# Inferring the Aggregate: Information Frictions and Fiscal Policy

Jonas Overhage[†]

IIES, Stockholm University

This version: November 9, 2026

Click here for the latest version

**Abstract**

Countercyclical fiscal transfers increase households' resources but may also signal weak economic conditions. To quantify this information channel, I develop a heterogeneous-agent model with dispersed information and a solution method combining Bayesian filtering with approximate aggregation. Households do not observe aggregate conditions directly, but rationally infer them from their own cash flows, which reflect aggregate and idiosyncratic movements. The information conveyed by transfers largely offsets their stimulus effects, reducing the initial aggregate consumption response from 38 cents per dollar under full information to 8 cents. Households with high cash on hand are most sensitive to the information channel and even reduce consumption upon receiving a transfer. Evidence from a randomized information experiment supports the mechanism: information about a fiscal stimulus lowers GDP forecasts and reduces spending intentions, with the decline in the latter strongest among high-income households. Targeting transfers toward low-income households mitigates the information channel, and the gains from targeting are larger than under full information.

I thank Per Krusell, Kurt Mitman and Kieran Larkin for their mentorship and support. I also thank Ludwig Straub, Brian Higgins, Alexandre Kohlhas, Timo Boppart, Yimei Zou, Ronja Helénsdotter, Amalia Repele, Karl Harmenberg, N. Gregory Mankiw, Hugo Reichardt, Daria Finocchiaro, Joel Flynn and participants at SUDSWEC 2025, the 14th National PhD Workshop at the Swedish House of Finance, the fifth PhD Workshop in Money and Finance at Sveriges Riksbank, the EEA-ESEM Congress 2026, the VfS annual conference 2026 and seminars at the IIES, Harvard University and the University of Mannheim for valuable comments and suggestions. I thank the Research Data and Service Centre (RDSC) of the Deutsche Bundesbank for providing access to the Bundesbank Online Panel – Households (BOP-HH) through the Scientific Use File project 2025\0107.

[†]web: joverhage.github.io; email: jonas.overhage@iies.su.se

# 1 Introduction

It is widely documented that households extrapolate from their own economic circumstances when forming expectations about the macroeconomy (Kuchler and Zafar, 2019; D'Acunto et al., 2021; Taubinsky et al., 2026). Such extrapolation can arise when households learn about the wider economy from their own cash flows. But cash flows are a noisy signal of aggregate conditions. For example, a higher wage may reflect household-specific factors or a stronger economy. In both cases, the household's resources rise, but expected future earnings also increase to the extent that the higher wage signals a stronger economy. Fiscal transfers can signal the opposite. When transfers are countercyclical, receiving one indicates that aggregate conditions are weak: a stimulus payment raises a household's resources today while lowering expected future earnings.

I study how important this information channel is for household spending and the efficacy of fiscal policy. The paper extends models of dispersed information to a heterogeneous-agent economy with endogenous aggregate output. Households observe their own cash flows but not aggregate conditions directly. They rationally infer the aggregate state from these observations, but inference is imperfect because different shocks can generate similar movements in observed cash flows. In the case of fiscal transfers, households cannot perfectly separate discretionary from countercyclical spending. Even a discretionary expansion can thus be interpreted partly as a response to weak aggregate conditions. I use survey data to validate expectation formation through rational inference as well as the importance of the information channel. In particular, a randomized information experiment on fiscal policy is used to test the model's predictions for expectations updating and household spending. To my knowledge, this paper is the first to model and quantify this information channel of fiscal transfers.

In the quantitative model, the information channel largely offsets the increase in consumption that countercyclical transfers would otherwise generate. Compared to a full-information benchmark, the initial consumption response to a discretionary fiscal expansion decreases from 38 cents per dollar transferred to 8 cents. The underlying mechanism is that receipt of the transfer causes households to revise down their expectations about aggregate conditions. Households with high cash on hand respond more strongly to this information and even reduce consumption upon receiving a transfer. This is because for these households, spending is less constrained by current resources and more sensitive to expected future income. Dispersed information also changes the timing of adjustment. Households learn about persistent aggregate shocks only gradually, dampening the initial consumption response and generating hump-shaped dynamics.

I provide empirical evidence for the importance of the information channel using a randomized information experiment. The evidence uses the Bundesbank Online Panel – Households (BOP-HH), in which survey respondents were informed of a EUR 750 billion fiscal package in April 2020. Consistent with Metiu and Stockerl (2024), I show that information about the package lowers expected GDP growth over the next twelve months by 1.76 percentage points and the stated probability of large durable purchases over the same period by 6.15 percentage points relative to respondents that did not receive the information treatment. I extend their analysis by examining heterogeneity across income groups. GDP expectations fall broadly across income groups, while the decline in spending intentions is concentrated among high-income households. This is consistent with less constrained households adjusting consumption more strongly in response to the same information.

A partial-equilibrium model then illustrates the mechanism. In the model, heterogeneous households face uninsurable income risk and a borrowing constraint. Households do not directly observe aggregate productivity but observe their own wages, and rationally infer the former from the latter. The first implication of the information structure is that, through the information channel, a wage increase now raises a household's expectations about aggregate productivity, with the household rationally inferring that aggregate conditions may be strong. Households with high cash-on-hand are less constrained in their ability to respond to the information, and are more responsive to the information channel. The second implication is that households learn slowly about an increase in productivity. The consumption response to an aggregate shock becomes hump-shaped, while responses to idiosyncratic shocks remain front-loaded.

To quantify the importance of the information channel for the efficacy of fiscal transfers, I extend the model to a quantitative general-equilibrium setting. This framework retains the household structure from the partial-equilibrium model. A demand externality captures in reduced form the productive role of demand emphasized by Bai et al. (2026): firms need consumers to turn productive capacity into realized output. The externality generates feedback from household spending to output and wage income. Fiscal policy operates through transfers to households, with both discretionary and countercyclical components. Government debt absorbs the initial financing needs, while lump-sum taxes respond to stabilize debt over time. The model is non-Ricardian, with borrowing constraints and incomplete markets implying that the timing of transfers and taxes can affect consumption. As before, households infer aggregates from their wage income. In addition, households now learn from their fiscal transfer receipts. However, they cannot perfectly distinguish their discretionary and countercyclical components, which households learn only over

time. The two implications from the basic model carry over, with transfers providing an additional signal about aggregate conditions. Because transfers respond to falling output, a larger payment can lead households to infer that aggregate conditions are weak. Following a discretionary expansion, this initial pessimism recedes as households gradually recognize the discretionary expansion, generating a delayed consumption response.

The full quantitative model presents a computational challenge, featuring heterogeneous agents facing borrowing constraints, dispersed information, and demand-determined aggregate output. Solving such models requires jointly determining individual policies, expectations, and the infinite-dimensional cross-sectional distribution over household assets, incomes, and beliefs. This poses a substantial computational challenge under dispersed information: Bayesian filtering can only proceed when the underlying state process is known. But in this class of models, that very process depends on households' decisions, which in turn depend on their expectations. Demand-determined output makes the computational challenge particularly severe because signals are contemporaneous, endogenous variables. Incomes are signals and affect households' expectations, expectations affect their decisions, and decisions then determine incomes through general equilibrium feedback.

Because existing methods do not directly apply to this setting, I develop a solution method combining Bayesian filtering and approximate aggregation to solve for an approximate equilibrium. The approximation enters through a parametric perceived law of motion. Conditional on the law of motion, households form expectations optimally using Bayesian filtering. Starting from an initial guess, the coefficients are iteratively updated until the perceived law of motion accurately matches simulated aggregate dynamics. The simulation involves solving for market clearing aggregates consistent with the signals observed by households. I find the approximation of aggregate dynamics to be highly accurate. At the household level, the Bayesian filter also tracks aggregate output more accurately than alternative machine-learning methods while requiring far fewer household state variables. For the targeting exercise described below, the method is extended to accommodate non-Gaussian signals using assumed density filtering (Minka, 2001).

To understand the response to a persistent discretionary increase in transfers, I decompose the consumption response into cash, policy, and information components. The cash component captures the increase in current resources. The policy component captures future transfers and taxes, as well as current and anticipated general-equilibrium effects. Both components are similar across information structures, while the information channel accounts for the decrease relative to full information. At the top of the cash-on-hand distribution, the information channel more than offsets the positive cash and policy components,

causing consumption to fall. This pattern follows from differences in responsiveness to information, with less constrained households adjusting spending more strongly in response to deteriorating expectations. The resulting heterogeneity matches the experimental evidence from the BOP-HH data, providing cross-sectional support for the key mechanism. In the model counterpart of the information experiment, dispersed information generates declines in GDP expectations and consumption, while full information predicts increases.

The results link two empirical patterns about countercyclical fiscal policy by showing how pessimistic expectation revisions can dampen consumption responses to stimulus payments. First, the quantitative results help account for modest household-level and aggregate consumption responses to countercyclical stimulus payments, partially reconciling high micro MPCs from windfall cash receipts with modest macro responses (Orchard et al., 2025; 2026).[1] Second, the information channel helps explain why expectation responses to fiscal news depend on the cyclical role of policy. Information about procyclical or acyclical fiscal expansions generally leads to more optimistic expectations (Andre et al., 2022; Ludolph et al., 2026). In contrast, information about countercyclical policy can induce pessimism (Coibion et al., 2022; Melosi et al., 2025). I show that the information channel rationalizes this pessimism, with the policy signaling weak aggregate conditions.

Lastly, I find that targeting transfers toward low-income households increases the effects of fiscal stimulus. Targeting redirects resources to households with higher spending responses already in a full information framework. Under dispersed information, targeting additionally reallocates transfers toward households that are less sensitive to the information channel. The gains from targeting relative to untargeted transfers are thus larger under dispersed information. With untargeted transfers, the impact consumption response under full information is about five times that under dispersed information. With targeting, it is only about 30 percent larger. Through the reallocation to less information-sensitive households, targeting also restores a front-loaded aggregate consumption response.

**Related literature.** The paper contributes to the literature on the information conveyed by fiscal policy. Metiu and Stockerl (2024) study the same BOP-HH experiment, while Coibion et al. (2022) and Melosi et al. (2025) provide further evidence that fiscal expansions can induce pessimistic expectation revisions. Gallegos et al. (2025) study price-related fiscal announcements during the euro area cost-of-living crisis. Georgarakos and Kenny (2022) show that improving perceptions of fiscal support can raise spending. More generally, macroeconomic expectations affect household spending (Coibion et al., 2023; D'Acunto et al., 2022; Roth & Wohlfart, 2020).

[1] See Appendix A for a detailed comparison.

The paper also relates to models of fiscal learning and signaling. Han (2021) studies learning about unknown long-run fiscal targets, showing how misperceptions affect decisions and fiscal multipliers. Guo and Yin (2026) study how the financing of government spending affects its signaling content, with debt-financed expansions inducing more pessimistic expectations than tax-financed ones. My focus is on households inferring aggregate conditions from cash flows: transfers provide both resources and information, with heterogeneous consumption responses depending on households' financial positions.[2]

A related literature studies consumption responses to cash receipts and transfer design. Strong household responses to cash receipts are documented by Souleles (1999) and Kueng (2018), while selected estimates for stimulus payments are smaller (Goldfayn-Frank et al., 2022; Orchard et al., 2025, 2026; Parker et al., 2022). At the aggregate level, Taylor (2009, 2022), Orchard et al. (2025), and Ramey (2026) document or discuss limited consumption effects of temporary transfers. These comparisons are suggestive as payment design, recipients, spending horizons, and estimation methods differ. Appendix A provides a detailed comparison. Quantitative heterogeneous-agent models emphasize redistribution (Oh & Reis, 2012), insurance (McKay & Reis, 2016), and targeting (Bayer et al., 2023). I identify an additional reason for modest stimulus responses and an additional gain from targeting: directing transfers toward low-income households also directs them toward households less sensitive to the information channel.

The household inference mechanism is motivated by evidence linking personal experiences to aggregate beliefs. House-price experiences shape house-price expectations (Kuchler & Zafar, 2019), while observed prices affect inflation expectations (Cavallo et al., 2017; D'Acunto et al., 2021; Weber et al., 2022). Personal experiences also influence attention to the macroeconomy (Link et al., 2026), and idiosyncratic shocks affect aggregate expectations (Taubinsky et al., 2026). Closest to the mechanism here, Adams and Rojas (2024) find that households cannot fully separate aggregate from idiosyncratic income movements. I model households as using observations from their own budget constraints to learn about endogenous aggregate conditions.

The theoretical framework builds on dispersed-information models, beginning with Lucas (1972) and including Lorenzoni (2009), Angeletos and La'O (2020), and Kohlhas and Walther (2021). Pischke (1995) connects inference from individual income to sluggish consumption adjustment. Other explanations for slow adjustment include sticky information (Auclert et al., 2020; Carroll, 2003; Carroll et al., 2020; Mankiw & Reis, 2002), rational inattention (Maćkowiak & Wiederholt, 2015), and behavioral expectations (Angeletos

[2]The paper also relates to the monetary-policy information literature, including Melosi (2017), Nakamura and Steinsson (2018), Kohlhas (2022), and Müller et al. (2024).

et al., 2021; Bordalo et al., 2018; Guarda, 2026). In my model, households update each period using Bayesian inference conditional on a perceived law of motion, which describes aggregate movements approximately. Sluggish adjustment and heterogeneous beliefs arise from noisy, dispersed observations of aggregate conditions. This is distinct from adaptive learning, which allows agents to learn about the underlying model process (Evans & Honkapohja, 2001; Marcet & Sargent, 1989). Relatedly, subjective beliefs and internal rationality provide complementary approaches to expectation formation (Adam & Marcet, 2011; Adam et al., 2016, 2017; Kurz et al., 2013).

Methodologically, I extend approximate aggregation (Krusell & Smith, 1998) to a dispersed-information economy with contemporaneous feedback between household decisions and signals. The perceived-law approach can be interpreted as a restricted perceptions equilibrium approximating rational expectations (Marcet & Sargent, 1989). Porapakkarm and Young (2008) and Guarda (2026) apply related methods to Krusell-Smith economies with imperfect information about endogenous capital, while Broer et al. (2026) incorporate endogenous information acquisition. In my framework, current consumption affects output and thus the signals used to form current expectations. Hellwig and Venkateswaran (2011, 2025) address a related computational problem in firm price-setting. Nimark (2017) and Huo and Takayama (2025) develop methods for linear models with higher-order beliefs. Closely related ongoing work by Auclert et al. (2026) and Overhage (2026) solves heterogeneous-agent models with dispersed information in sequence space, obtaining local dynamics around a full-information steady state. The present paper solves household decisions globally, combining Bayesian filtering with approximate aggregation.

My theoretical framework relates to an ongoing debate summarized by Moll (2026), who argues in favor of replacing rational expectations with beliefs over a more limited set of aggregate variables. One of his proposed solutions is to model expectation formation in line with survey evidence. The present paper demonstrates that an information friction can microfound this even in an approximate rational expectations equilibrium.

The remainder of the paper is organized as follows. Section 2 presents empirical evidence on expectation formation and the information channel. Section 3 illustrates the channel in a partial equilibrium model. Section 4 extends the model to the full quantitative model and describes its solution method. Section 5 evaluates the model against the information experiment and presents the main results. Section 6 discusses an extension featuring targeted transfers. Section 7 concludes.

# 2 Empirical evidence

## 2.1 Experience effects and forecast efficiency

The Survey of Consumer Expectations (SCE) asks respondents whether their household is financially better or worse off than twelve months earlier. The response, denoted by $Q1_{it}$, is recorded on a five-point scale from 1, much worse, to 5, much better. Respondents also report the percent chance that the aggregate unemployment rate will be higher twelve months later, denoted by $Q4new_{it}$.

