloom's (2014, p. 168) survey of the literature on uncertainty, the empirical evidence on these channels is at best "suggestive," and "more empirical work on the effects of uncertainty would be valuable, particularly work which can identify clear causal relationships." In this

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paper, we use randomized control trials (RCTs) in a new large cross-country survey of European households to induce exogenous variation in the macroeconomic uncertainty perceived by households and study the *causal* effects of the resulting change in uncertainty on their spending relative to that of untreated households. We find that higher uncertainty leads to sharply reduced total monthly spending by households in subsequent months. Households are also less likely to purchase large durable or luxury goods. In short, we provide direct causal evidence that the "almost surely" can be safely dropped: higher uncertainty makes households spend less on average.

Our results are based on the new Consumer Expectations Survey, a population-representative survey of households in Europe implemented by the European Central Bank (ECB). This survey spans the six largest euro area (EA) countries and thousands of households. In September 2020, we made use of the significant dispersion in professional forecasts about GDP growth in the euro area and implemented information treatments to randomly selected subsets of respondents to affect their expectations and uncertainty about future economic growth. Some treatments primarily targeted first moments of household expectations (e.g., by telling them about average professional forecasts of future GDP growth), some targeted the second moments of their expectations (e.g., by telling them about the uncertainty in professional forecasts of future GDP growth), and some targeted both (e.g., by telling them both about the average level and the uncertainty in professional forecasts of future growth). The differential effects of these information treatments on the first and second moments of households' growth expectations allow us to identify *exogenous* variation in the perceived macroeconomic uncertainty of households. With follow-up surveys tracking household spending, we can characterize the extent to which changes in uncertainty drive household spending decisions.

Our main result is that higher macroeconomic uncertainty, holding constant the first moment of expectations, reduces the spending of households over several months. The effect is economically large. As emphasized in Bloom (2014), a central challenge in the uncertainty literature has been separately identifying the effects of expectations about first and second moments since most large uncertainty events are also associated with significant deteriorations in the expected economic outlook. Our approach is able to address this identification challenge and provides clear causal evidence that macroeconomic uncertainty affects the overall spending of households: because of their lower average level of macroeconomic uncertainty, our treated households increase their spending on average by 0.5–0.8 percent relative to untreated households. These adjustments in spending hold across different categories of goods and services. We also identify a reduced likelihood of purchasing large items, such as holiday packages and luxury goods (e.g., watches), when macroeconomic uncertainty rises. Spending is most affected by uncertainty for those individuals working in riskier sectors, as well as households whose investment portfolios are most exposed to risky financial assets. We also find that when individuals face higher uncertainty, they report that they would be less likely to allocate new financial investments to mutual funds or cryptocurrencies.

These results contribute to a growing literature on uncertainty building on the seminal work of Bloom (2009). Work in this literature has focused empirically on how to measure uncertainty and quantify the effect of uncertainty on aggregate conditions (e.g., Bloom et al. 2018; Baker, Bloom, and Davis 2016; Jurado, Ludvigson, and

Ng 2015; Berger, Dew-Becker, and Giglio 2020) and theoretically on understanding the different channels through which uncertainty can affect decision-making (e.g., Leduc and Liu 2016; Basu and Bundick 2018). Much of this work has emphasized the effect of uncertainty on firms' decisions (Guiso and Parigi 1999; Bloom, Bond, and Van Reenen 2007; Baker, Bloom, and Davis 2016; Gulen and Ion 2016). There has been more limited research with mixed results on how households respond to uncertainty. Ben-David et al. (2018), for example, find that US households who are more uncertain about future economic outcomes are more cautious in their consumption and investment decisions, while Khan and Knotek (2011) conclude that uncertainty shocks have only modest effects, at best, on household spending. Christelis, Georgarakos, Jappelli, and van Rooij (2020) find that household uncertainty about future consumption induces a strong precautionary savings behavior. Dietrich et al. (2022) and Coibion, Gorodnichenko and Weber (2022b) consider the possible implications of the rise in uncertainty during the COVID-19 pandemic. D'Acunto, Rauter, Scheuch, and Weber (2021) use the provision of credit lines to first-time borrowers as a shock to precautionary savings demand and show that reduced precautionary savings needs increase spending.

A key challenge in the uncertainty literature is identifying exogenous variation in uncertainty since large uncertainty episodes are typically associated with events that affect first moments as well as second moments (e.g., the 9/11 attacks, Brexit, etc.). Baker, Bloom, and Terry (2020) utilize natural experiments like political shocks or natural disasters to try to identify uncertainty shocks. A more common strategy is to utilize timing restrictions in VARs (e.g., Caldara et al. 2016; Bachmann, Elstner, and Sims 2013). In contrast to this earlier body of work, we apply RCT methods to help identify exogenous changes in macroeconomic uncertainty. To the best of our knowledge, we are the first to apply such methods to create exogenous variation in the uncertainty of households that can then be used to characterize how uncertainty affects spending decisions. Moreover, given that we use micro data, we can explore the likely heterogeneous effects that uncertainty has across various population segments.

Our paper is part of a broader research agenda that is incorporating RCT methods in large-scale surveys of households and firms to address macroeconomic questions. Roth and Wohlfart (2020), for example, use information treatments about the economic outlook to study how households' expectations about future growth affect their consumption plans. Armantier et al. (2016) and Cavallo, Cruces, and Perez-Truglia (2017) study how different types of information about inflation or monetary policy affect households' inflation expectations. Coibion, Gorodnichenko, and Weber (2022a); Coibion et al. (2023); and D'Acunto et al. (2023) follow a similar strategy to show that exogenous variation in households' inflation expectations affect their subsequent spending decisions. Coibion, Gorodnichenko, and Kumar (2018) use RCT methods to study how firms' expectations affect their subsequent pricing, investment, and employment decisions. Common across these papers is the fact that information treatments in surveys have the capacity to change agents' economic expectations in meaningful ways, and in many cases, these papers also show that these changes in beliefs subsequently affect the economic decisions of agents. Relative to this earlier body of work, we are the first to use this identification strategy to characterize how economic uncertainty affects the spending decisions of households.

Our RCT results exploit the new Consumer Expectations Survey (CES), an ongoing panel administered by the ECB that interviews every month, since April 2020, about 10,000 households in the 6 largest euro area economies. The survey covers a wide range of questions on household expectations and behavior, similar to the coverage of the Survey of Consumer Expectations run by the New York Fed, but its scale is significantly larger. In September 2020, we implemented a special-purpose survey beyond the regular survey modules. In this special survey, randomly selected households were provided with certain types of information (or no information) about either euro area GDP growth, disagreement about that future growth, or both growth and disagreement. Subsequent survey waves in October 2020 and January 2021 allow us to assess whether household spending varied with the information treatments.

Our results support one of the main mechanisms via which uncertainty is thought to affect macroeconomic outcomes: changing household spending. The clear evidence we document on household spending speaks directly to policy discussions involving the extent to which high levels of uncertainty may depress economic activity. The COVID-19 pandemic has been associated with exceptionally high levels of uncertainty for certain groups of households and has contributed to a reduction in their spending (Binder 2020 and Coibion, Gorodnichenko, and Weber 2022b). Yet our inference is not driven by pandemic-induced uncertainty per se, as households impacted by the pandemic are equally present in the control and treatment groups. Still, our treatments may induce disproportionally more changes in macroeconomic uncertainty for households that are susceptible to the effects of COVID-19. In view of this, we also use our approach to shed light on such heterogeneous treatment effects by considering households with a different exposure to COVID-19 (e.g., sample splits by sector of employment).

The paper is organized as follows. Section I describes the survey. Section II presents results on how the information treatments affect expectations. Section III then provides evidence on the extent to which exogenous changes in uncertainty affect total monthly household spending. Section IV considers some of the underlying mechanisms as well as additional margins though which uncertainty may affect household decisions. Section V concludes.

I. Data and Survey Design

We use micro data from the ECB's CES, a new online high-frequency panel survey measuring euro area consumer expectations and behavior. The CES has a number of novel features that make it easier to explore the transmission of economic shocks in the euro area via the household sector. In what follows we provide a brief summary of the main survey features. Georgarakos and Kenny (2022) provide a more detailed description of the CES, and ECB (2021) contains a first evaluation of the survey.[1]

The CES was launched in a pilot phase in January 2020 and achieved its target sample size of approximately 10,000 households by April 2020. Households are interviewed on a monthly basis in the six largest euro area economies (Belgium,

[1] For more detailed information and survey updates, see https://www.ecb.europa.eu/stats/ecb_surveys/consumer_exp_survey/html/index.en.html.

France, Germany, Italy, the Netherlands, and Spain). The sample is comprised of anonymized household-level responses from approximately 2,000 households in France, Germany, Spain, and Italy and 1,000 households in Belgium and the Netherlands. Respondents are invited to answer online questionnaires every month and leave the panel between 18 and 24 months after joining. Three out of four participants in the four largest euro area countries are recruited by phone via random dialing, while the remainder are drawn from existing samples. Survey weights are employed to help ensure that the data are nationally representative. As the 6 countries covered by the CES account collectively for more than 85 percent of the euro area GDP, the survey also provides good coverage for the overall household sector in the euro area.

Following recruitment, all respondents receive and complete a set of online survey questionnaires at different frequencies. Initially, each respondent completes a background questionnaire, which covers a range of important information that hardly changes on a monthly frequency (e.g., family situation, education, household annual income). More time-sensitive information is collected in a series of monthly (e.g., on expectations) and quarterly (e.g., on household spending) questionnaires. Our results are based on four specific waves of the survey (August, September, and October 2020 as well as January 2021). The September wave was augmented to include a special-purpose survey in which we implemented our RCT and posed additional questions that we detail below. Respondents receive the questionnaires on the first day of each month, and the vast majority of them complete the survey tasks within the first ten days in each month. As a result, their reported spending over the past 30 days, e.g., in the October wave, regards the interim period since the time they received the information treatments in September.

Table 1 provides descriptive statistics about respondents. For example, the average age of respondents is 49, and the average household after-tax income is €34,500 per year for an average household size of 2.6. Around 46 percent of respondents are working full-time, with another 13 percent working part-time; 24 percent are out of the labor force, while the remaining 17 percent are either looking for a job or on leave from work (either temporarily or long term). Most respondents are quite educated, with 53 percent reporting that they had completed some tertiary schooling. The table also shows that the sample is balanced across treatment and control groups.

The additional questions we added in September focus partly on the expectations of households about aggregate economic growth, both in levels and in terms of uncertainty.[2] To measure their initial beliefs about euro area growth, we first ask the following question (online Appendix C provides the detailed questionnaire):

> Please give your best guess about the *lowest* growth rate (your prediction for the most pessimistic scenario for the euro area growth rate over the next 12 months) and the *highest* growth rate (your most optimistic prediction).