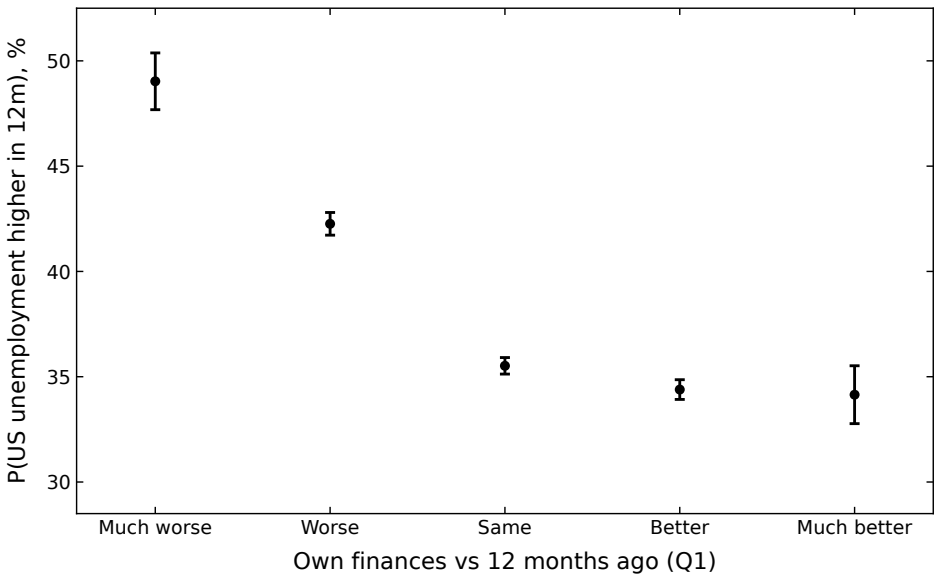



**Figure 1:** Aggregate unemployment expectations by household financial situation

Notes: Survey-weighted mean probabilities that US unemployment will be higher twelve months ahead, by respondents' assessment of their household's financial situation relative to twelve months earlier. Financial conditions range from much worse to much better. Error bars show 95% confidence intervals based on respondent-clustered standard errors. Data are from the SCE, June 2013–September 2025.

Figure 1 plots weighted mean unemployment expectations across the five financial-situation categories. Respondents who report that their household is financially worse off assign a substantially higher probability to an increase in aggregate unemployment. The relationship is monotonic across the financial-situation categories.

To quantify this relationship, I estimate

$$Q4new_{it} = \alpha_i + \delta_t + \beta Q1_{it} + \varepsilon_{it}, \tag{1}$$

where $\alpha_i$ denotes respondent fixed effects and $\delta_t$ denotes survey-month fixed effects. Month fixed effects absorb aggregate conditions and public information shared by respondents interviewed in the same month. Respondent fixed effects absorb persistent differences in beliefs and reporting behavior.

The main estimates use SCE survey weights, with an unweighted specification reported as a robustness check. Standard errors are clustered by respondent. The full fixed-effects ladder, including the pooled and respondent-fixed-effects-only specifications, with weighted and unweighted estimates, is reported in Appendix B.2. The survey-weighted specification with month fixed effects captures the within-month relationship. A one-category improvement in the household's financial situation is associated with an approximately 3.8 percentage point decline in the reported probability that unemployment will rise. Because this comparison is made within survey month, the estimate cannot be explained by financially worse-off households simply being observed during periods of weak aggregate conditions.

**Table 1:** Own financial situation and expected aggregate unemployment

| | P(unemployment higher) |
|---|---|
| No fixed effects | -3.94*** |
| | (0.16) |
| Month fixed effects | -3.76*** |
| | (0.16) |
| Respondent + month fixed effects | -1.60*** |
| | (0.13) |
| Unweighted, respondent + month FE | -1.58*** |
| | (0.09) |
| Observations | 185,086 |

Notes: Coefficients relate the reported probability that US unemployment will be higher twelve months ahead, on a 0–100 scale, to household financial conditions, coded from 1 (much worse) to 5 (much better) relative to twelve months earlier. Regressions use survey weights except where indicated, with fixed effects as listed. Respondent-clustered standard errors are in parentheses. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

When respondent fixed effects are added to this specification, the coefficient falls to approximately $-1.6$ percentage points but remains statistically significant. The smaller within-respondent estimate is consistent with the short length of the SCE panel and the limited variation in respondents' broad financial-status categories during their time in the survey. These results imply that households interviewed at the same time do not hold identical expectations about a purely aggregate outcome. Personal financial circumstances

predict disagreement even after conditioning on common aggregate information. This is consistent with dispersed information and experience-based inference.

I obtain complementary evidence from direct measures of household income. In the BOP-HH, declines in household income are associated with lower expectations of aggregate growth and higher expected aggregate unemployment, but only the latter relationship is statistically significant. The point estimates suggest larger responses to real-income losses than to gains, although formal evidence for asymmetry is limited. This is likely due to much of the data being collected during times of high inflation, in which nominal income increases do not necessarily imply real ones. Appendix B.2 reports the full BOP-HH income specification.

The SCE relationship between personal finances and aggregate beliefs is inconsistent with full information, but not necessarily with rational expectations. Households may hold different forecasts because they observe different signals, while still using those signals efficiently. I therefore compare the relationship of financial conditions with respondents' forecasts and with subsequent aggregate realizations. Following Taubinsky et al. (2026), this can be interpreted as a test of rational expectations updating under imperfect information.

Define the forecast as

$$F_{it} = Q4new_{it}/100, \tag{2}$$

and the realization as

$$R_{it} = \mathbf{1}\{u_{t+12} > u_t\}, \tag{3}$$

where $u_t$ is the US unemployment rate in the interview month. The forecast error is

$$FE_{it} = R_{it} - F_{it}. \tag{4}$$

For each outcome $d_{it} \in \{F_{it}, R_{it}, FE_{it}\}$, I estimate

$$d_{it} = \alpha + \beta_d Q1_{it} + \varepsilon_{it}. \tag{5}$$

The regressions use SCE survey weights and two-way clustering by survey month and respondent. Clustering by month is important because the realized outcome is common

to all respondents interviewed in the same month. Respondent clustering allows forecast and reporting errors to remain correlated within individuals.

**Table 2:** Forecast efficiency with respect to household finances

| | Slope on own finances |
|---|---|
| Forecast | -0.0391*** |
| | (0.0021) |
| Realization | -0.0362*** |
| | (0.0105) |
| Forecast error (realized minus forecast) | 0.0029 |
| | (0.0108) |
| Observations | 180,863 |

Notes: Each row reports a separate survey-weighted linear regression on household financial conditions, coded from 1 (much worse) to 5 (much better). The forecast is the probability, on a 0–1 scale, that US unemployment will be higher twelve months ahead. The realization equals one if the US unemployment rate twelve months after the interview exceeds its interview-month level, and zero otherwise. Forecast errors equal realizations minus forecasts. Standard errors clustered by survey month and respondent are in parentheses. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A one-category improvement in financial conditions is associated with a 3.9 percentage point decline in the forecasted probability of higher unemployment. The corresponding realization slope is a 3.6 percentage point decline. The forecast-error slope is 0.3 percentage points and is not statistically distinguishable from zero. Appendix B.2 reports the corresponding estimates under alternative one-way clustering conventions.

The similarity of the forecast and realization coefficients implies that the differences in unemployment expectations across financial-situation categories broadly reflect differences in the probability of unemployment subsequently increasing. Households may hold different forecasts because they possess different information, while their forecast errors remain orthogonal to that information. Taken together, the evidence is consistent with rational updating under dispersed information.

## 2.2 The fiscal-package signal

I next examine whether a fiscal-policy announcement conveys information about aggregate conditions and affects household spending plans. The analysis uses a randomized information experiment conducted in the April 2020 wave of the BOP-HH (Deutsche Bundesbank, 2020). A detailed discussion of this experiment is provided by Metiu and Stockerl (2024). Respondents were assigned to one of six information treatments. The

analysis in this section compares respondents receiving information about the German federal fiscal package, arm 5, with respondents receiving a placebo text about European human rights, arm 1. The remaining experimental arms are excluded. Covariate balance for the fiscal-package and placebo groups is reported in Appendix B.3.

Immediately after treatment, respondents report a probability distribution over German GDP movements during the following twelve months. I convert this distribution into a mean growth forecast using the midpoints of the eight response bins. Respondents also report propensities from 0 to 100 to purchase a car, purchase other large durable goods, and build up additional financial reserves over the following twelve months.[3]

For the effect on GDP expectations, I estimate

$$GDP_i^e = \alpha + \beta fp_i + X_i'\lambda + \varepsilon_i, \tag{6}$$

where $fp_i$ equals one for the fiscal-package treatment and zero for the placebo treatment. The vector $X_i$ contains gender, age, household size, employment status, and pre-treatment growth expectations. The regression uses BOP-HH survey weights and heteroskedasticity-robust standard errors. I estimate the same specification for the stated propensity of another large durable purchase. The fiscal-package announcement lowers expected GDP growth by 1.76 percentage points and the stated probability of a large durable purchase by 6.15 percentage points relative to the placebo treatment. The results summarized in Table 3 indicate that respondents interpret the announcement not only as information about the government's policy response, but also as information that underlying aggregate conditions are weak.

The average effects are consistent with Metiu and Stockerl (2024). Overall, informing households about the size of the fiscal package induces a similar degree of pessimism as informing them about general economic conditions. Figure 23 in Appendix B.3 places this effect in the context of all six experimental arms. Additionally, Appendix B.5 shows that the effect on expectations is persistent, although there is significant attrition in the panel over subsequent survey waves.

The increase in pessimism about future GDP appears in line with other expectations indicators, with exploratory results suggesting that treated households are more likely to identify the economy as a serious problem or report concerns about their finances going forward. Results regarding these additional indicators are collected in Appendix B.1.3.

[3]Savings-related outcomes and their interpretation are discussed in Appendix B.7.

**Table 3:** Policy information, GDP expectations, and durable spending intentions

| | Expected GDP growth | Durable propensity |
|---|---|---|
| Policy information | -1.76*** | -6.15** |
| | (0.56) | (3.09) |
| Controls | Yes | Yes |
| Observations | 628 | 628 |

Notes: BOP-HH wave 4 (April 2020). Outcomes are expected German GDP growth from the post-treatment eight-bin probability distribution and the stated probability (0–100) of another large durable purchase, both over the next twelve months. Effects are in percentage points. GDP compares the federal fiscal-package arm (5) with placebo; durables compares the federal fiscal-package arm (5) with placebo. Each column reports a survey-weighted linear regression with controls for gender, age, household size, employment status, and pre-treatment growth expectations.
Heteroskedasticity-robust standard errors are in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Covariate-adjusted placebo predictions are -1.86% for GDP growth and 38.95% for durable purchases, averaged over each weighted regression's estimation sample.

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Bundesbank Online Panel – Households (BOP-HH), April 2020, own calculations.

I next examine whether the treatment affects intended durable spending differently across the household-income distribution. Figure 2 reports treatment effects separately for households with monthly income below EUR 5,000 and households at or above EUR 5,000.

The fiscal-package treatment has little effect on intended durable spending among households below the threshold but produces a substantially larger decline among households with income of at least EUR 5,000. The difference suggests that the same information treatment produces heterogeneous spending responses, even among groups whose beliefs move in broadly similar directions.

A natural interpretation is that higher-income households have greater scope to adjust discretionary durable purchases in response to the information. The result is therefore consistent with a common information update combined with heterogeneous marginal spending responses. Appendix B.4 reports the income-bracket profiles.

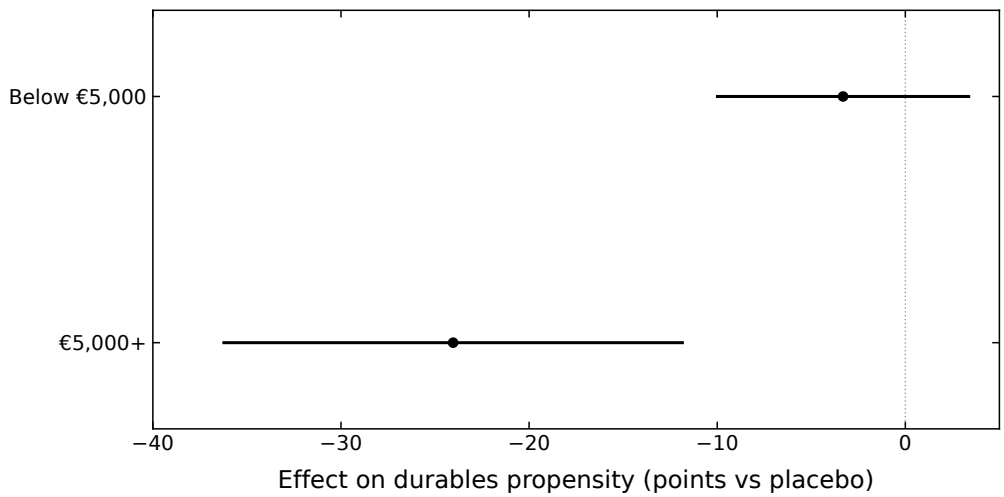



**Figure 2:** Fiscal-package information and intended durable spending by household income

Notes: Treatment effects on the stated probability of another large durable purchase over the next twelve months, in percentage points, comparing fiscal-package information with placebo. Estimates use a survey-weighted linear regression with a treatment–income-group interaction and controls for gender, age, household size, employment status, and pre-treatment growth expectations. Error bars show 95% confidence intervals based on heteroskedasticity-robust standard errors.

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Bundesbank Online Panel – Households (BOP-HH), April 2020, own calculations.

Overall, the experiment supports the interpretation of fiscal policy as both an economic intervention and an information signal. Information about the fiscal package lowers expected growth and reduces intended spending among households with substantial capacity to adjust durable purchases. Existing empirical evidence likewise suggests that household resources matter for spending responses to changes in expectations. Lieb and Schuffels (2022) find related evidence for inflation expectations, while Yin (2026) documents the importance of financial constraints for responses to credit-related information. These findings motivate a heterogeneous-agent model in which financial resources affect the consumption response to information.

# 3 Information mechanism

This section uses a simple partial-equilibrium consumption–savings environment to isolate the information mechanism underlying the quantitative model below. Households infer aggregate productivity from their own income, which contains both an aggregate and an idiosyncratic component. The setup highlights two implications. First, cash flows affect

consumption through both resources and information. Second, gradual learning about aggregate shocks can generate delayed aggregate responses.

## 3.1 Setup and signal extraction

Time is discrete, $t = 0, 1, 2, \ldots$. There is a unit mass of identical firms and a unit mass of households. Labor supply is inelastic and normalized to one. Firms produce with linear technology

$$Y_t = Z_t, \tag{7}$$

where, denoting log variables using lowercase letters, aggregate productivity follows

$$z_{t+1} = \rho_z z_t + \mu_{t+1}, \qquad \mu_{t+1} \sim \mathcal{N}(0, \sigma_\mu^2). \tag{8}$$

Under perfect competition and constant returns, a common wage $W_t = Z_t$ would reveal the aggregate state exactly. Instead, I introduce wage scrambling following the idea of Boppart et al. (2024). Individual wages are dispersed deviations from aggregate productivity:

$$\int_0^1 W_{it}\, di = Z_t, \qquad w_{it} = z_t + \xi_{it} - \frac{\sigma_\xi^2}{2}, \qquad \xi_{it} \sim \mathcal{N}(0, \sigma_\xi^2). \tag{9}$$

The adjustment by $-\sigma_\xi^2/2$ ensures that average wages remain equal to $Z_t$.

Households have CRRA preferences,

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{C_{it}^{1-\sigma}}{1-\sigma}, \tag{10}$$

and access to a storage technology with exogenous gross return $R^*$. Their budget constraint is

$$C_{it} + A_{i,t+1} = R^* A_{it} + W_{it}, \qquad A_{i,t+1} \geq \bar{a}, \qquad \bar{a} = 0. \tag{11}$$

Households do not observe $Z_t$ directly. They observe their own wage and understand the processes for $Z_t$ and $\xi_{it}$. Defining

$$s_{it} \equiv w_{it} + \frac{\sigma_\xi^2}{2}, \tag{12}$$

the state and signal processes are

$$z_{t+1} = \rho_z z_t + \mu_{t+1}, \qquad \mu_{t+1} \sim \mathcal{N}(0, \sigma_\mu^2), \tag{13}$$

$$s_{it} = z_t + \xi_{it}, \qquad \xi_{it} \sim \mathcal{N}(0, \sigma_\xi^2). \tag{14}$$

Individual income therefore provides a noisy signal about aggregate productivity.

The system is linear and Gaussian, so households apply the Kalman filter. Let $\hat{z}_{i,t|t-1}$ denote household $i$'s prior estimate of $z_t$. After observing $s_{it}$,

$$\hat{z}_{i,t|t} = (1 - k_t)\hat{z}_{i,t|t-1} + k_t s_{it}, \tag{15}$$

$$k_t = \frac{P_{t|t-1}}{P_{t|t-1} + \sigma_\xi^2}, \tag{16}$$

where $P_{t|t-1}$ is the prior variance. The posterior variance follows the standard Kalman recursion and converges to a common stationary value. Because $k_t \in (0, 1)$, households only partially incorporate an income realization into their estimate of the aggregate state. Beliefs therefore adjust gradually to aggregate shocks.

Define cash on hand as

$$M_{it} = R^* A_{it} + W_{it}. \tag{17}$$

Once the posterior variance has converged, the household problem can be written using $(M_{it}, \hat{z}_{i,t|t})$ as individual states:

$$V(M_{it}, \hat{z}_{i,t|t}) = \max_{A_{i,t+1} \geq \bar{a}} \left\{ u(C_{it}) + \beta \mathbb{E}_{it} \left[ V(M_{i,t+1}, \hat{z}_{i,t+1|t+1}) \right] \right\}, \tag{18}$$

where

$$C_{it} = M_{it} - A_{i,t+1}, \tag{19}$$

$$M_{i,t+1} = R^* A_{i,t+1} + W_{i,t+1}. \tag{20}$$

An observed income change therefore affects consumption through current cash on hand as well as through beliefs about future income.

## 3.2 Consumption implications

The information friction has two closely related implications for consumption dynamics. Aggregate shocks are incorporated into household beliefs only gradually, generating

delayed aggregate adjustment. At the household level, the response to an observed income change depends not only on the additional resources it provides, but also on what it reveals about the aggregate state.

Figure 3 illustrates the first mechanism. For the results presented here, I calibrate the aggregate productivity process, standard deviation of idiosyncratic shocks, utility curvature, discount factor and interest rates to the same values used in the full quantitative model, described in Subsection 4.7.

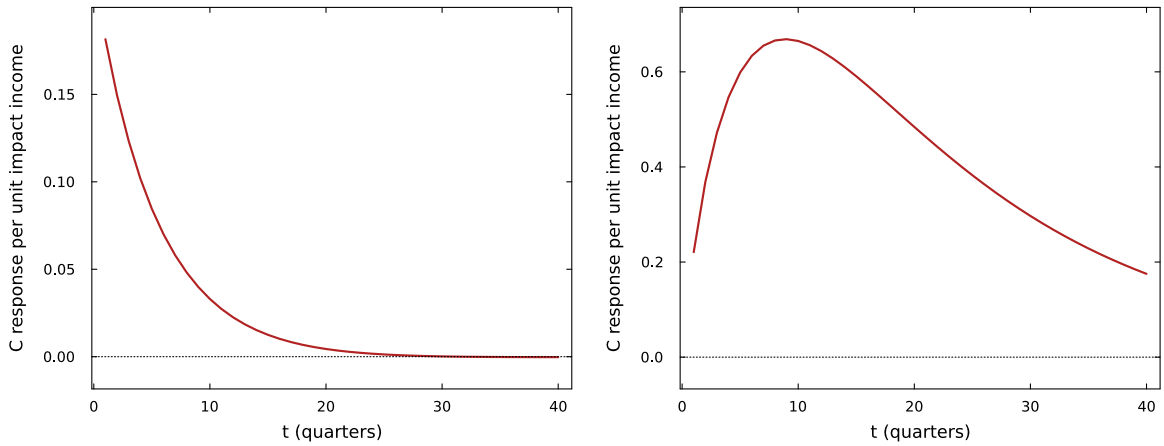



**Figure 3:** Consumption responses to one-standard-deviation shocks

Notes: Consumption responses under dispersed information in the basic partial-equilibrium model. The left panel shows an individual household's response to a one-standard-deviation positive idiosyncratic wage shock, evaluated at median cash on hand. The right panel shows the aggregate response to a one-standard-deviation positive productivity innovation. Responses are normalized by the respective impact income increase. Periods are quarters, and vertical scales differ across panels.

The left panel shows the consumption response of an individual household to a one-standard-deviation idiosyncratic wage shock, evaluated at median cash on hand. This response is front-loaded. The right panel shows the response of aggregate consumption to a one-standard-deviation aggregate productivity shock. On impact, consumption rises by about one-third of its eventual peak, with the maximum effect occurring only several quarters later.

The contrast reflects signal extraction. Aggregate shocks must first pass through dispersed income signals and Bayesian updating before they are fully incorporated into household beliefs, so their effect on aggregate consumption is spread over time. An idiosyncratic income innovation instead changes household resources immediately. This generates a front-loaded individual response alongside a delayed aggregate response.

The same mechanism implies that MPCs depend on the informational content of an income change. It is useful to distinguish between a pure cash-flow effect, which changes current

resources while holding beliefs fixed, and the information channel, operating through the household's posterior belief about aggregate productivity. Figure 4 illustrates this decomposition. The decomposition changes beliefs first, holding cash on hand at its no-shock value, and then changes cash on hand while holding beliefs at their updated values. The two components thus sum to the total effect.

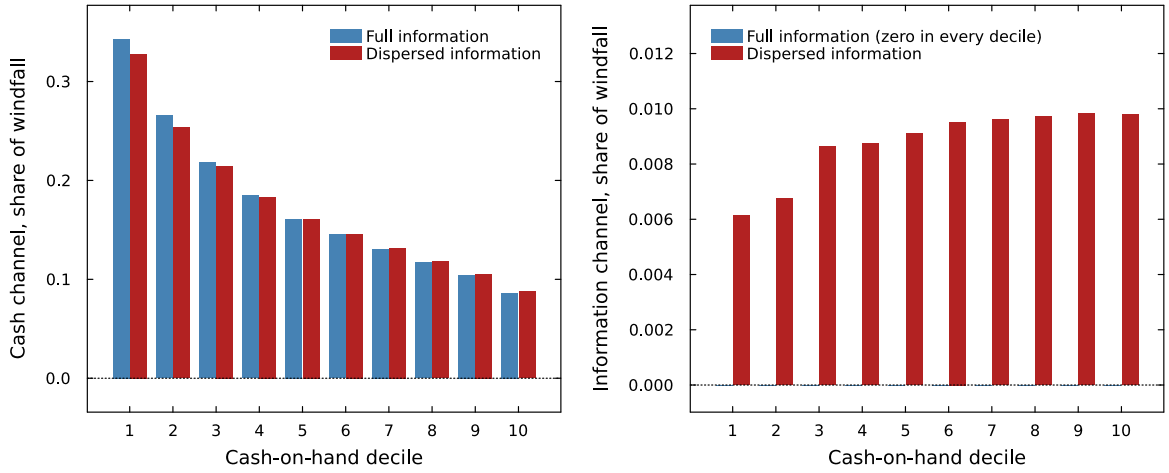



**Figure 4:** Quarterly responses to an idiosyncratic income shock

Notes: Impact consumption responses to a one-standard-deviation positive idiosyncratic wage innovation, per unit of the induced increase in cash on hand. The information component changes beliefs while holding cash on hand fixed. The cash component then changes resources at the updated beliefs. Deciles refer to pre-shock cash on hand in each economy's stationary distribution (1 = lowest; 10 = highest). The information component is zero under full information. Vertical scales differ across panels.

As in standard incomplete-markets models, the pure cash-flow effect is largest for households with little cash on hand and declines along the distribution. Under dispersed information, however, the same income realization also changes expectations. A positive wage innovation is partly interpreted as evidence that aggregate productivity, and therefore future income, is higher. The total consumption response can therefore differ from the pure MPC that holds beliefs fixed.

In this basic model, these effects are relatively minor overall. The information channel is less pronounced at the bottom of the distribution in absolute terms, and especially relative to the cash component. Constraints play the main role here, with households closer to the borrowing constraint less sensitive to expectations about future income. It is only at the top of the distribution that the information channel is about 10% as big as the cash component. While the size is small in this basic framework, the pattern of information mattering more at the top of the distribution holds true in the more involved model from Section 4 onward.

The environment therefore isolates the two mechanisms used in the fiscal-policy model below. Dispersed information delays aggregate adjustment because households learn about aggregate conditions over time, while the response to a cash flow depends on what that cash flow reveals about future economic conditions. In the fiscal-policy model, transfers themselves play this dual role as both resources and signals.

# 4 Fiscal-policy model

This section introduces fiscal transfers into the heterogeneous-household model with dispersed information and studies their quantitative effects. As in the basic model, households have fixed labor supply. Idiosyncratic income risk is now more general and allows for persistence. Transfers provide households with resources, but also convey information about aggregate conditions. Aggregate output responds to household consumption through a reduced-form demand externality, following, for example, Boppart et al. (2018) and Krueger et al. (2016).

Households observe the variables entering their own budget constraints, but cannot separate aggregate output from the idiosyncratic component of their labor income. They also observe aggregate transfers, but cannot determine whether a high transfer reflects a discretionary fiscal intervention or the systematic countercyclical response of fiscal policy. Households therefore use labor income and transfers to infer aggregate output, their own idiosyncratic efficiency, and the discretionary component of fiscal policy.

## 4.1 Environment

There is a unit mass of households indexed by $i \in [0, 1]$. Households save in an internationally traded asset with exogenous gross return

$$R^* = 1 + r^*, \qquad \beta R^* < 1. \tag{21}$$

Aggregate productivity follows the log AR(1) process

$$z_t = \rho_z z_{t-1} + \mu_t, \qquad \mu_t \sim \mathcal{N}(0, \sigma_\mu^2), \qquad |\rho_z| < 1, \tag{22}$$

where $z_t = \log Z_t$.

Households differ in persistent idiosyncratic efficiency. Let

$$e_{i,t+1} = \rho_e e_{it} + \zeta_{i,t+1}, \qquad \zeta_{i,t+1} \sim \mathcal{N}(\mu_\zeta, \sigma_\zeta^2), \qquad |\rho_e| < 1, \tag{23}$$

where $e_{it} = \log E_{it}$. The stationary variance of log efficiency is

$$\sigma_e^2 = \frac{\sigma_\zeta^2}{1 - \rho_e^2}. \tag{24}$$

I normalize mean efficiency in levels to one:

$$\mathbb{E}[E_{it}] = 1. \tag{25}$$

Since $e_{it}$ is normally distributed, this requires

$$\mathbb{E}[e_{it}] = -\frac{\sigma_e^2}{2}. \tag{26}$$

The corresponding drift in the innovation process is

$$\mu_\zeta = -(1 - \rho_e)\frac{\sigma_e^2}{2} = -\frac{\sigma_\zeta^2}{2(1 + \rho_e)}. \tag{27}$$

With a continuum of households, the normalization implies

$$\int_0^1 E_{it}\, di = 1. \tag{28}$$

Household $i$ has preferences

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(C_{it}), \qquad u(C) = \frac{C^{1-\sigma}}{1 - \sigma}. \tag{29}$$

Labor supply is fixed. Household $i$ receives individual labor income $W_{it}$, an aggregate transfer $T_t$, and pays a lump-sum tax $\tau_t$. Its budget constraint is

$$C_{it} + A_{i,t+1} = R^* A_{it} + W_{it} + T_t - \tau_t, \tag{30}$$

subject to

$$A_{i,t+1} \geq 0. \tag{31}$$

Cash on hand is therefore

$$M_{it} = R^* A_{it} + W_{it} + T_t - \tau_t. \tag{32}$$

Aggregate consumption is

$$C_t = \int_0^1 C_{it}\, di, \qquad c_t = \log C_t. \tag{33}$$

Aggregate output is determined by productivity and the aggregate consumption externality:

$$Y_t = Z_t C_t^{\omega}, \qquad \omega \geq 0. \tag{34}$$

Define $y_t = \log Y_t$. The production relation in logs is

$$y_t = z_t + \omega c_t. \tag{35}$$

Aggregate labor income equals output,

$$W_t = Y_t, \tag{36}$$

and individual labor income is

$$W_{it} = Y_t E_{it}. \tag{37}$$

Consequently, observed individual log labor income satisfies

$$w_{it} = y_t + e_{it}, \tag{38}$$

where $w_{it} = \log W_{it}$. When $\omega = 0$, aggregate output is determined entirely by productivity. When $\omega > 0$, higher household consumption raises output and labor income, which feeds back into household consumption.

## 4.2 Fiscal policy

Fix an output reference level $Y^{\text{ref}}$ and define

$$y^{\text{ref}} = \log Y^{\text{ref}}, \qquad \widetilde{y}_t = \log\left(\frac{Y_t}{Y^{\text{ref}}}\right) = y_t - y^{\text{ref}}. \tag{39}$$

Normalized aggregate transfers are

$$\widetilde{T}_t = \frac{T_t}{Y^{\text{ref}}}. \tag{40}$$

Transfers respond countercyclically to output and contain a persistent discretionary component:

$$\widetilde{T}_t = -\psi_y \widetilde{y}_t + \nu_t, \qquad \nu_t = \rho_\nu \nu_{t-1} + \varepsilon_t^\nu, \qquad \varepsilon_t^\nu \sim \mathcal{N}(0, \sigma_\nu^2). \tag{41}$$

Equivalently,

$$T_t = Y^{\text{ref}} \left[ -\psi_y (y_t - y^{\text{ref}}) + \nu_t \right]. \tag{42}$$

A high transfer may therefore reflect weak aggregate output or a positive discretionary fiscal state:

$$\widetilde{T}_t \uparrow \quad \Longrightarrow \quad y_t \downarrow \quad \text{or} \quad \nu_t \uparrow. \tag{43}$$

Government debt evolves according to

$$B_{t+1}^g = R^* B_t^g + T_t - \tau_t. \tag{44}$$

Define government debt relative to its reference level as

$$D_t = B_t^g - \bar{B}. \tag{45}$$

Taxes stabilize government debt according to

$$\tau_t = \bar{\tau} + \kappa D_t. \tag{46}$$

At the reference point, $\widetilde{y}_t = 0$, $\nu_t = 0$, and $B_t^g = \bar{B}$, so transfers are zero and

$$\bar{\tau} = (R^* - 1)\bar{B}. \tag{47}$$

Combining the government budget constraint with the fiscal rules gives

$$D_{t+1} = (R^* - \kappa) D_t + Y^{\text{ref}} \left[ -\psi_y (y_t - y^{\text{ref}}) + \nu_t \right]. \tag{48}$$

Because taxes are observed, households infer the current debt deviation exactly:

$$D_t = \frac{\tau_t - \bar{\tau}}{\kappa}. \tag{49}$$

Government debt is therefore an observed aggregate state, and not an additional hidden signal.