[2] Because time allocated to the special-purpose (RCT) module in the September wave of the survey was limited and questions eliciting probability distributions are cognitively demanding, we could measure uncertainty for only one macroeconomic variable.

Table 1—Descriptive Statistics by Treatment Status

Variables	Control	Treat #1: EA first moment	Treat #2: EA second moment	Treat #3: EA first and second moments	Treat #4: Country second moment	Full sample	
	Treatment group						
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	p-val
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	49.29	49.18	49.02	48.59	48.39	48.88	0.33
	(16.75)	(16.16)	(16.82)	(17.04)	(16.55)	(16.66)	
Household size	2.57	2.6	2.56	2.65	2.64	2.61	0.13
	(1.35)	(1.27)	(1.29)	(1.26)	(1.27)	(1.29)	
Annual household income ('000€)	1.63	1.63	1.69	1.64	1.66	1.65	0.67
	(1.09)	(1.07)	(1.14)	(1.11)	(1.19)	(1.12)	
Monthly spending on nondur. goods ('000€)	49.29	49.18	49.02	48.59	48.39	48.88	0.50
	(16.75)	(16.16)	(16.82)	(17.04)	(16.55)	(16.66)	
Male	0.47	0.49	0.48	0.49	0.48	0.48	0.63
Employment status							
Working full-time	0.45	0.47	0.46	0.45	0.47	0.46	0.63
Working part-time	0.12	0.12	0.14	0.14	0.13	0.13	0.51
Temporarily laid off	0.02	0.01	0.01	0.01	0.01	0.01	0.42
On extended leave	0.05	0.05	0.05	0.04	0.04	0.05	0.19
Have no job but would like to have a job	0.11	0.11	0.10	0.11	0.12	0.11	0.33
Have no job and don't want a job	0.24	0.24	0.23	0.25	0.23	0.24	0.38
Education							
Primary	0.16	0.15	0.15	0.16	0.15	0.15	0.58
Secondary	0.32	0.32	0.32	0.31	0.33	0.32	0.67
Tertiary	0.52	0.53	0.53	0.53	0.52	0.53	0.71
Housing arrangement							
Owner-occupied property with mortgage	0.26	0.27	0.25	0.26	0.23	0.25	0.44
Owner-occupied property w/o mortgage	0.36	0.35	0.37	0.37	0.39	0.37	0.43
Rented house/flat	0.33	0.34	0.33	0.33	0.34	0.34	0.75
Country							
Belgium	0.06	0.05	0.05	0.05	0.00	0.04	0.62
Germany	0.28	0.31	0.29	0.30	0.32	0.3	0.12
Spain	0.17	0.15	0.15	0.17	0.19	0.17	0.05
France	0.21	0.21	0.21	0.19	0.25	0.22	0.30
Italy	0.21	0.21	0.22	0.21	0.24	0.22	0.84
Netherlands	0.07	0.07	0.09	0.08	0.00	0.06	0.23
Observations	2,049	2,046	2,055	2,051	2,047	10,248	

Notes: The table reports means and standard deviation (SD) for sociodemographic variables. Household income and spending are winsorized at bottom and top 1 percent. Sampling weights are applied. p-value in column 7 is for equality across treatment groups.

From the answers about how low and how high economic growth (denoted with y_m and y_M, respectively) could potentially be, we compute the moments of the subjective distribution of economic growth by assuming that it follows a simple triangular distribution around $(y_m + y_M)/2$ (see Guiso, Jappelli, and Pistaferri 2002). Based on the elicited values for y_m, y_M, we compute the household-specific mean forecast of growth and the uncertainty in their forecast as the standard deviation of the distribution of expected economic growth (formulas are reported in online Appendix B).[3]

We examine both the raw mean, uncertainty, and cross-sectional standard deviations across all respondents and within each country, as well as Huber (1964) robust versions of these moments to systematically control for outliers. The average forecast of growth of the euro area was around 0.2 percent with a large standard deviation of 12.3 percent.[4] Using robust methods yields a mean forecast of 1.5 percent and a cross-sectional standard deviation of 6.5 percent, indicating pervasive disagreement across households. Households are also very uncertain, with the Huber-robust average household level of uncertainty being 1.5 percent. But just as with the mean forecasts, there is a lot of heterogeneity across households in the amount of uncertainty associated with their forecasts, indicating that some households are quite confident in their beliefs, while others are extremely uncertain.

This heterogeneity in beliefs can also be seen in Figure 1. Panel A plots the distribution of mean forecasts across all countries as well as by country, and panel B does the same for the distribution of uncertainty in forecasts. In terms of mean forecasts, we can observe some significant differences across countries. For example, the mean forecasts of Belgian and Dutch households are significantly more pessimistic than those of Italian and Spanish households, although the cross-sectional dispersion in forecasts is broadly similar. Panel B confirms that while many households are relatively confident in their forecasts, there is a large tail of people who report much more uncertainty in their forecasts about future euro area growth. Panel C plots the cross-sectional relationship between first and second moments: generally, households with more extreme negative/positive views for the growth rate of GDP in the euro area have higher uncertainty in their forecasts. Online Appendix Table 3 shows that households with higher uncertainty tend to be richer and less liquidity constrained than households who are more confident in their economic outlook.

Following the initial measurement of household views about the macroeconomic outlook for the euro area, we implemented the information treatment. Households were randomly allocated to one of five groups. The first was a control group that received no information. The second group (treatment 1) was told about the average professional forecast for euro area growth:

> The **average** prediction among professional forecasters is that the euro area economy **will grow at a rate of 5.6%** in 2021. By historical standards, this is a strong growth.

[3] Following their answers to this question, respondents are also asked a more cognitively demanding question, namely, to assign a probability of growth being higher than the average of the two: "What do you think is the percentage chance that the growth rate of the euro area economy over the next 12 months will be greater than ([low growth rate]+[high growth rate])/2%?" We use this information to calculate a split triangular distribution, and we check the robustness of our baseline results to this alternative measure, as described in Section IVA.

[4] We report results by country in online Appendix Table 2.

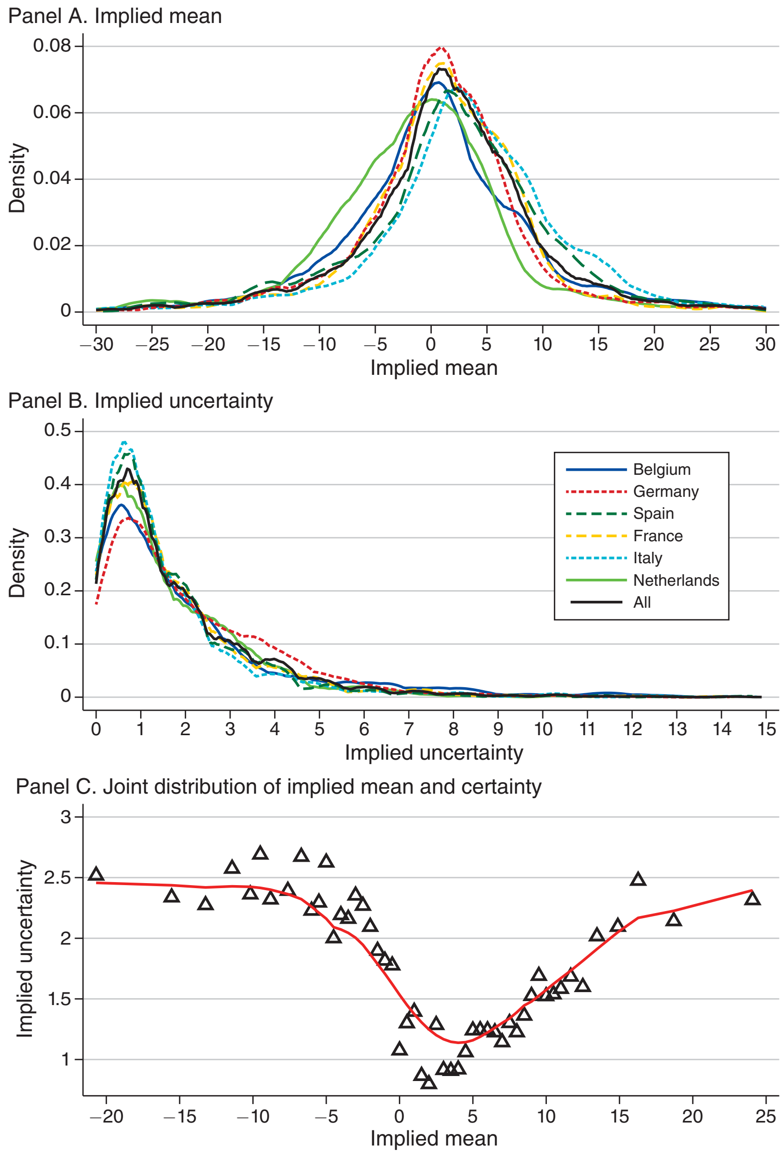

Figure 1. Distribution of Forecasts for EA GDP Growth

Notes: Panels A and B show kernel density (with sampling weights) of first and second moments for households' predictions for the growth rate of GDP in the euro area implied by the distributions of forecasts reported by households. Panel C is a binscatter plot (with sampling weights) where each triangle represents approximately 1 percent of the sample. The implied mean and uncertainty are computed using pretreatment beliefs. Data are from the September 2020 waves of the survey.

The treatment includes both a quantitative forecast (5.6 percent for 2021) as well as a qualitative one ("strong growth"). The combination of quantitative and qualitative information was designed to provide a clear positive signal about the first moment to recipients. Note that this and subsequent treatments provide households with publicly available information, and hence, zero response to the treatments should occur if households have full-information rational expectations (FIRE). Thus, any response of expectations to this treatment indicates a departure from FIRE.

The third group (treatment 2) received information about the amount of disagreement across professional forecasters. Specifically, the information provided was

> Professional forecasters are uncertain about economic growth in the euro area in 2021, with **the difference between the most optimistic and the most pessimistic predictions being 4.8 percentage points**. By historical standards, this is a big difference.

As with the previous information treatment, the statement includes both quantitative and qualitative information about disagreement. The purpose was to make clear that the provided level of disagreement across professionals was high because households might not be familiar with the extent to which professionals disagree about the outlook. Although disagreement is different from uncertainty, during the sample period, high disagreement was accompanied by high uncertainty, and hence, this treatment was meant to make clear to households that the economic outlook was particularly uncertain. At the same time, the ranges $(y_M - y_m)$ reported by households (the mean range is 9.5 percentage points and the Huber-robust mean for the range is approximately 6.5 percentage points) suggest that households were even more uncertain than professional forecasters. One should also note that the two quoted numbers in the first two treatment arms (5.6 and 4.8) are comparable in terms of magnitude; thus, it is unlikely that the effects we estimate are driven by biases due to size effects.