## 4.3 Information structure and timing

Households observe all variables entering their current budget constraints:

$$\mathcal{I}_{it} \supseteq \{A_{it}, W_{it}, T_t, \tau_t\}. \tag{50}$$

They do not directly observe aggregate output $y_t$, idiosyncratic efficiency $e_{it}$, or the discretionary fiscal state $\nu_t$. Aggregate productivity $z_t$ and its innovation $\mu_t$ are also unobserved. The two signals about hidden current conditions are

$$w_{it} = y_t + e_{it}, \tag{51}$$

$$\widetilde{T}_t = -\psi_y y_t + \psi_y y^{\text{ref}} + \nu_t. \tag{52}$$

Labor income confounds aggregate output with idiosyncratic efficiency. Transfers confound discretionary fiscal policy with the systematic countercyclical response to aggregate output. Taxes reveal $D_t$ exactly through (49).

The timing within period $t$ is as follows. Aggregate productivity and the fiscal innovation are realized. Given predetermined government debt and the cross-sectional distribution of household states, aggregate consumption, output, transfers, and labor income are determined jointly. Household $i$ observes $(W_{it}, T_t, \tau_t)$, updates its beliefs, and chooses consumption and next-period assets.

Absent an approximation, the aggregate state includes productivity, government debt, the fiscal state, and the cross-sectional distribution of household assets, efficiencies, and beliefs. Household beliefs affect saving, saving determines aggregate consumption, aggregate consumption affects output, and output changes the signals households use to form beliefs. The exact forecasting problem is therefore infinite dimensional.

## 4.4 Perceived law of motion and Bayesian updating

I approximate aggregate log output directly with the perceived law of motion

$$y_t = b_0 + b_y y_{t-1} + b_B D_t + b_\nu \nu_t + b_\mu \mu_t. \tag{53}$$

The productivity innovation enters the perceived law directly. The law in (53) is a restricted approximation to the simulated equilibrium, not an algebraic consequence of (34).

Because the current transfer and tax payment determine next-period debt exactly, $D_{t+1}$ is known at the end of period $t$. Under the perceived law, output evolves according to

$$y_{t+1} = b_0 + b_y y_t + b_B D_{t+1} + b_\nu \rho_\nu \nu_t + b_\mu \mu_{t+1} + b_\nu \varepsilon^\nu_{t+1}. \tag{54}$$

For filtering, it is convenient to collect the hidden states in

$$q_{it} = (y_t, e_{it}, \nu_t)'. \tag{55}$$

Define the centered idiosyncratic innovation

$$\varepsilon^e_{i,t+1} = \zeta_{i,t+1} - \mu_\zeta, \qquad \varepsilon^e_{i,t+1} \sim \mathcal{N}(0, \sigma^2_\zeta). \tag{56}$$

The perceived transition can be written as

$$q_{i,t+1} = d_q + A_q q_{it} + D_q D_{t+1} + G_q \boldsymbol{\varepsilon}_{i,t+1}, \tag{57}$$

where

$$d_q = \begin{pmatrix} b_0 \\ \mu_\zeta \\ 0 \end{pmatrix}, \qquad D_q = \begin{pmatrix} b_B \\ 0 \\ 0 \end{pmatrix}. \tag{58}$$

The transition matrix is given by

$$A_q = \begin{pmatrix} b_y & 0 & b_\nu \rho_\nu \\ 0 & \rho_e & 0 \\ 0 & 0 & \rho_\nu \end{pmatrix}, \tag{59}$$

and exogenous aggregate shocks as well as the individual-level shock enter through

$$\boldsymbol{\varepsilon}_{i,t+1} = \begin{pmatrix} \mu_{t+1} \\ \varepsilon^\nu_{t+1} \\ \varepsilon^e_{i,t+1} \end{pmatrix}, \qquad G_q = \begin{pmatrix} b_\mu & b_\nu & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix}. \tag{60}$$

The covariance matrix of the primitive innovations is

$$\Sigma_\varepsilon = \begin{pmatrix} \sigma^2_\mu & 0 & 0 \\ 0 & \sigma^2_\nu & 0 \\ 0 & 0 & \sigma^2_\zeta \end{pmatrix}, \qquad Q_q = G_q \Sigma_\varepsilon G_q'. \tag{61}$$

Define the observation vector as

$$s_{it} = (w_{it}, \widetilde{T}_t)'. \tag{62}$$

The two exact observation equations are

$$s_{it} = h + Hq_{it}, \qquad h = \begin{pmatrix} 0 \\ \psi_y y^{\text{ref}} \end{pmatrix}, \qquad H = \begin{pmatrix} 1 & 1 & 0 \\ -\psi_y & 0 & 1 \end{pmatrix}. \tag{63}$$

Let

$$m^q_{i,t|t-1} = \mathbb{E}_{it-1}[q_{it}] \tag{64}$$

denote household $i$'s prior mean and let $P_{t|t-1}$ denote the corresponding prior covariance matrix. Since $D_t$ is observed, the prediction step is

$$m^q_{i,t|t-1} = d_q + A_q m^q_{i,t-1|t-1} + D_q D_t, \tag{65}$$

$$P_{t|t-1} = A_q P_{t-1|t-1} A_q' + Q_q. \tag{66}$$

After observing $s_{it}$, the Kalman gain is

$$K_t = P_{t|t-1} H' \left( H P_{t|t-1} H' \right)^{-1}. \tag{67}$$

The posterior mean and covariance are

$$m^q_{i,t|t} = m^q_{i,t|t-1} + K_t \left( s_{it} - h - H m^q_{i,t|t-1} \right), \tag{68}$$

$$P_{t|t} = (I - K_t H) P_{t|t-1}. \tag{69}$$

The covariance matrices are common across households. For a given perceived law of motion, they converge to stationary matrices and do not enter the individual household state. The two exact observations for wage and transfer income leave only one independent posterior mean. I use

$$\widehat{y}_{i,t|t} = \mathbb{E}_{it}[y_t] \tag{70}$$

as the reduced belief state. The posterior means of individual log efficiency and the fiscal state are implied by the current signals:

$$\widehat{e}_{i,t|t} = w_{it} - \widehat{y}_{i,t|t}, \tag{71}$$

$$\widehat{\nu}_{i,t|t} = \widetilde{T}_t + \psi_y (\widehat{y}_{i,t|t} - y^{\text{ref}}). \tag{72}$$

One-period-ahead expectations satisfy

$$\mathbb{E}_{it}[\nu_{t+1}] = \rho_\nu \widehat{\nu}_{i,t|t}, \tag{73}$$

$$D_{t+1} = (R^* - \kappa) D_t + T_t, \tag{74}$$

$$\mathbb{E}_{it}[e_{i,t+1}] = \mu_\zeta + \rho_e \widehat{e}_{i,t|t}, \tag{75}$$

$$\mathbb{E}_{it}[y_{t+1}] = b_0 + b_y \widehat{y}_{i,t|t} + b_B D_{t+1} + b_\nu \rho_\nu \widehat{\nu}_{i,t|t}. \tag{76}$$

The deterministic transition for $(y_t, D_t, \nu_t)$ implied by the perceived law and fiscal rules has transition matrix

$$\mathcal{A} = \begin{pmatrix} b_y - b_B \psi_y Y^{\text{ref}} & b_B(R^* - \kappa) & b_B Y^{\text{ref}} + b_\nu \rho_\nu \\ -\psi_y Y^{\text{ref}} & R^* - \kappa & Y^{\text{ref}} \\ 0 & 0 & \rho_\nu \end{pmatrix}. \tag{77}$$

The converged perceived system must satisfy

$$\rho(\mathcal{A}) < 1, \tag{78}$$

where $\rho(\mathcal{A})$ denotes the spectral radius. This joint condition replaces a stability check based only on the partial debt coefficient $R^* - \kappa$.

## 4.5 Household problem and equilibrium

A convenient post-signal household state is

$$x_{it} = \left( A_{it}, W_{it}, T_t, \tau_t, \widehat{y}_{i,t|t} \right). \tag{79}$$

The remaining posterior means are recovered from current observations using (71) and (72). The household problem can be written recursively as

$$V(x_{it}) = \max_{A_{i,t+1} \geq 0} \left\{ u(C_{it}) + \beta \mathbb{E}_{it} \left[ V(x_{i,t+1}) \right] \right\}, \tag{80}$$

where current consumption is

$$C_{it} = R^* A_{it} + W_{it} + T_t - \tau_t - A_{i,t+1}. \tag{81}$$

Future household states are generated by the perceived output law, the fiscal rules, the idiosyncratic efficiency process, and the Kalman update.

For given productivity $Z_t$, fiscal state $\nu_t$, debt $D_t$, and the household distribution, aggregate consumption determines output through (34). Output in turn determines individual labor income and the systematic component of transfers. Current consumption, output, transfers, and posterior beliefs must therefore be determined jointly within the period. For a candidate value of $C_t$, implied output determines the labor-income and transfer signals, households update their beliefs and choose consumption, and the candidate must satisfy

$$C_t = \int_0^1 C\left(A_{it}, W_{it}(C_t), T_t(C_t), \tau_t, \widehat{y}_{i,t|t}(C_t)\right) di. \tag{82}$$

Once this fixed point is found, output, transfers, household choices, and next-period government debt are determined.

## 4.6 Solution method

The model is solved as a fixed point in the perceived output-law coefficients $(b_0, b_y, b_B, b_\nu, b_\mu)$. Converged coefficients are evaluated in terms of accuracy and compared to alternate signal extraction methods, to assess whether the results approximate a rational expectations equilibrium as intended.

First, I guess the coefficients in (53). Given these coefficients, I construct the perceived state-space system and solve for the stationary Kalman covariance matrices and gain. I then solve the household consumption-saving problem under the perceived aggregate law.

Next, I simulate aggregate productivity, fiscal innovations, idiosyncratic efficiency, government debt, and a unit mass, discretized distribution on a grid. In each period, I solve the within-period aggregate-consumption fixed point in (82), then update household assets, efficiencies, and posterior beliefs using the household policy functions and the Kalman recursion. This step is computationally intensive, ensuring markets clear in every period and that the signals observed by households are consistent with the aggregate state of the economy.

Using the simulated time series, I estimate

$$y_t = b_0 + b_y y_{t-1} + b_B D_t + b_\nu \nu_t + b_\mu \mu_t + u_t^y. \tag{83}$$

The estimated coefficients update the perceived law of motion. This outer loop is repeated until the perceived coefficients coincide with those generated by the simulated equilibrium. I verify joint fiscal-output stability using (78). Approximation accuracy is evaluated using

the fit of the aggregate output law, iterated forecasts, and household-level signal-extraction checks.

I next study how dispersed information changes the effects of fiscal transfers. I first describe the calibration and the behavior of household beliefs in the simulated equilibrium. I then compare the response to a one-standard-deviation discretionary fiscal innovation under full and dispersed information.

## 4.7 Calibration

The model is calibrated at a quarterly frequency. Table 4 reports the primitive parameters used for the quantitative results. Compared to the basic model from Section 3, the calibration now features persistent income shocks also at the individual level, with $\rho_e > 0$. Other than this, the aggregate productivity process, interest rate, discount factor and utility curvature remain unchanged.

**Table 4:** Calibration, fiscal-policy model

| Parameter | Value | Description | Source |
|---|---|---|---|
| *Households and idiosyncratic income* | | | |
| $\beta$ | 0.982 | Quarterly discount factor | McKay and Reis (2021) |
| $r^*$ | 0.0074 | Quarterly net interest rate | McKay and Reis (2021) |
| $\sigma$ | 1.5 | CRRA coefficient | Attanasio and Weber (1995) |
| $\rho_e$ | 0.863 | Idiosyncratic persistence | Guvenen (2009); Guarda (2026) |
| $\sigma_\zeta$ | 0.162 | Idiosyncratic innovation s.d. | Guvenen (2009); Guarda (2026) |
| *Aggregate process and demand amplification* | | | |
| $\rho_z$ | 0.95 | Aggregate persistence | Boppart et al. (2018) |
| $\sigma_\mu$ | 0.007 | Productivity innovation s.d. | Boppart et al. (2018) |
| $\omega$ | 0.30 | Consumption externality | Krueger et al. (2016) |
| *Fiscal policy* | | | |
| $\psi_y$ | 0.187 | Countercyclicality coefficient | Reicher (2011) |
| $\kappa$ | 0.05 | Tax response to government debt | Kindberg-Hanlon (2024) |
| $\bar{B}$ | 2.0 | Reference government debt | Normalization |
| $\rho_\nu$ | 0.90 | Fiscal persistence | McKay and Reis (2021) |
| $\sigma_\nu$ | 0.0036 | Fiscal innovation s.d. | McKay and Reis (2021); Leeper et al. (2010) |

The discount factor and quarterly net interest rate are set to $\beta = 0.982$ and $r^* = 0.0074$. Thus, $\beta(1 + r^*) < 1$ ensures that incomplete markets do not generate unbounded asset accumulation. The CRRA coefficient is $\sigma = 1.5$, and households cannot borrow.

The idiosyncratic-income process uses $\rho_e = 0.863$ and $\sigma_\zeta = 0.162$, following Guarda's (2026) quarterly mapping of the earnings process estimated by Guvenen (2009) to a simple AR(1) process. Aggregate productivity has persistence $\rho_z = 0.95$ and innovation standard deviation $\sigma_\mu = 0.007$. The demand-amplification coefficient is $\omega = 0.30$.

Fiscal policy has countercyclicality coefficient $\psi_y = 0.187$, following Reicher (2011). The discretionary fiscal state has persistence $\rho_\nu = 0.90$ and innovation standard deviation $\sigma_\nu = 0.0036$, set following McKay and Reis (2021), where the latter is obtained by scaling their parameter using the roughly 14% transfers-to-GDP ratio from Leeper et al. (2010). Taxes respond to debt with $\kappa = 0.05$, and reference debt is normalized to $\bar{B} = 2.0$. This is chosen such that, in the solved model it implies an annual debt-to-GDP ratio around 50%.

## 4.8 Aggregate approximation and household beliefs

Solving the model yields the perceived output law reported in Table 5. The aggregate approximation is very accurate, with $R^2 = 0.9999863$.

**Table 5:** Estimated output law of motion

| | $b_0$ | $b_y$ | $b_B$ | $b_\nu$ | $b_\mu$ | $R^2$ |
|---|---|---|---|---|---|---|
| Coefficient | $8.256 \times 10^{-6}$ | 0.961053 | $-4.59677 \times 10^{-4}$ | 0.00881127 | 1.11618 | 0.9999863 |

Notes: Converged perceived-law coefficients estimated by OLS on 1,499 quarters of the dispersed-information economy after a 300-quarter burn-in. Output is measured as log deviation from reference output. The slope coefficients multiply lagged output, beginning-of-period government debt minus reference debt, the discretionary fiscal state, and the productivity innovation, respectively. The household distribution is tracked on a grid. Reported $R^2$ measures in-sample one-step fit.

Figure 5 compares simulated output with the path implied by the converged perceived law. The two series are nearly indistinguishable. The low-dimensional law therefore captures the aggregate dynamics generated by the full distribution of household states and beliefs.

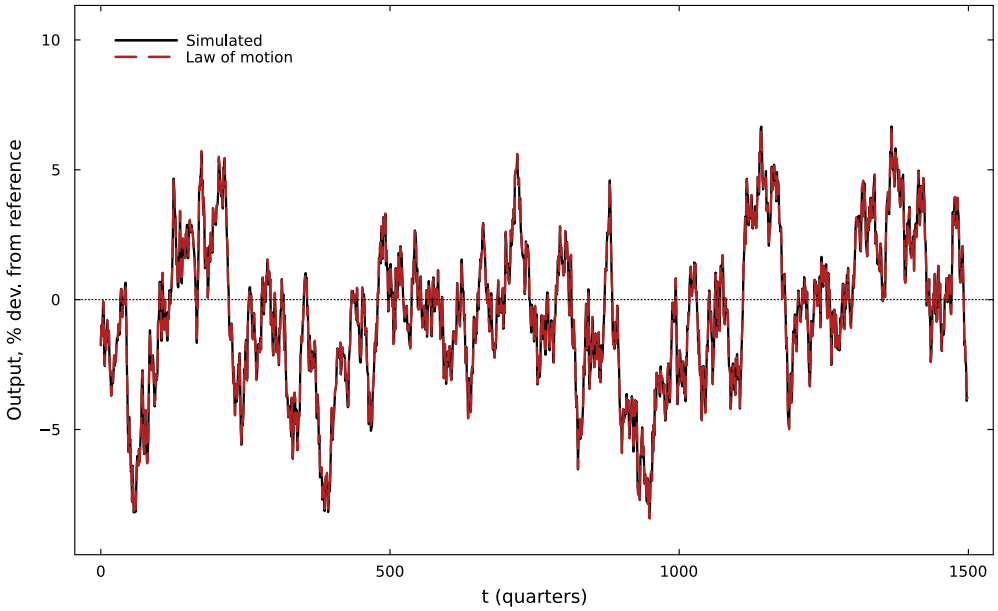



**Figure 5:** Simulated aggregate output and the perceived law of motion

Notes: Simulated output and the path generated by iterating the perceived law of motion forward from the initial simulated state. The iterated path uses its own lagged output and implied government debt, together with realized fiscal states and productivity innovations. Output is expressed as log percentage deviations from reference output. The figure covers 1,499 post-burn-in quarters.

This high aggregate fit does not imply that households know the current aggregate state. Households observe the signals generated by the economy, not realized aggregate output itself. Figure 6 compares true output with household output beliefs. Plotted is the cross-sectional average belief at each point in time, which tracks true output. Dispersed information leads to underreaction of beliefs to movements in aggregate output.

Additionally, individual posteriors remain dispersed because labor income combines aggregate output with idiosyncratic efficiency, while transfers combine the countercyclical policy response with the discretionary fiscal state. The shaded area in Figure 6 indicates two posterior standard deviations of an agent with the exact mean belief at any given point in time. Note that this individual posterior variance is always higher than the cross-sectional variance of posterior estimates $\text{Var}_i(\hat{y}_{it|t})$, see e.g. Lahiri and Sheng (2010).

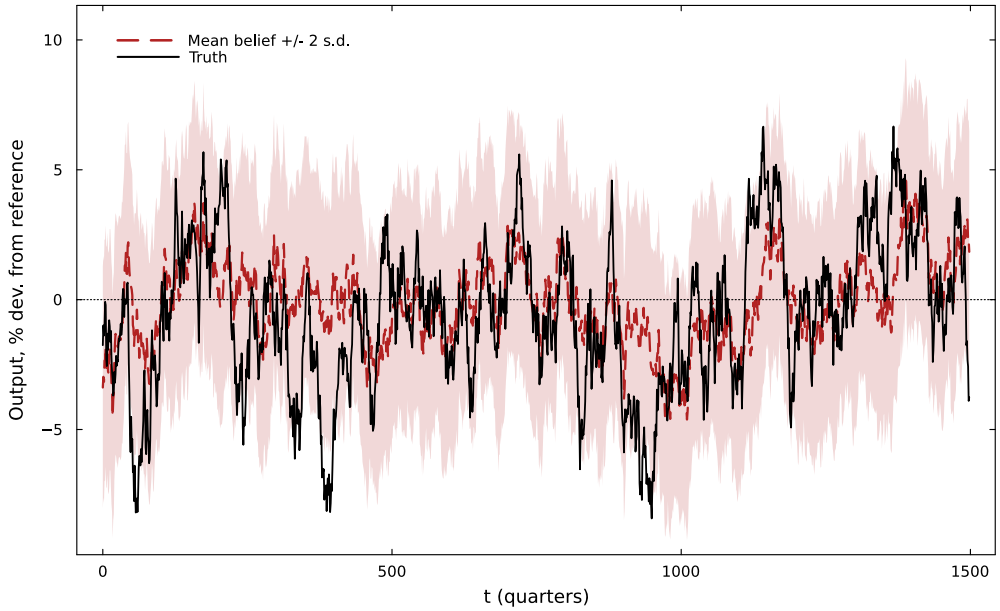



**Figure 6:** Aggregate output and household beliefs

Notes: Simulated aggregate output and the cross-sectional mean of households' posterior output beliefs over 1,499 post-burn-in quarters, in log percentage deviations from reference output. Shading extends two stationary posterior standard deviations around the mean belief. It represents the uncertainty of a household holding the mean belief.

### 4.8.1 Ex-post signal-extraction checks

The perceived law of motion approximates aggregate output extremely closely, but it remains possible that the Kalman filter imposes an overly restrictive mapping from household observations to output beliefs. I assess this possibility using ex-post machine-learning counterfactuals. These exercises hold the simulated equilibrium fixed and replace the model's filtering rule with alternative forecasting methods. They do not re-solve the household problem or recompute the equilibrium under the alternative beliefs. I consider a ridge regression and a $k$-nearest-neighbor estimator using twelve quarters of observations, as well as a gated recurrent unit that summarizes the history recursively.

Each method is trained to forecast current aggregate output $y_t$. The methods are trained on the equilibrium simulation and evaluated on 10 independent continuations of the solved economy under new shocks, each scored over 1,000 quarters for 25 households. The alternatives receive the same current observables as households in the model:

$$o_{it} = (w_{it}, \widetilde{T}_t, D_t)'. \tag{84}$$

Table 6 reports out-of-sample forecast performance. To compare with the implementation, the baseline is listed as storing the three posterior means associated with $(y_t, e_{it}, \nu_t)$. The final column compares rules household by household: for each evaluation household on each simulated path, I compute the root mean squared error of each rule over the scored quarters, and report the share of these household-path pairs in which the alternative's error exceeds that of the model belief.

**Table 6:** Ex-post recovery of aggregate output from household observations

| Belief rule | Stored states per household | $R^2$ | Larger error than model belief |
|---|---|---|---|
| Model baseline | 3 | 0.281 | N/A |
| GRU ($H = 16$) | 16 | 0.232 | 80% |
| Ridge ($L = 12$) | 33 | 0.237 | 80% |
| $k$NN ($L = 12, k = 160$) | 33 | 0.194 | 88% |

Notes: Rules estimate current aggregate output from households' wage, transfer, and tax-implied debt observations, holding the solved equilibrium fixed. Alternative rules are trained on the equilibrium simulation and evaluated on ten independent continuation paths, each with 25 households and 1,000 scored quarters after a 200-quarter warm-up. Reported $R^2$ averages one minus mean squared error divided by output variance across household–path pairs; the final column reports the share of these pairs with higher RMSE than the model belief. Stored states count the variables carried recursively by each household.

None of the alternative forecasting methods improves on the model belief. The baseline filter achieves an $R^2$ of 0.281, compared with 0.237 for Ridge, 0.232 for the GRU, and 0.194 for $k$NN. The alternatives also track output less accurately than the model belief for at least 80% of evaluated households.

This result is consistent with the near-exact fit of the perceived aggregate law. *If* the perceived law of motion were exact, the linear-Gaussian structure would make the Kalman posterior mean the minimum-mean-squared-error forecast conditional on household observations. The ex-post exercise shows that the small approximation error in the perceived law is not large enough to allow different signal extraction frameworks to confer better information.

These alternatives are also infeasible as equilibrium belief rules in the current solution method. Even the GRU, which requires the fewest additional state variables, carries a sixteen-dimensional recursive state. Under the discretization used to solve the household problem, incorporating this state would expand the computational burden by more than a factor of $10^8$. Appendix C provides the construction and details for the three counterfactual forecasting rules.

# 5 Quantitative results

Before turning to fiscal-policy responses, I compare the calibrated model with several moments not targeted in the calibration. Table 7 reports measures of household wealth, consumption responses, and beliefs about aggregate output.

**Table 7:** Untargeted model moments

| Moment | Full information | Dispersed information | Data |
|---|---|---|---|
| Standard deviation, GDP beliefs | 0 | 0.195 | 0.27 |
| GDP-belief/income-change slope | 0 | 0.374 | $0.123 - 0.443$ |
| Liquid wealth / annual income | 0.56 | 0.57 | 0.56 |
| Consumption growth persistence | 0.24 | 0.43 | 0.47 |
| Average quarterly cash MPC | 0.119 | 0.116 | 0.25 |

Notes: GDP beliefs are in log percentage points. The model moments concern beliefs about current output levels, while the survey moments concern assessments of past-quarter GDP growth. The income slope relates GDP beliefs to six-month changes in log household income, for households whose reported income changed by at most a factor of two. The table reports the empirical 95% confidence interval for this slope, with 0.283 being the point estimate. The survey SD may contain reporting variation. The MPC benchmark includes nondurables and services, excluding the durable expenditures included in Appendix A.1. Appendix B.8 details the construction of the survey and model belief moments.

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH waves 62 and 68, own calculations (belief moments); Kaplan and Violante (2022) (liquid wealth); U.S. Bureau of Economic Analysis (2026) (Consumption growth); Kueng (2018) (MPC). Model calculations by author.

The model generates liquid wealth close to the empirical benchmark, while its average cash MPC falls below the estimate from Kueng (2018). This is consistent with Kaplan and Violante (2022), who document that relatively low MPCs are a common feature of one-asset incomplete-markets models, which face a trade-off between generating large spending responses and matching realistic household wealth holdings. Overall, neither moment differs substantially between full and dispersed information. Persistence in consumption growth in the data is obtained from AR(1) persistence in annual growth in aggregate personal consumption expenditure (U.S. Bureau of Economic Analysis, 2026) between 1960 and 2019. This is compared with annualized persistence in aggregate consumption growth from the model, obtained by averaging over four quarters, from long-run simulations. The dispersed information model is substantially closer to the data, with slow-moving expectations increasing the persistence of consumption growth.

Turning to beliefs, dispersed information generates disagreement about aggregate conditions that is absent under full information. Since the BOP-HH elicits assessments of

past GDP growth rather than current output levels, I use these assessments as the closest available empirical counterpart to $\hat{y}_{it|t}$, the model's measure of beliefs about current output, and apply this interpretation to both belief moments. The model generates somewhat less disagreement than observed in the survey, although the latter may also reflect measurement and reporting variation. More directly related to the information mechanism, the model reproduces the positive association between household income changes and output beliefs observed in the data, which is absent under full information. The model slope lies within the empirical 95% confidence interval. Appendix E considers an extension with idiosyncratic noise in transfer receipts and tax payments, which increases disagreement.

Section 5.1 next evaluates the information channel more directly using the randomized fiscal-policy information experiment.

## 5.1 Validation against the fiscal-policy information experiment

I next map the BOP-HH expectations into the quantitative model. Wave 4 of the data is particularly useful, because it contains the information treatment described in section 2.2. First, all households in this wave are asked about GDP expectations going forward. The data can thus be used to observe how much households' expectations adjust following a large output decrease. Second, the information treatment can be used to directly measure my proposed information channel: households are informed about a fiscal expansion, and their expectations and spending responses can be compared to the quantitative model.

I set $Y^{\text{ref}}$ equal to Q1 2020 output and use a negative shock to aggregate productivity $z_t$ to reproduce the observed decline in German output between Q1 and Q2 2020, a contraction of roughly 9%. Figure 7 shows this decline, the subsequent realized output path, and the model's conditional output distribution following the announcement. The survey was conducted in April 2020. In the quarterly model, the realized Q2 contraction calibrates the economic environment at which households form their forecasts. Households under dispersed information continue to infer aggregate conditions from their usual observations of labor income, transfers, and taxes, whereas households under full information observe the current aggregate state.

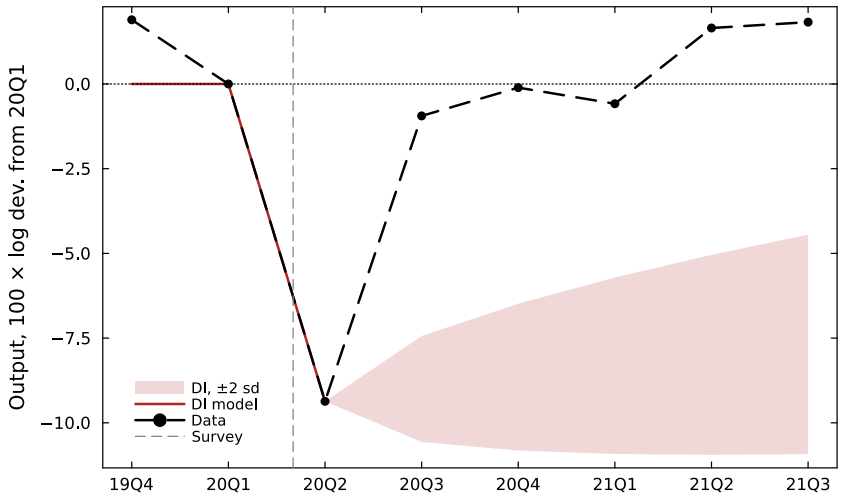



**Figure 7:** Output around the fiscal-policy information experiment

Notes: German real GDP and the dispersed-information model's conditional output distribution, relative to Q1 2020. The vertical line marks the April 2020 survey. Shading covers two conditional standard deviations on either side of the mean following the announcement.

First, consider the untreated households in the data. I map these into the dispersed information model as households that have observed their individual cash flows, but not aggregate conditions. Because their signals are noisy, households' expectations do not fully adjust. On average, the posterior estimate about current output will then sit above the realized aggregate $-9\%$ relative to the reference level. In the full information economy, households instead perfectly observe the productivity shock and resulting output movement. From these posterior estimates, forecasts about output going forward can then be computed. The questionnaire elicits expectations about GDP changes over the next twelve months. The model counterpart is expected average output over Q2 2020 through Q1 2021, expressed relative to Q1 2020 output. The resulting data and model results are displayed in Figure 8.

Whereas full information implies full adjustment, vastly overshooting the empirical belief response, the untreated dispersed-information forecast places average output over the four-quarter window approximately 1.9% below Q1 2020 output, close to the empirical GDP-growth forecast of $-1.86\%$.[4] Despite the large realized contraction, households' usual cash-flow observations only partially reveal the deterioration in aggregate conditions. Their forecasts therefore adjust much less than those of full-information households, who observe the current aggregate state and anticipate that the contraction will persist.

[4]This is the survey-weighted, covariate-adjusted placebo forecast, which is close to the mean across all untreated households of $-1.73\%$.

The model thus reproduces the relatively modest pessimism of untreated respondents following a large aggregate downturn.