The fourth group (treatment 3) was provided with a combination of the previous two, providing information about both the average forecast and disagreement among professional forecasts. Specifically, it read,

> The **average** prediction among professional forecasters is that the euro area economy **will grow at a rate of 5.6%** in 2021. By historical standards, this is a strong growth. At the same time, professional forecasters are uncertain about economic growth in the euro area in 2021, with **the difference between the most optimistic and the most pessimistic predictions being 4.8 percentage points**. By historical standards, this is a big difference.

As with the two previous treatments, both qualitative and quantitative information about the outlook was provided. The purpose of this treatment was to help identify any interaction effect of providing information about first and second moments of macroeconomic forecasts on households' beliefs and decisions.

The final group (treatment 4) was told about disagreement among professional forecasters about the economic outlook of the specific country in which a given household resides:

> Professional forecasters are uncertain about economic growth in the country you are living in in 2021, with **the difference between the most optimistic and the most pessimistic predictions being <X%> percentage points**. By historical standards, this is a big difference.

The purpose of this treatment was to protect against the possibility that households would be unaffected by information about the euro area. Providing information about their country was therefore a way to assess whether they placed disproportionate weight on country-specific information when thinking about the broader economic outlook. On the other hand, the design of this treatment arm implies significant variation is present in the intensity of the underlying treatment information by country (e.g., the professional forecasters' disagreement that is told to respondents varies from 5.2 percentage points in France to 8.4 percentage points in Spain).

Following the information treatments, respondents (including those in the control group, who did not receive any information) were asked a few follow-up questions to measure the instantaneous effect of the treatments. In particular, we aim to again measure households' expected euro area output growth and their uncertainty but without reusing the exact same question (to avoid survey fatigue). We do so by first asking the following:

> What do you think will be the approximate growth rate in the euro area **over the next 12 months** for each of the scenarios below? We start with your prediction for the most pessimistic scenario for the euro area growth rate over the next 12 months (LOWEST growth rate) and end with your most optimistic prediction (HIGHEST growth rate).

Respondents are then asked to provide specific growth rates for three different scenarios: the lowest outcome scenario, a medium scenario, and the highest outcome scenario. Once they have provided forecasts of growth rates for each scenario, we then ask them to assign probabilities to each scenario:

> Please assign a **percentage chance** to each growth rate to indicate how likely you think it is that this growth rate will actually happen in the euro area economy over the next 12 months. Your answers can range from 0 to 100, where 0 means there is absolutely no chance that this growth rate will happen, and 100 means that it is absolutely certain that this growth rate will happen. The sum of the points you allocate should total to 100.

This question follows the structure developed by Altig et al. (2022) to measure the uncertainty of firms about their future sales. Unlike them, we restrict the set of scenarios to three rather than five to simplify the question for households. This question allows us to measure both mean forecasts and the uncertainty of the forecasts for each household without repeating the same triangular question used to extract prior beliefs.

Finally, in every quarter households are asked to report their overall spending (excluding large one-time purchases) over the previous month for a range of different categories including (i) food, beverages, groceries, tobacco; (ii) restaurants, cafés; (iii) housing (including rent); iv) utilities; (v) furnishing, housing equipment, small appliances, and routine maintenance of the house; (vi) debt payment; (vii) clothing, footwear; (viii) personal care and health care products and services; (ix) transportation; (x) travel, recreation, entertainment, and culture; (xi) education; and (xii) other. The survey design for this question follows that of the American Life Panel (ALP). We measure total monthly spending as the sum of the total amount spent on these categories excluding debt payments. This measure also excludes purchases of large durable goods, like cars or refrigerators.

Making use of the panel structure of the survey, we measure monthly spending from the quarterly module in October 2020. It is worth noting that reported amounts refer to consumption in September, i.e., the period following the implementation of our RCT. This way, we are able to track the spending behavior of households in the immediate aftermath of our RCT by relying on an independent module that was fielded one month later, and thus, our findings are unlikely to suffer from short-term framing effects that information treatments may create. We also use equivalent spending measures from the January 2021 wave (i.e., four months after the treatment). This allows tracking the immediate and more persistent effects of uncertainty on household spending.[5]

While self-reported spending naturally has some associated measurement error due to rounding and the difficulty of recalling spending on specific categories with precision, the quality of the reported information has generally been found to be high (see ECB 2021). Similarly, Coibion, Gorodnichenko, and Weber (2022a) document consistency between self-reported spending and scanner-tracked spending of US households participating in the Nielsen Homescan Panel. In any case, one should note that the RCT is robust by design to measurement error, as respondents who are more prone to misreport their spending are equally represented (due to randomization) in the control and treatment groups (Georgarakos and Kenny 2022).

In addition to this monthly spending measure, households were asked in October if they had purchased any of the following large durable or luxury goods over the previous month: (i) house, (ii) car, (iii) other durable goods (e.g., home appliance, furniture, electronic items including gadgets), (iv) travel vacation, or (v) luxury goods (e.g., jewelry, watches). Jointly, these questions allow us to assess whether expectations about future aggregate economic conditions, in terms of both first and second moments, lead to changes not only in monthly spending on nondurable goods and services but also on larger durable good purchases, although the latter is only along the extensive margin.

Finally, in order to assess whether such expectations are likely to impact household investment behavior, we ask respondents to complete a hypothetical portfolio allocation task. In particular, after the information treatments, households are asked to characterize how they would invest hypothetical funds across different financial asset classes. Specifically, they were asked the following:

> Imagine that you receive €10,000 to save or invest in financial assets. Please indicate in which of the following asset categories you will save/invest this amount.

The categories among which they can choose to invest are (i) checking and savings accounts, (ii) stocks and shares, (iii) mutual funds and collective investments, (iv) retirement or pension products, (v) short-term bonds, (vi) long-term bonds, and (vii) Bitcoin or other crypto assets.

[5] Online Appendix Table 4 documents that information treatments do not have systematic effects on attrition in the follow-up waves.

II. The Effects of Information Treatments on Expectations

The key to characterizing whether and how uncertainty affects economic decisions is identifying exogenous variation in uncertainty. Our RCT approach was designed precisely for this purpose by using information treatments that provide different types of information about consensus projections and disagreement among professional forecasters for euro area growth.

To assess the effects of different information treatments on expectations, we run regressions of the form

$$(1) \qquad Post_{i,t} = a_0 + b_0 Prior_{i,t} + \sum_{j=1}^{4} a_j \times I\{i \in Treatj\} + \sum_{j=1}^{4} b_j \times I\{i \in Treatj\} \times Prior_{i,t} + error_{i,t},$$

where i denotes respondent, $Prior_{i,t}$ denotes the respondent's prior belief, $Post_{i,t}$ refers to the respondent's posterior belief, and $I\{i \in Treatj\}$ is an indicator variable if respondent i is in treatment group j. The omitted category is the control group, so that coefficients $\{a_j\}_{j=1}^{4}$ and $\{b_j\}_{j=1}^{4}$ can be interpreted as being relative to the control group. We run these regressions for beliefs about the level of future economic growth and the uncertainty about economic growth separately. In each case, we use Huber-robust regressions to systematically control for outliers and also control for country fixed effects. We also drop all respondents who spent less than 100 seconds taking our ad hoc module (which was designed to take 10 minutes).[6]

By regressing posterior beliefs on prior beliefs, this specification is consistent with Bayesian learning in which agents form beliefs as a combination of their priors and the signals they receive. As discussed in Coibion, Gorodnichenko, and Kumar (2018), the weight on their prior belief (coefficients b) is an indication of how noisy/informative they perceive the signals to be. The coefficient on the prior belief for treated households ($b_0 + b_1, b_0 + b_2, b_0 + b_3, b_0 + b_4$) should generally be between zero and one, with a value of one indicating that no weight is being assigned to new information and full weight is being assigned to prior beliefs. A coefficient of zero on priors for treated households indicates that agents are changing their beliefs fully to the provided signal regardless of their prior beliefs. We allow this slope coefficient to vary across treatment groups. This variation informs us about the extent to which agents respond to different signals in updating their beliefs. Coefficients $\{a_j\}_{j=1}^{4}$ inform us where the signal is relative to the average prior belief.

We present results of these regressions in Table 2, for mean expectations in column 1 and uncertainty about growth in column 2. Looking first at the results for the control group (row 1), the coefficients on prior beliefs are approximately 0.76 for growth expectations and 0.72 for uncertainty. Given that this group is provided no information, one might expect the slope coefficient to be 1. But because the prior

[6] We calculate the total number of seconds per respondent to complete the survey without taking into account the time spent on reading RCT's information screen, as this screen is shown only to the treatment groups. As a result, we eliminate a comparable number of survey "speeders" (defined as respondents who spent less than 100 seconds on the "ad hoc" module of the survey, which included our prior questions) across the control and treatment groups.

and posterior expectations are measured using different questions, the additional noise leads to a benchmark coefficient on priors that is less than 1.

Overall, the treatments are largely successful in generating variation in both the first and second moments of household beliefs. Considering first the effects on beliefs about the level of future growth, we see that treatments 1 and 3 lead to large revisions in beliefs toward the provided signal since the resulting coefficients on the prior beliefs for these treatments ($b_0 + b_1$ and $b_0 + b_3$) are less than 0.2. Thus, informing households about the forecast of professional forecasters for the future growth rate of the euro area (which is included in both treatments) leads households to significantly revise the first moment of their beliefs. Binscatter plots reported in Panel A of Figure 2 indicate that this result is not driven by outliers or parts of the distribution and that the relationship is approximately linear.[7] Since the coefficients on the two treatments are almost identical, this implies that the marginal effect of providing information about the disagreement among forecasters (which is included in treatment 3 but not treatment 1) once mean forecasts are included is minimal when it comes to the expectations of households for the future growth rate. A similar message comes from looking at the coefficients on the prior beliefs about the level of future growth for households in treatments 2 and 4, which only provide information about disagreement among forecasters. In each case, the coefficient on the prior ($b_0 + b_2$ and $b_0 + b_4$) is only marginally smaller than it is for the control group (b_0). This result can also be seen clearly in panel A of Figure 2, which plots the prior beliefs about future growth rates of respondents against their posterior beliefs in binscatter form separately for each treatment group. Beliefs for households receiving information only about the disagreement among forecasters line up closely with those of the control group, indicating that this information does not lead households to change their views much about growth.

Turning to the effects on uncertainty, Table 2 documents that treatment 1, which only involved providing information about the mean forecast of professionals, leads to large revisions in uncertainty of households, as the associated slope coefficient ($b_0 + b_1$) is less than 0.2. Providing information about the disagreement among professionals in addition to providing information about the mean forecast (treatment 3) further reduces the slope coefficient ($b_0 + b_3$) but not in an economically significant way. For comparison, providing information *only* about disagreement among forecasters about euro area growth (treatment 2) leads to a large reduction in the slope coefficient relative to the control group, but not as large as that coming from treatment 1. Intuitively, although professional forecasters have a high level of disagreement, many households have even more subjective uncertainty, so that the disagreement treatment lowers uncertainty for households on average. Providing information only about disagreement among forecasters about growth in the respondent's home country has an even smaller effect on their uncertainty about euro area

[7] As we discuss below, information treatments can be used as instrumental variables. These instrumental variables are weak when the signal is close to the prior, as there is little exogenous variation in the posterior. Thus, our identification relies on variation in beliefs that are discernibly different from the signals. A limitation of this research design is that tails of the prior distribution provide power. Specifically, we find similar estimates if we drop the bottom and top 10 percent of the sample, but we lose precision in this case, which also reflects the need to have large cross sections to separate first- and second-moment effects. To minimize the sensitivity of our results to potential outliers, we use the Huber robust regression.

Table 2—Treatment Effects on First and Second Moments of Expected GDP Growth in the Euro Area

	Mean expectations (1)	Expected uncertainty (2)
Prior	0.758	0.722
	(0.011)	(0.024)
I{Treatment 1} × Prior	−0.655	−0.553
	(0.014)	(0.030)
I{Treatment 2} × Prior	−0.168	−0.399
	(0.017)	(0.030)
I{Treatment 3} × Prior	−0.619	−0.602
	(0.014)	(0.030)
I{Treatment 4} × Prior	−0.150	−0.347
	(0.016)	(0.030)
Indicator variables, **I**{}		
Treatment 1 (EA GDP – 1st m)	2.536	0.491
	(0.091)	(0.050)
Treatment 2 (EA GDP – 2nd m)	0.628	0.323
	(0.096)	(0.049)
Treatment 3 (EA GDP – 1st and 2nd m)	2.623	0.385
	(0.091)	(0.049)
Treatment 4 (C GDP – 2nd m)	0.548	0.377
	(0.098)	(0.049)
Observations	8,565	8,819
R^2	0.662	0.264

Notes: The table reports estimates of specification (1). All estimates are based on Huber-robust estimator. All regressions use sampling weights. Heteroskedasticity-robust standard errors are reported in parentheses.

growth, indicating that households draw different inferences from country-specific information than they do from euro area information. Panel B of Figure 2 presents a visual depiction of these results with nonparametric (lowess) estimates of the relationship between posteriors and priors for uncertainty. We observe a similar pattern, although the results suggest that the effects are particularly strong for households with high initial levels of uncertainty.[8] Treatment 1, despite only including information about the mean forecast of professionals, leads to pronounced revisions in uncertainty, surpassed only by the treatment that includes information about both professionals' forecasts in levels and disagreement (treatment 3). The treatment involving only disagreement about euro area growth (treatment 2) leads to significant revisions in beliefs but less than the treatment involving only the mean forecast. Finally, the treatment about country-specific disagreement (treatment 4) has only limited effects on uncertainty.

[8] If we use the log of uncertainty, panel B of Figure 2 becomes linear like panel A. Furthermore, because using the log allows us to decompress the distribution for low levels of uncertainty, one can see more clearly that households with low pretreatment uncertainty become more uncertain when they are presented with the disagreement of professional forecasters (see online Appendix Figure 1). Using the log of uncertainty in subsequent results yields the same qualitative results as using the level of uncertainty, as shown in Section IV. Because no strong a priori reason exists to use the log of uncertainty and using logs forces us to drop households that initially report zero uncertainty, we focus on level specifications as our baseline.

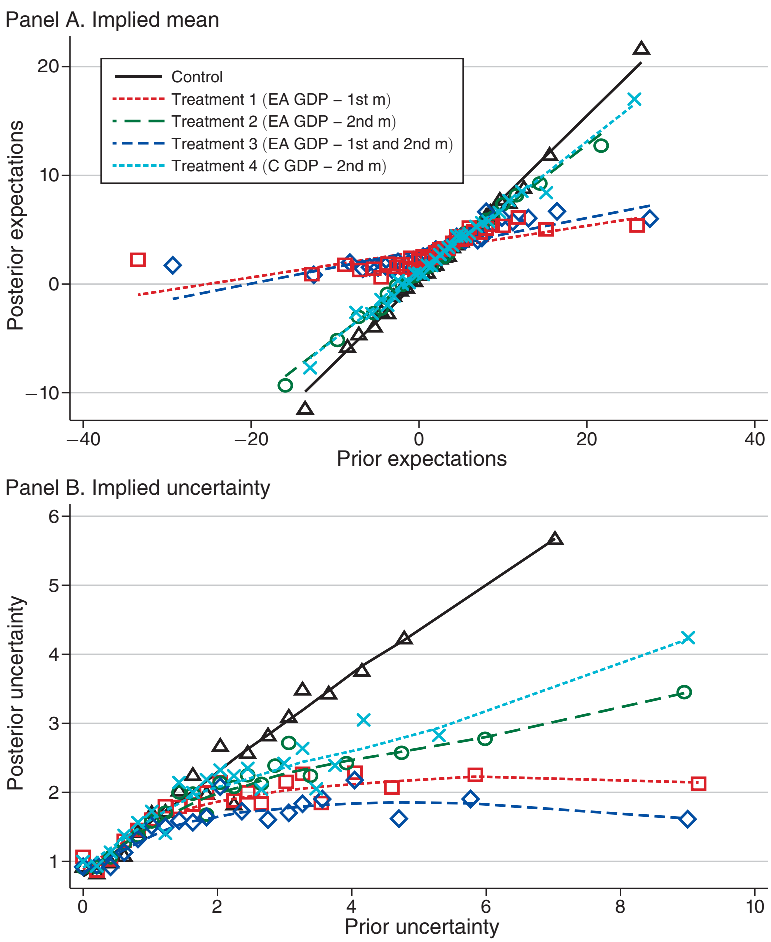

Figure 2. Treatment Effects on Household Beliefs about EA GDP Growth

Note: The figure shows binscatter plots (with sampling weights) for the first and second moments for households' predictions for the growth rate of GDP in the euro area implied by the distributions of forecasts reported by households.

In short, the information treatments lead to revisions in the beliefs of households about both the future level of growth and the uncertainty about growth. These revisions are in line with Bayesian learning, where households learn about the mean and the variance of a random variable (DeGroot 1970). Importantly, these treatments do not lead to the same pattern of revisions across treatments. The treatment involving country-specific forecaster disagreement conveys little information about either the level or uncertainty of future euro area growth. In contrast, the two treatments that include the first moment of growth have large effects on beliefs about both the level of growth and uncertainty about that growth. In turn, the treatment focusing on disagreement among professional forecasters about euro area growth has small effects on beliefs about the level of growth but large effects on uncertainty about growth. Our information treatments are therefore successful in inducing *strong*, *exogenous*, *and differential* movements in the first and second moments of households' beliefs about future growth. As a result, these treatments can serve as powerful instruments to help us identify how/whether uncertainty affects household decisions measured in independent, follow-up surveys.

These treatment effects are also useful because they speak to the nature of the expectation formation process: strong responses to publicly available information imply a rejection of FIRE. The success of the information treatments in shaping beliefs is a reflection of the fact that households have only limited information about GDP growth in the first place. In addition, households *realize* that they are not very informed and therefore respond strongly when given new information. Were households to believe they were well informed, they would not adjust their forecasts when given this information. Or if they actually were well informed, they would again not adjust their forecasts. The fact that households are initially poorly informed about GDP is therefore central to the exercise: it is a feature, not a bug. Why would households be so unaware of macroeconomic developments? One interpretation is rational inattention (Sims 2003): due to the many other pressing concerns faced by households and binding time constraints, tracking macroeconomic conditions is rarely a top priority for the average person. Another interpretation could be that households ignore macroeconomic variables because they think that they do not matter for their decisions. Determining whether macroeconomic uncertainty actually matters to households for their decisions is therefore the question we now turn to.

III. The Effects of Uncertainty on Household Spending

With a source of exogenous variation in beliefs about future growth and uncertainty in those beliefs, we can now assess if those beliefs translate into household spending decisions.

A. *The Identified Effect of Uncertainty on Monthly Total Household Spending*

Our approach to estimating the effect of uncertainty on household spending exploits the fact that we have measures of both first and second moments of households' macroeconomic expectations, measures of their total monthly spending in subsequent months, and a source of exogenous variation in expectations. Specifically, we regress ex post total monthly spending of households on their beliefs:

$$(2)\quad \left(logSpend_{i,\,t+h}\right) \times 100 \;=\; \alpha_1 Post_{i,t}^{mean} + \beta_1 Post_{i,t}^{uncert} + Controls_{i,t} + error_{i,t+h},$$

where the dependent variable is the log of total reported household spending over the previous month reported either one month after the information treatment ($h = 1$) or four months after the information treatment ($h = 4$), $Post_{i,t}^{mean}$ is the posterior (immediately after treatment) belief of household i for the future growth rate of GDP in the euro area, and $Post_{i,t}^{uncert}$ is the posterior (immediately after treatment) uncertainty of household i about the future growth rate of euro area GDP. This specification therefore includes both first and second moments of households' macroeconomic expectations, which is important because of the strong correlation between first and second moments. We also include a vector of household-level controls including their prior beliefs (measured before the information treatments), as well as household characteristics such as age, household size, log income, education, liquidity status, and country fixed effects. Note that equation (2) does not estimate a consumption Euler equation; instead, it is best interpreted as estimating the reduced-form ex post response of consumption to changes in perceived macroeconomic uncertainty and outlook.