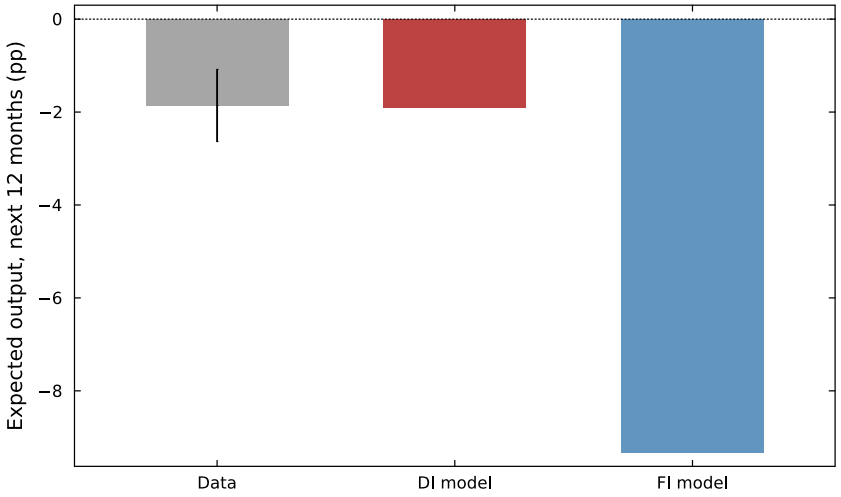



**Figure 8:** GDP expectations, untreated households

Notes: Data shows the covariate-adjusted placebo forecast from the survey-weighted regression in Table 3, averaged over the estimation sample's covariate distribution. The dispersed information (DI) model shows an average across households that have observed their current cash-flows. Full information (FI) expectations are uniform across households. Data measures expected GDP growth over twelve months. Model forecasts measure average output over Q2 2020–Q1 2021 relative to Q1 2020.

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Bundesbank Online Panel – Households (BOP-HH), April 2020, own calculations. Model calculations by author.

Next, I make use of the information treatment from the data. In the model, the treatment is given to a measure zero of households. It thus does not affect current aggregates. Treated households do however fully anticipate future general-equilibrium feedback the transfers will induce once they are paid out. Within each information structure, I compare households that retain their usual information set with households that additionally receive the fiscal announcement.

The treatment describes a EUR 750 billion federal fiscal package, including a EUR 600 billion support envelope for firms, of which EUR 400 billion was earmarked for guarantees (Deutsche Bundesbank, 2020). These figures refer to announced support capacity. I map the remaining EUR 150 billion to the model's cumulative household-transfer component over four quarters, from Q2 2020 through Q1 2021.[5] Using EUR 884 billion as the Q1 2020 reference value of quarterly output, the normalized announced amount is

[5]For comparison, tax and social-contribution relief and direct income support totalled EUR 126 billion in 2020 relative to 2019, mostly supporting households and small businesses (van Deuverden, 2022, p. 177). The model's EUR 150 billion transfer mapping extends through Q1 2021.

$$s = \mathbb{E}_t^G \left[ \sum_{j=0}^{3} \widetilde{T}_{t+j} \right] = 0.1696 \approx \frac{150}{884}. \tag{85}$$

Households have already observed the current transfer. The announcement commits the government to a discretionary fiscal plan over the following three quarters. Realized transfers continue to respond to future productivity through the transfer rule, so the announcement only fixes expected cumulative transfers, not realized ones. The announcement does not reveal the quarterly fiscal plan. Households thus infer how much of the announcement reflects previously unobserved current economic conditions and how much reflects planned discretionary fiscal interventions over the following three quarters.

The government is assumed to know the current economic state and its own fiscal plan, but not future productivity innovations. Consequently, the announcement contains no additional information about future productivity shocks. It provides one signal about two conceptually distinct objects: the current hidden state, including output, and the sequence of planned fiscal innovations. Under full information, it would instead exclusively inform households about planned fiscal innovations, with the current aggregate state already perfectly observed.

Households allocate the announcement surprise between these explanations according to their prior uncertainty. The inferred plan is front-loaded because an innovation in the first future quarter affects transfers in all three remaining quarters, whereas a later innovation affects fewer quarters. The announcement fixes expected cumulative transfers, but individual quarterly transfers and the realized cumulative total remain uncertain. Appendix D provides the exact signal-extraction problem and the numerical decomposition of the announcement surprise.

Learning about the current state is central for GDP expectations because a downward revision in current output persists throughout the four-quarter forecast window. Figure 9 compares the treatment effect from the data with the effect of the policy announcement in the dispersed information and full information model.

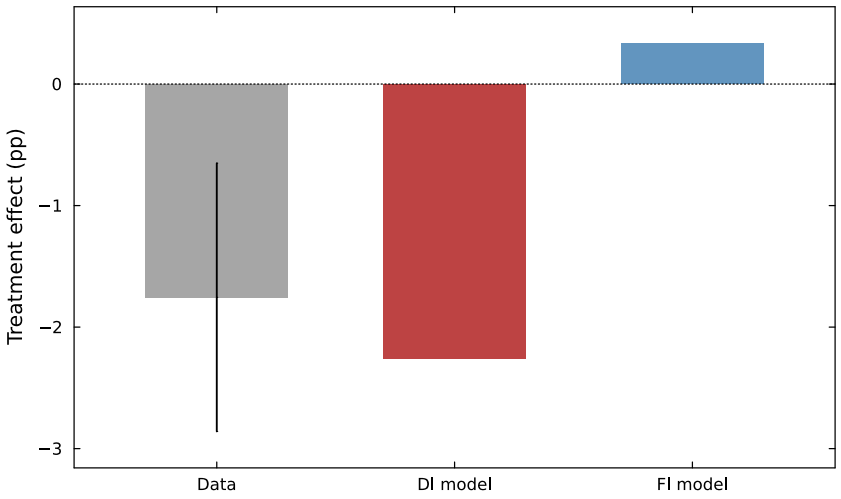



**Figure 9:** GDP expectations, treatment effect

Notes: The treatment provides information about Germany's EUR 750 billion fiscal package. The model maps EUR 150 billion to household transfers over four quarters. Plotted is the treated-minus-untreated difference in percentage points. The empirical estimate concerns treatment effects on twelve-month GDP-growth forecasts. Model effects concern expected average output over Q2 2020–Q1 2021 relative to Q1 2020.

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Bundesbank Online Panel – Households (BOP-HH), April 2020, own calculations. Model calculations by author.

The information treatment, or policy announcement, lowers expected output by approximately 2.3 percentage points in the model, compared with 1.76 percentage points in the data. Under full information, households already know the current state and interpret the announcement only as news about the fiscal plan. The resulting treatment effect is positive, at approximately 0.34 percentage points. In the model, matching the negative empirical response requires households to infer weaker current aggregate conditions from the announcement.

Household-income expectations provide a complementary check on how the announcement is mapped into expected resources. The survey elicits a probability distribution over changes in monthly net household income over the following twelve months, including after-tax labor income, pensions, and transfers. Panel A of Table 8 compares the treatment effect in the data and model. The empirical estimate is a positive but imprecise 2.21%, compared with 2.98% under dispersed information and 3.39% under full information. Both model predictions are consistent with this evidence, so the result does not distinguish between the information structures. In the dispersed-information model, higher expected

transfers more than offset lower expected labor income. Pessimism about aggregate conditions can therefore coexist with higher expected household income. Appendix D.6 reports the income decomposition and heterogeneity estimates.

**Table 8:** Income expectations and consumption revisions in the experiment and model

| | Data | Dispersed information | Full information |
|---|---|---|---|
| *Panel A: Household-income expectations* | | | |
| Expected net-income revision | 2.21 | 2.98 | 3.39 |
| | (2.73) | | |
| *Panel B: Consumption revisions* | | | |
| Average consumption revision | −2.54 | −0.31 | 1.43 |
| | (1.54) | | |
| Slope across income brackets | −1.83 | −0.53 | −0.40 |
| | (1.30) | | |
| Slope across prior categories | −2.42 | −0.60 | – |
| | (1.66) | | |

Notes: Entries are treated-minus-untreated revisions in expected household net income and consumption, in percent. Empirical consumption revisions are consumption-equivalent measures obtained from purchase intentions using the mapping in Appendix D.5. Model entries are average consumption revisions over four quarters. Slope rows report the change in the consumption revision, in percentage points, per one-category increase in household income or prior optimism about growth. Empirical standard errors are in parentheses.

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Bundesbank Online Panel – Households (BOP-HH), April 2020, own calculations. Expenditure inputs: EVS 2018, Destatis (2020). Model calculations by author.

To compare spending magnitudes, I translate the empirical purchase-probability responses into consumption-equivalent revisions, referred to below as consumption revisions. First, control-group purchase probabilities and baseline expenditure on cars and other durables convert the probability responses into changes in expected durable expenditure, holding expenditure conditional on purchase fixed. The categories are weighted by baseline net expenditure, using the German EVS 2018 expenditure data reported by Destatis (2020) and deducting resale proceeds for cars. Second, following the durable-stock mapping in Laibson et al. (2022, Appendix B), I assume that desired durable stocks move proportionally with consumption and use quarterly depreciation of 5% to translate durable expenditure into a consumption revision. Appendix D.5 gives the derivation and calibration. The raw purchase-probability estimates are reported in Appendix B.4.2.

Panel B of Table 8 compares these consumption revisions with the model. The empirical point estimate is −2.54%, while the dispersed-information model produces a smaller

decline of 0.31%. The full-information model instead predicts an increase of 1.43%. The approximate empirical 95% confidence interval includes the dispersed-information prediction and zero, but excludes the full-information prediction. The comparison therefore supports the negative response generated by dispersed information, although the empirical magnitude is imprecisely estimated.

Dispersed information also reproduces the negative income and prior-belief gradients: consumption revisions become more negative among households with higher incomes or more optimistic priors. Both empirical gradients are imprecisely estimated. The negative income gradient is present under both information structures and therefore does not by itself identify the information channel. By contrast, heterogeneity by prior beliefs is inherently linked to dispersed information.

I do not use the survey's savings-related outcomes as quantitative validation targets. The estimated treatment effect on the probability of building additional financial reserves is negative but statistically insignificant, whereas respondents in the following survey wave report lower probabilities of difficulty covering expenditure. Building reserves may be interpreted as longer-term accumulation, while the follow-up questions concern near-term liquidity and the ability to finance expenses from income or available funds. These outcomes therefore do not provide a clean counterpart to model saving. Appendix B.7 reports the estimates and question wording.

Taken together, the exercise evaluates the model against aggregate expectations, household-income expectations, and consumption revisions. The dispersed-information model approximately reproduces the level and negative treatment effect of GDP expectations, while both information structures yield household-income revisions consistent with the imprecise empirical estimate. For consumption, dispersed information reproduces the negative average response and the heterogeneity gradients, with a smaller decline than the empirical point estimate. The next subsection returns to the model's aggregate consumption response to a discretionary fiscal intervention.

## 5.2 Main results, fiscal policy

### 5.2.1 Aggregate consumption response

I next use the model to study a one-standard-deviation positive innovation to the discretionary fiscal state, $\varepsilon_t^{\nu} = \sigma_{\nu}$. Because $\nu_t$ is persistent, the innovation raises both current and expected future transfers. The shock is evaluated at the stationary distribution of both the full- and the dispersed-information economy.

Figure 10 compares the aggregate consumption responses directly. Under full information, the impact consumption response, normalized by the fiscal payment, is about 0.38. Under dispersed information, the corresponding response is approximately 0.08 and the consumption adjustment is substantially more gradual, as households learn about the discretionary component of transfers over time. As households increasingly attribute transfers to this component, the information channel weakens, allowing consumption to rise and generating the hump-shaped aggregate response. On balance, the fiscal payment is much less effective at raising near-term aggregate consumption when households must infer why it was paid.

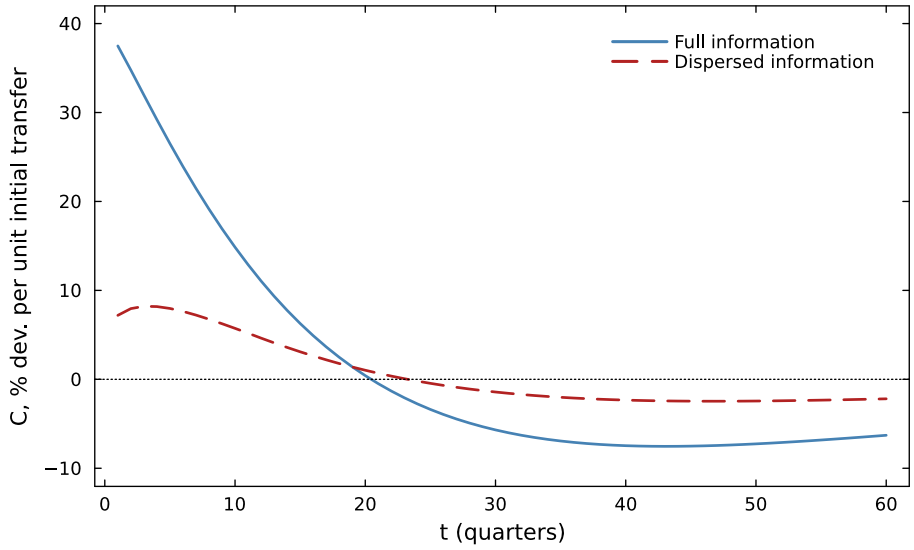



**Figure 10:** Aggregate consumption response under full and dispersed information

Notes: A one-standard-deviation discretionary fiscal innovation raises current and expected future transfers. Consumption responses are normalized by the initial transfer and multiplied by 100, so a value of 38 denotes 38 cents per dollar. Periods are quarters.

Note that, in this model, the aggregate consumption response follows from an aggregation over all micro responses. Empirical estimates of spending responses to payments can then serve as a benchmark for the response, allowing for a comparison between the model and empirical evidence. Appendix A.1 describes these studies in more detail.

Empirical estimates of household spending responses to cash receipts, such as Souleles (1999) and Kueng (2018), are generally large. For countercyclical payments, the empirical evidence is mixed. Orchard et al. (2026) find a negative quarterly MPC of $-0.07$ out of the 2001 rebate payments, although the estimate is imprecise. For the 2008 stimulus episodes, Orchard et al. (2025) find an MPC of 0.28, although the estimated response excluding cars is $-0.02$. For transfers during the COVID-19 pandemic, Parker et al. (2022) find an

unweighted average MPC of 0.16 across the three EIP rounds. The response is especially low in the third round of payments, with an MPC of 0.015. Goldfayn-Frank et al. (2022) find a similarly low MPC of 0.054 from payments in Germany during the same time period, although this is a monthly estimate.

The studies mentioned cover several (near) zero MPC estimates from countercyclical transfers. Compared with the 0.25 MPC (0.38 when including durables) estimate from Kueng (2018), these observations suggest a gap between the spending response to some pro- or acyclical payments and the much weaker response observed in countercyclical episodes. The full information model has consumption move 0.38 in response to a fiscal expansion, although this is not a pure MPC as it contains an (anticipated) policy component as well. The pure cash MPC in the model is about 0.12. Turning to the consumption responses to countercyclical payments, I consider a zero spending response as a benchmark for these low responses. In terms of explaining why a countercyclical payment may instead imply a (near) zero spending response, the dispersed information model closes 80% of the gap between the full information response and this benchmark, with the impact response of 0.08 much closer to the zero benchmark.

Appendix E allows for idiosyncratic noise in transfer receipts and tax payments. Although this reduces the informativeness of individual fiscal receipts, the gap between full and dispersed information remains quantitatively large. Appendix F shows how results change when households have additional information about output, expressed through an additional idiosyncratic signal. As the information channel follows entirely from inference about the underlying aggregate state, giving households additional information about output moves the initial consumption response to a fiscal expansion monotonically closer to its full-information equivalent.

### 5.2.2 Consumption responses across the household distribution

The experiment is a positive discretionary fiscal innovation, which raises transfers to all households. Under dispersed information, households observe the payment but cannot perfectly distinguish a discretionary increase from the policy's countercyclical response to weak aggregate output.