We instrument for each set of posterior beliefs using the treatments as follows:

$$(3') \quad Post_{i,t}^{mean} = a_0 + \sum_{j=1}^{3} a_j \times I\{i \in Treatj\} + \sum_{j=1}^{3} b_j \times I\{i \in Treatj\} \times Prior_{i,t}^{mean} + \sum_{j=1}^{3} c_j \times I\{i \in Treatj\} \times Prior_{i,t}^{uncert} + Controls_{i,t}\, error_{i,t}$$

$$(3'') \quad Post_{i,t}^{uncert} = \tilde{a}_0 + \sum_{j=1}^{3} \tilde{a}_j \times I\{i \in Treatj\} + \sum_{j=1}^{3} \tilde{b}_j \times I\{i \in Treatj\} \times Prior_{i,t}^{mean} + \sum_{j=1}^{3} \tilde{c}_j \times I\{i \in Treatj\} \times Prior_{i,t}^{uncert} + Controls_{it}\, error_{i,t}.$$

This first-stage specification essentially consists of regressing posteriors on priors along with an interaction of priors with treatment group indicators, effectively reproducing the visual evidence presented in Figure 2. Intuitively, the information treatments serve to generate exogenous variation in first and second moments, thereby allowing us to separately identify the role of each in affecting consumption. But because the variation in beliefs in treatments is not an average effect (e.g., the average mean expectation of GDP growth is not meaningfully different between control and treatment groups), it is important to also condition on households' prior beliefs. Effectively, our identification relies on the fact that people with high GDP growth expectations tend to lower their first-moment beliefs when they receive a first-moment treatment, while those with low GDP expectations do the reverse, with similar characteristics obtaining for second moments. Because the information treatments induce different *relative* changes in first and second moments, we are then able to isolate the effects of each on ex post household spending. Note that we drop households that receive treatment 4 (about 2,000 households) because this treatment is not successful in changing either first- or second-moment beliefs of households and therefore does not provide us with enough exogenous variation in beliefs. Following Coibion, Gorodnichenko, and Weber (2022a) and Coibion et al. (2023), the first stage is estimated by Huber regression, and a jackknife approach is used in the second stage to control for outliers in both stages. The Huber regression removes (assigns a weight of 0) approximately 2,000 observations as outliers, and a number of other observations are dropped due to missing values for consumption or control variables.

Results from this baseline estimation are reported in panel A of Table 3. First, the information treatments provide a strong source of variation in the first stage: the first-stage F-statistic for forecasts of the level of growth is around 150, while the first-stage F-statistic for uncertainty about growth is around 40. Thus, the RCT approach is successful in generating strong exogenous variation in beliefs to help identify the causal effect of macroeconomic uncertainty on household spending.

The main result of this regression is that higher uncertainty about euro area growth, after controlling for first moments, leads to lower household spending. The effect occurs in the first month after the information treatment. It continues to hold

Table 3—Effects of First and Second Moments for Expected EA GDP Growth Rate on Household Spending

	One month after treatment		Four months after treatment	
	Coef. (1)	(SE) (2)	Coef. (3)	(SE) (4)
Panel A. Baseline specification				
Posterior: Mean	−0.81	(0.44)	−0.46	(0.44)
Posterior: Uncertainty	−3.43	(1.71)	−3.10	(1.70)
Observations	5,254		4,747	
R^2	0.21		0.20	
First-stage F-stat (mean)	157.2		148.6	
First-stage F-stat (uncertainty)	40.2		36.0	
Panel B. Flexible triangular distribution for measuring implied mean and uncertainty				
Posterior: Mean	−0.59	(0.50)	−0.35	(0.50)
Posterior: Uncertainty	−3.77	(1.72)	−2.74	(1.69)
Observations	4,900		4,435	
R^2	0.21		0.20	
First-stage F-stat (mean)	129.8		125.3	
First-stage F-stat (uncertainty)	38.12		34.93	
Panel C. Using log of uncertainty				
Posterior: Mean	−0.74	(0.44)	−0.40	(0.44)
Posterior: log(uncertainty)	−11.05	(5.58)	−10.12	(5.63)
Observations	5,254		4,747	
R^2	0.20		0.19	
First-stage F-stat (mean)	157.5		149.7	
First-stage F-stat (uncertainty)	27.4		24.1	
Panel D. Controlling for skewness				
Posterior: Mean	−0.80	(0.44)	−0.46	(0.44)
Posterior: Uncertainty	−3.45	(1.71)	−3.09	(1.70)
Posterior: Skewness	−0.72	(0.96)	0.35	(1.02)
Observations	5,254		4,747	
R^2	0.21		0.20	
First-stage F-stat (mean)	156.8		149.2	
First-stage F-stat (uncertainty)	40.4		36.4	
Panel E. Controlling for micro expectations				
Posterior: Mean	−0.94	(0.46)	−0.50	(0.46)
Posterior: Uncertainty	−3.61	(1.85)	−3.11	(1.87)
Observations	4,515		4,126	
R^2	0.21		0.20	
First-stage F-stat (mean)	144.9		138.6	
First-stage F-stat (uncertainty)	35.8		31.8	

Notes: The table reports estimates of specification (2). The dependent variable is log(nondurable consumption) × 100. The first stages for mean and uncertainty are given by specifications (3') and (3''), respectively. All regressions use sampling weights. Treatment status does not predict whether a household participates in posttreatment waves. For panel B, pretreatment expectations are computed using the generalized triangular distribution (i.e., the assumption of symmetric triangular distribution is relaxed); see online Appendix B for more details. Skewness is measured as the subjective probability of observing growth rate of GDP above the midpoint of the reported range in the pretreatment question. Household controls are included but not reported. Heteroskedasticity-robust standard errors are reported in parentheses.

with about the same order of magnitude four months later. The implied magnitude is large. Recall that the cross-sectional standard deviation of uncertainty is just above 1 percentage point (online Appendix Table 2). Thus, the estimated coefficient corresponds approximately to the effect of increasing uncertainty by one standard deviation. Table 3 suggests that a 1 standard deviation increase in uncertainty lowers monthly spending by over 3 percentage points both within the first month and four months later, a large and persistent effect. These effects are statistically different from 0 at the 5 percent level after a month and at the 10 percent level after four months.[9] Another way to think about the order of magnitude is to note that the average posterior uncertainty across our treatment groups is lower than the average posterior uncertainty of our control group by about 0.2–0.3 percentage points, implying an approximate 0.5–0.8 percent higher average level of spending coming from reduced uncertainty in treated households relative to untreated households. This provides unique causal evidence that the macroeconomic uncertainty perceived by households negatively affects their spending.

The effects of first moments on spending are not significantly different from 0 at the four-month horizon but are statistically significant at the 10 percent level after one month. While the point estimates are negative over both horizons, they are very small in magnitude given the high dispersion in beliefs about first moments. The cross-sectional standard deviation of first moments is 6 percentage points; thus, a 1 standard deviation increase in the first moment is followed by a decline in spending of about 0.1 percent after one month and 0.05 percent after four months, a very small effect relative to the wide dispersion in spending levels across the population. In other words, the dispersion in beliefs about first moments about euro area growth cannot account for any quantitatively meaningful variation in ex post spending decisions of households. When we assume a flexible (instead of a simple) triangular distribution (see footnote 3) for pretreatment first- and second-moments expectations, we obtain similar results (panel B of Table 3) to those shown in panel A.

One possible concern may be that the effects of the treatments on uncertainty in the first stage appear nonlinear, whereas our first stage is assumed to be linear. One way to address this concern is to use the log of uncertainty instead of the level for both the first and the second stage. As shown in online Appendix Figure 1, the treatment effects on uncertainty are linear when expressed in log of uncertainty. Results for the second stage using the log of uncertainty are presented in panel C of Table 3. The results are qualitatively similar in that we observe lower levels of spending for households with exogenously higher uncertainty.

One may also be concerned that higher moments of the distribution of expectations could matter as well. For example, uncertainty could potentially affect spending only to the extent that it reflects occasional large downside risk. We therefore augment our baseline specification with the skewness of households' beliefs over future GDP growth, including both prior and posterior versions of this measure. We do not have enough independent variation in our treatments to separately identify exogenous variation in all three moments, so we continue to instrument for both first and second moments and simply include skewness as a control variable. Note that if spending was responding to the skewness rather than uncertainty, controlling for skewness would be sufficient to remove the predictive power of uncertainty. As shown in panel D of Table 3, we find that including skewness has no

[9] Rejections of the null hypothesis are even stronger when we adjust for multiple hypothesis testing as in Anderson (2008). The other estimated coefficients are largely as expected. For example, we find that household spending increases with income, age, and education. Larger households also tend to spend more per month. Similarly, households with sufficient liquid resources to meet an unexpected payment of one month of household income have higher spending.

meaningful effects on our estimates. Uncertainty matters for the spending decisions of households above and beyond any perceived skewness in households' subjective distributions.

In short, our results indicate that changes in uncertainty of households have clear effects on their subsequent monthly spending, with these effects lasting for several months. Because we can identify exogenous variation in uncertainty and control for how first moments respond to new information, our approach therefore allows us to speak to the causal effects of uncertainty on household spending in a novel and direct fashion. This finding is notable because a major stumbling block in the uncertainty literature emphasized by Bloom (2014) has been separating first- and second-moment effects: big changes in macroeconomic uncertainty tend to also be accompanied by large changes in first-moment expectations. Our approach allows us to distinguish between first- and second-moment effects of aggregate economic expectations because our instruments generate exogenous but differential variation in the two. Strikingly, only uncertainty seems to play a quantitatively important role in changing household spending.

B. *Reduced-Form Evidence*

What lies behind the strong effect of uncertainty on household spending identified in the previous section? To get a sense of this, we examine more reduced-form, nonparametric evidence on the ex post spending decisions of households. Because our information treatments do not induce any meaningful changes in the average first moment of beliefs (since some people raise their forecasts while others lower their forecasts when told about the average professional forecasts of GDP growth) and relatively small average effects on uncertainty, examining average spending levels across treatments will not speak to the effectiveness of the treatments in terms of moving spending. Instead, one has to condition on the priors of households to be able to identify the effects of treatments on spending.

We do so visually in Figure 3. Panel A plots the nonparametric (lowess) estimates for the relationship between ex post nondurable spending and prior first-moment expectations of GDP growth, separated by treatment groups. The inverted U-shape pattern in the control group indicates that households with either very high or low forecasts of GDP growth tend to spend less than other households. Note that, as shown in Figure 1, these households also tend to have higher uncertainty in their forecasts. What we can see in panel A is that across all three treatment groups, those households with either low or high initial expectations of GDP growth end up consuming more than comparable households in the control group. For households in treatments 1 and 3, we know that their first moments are moving toward the signal (so low-expectation households are raising their forecasts, while those with high expectations are lowering their forecasts), and their uncertainty is mostly decreasing. By itself, this suggests that first moments of expectations should not affect spending since those households are increasing their spending regardless of whether they are reducing their forecasts (for those with high initial forecasts) or raising them (for those with low initial forecasts). But since the uncertainty of both groups is falling on average while their spending is higher relative to the control group, this produces the negative effect of uncertainty on spending.

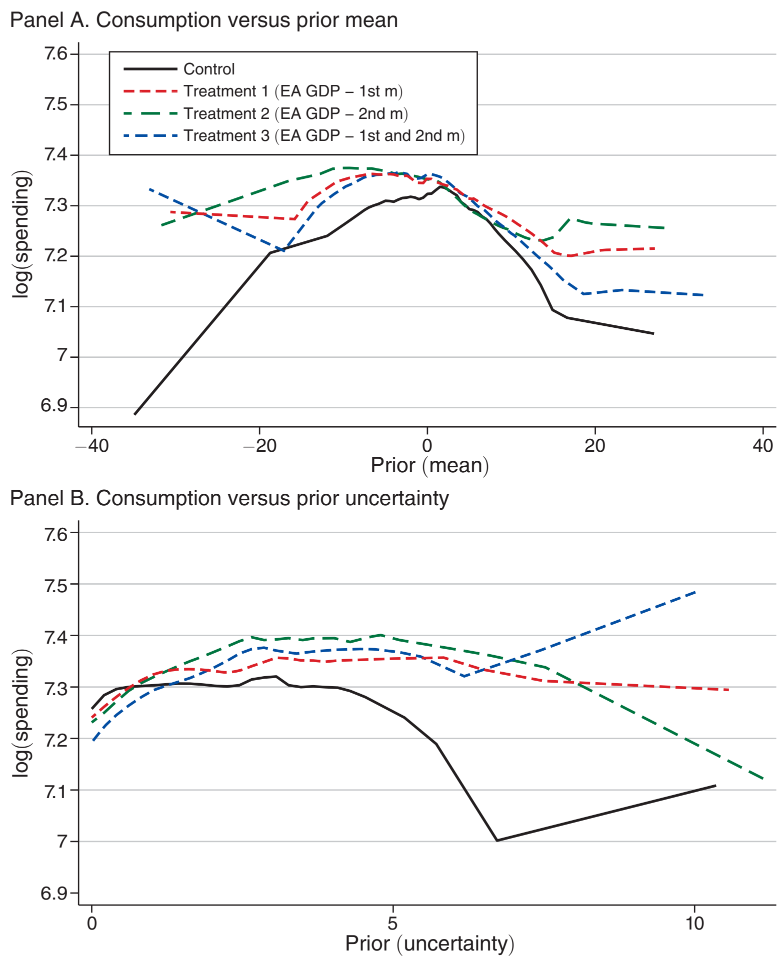

Figure 3. Reduced-Form Effects of Treatments on Household Spending

Notes: The lines are nonparametric (lowess) estimates of the relationship between log spending on nondurable goods (vertical axis) and prior beliefs about EA GDP growth rate (horizontal axis) by treatment group. Panel A uses the implied mean of the prior beliefs. Panel B uses the implied uncertainty (standard deviation) of the prior beliefs.

This is even starker for households in treatment group 2. These households are not revising their first moments at all, as shown in panel A of Figure 2, yet we can see in panel A of Figure 3 that those households in treatment 2 with initially low forecasts or high forecasts end up consuming more than comparable households in the control group, indeed as much as those in treatment groups 1 and 3. This again suggests that first moments are not behind the changes in spending that we observe. Instead, since the only effect of treatment 2 is to change uncertainty and uncertainty is falling on average for households in treatment 2, the clear implication is that it is the reduction in uncertainty that is causing these households to raise their spending. This effect is concentrated on households with initially high or low GDP forecasts since these are the households who are initially more uncertain and therefore revise their uncertainty down by more and their spending up.

Panel B of Figure 3 plots an equivalent for the relationship between households' ex post spending and households' initial uncertainty. We know from Figure 2 that, across treatment groups 1–3, households with low uncertainty tended to raise their uncertainty, whereas those with high uncertainty tended to lower their uncertainty, with the average effect on uncertainty across all households being negative. The spending patterns in panel B are again consistent with uncertainty having negative effects on spending: households with very low initial uncertainty end up consuming less when in treatment groups than in the control group (since their uncertainty goes up from treatments), whereas other households with higher initial levels of uncertainty consume more than comparable ones in the control group (since their uncertainty goes down from treatments). Again, the fact that levels are very similar across all three treatment groups is consistent with uncertainty driving the results rather than first moments since all three treatments induce similar qualitative effects on uncertainty, whereas treatments 1 and 3 also have large effects on first moments. If those first moments were important for spending decisions, we would see larger differences in spending levels across the different treatment groups in panels A and B of Figure 3.

Thus, the reduced-form evidence makes clear why our baseline empirical estimates find such strong effects of uncertainty on spending. Conditioning on either prior first or second moments of households, the evidence of ex post spending across the treatment groups compared to the control group cannot be reconciled with first moments playing an important role. Instead, it is the revisions in uncertainty across the treatments that can account for the ex post spending patterns that we observe.

C. *Economic Significance and Plausibility*

Our finding that higher uncertainty leads households to reduce their spending is qualitatively consistent with other evidence.[10] For example, Christelis, Georgarakos, Jappelli, and van Rooij (2020) estimate within an Euler equation framework that an increase in the uncertainty perceived by households about their future consumption growth is associated with a decrease in the growth rate of their consumption. Ben-David et al. (2018) regress an extensive margin for changes in consumer spending on a measure of household uncertainty that mixes micro- and macro-level uncertainty and find similar results. Roth and Wohlfart (2020) show that an increase in the perceived likelihood of a recession (which combines first- and second-moment effects) by households leads them to reduce their consumption plans. Because our approach differs from this prior work along many dimensions, results are not directly comparable, but the qualitative finding is similar across studies.

Our results are more difficult to compare to microeconomic estimates of the effect of uncertainty on spending. These studies typically relate individual spending changes to uncertainty about households' future consumption growth or own household income growth (e.g., Christelis, Georgarakos, Jappelli, and van Rooij 2020 or Crump et al. 2015). In contrast, we focus on actual changes in consumption

[10] More generally, our results are consistent with the nascent literature (e.g., Coibion, Gorodnichenko, and Weber 2022a; Coibion, Gorodnichenko, and Kumar 2018; Coibion, Gorodnichenko, and Ropele 2020; Kumar, Gorodnichenko, and Coibion 2022; Armona, Fuster, and Zafar 2019; Conlon 2021) that uses information treatments and documents large behavioral responses (e.g., decisions about prices, purchases of homes, occupational choices) to the treatments.

rather than expected changes in consumption. In addition, uncertainty about personal income growth represents just one of many channels through which macroeconomic uncertainty can affect the spending decisions of households. For example, uncertainty about future GDP growth can correlate with uncertainty about future interest rates, uncertainty about future taxes or government quality more generally, which should also affect household spending as emphasized in Baker, Bloom, and Davis (2016). Our estimates will capture all of these different channels, so they should naturally be larger than approaches that focus only on uncertainty about own income growth.

To quantify the importance of expectations of personal income growth in accounting for our results, we consider two exercises. First, we use households' first and second moments of their beliefs about their income growth over the next 12 months as dependent variables in equation (2) while also conditioning on their priors about these moments. Beliefs about personal income growth are available immediately after the treatments as well as in each subsequent month. Results are reported in Table 4. We find (panel A) that changes in households' mean expectations about GDP growth affect their mean expectations about their own household income growth, with a pass-through of about 25 percent, but they have no discernible effect on uncertainty about income growth. Changes in households' macroeconomic uncertainty have relatively small effects on households' uncertainty about their future household income and no discernible effects on their expected level of income (panel B). The effects are largely transitory. These results indicate that the effects of macroeconomic uncertainty on household spending observed in Table 3 are not only driven by a corresponding change in households' uncertainty about their own income growth.

The second exercise we consider is to explicitly control for ex post changes in households' uncertainty about their personal income when estimating equation (2), thereby controlling for the channel of own income expectations. Our results (panel E of Table 3) are both qualitatively and quantitatively unchanged. This finding indicates that changes in uncertainty about GDP growth likely lead households to revise their uncertainty about future macroeconomic policies (e.g., taxes or government quality more generally) and/or future asset prices in ways that then affect household spending. Because we do not observe expectations for all these variables, we cannot directly identify this chain of beliefs. But we can clearly rule out that the effects are operating solely through households' expectations about their own income growth.

IV. Underlying Mechanisms and Margins of Adjustment

We have documented a large negative effect of uncertainty on household spending that goes above and beyond associated changes in first moments. What drives these results? One potential source is precautionary saving, following Kimball (1990). Other research has emphasized additional forces through which uncertainty may affect the spending decisions of households, especially "wait-and-see" real option effects (Pyndick 1991; Stokey 2016). We now consider evidence from additional dimensions of our data that help identify which mechanisms are at work in accounting for our results, as well as document additional margins of adjustment by households.

Table 4—Effects of First and Second Moments for Expected EA GDP Growth Rate on Expected Own Household Net Income Growth

	Beliefs about future household income growth			
	Immediately after treatment	One month after treatment (October 2020)	Two months after treatment (November 2020)	Three months after treatment (December 2020)
	(1)	(2)	(3)	(4)
Panel A. Effects on mean expected household income growth				
Posterior: Mean GDP growth	0.27	0.03	0.02	0.04
	(0.08)	(0.03)	(0.03)	(0.03)
Posterior: Uncertainty about GDP growth	−0.66	0.14	−0.19	0.14
	(0.39)	(0.12)	(0.12)	(0.13)
Observations	5,034	4,609	4,398	4,321
R^2	0.10	0.37	0.31	0.31
First-stage *F*-stat (mean)	162.6	162.4	155.4	147.2
First-stage *F*-stat (uncertainty)	37.9	36.7	32.6	34.4
Panel B. Effects on uncertainty about expected household income growth				
Posterior: Mean GDP growth	−0.00	−0.00	−0.01	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Posterior: Uncertainty about GDP growth	0.23	0.04	0.07	0.02
	(0.06)	(0.03)	(0.03)	(0.03)
Observations	4,371	4,590	4,379	4,326
R^2	0.17	0.55	0.54	0.51
First-stage *F*-stat (mean)	144.2	157.4	153.9	149.6
First-stage *F*-stat (uncertainty)	29.9	39.3	34.9	34.2

Notes: The table report results for specification (2), where the dependent variable is either implied mean for household net income growth (panel A) or implied uncertainty (standard deviation) for household net income growth (panel B). All regressions use sampling weights. Treatment status does not predict whether a household participates in posttreatment waves. Household controls are included but not reported. Heteroskedasticity-robust standard errors are reported in parentheses.