Figure 11 reports the impact consumption response by pre-shock cash-on-hand decile under full information. Responses are divided by the size of the current transfer and can be interpreted as impact consumption responses per unit of fiscal payment.

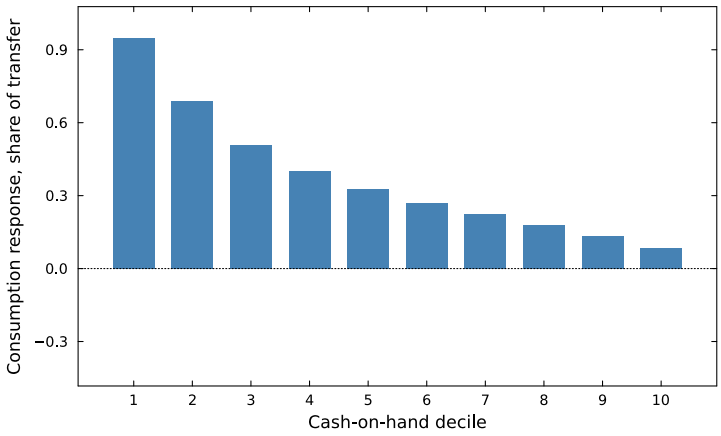



**Figure 11:** Impact consumption response under full information

Notes: Mean impact consumption responses per dollar transferred after a one-standard-deviation discretionary fiscal innovation, by pre-shock cash-on-hand decile (1 = lowest; 10 = highest). Under full information, households observe aggregate conditions and recognize the discretionary innovation.

Under full information, the impact response has the standard incomplete-markets shape. It is largest among households with low cash on hand and declines along the distribution. Part of the consumption change is driven by GE feedback, with the increase in aggregate consumption increasing wages. Moreover, households know that the payment reflects a persistent discretionary fiscal innovation and therefore anticipate additional future transfers, as well as the associated future general-equilibrium feedback. Anticipated future taxes are also part of this policy component, and decrease the response, but are outweighed by the aforementioned forces.

I decompose the response to the payment into two effects. First, a cash effect, with a transfer of size $T$ raising a household's current resources directly, increasing their consumption. In model notation, this is the consumption response to the transfer-induced increase in cash on hand. Second, the realized and anticipated effects of the policy, including future transfers, taxes, and changes in household income driven by general-equilibrium feedback. This second term follows from changed wages and a household's expectations.

Figure 12 reports the total consumption change under dispersed information. While responses are now generally lower across the distribution, the change is especially striking towards the top: households with substantial cash on hand actually lower their consumption upon this increase in resources.

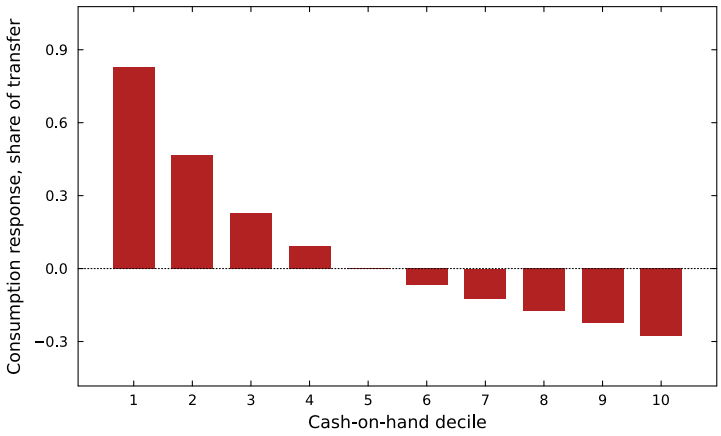
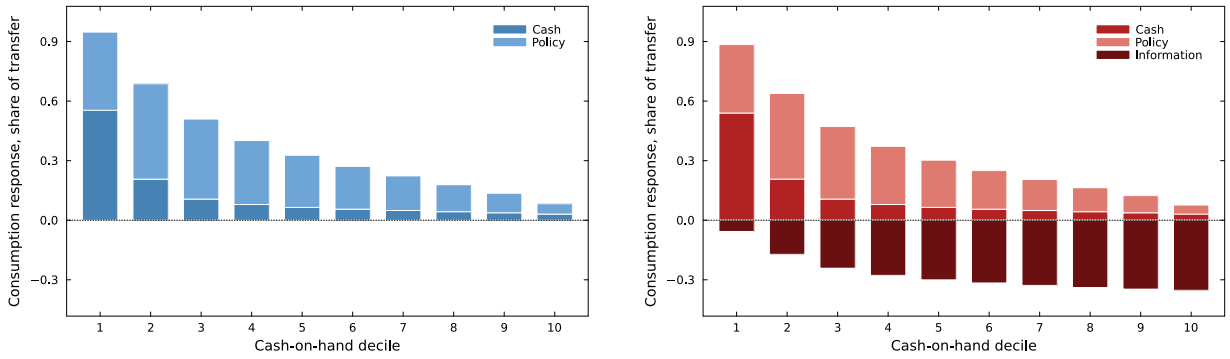



**Figure 12:** Impact consumption response under dispersed information

Notes: Mean impact consumption responses per dollar transferred after a one-standard-deviation discretionary fiscal innovation, by pre-shock cash-on-hand decile (1 = lowest; 10 = highest). Households observe the payment but cannot fully distinguish discretionary from countercyclical stimulus.

The cash and policy components remain positive under dispersed information. Additional resources raise consumption through the cash effect. Households also anticipate continued fiscal expansion, even though they cannot perfectly identify the discretionary component of transfers. Current and anticipated general-equilibrium feedback and expected future transfers outweigh anticipated future taxes, making the policy component positive. At the same time, the payment provides information about aggregate conditions: households partly attribute the transfer to the policy's countercyclical response to weak output. The resulting downward revision in expected output and household income reduces consumption through the information channel.

Figure 13 reports the resulting decomposition under both information structures, with components labelled Cash, Policy, and Information. Despite the two economies differing in the degree of risk households are exposed to, and thus in their wealth distributions, the direct cash effect and indirect policy effects are very close across the two information structures. The difference between them stems almost entirely from the information channel.




(a) Full information

(b) Dispersed information

**Figure 13:** Cash, policy, and information components of the impact consumption response

Notes: Impact responses per dollar transferred after a discretionary fiscal innovation, by pre-shock cash-on-hand decile. Cash captures additional current resources; Policy captures expected future transfers and taxes, as well as current and anticipated general-equilibrium effects. Information captures spending changes arising from what the payment reveals about current aggregate conditions.

Under full information, there is no additional inference from a transfer payment about aggregate conditions, so the cash and policy components account for the entire response. Under dispersed information, the information channel is negative throughout the distribution and becomes increasingly negative with cash on hand. At the top of the distribution, it more than offsets the positive cash and policy components, reversing the sign of the total response. The same channel also generates the hump-shaped aggregate response discussed above. As households increasingly attribute transfers to the discretionary component, the initial pessimism about aggregate conditions recedes, leading to increased consumption.

The increasing importance of the information channel across the distribution does not reflect larger downward revisions in output expectations among households with more cash on hand. Figure 14 compares average beliefs about current aggregate output with and without the fiscal innovation, by cash-on-hand decile. Households toward the top of the distribution are generally more optimistic about current aggregate output. This relationship is driven by wages: positive wage shocks raise current resources and, because wages are a signal of aggregate output, also imply more optimistic beliefs about aggregate conditions.

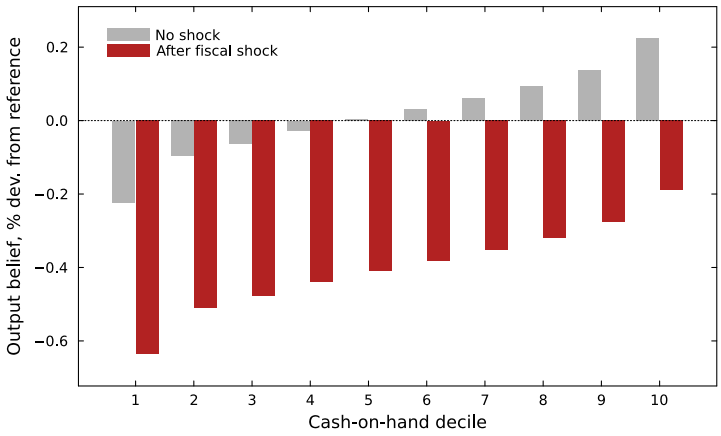



**Figure 14:** Beliefs about current aggregate output by cash-on-hand decile

Notes: Mean beliefs about current aggregate output with and without a discretionary fiscal innovation under dispersed information. Households are grouped by pre-shock cash-on-hand decile (1 = lowest; 10 = highest). Beliefs are expressed as percentage deviations from reference output.

Following the fiscal innovation, output beliefs fall by a similar amount across deciles. The stronger negative consumption response at the top of the distribution therefore follows from differences in spending responses to deteriorating expectations, rather than larger belief revisions. Households closer to the borrowing constraint are less responsive to the implied decrease in future income, while the additional current resources provided by the transfer have large effects on their consumption.

Taken together, the results show that the information channel of fiscal policy materially changes both the distributional and aggregate effects of transfers. The direct cash-flow and policy responses remain similar across the two structures. What changes is the interpretation of the policy. Because a transfer can signal weak aggregate conditions, the information channel reduces households' consumption, especially among high cash-on-hand households with substantial scope to adjust.

# 6 Extension: Targeted transfers

The results above suggest that targeting transfers toward households at the bottom of the distribution may increase the effectiveness of fiscal policy through both resources and information. Households with few resources respond to additional cash flows with larger consumption increases, while households with substantial cash on hand respond to the information channel with larger decreases. Targeting can thus direct resources toward

households with high spending responses while decreasing the impact of the information channel among households whose consumption is particularly sensitive to expectations.

I compare universal transfers with two settings in which payments are directed toward the bottom half of the contemporaneous income distribution. A simplified exercise retains the baseline household policies and perceived law of motion, while allowing output to adjust endogenously. The full general-equilibrium model additionally has households incorporate the targeted transfer rule into their decisions and expectations. This implies that households learn about the aggregate state not only from observed transfers, but also from whether they are targeted at all: households observe their own wage directly, and learn from their transfer eligibility whether their wage sits below or above the median. Because this introduces a non-Gaussian signal, the solution approach is extended to incorporate this.

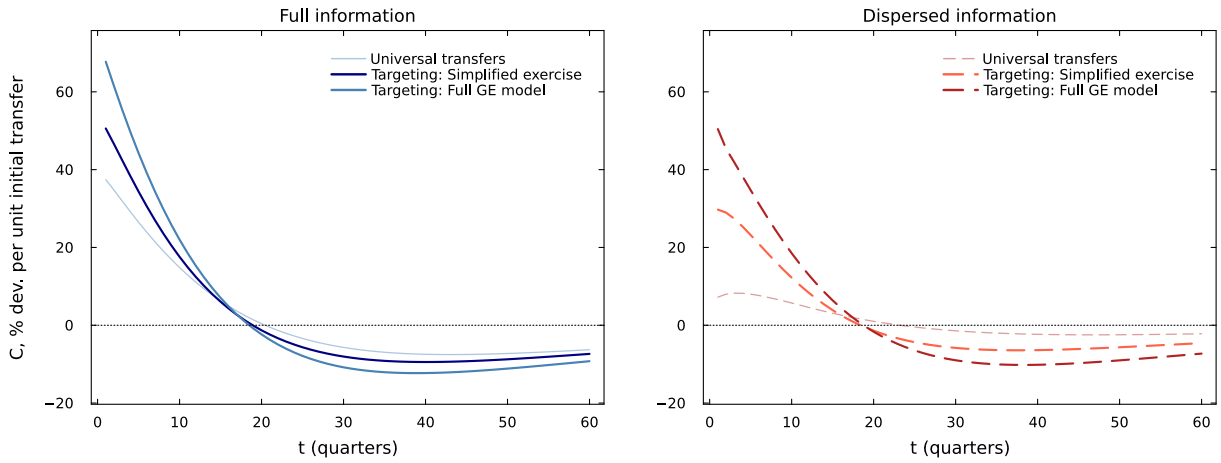



**Figure 15:** Aggregate consumption responses under universal and targeted transfers

Notes: Responses to a one-standard-deviation positive discretionary fiscal innovation under universal transfers and transfers targeted to the bottom half of the current labor-income distribution. The simplified targeting exercise retains baseline household policies and the perceived law of motion. The full targeted model re-solves both under quarterly reassessment of eligibility. Responses are normalized by aggregate transfers at impact and expressed in cents per dollar. Periods are quarters.

Figure 15 compares the aggregate response paths across the three settings. Targeting increases the initial consumption response under both information structures, with a larger gain under dispersed information. It also makes the response front-loaded rather than hump-shaped. Solving the full model raises the response further relative to the simplified exercise. Dispersed information continues to reduce the initial response, but the difference from full information is much less than under universal transfers.

I first examine the simplified exercise to explain why reallocating transfers is particularly effective under dispersed information. I then describe the full targeted model, the method

used to solve it, and examine the additional increase in consumption when households incorporate the targeted rule into their decisions.

## 6.1 Results: Simplified targeting exercise

I reallocate transfers toward the bottom half of the current income distribution. Since individual labor income satisfies $W_{it} = Y_t E_{it}$, households' income ranks coincide with their ranks in idiosyncratic efficiency. Let $\bar{e} = -\sigma_e^2/2$ denote the median of log efficiency. Eligibility and individual transfers are

$$d_{it} = \mathbf{1}\{e_{it} \leq \bar{e}\}, \tag{86}$$

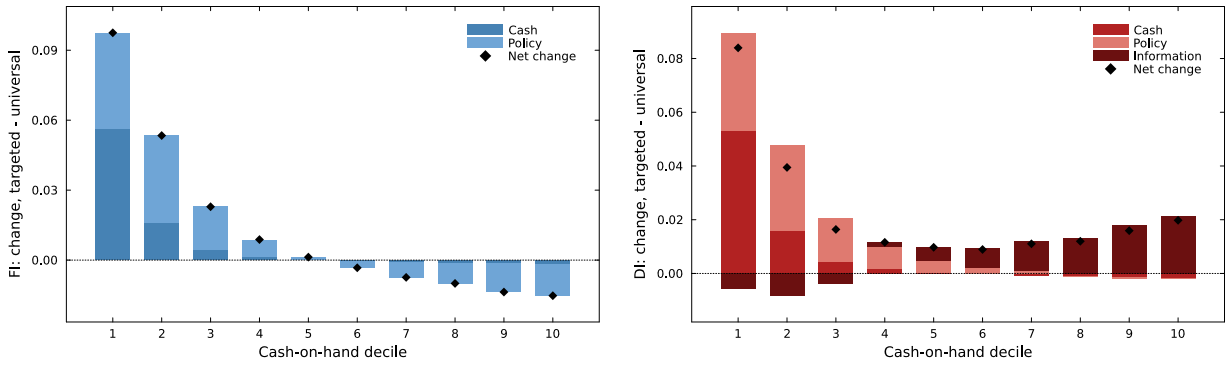
$$T_{it} = 2T_t d_{it}. \tag{87}$$

Half of the population receives twice the universal payment, while the remaining households receive no transfer. At any given aggregate state, total payments remain $T_t$. The aggregate fiscal rule, the discretionary fiscal innovation, and the tax rule are the same as in the universal-transfer economy.

The exercise retains the baseline consumption functions, perceived output law, and initial household distribution for each information structure. Output remains endogenous: changes in consumption feed back into output and individual labor income through the consumption externality. The exercise therefore includes realized general-equilibrium feedback, but does not re-solve household decisions or the perceived law of motion under a targeted rule.