A. *Composition of Spending*

Precautionary motives should apply broadly to all types of spending, whereas "wait-and-see" effects should apply primarily to durable or storable goods for which households can rely on existing stocks to maintain consumption even in the absence of new purchases. Because the ECB survey provides a detailed decomposition of monthly household spending across a wide range of categories of goods, we can assess whether the changes in spending due to uncertainty are concentrated in particular types of goods or are broad based. To do so, we regress the share of household spending that is allocated to a specific category of goods/services on household beliefs, with the same IV strategy as done before with total spending:

$$(4)\quad BudgetShare_{i,t+1}^{k} = \alpha_1^{(k)} Post_{i,t}^{mean} + \beta_1^{(k)} Post_{i,t}^{uncert} + Controls_{i,t} + error_{i,t+1}^{(k)},$$

where $BudgetShare_{i,t+1}^{k}$ is the share (measured on 0 to 100 scale) of household i's budget spent on nondurable category k. We report results in Table 5. We do not find strong evidence that changes in spending are concentrated in specific categories. For most categories of spending, we cannot reject the null hypothesis that their share of total spending is unchanged when uncertainty changes, indicating that overall

Table 5—Effects of First and Second Moments for Expected EA GDP Growth Rate on Budget Shares for Household Spending

	Food (1)	Housing, utilities, furniture, home equipment (2)	Clothing (3)	Personal care (4)	Transport (5)	Recreation (6)	Education and other (7)
Posterior: Mean	0.15	−0.16	0.06	0.00	−0.00	0.03	−0.03
	(0.11)	(0.15)	(0.03)	(0.05)	(0.05)	(0.05)	(0.06)
Posterior: Uncertainty	0.10	−0.44	0.13	−0.48	0.14	−0.55	0.11
	(0.43)	(0.63)	(0.16)	(0.24)	(0.21)	(0.22)	(0.25)
Observations	5,289	5,291	5,290	5,289	5,286	5,290	5,288
R^2	0.07	0.07	0.03	0.10	0.06	0.05	0.03
First-stage F-stat (mean)	158.2	161.9	164	161.3	160.8	163.4	162.3
First-stage F-stat (uncertainty)	39.28	37.67	39.49	40.74	39.89	40.03	39.57

Notes: The table reports estimates of specification (4). The dependent variable is the budget share of spending category k, measured on the 0–100 scale. The first stages for mean and uncertainty are given by specifications (3') and (3''), respectively. All regressions use sampling weights. Household controls are included but not reported. Heteroskedasticity-robust standard errors are reported in parentheses. p-value for the equality of responses to uncertainty across budget shares is 0.045.

variation in spending is broad based. This suggests that precautionary motives are important in response to changes in macroeconomic uncertainty.

We do find two categories of goods that seem to respond somewhat more than others. One is personal care and health care goods and services, which includes haircuts, make-up, massages, dentist visits, etc. Note that, unlike the United States, countries covered in the CES provide substantial government-run health care schemes with modest out-of-pocket spending for households. As a result, consumer spending in this category is heavily tilted to more discretionary spending. The second category of spending that responds relatively more to uncertainty is recreation, which includes theater/movie tickets, gym memberships, etc. The share of spending going to recreation falls by about 0.6 percent with each extra unit of uncertainty. This category of spending is one that experienced a particularly large decline over the course of the COVID-19 crisis (e.g., Dunn, Hood, and Driessen 2020; Christelis, Georgarakos, Jappelli, and Kenny 2020). Our results suggest that rising macroeconomic uncertainty may have also contributed to the decline in spending on these categories of goods.

B. *Extensive Margin of Durable Goods Purchases*

"Wait-and-see" effects are most commonly associated with discrete purchases of large durable goods, for which households may have wide inaction bands. Because the ECB survey also asks households whether they have engaged in purchases of large durable goods, expensive luxury goods, and vacations in the previous month, we can therefore assess whether changes in uncertainty made households more or less likely to buy these types of goods and services. Because we do not observe the euro amount spent on these purchases, we can focus only on the extensive margin of purchases, so results are not directly comparable to those in Section IV.

We estimate the effect of uncertainty on purchases of larger goods and services by regressing indicator variables for specific purchases on ex ante expectations and household controls:

$$(5)\quad PurchDur^{k}_{i,t+1} \times 100 \;=\; \alpha^{(k)}_{1} Post^{mean}_{i,t} + \beta^{(k)}_{1} Post^{uncert}_{i,t} + \gamma\Big(PlanDur^{k}_{i,t} \times 100\Big) + Controls_{i,t} + error^{(k)}_{i,t+1},$$

where $PurchDur^{k}_{i,t+1}$ is an indicator variable equal to one if household i purchased a large durable good/service of type k in the previous month. This specification is therefore directly comparable to specification (2), except that we now focus on an extensive margin for purchasing large durable goods/services. Following Georgarakos and Kenny (2022), we also include an additional indicator variable ($PlanDur^{k}_{i}$) that represents households that reported prior to the information treatments that they plan to purchase large durable goods/services of type k in the next 12 months. Our approach is therefore effectively focusing on either surprise purchases or surprise postponement of purchases. Given that large purchases are relatively infrequent, conditioning on whether any purchases are planned or not helps yield more precise estimates, although the time horizon for the question about planned purchases is longer than the horizon over which we measure realized purchases. As before, we instrument for posterior beliefs about the level of future euro area growth and the uncertainty around those beliefs using the information treatments and their interactions with household priors.

Our results (Table 6) again point to a negative causal link between uncertainty and household spending, but this time in terms of purchases of larger/durable goods and services. For every type of purchase, the estimated coefficient is negative. It is statistically significant for three of the five categories: houses, holiday packages, and luxury goods. The coefficients indicate that higher uncertainty of 1 percentage point reduces the probability of a household having purchased a holiday package in the 4 weeks after our information treatments by nearly 3 percentage points, a luxury item by 1 percentage point, and a house by 0.3 percentage points. However, all of these effects have faded after four months. We interpret these results as providing further evidence that uncertainty about the macroeconomic outlook reduces household expenditures, not just on typical monthly spending but also on larger and less frequently purchased durable goods and services. In particular, the effects on large durable goods purchases are consistent with a “wait-and-see” channel.

C. *Desired Investment Portfolios*

Spending is not the only margin through which households may respond to uncertainty. Another potentially important choice concerns their investment decisions. To quantify this margin of adjustment, one should take into account that the majority of households exhibit significant inertia in portfolio rebalancing and that multiple survey waves would be necessary in order to trace any actual changes in portfolio shares. In light of this, we instead used a hypothetical portfolio allocation question after the information treatment was implemented in the September wave. Specifically, respondents were asked how they would save or invest among different

Table 6—Effects of First and Second Moments for Expected EA GDP Growth Rate on Actual Purchases of Durable/Luxury Goods and Services

	Home	Durable	Car	Holiday	Luxury
	(1)	(2)	(3)	(4)	(5)
Posterior: Mean	0.03	0.11	0.07	0.04	−0.07
	(0.04)	(0.29)	(0.09)	(0.20)	(0.10)
Posterior: Uncertainty	−0.35	−1.47	−0.49	−2.72	−1.02
	(0.16)	(1.25)	(0.35)	(0.88)	(0.53)
Plan to buy a given durable	0.04	0.22	0.06	0.15	0.17
	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)
Observations	5,328	5,345	5,330	5,343	5,332
R^2	0.01	0.08	0.02	0.07	0.05
First-stage F-stat (mean)	160.5	165.1	161.2	162.9	161.8
First-stage F-stat (uncertainty)	40.32	38.71	39.51	40.02	37.35

Notes: The table reports estimates of specification (5). The dependent variable is an indicator variable ($\times 100$) equal to 1 if a household purchased a given type of durable/luxury good/service over a 30-day period, measured one month after the treatment. Plan to buy a given durable is also multiplied by 100. The first stages for mean and uncertainty are given by specifications (3') and (3''), respectively. All regressions use sampling weights. Household controls are included but not reported. Heteroskedasticity-robust standard errors are reported in parentheses.

types of possible investments a €10,000 windfall after having been exposed to our information treatments.

Given their responses to this question, we then run the following regression for each type of investment k:

$$PostShare_{i,t}^{k} = \alpha_1^k Post_{i,t}^{mean} + \beta_1^k Post_{i,t}^{uncert} + \gamma ActSh_{i,t-1}^{k} + Controls_{i,t} + error_{i,t}^{(k)}, \tag{6}$$

where $PostShare_{i,t}^{k}$ is the posttreatment share of the total investment that household i assigns to investment type k. This specification is again directly comparable to the one used for total spending, except that we now focus on the allocation of hypothetical investments. We also include an additional control variable ($ActSh_{i,t-1}^{k}$) that is the actual share of investment type k in household i's investment portfolio. Conditioning on this actual share helps with the interpretation of our findings, as we effectively focus on how a household would ideally like to change its current portfolio given new information. Actual investment portfolios are collected in the August wave (i.e., in the month prior to the RCT implementation). There are missing values for a subset of respondents, as only those who provide complete information on their invested amounts for each of the asset categories they own are considered for calculating (pretreatment) portfolio shares. As a result, the sample size is smaller than the one used for spending behavior. As before, we instrument for posterior beliefs about the level of future euro area growth and the uncertainty around those beliefs using the information treatments and their interactions with household priors.

We present results from these regressions in Table 7. The asset classes for which we can identify a change in the desired share are mutual funds and cryptocurrencies,

Table 7—Effect of First and Second Moments for the Expected EA GDP Growth Rate on the Allocation of Hypothetical €10,000 across Asset Classes

	Saving account (1)	Stocks (2)	Mutual funds (3)	Investment retirement account (4)	Bonds (5)	Crypto-currencies (6)
Posterior: Mean	−0.26	0.37	0.05	−0.15	0.02	−0.04
	(0.34)	(0.17)	(0.17)	(0.18)	(0.18)	(0.05)
Posterior: Uncertainty	−1.70	0.03	−2.14	0.38	−0.51	−0.46
	(1.54)	(0.69)	(0.74)	(0.81)	(0.71)	(0.19)
Actual share of investment	0.29	0.38	0.47	0.14	0.30	0.02
	(0.02)	(0.04)	(0.04)	(0.02)	(0.09)	(0.01)
Observations	3,106	3,099	3,102	3,099	3,100	3,095
R^2	0.17	0.14	0.20	0.07	0.07	0.04
First-stage F-stat (mean)	103.9	99.60	101.7	101.2	100.2	98.99
First-stage F-stat (uncertainty)	27.55	27.78	27.07	25.42	26.68	28.02

Notes: The table reports estimates of specification (6). The dependent variable is the share of the hypothetical €10,000 allocated to a given asset class. Shares are measured on the 0–100 scale. The first stages for mean and uncertainty are given by specifications (3’) and (3’’), respectively. All regressions use sampling weights. Household controls are included but not reported. Heteroskedasticity-robust standard errors are reported in parentheses.

which households would like to divest from when facing higher macroeconomic uncertainty. As these are some of the riskier assets, this pattern is consistent with the findings in Ben-David et al. (2018) reporting that the share of assets allocated to risky instruments is negatively correlated with uncertainty of households participating in the SCE.[11] The estimated sign on stocks is similarly negative but statistically insignificant. With first moments, the only coefficient significantly different from zero is on directly held stocks, indicating that households would like to increase their stock investing (and exposure to stock prices) when they expect higher rates of economic growth. We do not find clear evidence that first-moment expectations affect the perceived desirability of other asset classes, but standard errors are quite large in some cases.

D. *Heterogeneity in Effects*

As we utilize micro-level data, we also explore whether results vary along different subsamples. One limitation of doing so is that given the noise in self-reported spending data and the limited number of observations, we naturally lose a lot of precision in the estimates when considering subsamples. Furthermore, the sample size limits our ability to consider splits along two or more characteristics. Because a given characteristic (e.g., education) may be correlated with another characteristic (e.g., financial wealth), this exercise can then provide only suggestive evidence.

First, we split the sample by whether the respondent is male or female and reestimate equation (2) for each subsample. As reported in panel A of Table 8, the

[11] Our main risky financial asset categories regard directly held stocks, mutual funds, and cryptocurrencies. Retirement accounts consist of the value of life insurances and voluntary pension funds. The latter mainly refer to employer-managed pension funds, over which individuals have typically little say regarding the investment allocation of contributed amounts. Moreover, they represent longer-term investments that aim to finance retirement with very rare adjustments in their portfolio composition over individuals’ working life.

estimated effects of macroeconomic uncertainty on the two subsamples are quite similar, and we cannot reject the null of equality between them.[12] We find little variation as well when we split the sample by geography. One natural split is grouping northern countries (Belgium, France, Germany, and the Netherlands) and southern countries (Spain and Italy). As shown in panel B of Table 8, the estimated effect of uncertainty on spending is a little larger for southern countries than northern countries, but the point estimates are not statistically distinguishable.

Another sample split we consider is by the type of work done by the respondent and in particular, the exposure of her sector of employment to the COVID-19 shock. We define a respondent as working in a high-risk sector if her job is in agriculture, manufacturing, construction, trade, transportation, hotels, bars, restaurants, arts, or entertainment. The low-risk sector includes information/communication services, administrative services, public administration, education, and health sectors.[13] We also consider separately retired respondents because this group has the highest mortality risk due to COVID-19 but likely has the lowest income risk. We find in panel C of Table 8 that spending on nondurable goods is much more sensitive to macroeconomic uncertainty for respondents working in the high-risk sectors than for respondents in the low-risk sectors. This behavior is consistent with the greater need of respondents working in high-risk sectors to engage in precautionary savings in the face of uncertainty. Retirees have a similar estimate for the sensitivity to uncertainty, but the estimate is not precisely estimated due to the small size of the sample.

In addition, we split the sample based on how households allocate their financial wealth between risky and safe financial assets. Specifically, we consider a household as holding a risky portfolio if it owns stocks or shares in mutual funds. Because stock prices tend to be more volatile than other asset classes and most sensitive to macroeconomic uncertainty, a rise in uncertainty should signal to households owning stocks a greater loss of wealth and potentially income. In agreement with this conjecture, panel D of Table 8 shows that households owning risky portfolios exhibit a strong sensitivity of spending on nondurable goods and services to macroeconomic uncertainty: increasing their uncertainty by 1 percentage point lowers their subsequent spending by 14 percentage points. In contrast, the respondents with relatively safe portfolios demonstrate effectively zero sensitivity to macroeconomic uncertainty. This result corroborates the findings in Mankiw and Zeldes (1991) from repeated waves of the Panel Study of Income Dynamics, namely that the consumption of stockholders is more volatile and displays a higher correlation with stock market returns than the consumption of nonstockholders.

Finally, we split the sample by the education level of the respondent: primary, secondary, or tertiary. We find that individuals with primary or secondary levels of education tend to adjust their household spending more to changes in their macroeconomic

[12] Although an information treatment is provided to a specific household member, consumption decisions may be made by another member or at the household level. Because we do not know which household member is responsible for spending decisions, our results may understate the power of treatments due to this discrepancy (i.e., information in a treatment may be not communicated to other household members). However, as documented in D'Acunto, Malmendier, Ospina, and Weber (2021); D'Acunto, Malmendier, and Weber (2021) and elsewhere, women are more likely to do grocery and other shopping. Since we find similar effects for men and women, the quantitative importance of this discrepancy may be small.

[13] This sector split is in line with changes in employment and value added by sector in the euro area during the COVID-19 pandemic, as shown, e.g., in Figure 1 of Canton et al. (2021).

Table 8—Heterogeneity in the Effects of First and Second Moments for Expected EA GDP Growth on Household Spending

	Effect on spending coming from							
	Posterior: Mean		Posterior: Uncertainty				First-stage F-stat	
	α (1)	(SE) (2)	β (3)	(SE) (4)	N (5)	R^2 (6)	F(mean) (7)	F(uncert.) (8)
Panel A. By gender								
Men	−0.34	(0.72)	−2.29	(3.19)	2,652	0.24	68.99	14.45
Women	−0.85	(0.60)	−3.19	(2.14)	2,602	0.19	80.25	27.44
p-value for equality	0.58		0.82					
Panel B. By geography								
North	−0.83	(0.62)	−2.91	(2.26)	3,301	0.21	82.40	22.83
South	−0.40	(0.69)	−4.12	(2.78)	1,953	0.18	73.94	23.91
p-value for equality	0.64		0.73					
Panel C. By working sector exposure to COVID-19								
High-risk work	−0.93	(0.90)	−6.11	(2.91)	1,476	0.21	43.37	13.41
Low-risk work	−0.81	(0.59)	3.20	(2.35)	2,170	0.22	68.07	18.23
Retired	−0.22	(1.15)	−8.60	(6.59)	706	0.23	34.64	6.01
p-value for equality	0.88		0.02					
Panel D. By riskiness of portfolio								
Risky portfolio	−0.74	(0.92)	−8.65	(3.44)	1,514	0.18	47.54	14.88
Safe portfolio	−0.64	(0.57)	−0.34	(2.24)	2,825	0.20	97.41	23.61
p-value for equality	0.93		0.04					
Panel E. By education								
Primary	−0.55	(1.45)	−7.38	(5.07)	676	0.24	17.20	8.474
Secondary	−0.25	(0.78)	−7.87	(2.89)	1,571	0.20	45.83	17.76
Tertiary	−0.77	(0.57)	1.16	(2.33)	3,007	0.21	92.00	18.61
p-value for equality	0.87		0.03					

Notes: The table reports estimates of specification (2) for various subsamples of respondents. The dependent variable is log(nondurable consumption) × 100. The first stages for mean and uncertainty are given by specifications (3') and (3''), respectively. The "High-risk" (affected) sector includes Agriculture; Industry; Construction; Trade; Transport; Hotels, bars, and restaurants; Arts and entertainment. The "Low-risk" (less affected) sector includes Information and communication services; Administrative and support services; Public admininistration including military; Education; Health sector; Other. "Retired" includes respondents who are retired at the time of the survey. "Portfolio incl. risky assets" includes respondents who own stocks and/or shares in mutual funds. "Portfolio only in safe assets" includes respondents who own neither stocks nor shares in mutual funds. All regressions use sampling weights. Household controls are included but not reported. Heteroskedasticity-robust standard errors are reported in parentheses.

uncertainty than their higher-educated counterparts, though the effects for those with primary education are very imprecise due to the small sample. There are likely two forces here at work. On the one hand, the highly educated are more likely to own high-risk assets. On the other hand, this group is also likely to work in sectors that are less sensitive to cyclical fluctuations. Our results by educational attainment are consistent with the second factor dominating the first. In addition, given that individuals with higher uncertainty tend to be more educated (online Appendix Table 3), this finding also indicates that our results are not only driven by those individuals with initially high levels of uncertainty.

V. Conclusion

When describing his approach to fighting the Great Depression, former US President Franklin D. Roosevelt famously said, "The only thing we have to fear is fear itself." Indeed, macroeconomic uncertainty can instill fear into anybody who has lived through a catastrophe in which many lost livelihoods or even lives. Yet measuring the effects of macroeconomic uncertainty on households' choices has proven remarkably difficult because this uncertainty is often accompanied by other calamities (pandemics, revolutions, natural disasters, and economic crises) that potentially confound the estimated effects of macroeconomic uncertainty.

Using a randomized controlled trial, we address this identification challenge and provide unambiguous evidence that elevated macroeconomic uncertainty strongly and persistently reduces monthly household spending and makes it less likely that households will purchase large items, such as holiday packages or luxury goods. Our results point to the relevance of both real and financial channels in the propagation of macroeconomic uncertainty. Regarding the former, we find a clear role for job security, with the impact of aggregate uncertainty on spending being largely driven by households that are employed in more cyclically sensitive sectors. Regarding financial channels of transmission, macroeconomic uncertainty also directly influences risk-taking behavior by reducing exposure to more risky assets, such as mutual funds. These estimated causal effects thus shed new light on the mechanisms behind business cycles and specifically the role of macroeconomic uncertainty in causing and/or amplifying fluctuations in consumer spending.

Our work suggests a number of directions for future research. For example, our findings point to important heterogeneous effects by sector of employment, portfolio composition, and education. One can use larger sample sizes to estimate further heterogeneous effects of macroeconomic uncertainty on particular groups of the population. These estimates will allow for more targeted policy responses. Furthermore, one can combine our RCT design with other treatments based on actual or hypothetical policy responses (e.g., provide information about potential government transfers to households) to build more effective tools to combat economic downturns. Our results can also contribute directly to developing better countercyclical policies. For example, recessions are characterized by increased uncertainty, and so an economic recovery may require management of expectations and assurances by policymakers (e.g., as was done by President Franklin D. Roosevelt; see Pedemonte 2020). In addition, policies that provide a stronger safety net for the more vulnerable groups (e.g., in affected sectors) will support aggregate demand. More generally, our estimates suggest that macroeconomic uncertainty can play a key role in the dynamics of aggregate variables, and thus, theoretical work should incorporate uncertainty as an important mechanism for amplification and propagation of business cycles.

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