Reallocation raises the impact consumption response from approximately 0.38 to 0.51 per dollar under full information, and from approximately 0.08 to 0.30 under dispersed information. Targeting thus produces a larger absolute gain under dispersed information, increasing the response by about 0.22 rather than 0.13.

Figure 16 decomposes these gains by pre-shock cash-on-hand decile. These bars report each decile's contribution to the change in the aggregate response, and thus do not measure a response per dollar received. Eligibility is based on current income. The horizontal axis groups households by cash on hand, which includes wealth. Recipients can therefore appear throughout the cash-on-hand distribution.




(a) Full information

(b) Dispersed information

**Figure 16:** Contributions to the change in the consumption response from reallocation

Notes: Differences between the simplified targeting exercise and universal transfers, decomposed into cash, policy, and information components. Bars report contributions by pre-shock cash-on-hand decile to the change in the aggregate consumption response per dollar of aggregate transfers.

Under full information, the gains are concentrated among households with little cash on hand. Reallocating resources toward these households increases spending because their consumption responds strongly to current resources. Contributions decline toward the top of the distribution and eventually become negative as households receive fewer transfers than in the universal regime.

Under dispersed information, the net change is positive throughout the cash-on-hand distribution. At the bottom, additional cash and policy effects raise consumption. Toward the top, the improvement instead comes mainly from the information channel: these households receive fewer transfers, but are also less affected by the information channel. The reduction in the information channel more than offsets the decrease in the cash and policy components for these households. This reduction also makes the aggregate response front-loaded. Targeting shifts payments toward households whose spending responds strongly to current resources and less strongly to expectations, while reducing the information channel among households most sensitive to it. The immediate spending response therefore dominates the later adjustment associated with learning.

Targeting therefore operates through two margins. It directs payments toward households whose spending responds strongly to resources, as in the full-information economy. In addition, it lessens the information channel among households whose consumption responds most strongly to deteriorating expectations. The latter margin accounts for the larger gain under dispersed information.

## 6.2 General equilibrium with targeted transfers

I next solve the model with the targeted rule in equations (86) and (87). Eligibility is reassessed every quarter, and households understand that their future payments depend on their future income ranks. Household consumption functions and the perceived aggregate law are solved jointly in general equilibrium under this rule.

Targeting changes the information available to households. Recipients observe the payment amount and can recover aggregate transfers as $T_t = T_{it}/2$. They also learn that their idiosyncratic efficiency lies below the eligibility cutoff. Nonrecipients do not observe the current aggregate payment, but learn that their efficiency lies above the cutoff.

Since households observe their own labor income, eligibility also contains information about aggregate output. Receiving a transfer implies $e_{it} \leq \bar{e}$, and therefore $y_t \geq w_{it} - \bar{e}$. Nonreceipt implies the opposite inequality. Let $\pi^G_{R,it}$ and $\pi^G_{N,it}$ denote the Gaussian distributions obtained after processing the continuous observations available to recipients and nonrecipients, respectively. Incorporating eligibility gives

$$\pi_{it}(dq) \propto \begin{cases} \mathbf{1}\{y_t \geq w_{it} - \bar{e}\}\, \pi^G_{R,it}(dq), & \text{if recipient,} \\ \mathbf{1}\{y_t < w_{it} - \bar{e}\}\, \pi^G_{N,it}(dq), & \text{if nonrecipient.} \end{cases} \tag{88}$$

Eligibility thus removes output values inconsistent with the household's observed income and transfer status. Conditional on the continuous observations, eligibility shifts output beliefs upward, while noneligibility shifts them downward. This information is distinct from the signal about aggregate conditions that the payment amount can convey.

Taxes continue to reveal current government debt. Thus, nonrecipients can recover the previous quarter's aggregate transfer once next-period taxes reveal the resulting debt. Targeting therefore changes both the distribution and timing of information, rather than permanently hiding fiscal policy from nonrecipients.

The eligibility signal requires an extension of the baseline filtering method. Conditional on the perceived law of motion, continuous observations are processed through a Gaussian update. Eligibility then truncates the resulting distribution according to (88). The moments of this truncated distribution are available analytically. I approximate the posterior by a Gaussian distribution with the same mean and covariance, using assumed density filtering following Minka (2001). Unlike in the baseline model, posterior covariance matrices $P_{it|t}$ now differ across households and time, introducing an additional state variable. Intuitively, this arises because the information content of the eligibility signal depends on a household's wage: a low-wage household that believes its wage is far below the median

already expects to be eligible and learns little from it. On the other hand, a household that is uncertain whether its wage lies above or below the median learns more from observing the eligibility status. The observation rules out a large range of possible aggregate output values and therefore reduces its posterior uncertainty.

The remaining solution procedure follows the baseline approximate-aggregation approach. For a candidate perceived output law, I solve household decisions using the extended filter, simulate the economy while imposing the within-period equilibrium condition, and update the output-law coefficients. Appendix G provides the filtering equations and evaluates the additional approximation. In these checks, the root mean squared error in output beliefs is 4.4% of households' posterior standard deviation, and the corresponding error in next-quarter eligibility probabilities is 0.09 percentage points. These checks indicate that the additional filtering approximation introduces small errors in household beliefs and predicted eligibility.

## 6.3 Results: Full targeted transfer model

The full targeted model preserves the main result of the simplified exercise: targeting raises the impact consumption response under both information structures, with a larger gain under dispersed information. Table 9 reports the impact responses underlying Figure 15. Under full information, the response rises from approximately 0.38 under universal transfers to 0.68 under the targeted rule. Under dispersed information, it rises from approximately 0.08 to 0.52. Targeting therefore roughly halves the absolute gap between the two information structures. Expressed in relative terms, the effect is even larger. Whereas the full information impact response is about five times as big as the dispersed information one in the universal regime, it is only about 30% larger in the full targeting model.

**Table 9:** Impact consumption responses under universal and targeted transfers

| Information structure | Universal | Simplified exercise | Full GE model |
|---|---|---|---|
| Full information | 0.38 | 0.51 | 0.68 |
| Dispersed information | 0.08 | 0.30 | 0.52 |

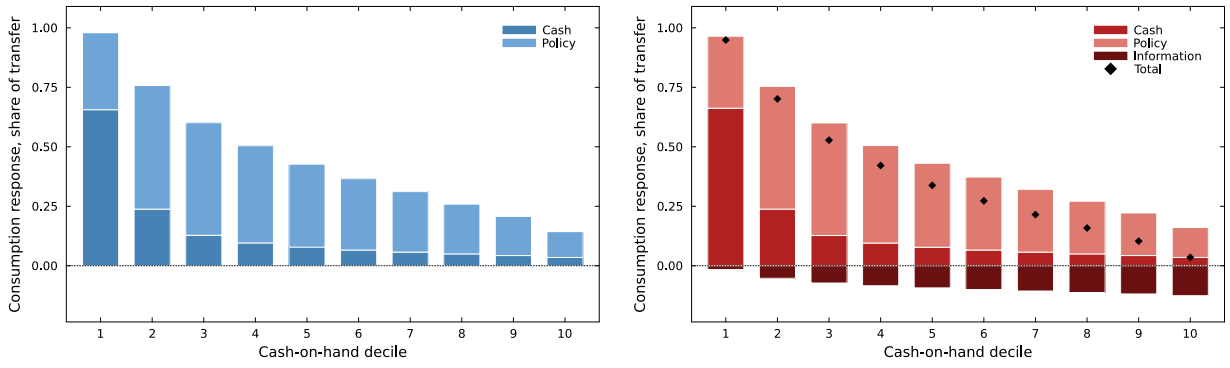
Notes: Approximate aggregate impact consumption responses per dollar of aggregate transfers. The simplified exercise retains baseline household policies and the perceived law of motion. The full model re-solves household decisions and aggregate dynamics under quarterly reassessment of eligibility.

Much of the additional increase relative to the simplified exercise reflects the state contingency of future transfers. With eligibility reassessed every quarter, a fiscal expansion

provides support not only to households with low income today, but also to households whose income falls below the cutoff while the expansion persists. Households anticipate receiving payments in low-income states, when marginal utility is high. Relative to payments of the same expected value that do not depend on future income realizations, this support reduces expected future marginal utility and precautionary saving, raising consumption today. The effect also applies to households that are not currently eligible.

To quantify this channel, I replace reassessed eligibility with a schedule of expected payments fixed at impact. Each household receives its expected future transfers conditional on its income at impact. The schedule matches expected payments when it is constructed, but removes their dependence on subsequent household income shocks. Under full information, this counterfactual yields an impact consumption response of approximately 0.51 per dollar, compared with 0.68 under quarterly reassessment. The state contingency of future payments therefore accounts for essentially the entire additional gain over the simplified exercise. For households, state contingency implies additional insurance against negative income shocks during a fiscal expansion.

This insurance effect is also the largest source of the additional increase under dispersed information. Anticipated general-equilibrium feedback plays a more substantial role here, however. Targeting changes the output response more strongly than under full information, and households incorporate the larger response into their expectations about future labor income. This adjustment accounts for more than 10% of the increase in the impact consumption response relative to the simplified exercise.




(a) Full information

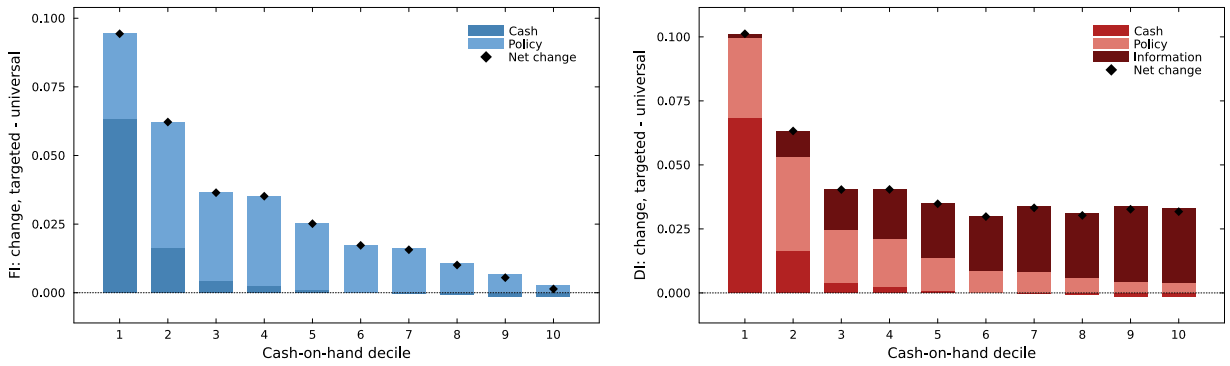
(b) Dispersed information

**Figure 17:** Impact consumption responses among recipients in the targeted model

Notes: Average impact consumption responses per dollar received among recipients in each pre-shock cash-on-hand decile, decomposed into cash, policy, and information components. Eligibility covers the bottom half of the current labor-income distribution and is reassessed quarterly.

Figure 17 reports the impact response per dollar received among recipients in each cash-on-hand decile. Cash and policy effects remain positive under both information structures. Under dispersed information, the information component continues to reduce spending, particularly among households with substantial cash on hand. Targeting therefore does not eliminate the information channel, but alleviates its effects on aggregate consumption and output.

Lastly, Figure 18 reports decile contributions to the change relative to universal transfers, including recipients and nonrecipients. Targeting increases consumption contributions in every cash-on-hand decile under both information structures. Under full information, the largest gains occur at the bottom. Under dispersed information, the information component also makes a substantial positive contribution toward the top. The mechanism identified in the simplified exercise therefore survives when households understand the targeted rule and adjust their decisions accordingly.




(a) Full information

(b) Dispersed information

**Figure 18:** Contributions to the change in the impact consumption response under the targeted rule

Notes: Differences between the full targeted and universal-transfer models. Bars report contributions by pre-shock cash-on-hand decile to the change in the aggregate consumption response per dollar of aggregate transfers. Contributions include recipients and nonrecipients.

The targeted model thus speaks to the distinction between resources and information. Targeting directs resources toward households with strong spending responses to cash flows and reduces the effects of the information channel among households whose spending is most sensitive to expectations. Quarterly reassessment additionally provides support against future low-income realizations. While this insurance raises consumption responses under both information structures, the larger gain from targeting under dispersed information remains.

# 7 Conclusion

Countercyclical transfers affect household spending through both resources and information. When households infer aggregate conditions from their own cash flows, receiving a transfer can signal that aggregate conditions are weak. This paper shows that this (dispersed) information channel can substantially reduce the consumption response to fiscal stimulus. Its importance depends on households' financial resources: less constrained households respond more strongly to deteriorating expectations and can lower their consumption even as transfers raise their current resources.

Empirical evidence supports this mechanism. A large literature documents that households extrapolate from their own economic circumstances when forming expectations about aggregate conditions. This paper contributes to that literature and links it to evidence on how households react to information about fiscal policy. In a randomized information experiment, information about a countercyclical fiscal package lowers expected GDP and durable spending intentions. Expectations fall broadly across income groups, while the decline in spending intentions is concentrated among high-income households. These findings support the interaction between information and financial resources central to the model.

In a basic consumption–savings model, inference from cash flows generates hump-shaped aggregate consumption responses to aggregate shocks, while responses to idiosyncratic shocks remain front-loaded. MPCs depend on the information carried by shocks, and consumption responses to transitory shocks can be larger than pure MPCs that hold beliefs fixed. To study this mechanism in a heterogeneous-agent economy with endogenous aggregate output, I develop a global solution method combining Bayesian filtering with approximate aggregation.

The quantitative general-equilibrium model demonstrates the importance of the information channel for fiscal policy. Mapping the information experiment into the model produces a decline in GDP expectations of similar magnitude to that observed in the data and reproduces the direction and heterogeneity of spending responses. In response to a discretionary transfer innovation, the initial aggregate consumption response falls from about 38 cents per dollar under full information to about 8 cents under dispersed information. The information channel accounts for most of this difference and becomes increasingly important toward the top of the cash-on-hand distribution. Households with substantial cash on hand actually lower their consumption upon receiving a transfer, as information outweighs the positive cash and anticipated policy effects. This heterogeneity reflects stronger spending responses to deteriorating expectations among less constrained

households, consistent with the experimental evidence. The results also help account for suggestive evidence that large countercyclical payment programs induce smaller consumption responses than similarly sized procyclical or acyclical payments.

Lastly, I find that targeting transfers toward low-income households becomes much more effective under dispersed information. While targeting already increases the consumption response under full information, the information channel amplifies this gain. Targeting directs resources toward households whose consumption responds strongly to current cash flows and less strongly to the information conveyed by transfers. The effectiveness of fiscal transfers thus depends on both the resources they provide and the aggregate conditions households infer from receiving them.

# References


Adam, K., & Marcet, A. (2011). Internal rationality, imperfect market knowledge and asset prices. *Journal of Economic Theory*, *146*(3), 1224–1252. https://doi.org/10.1016/j.jet.2010.11.003

Adam, K., Marcet, A., & Beutel, J. (2017). Stock price booms and expected capital gains. *American Economic Review*, *107*(8), 2352–2408. https://doi.org/10.1257/aer.20140205

Adam, K., Marcet, A., & Nicolini, J. P. (2016). Stock market volatility and learning. *The Journal of Finance*, *71*(1), 33–82. Retrieved June 10, 2026, from http://www.jstor.org/stable/43869095

Adams, J. J., & Rojas, E. (2024). Household Consumption and Dispersed Information. *Journal of Monetary Economics*, *147*, 103592. https://doi.org/10.1016/j.jmoneco.2024.103592

Agarwal, S., & Qian, W. (2014). Consumption and debt response to unanticipated income shocks: Evidence from a natural experiment in singapore. *American Economic Review*, *104*(12), 4205–30. https://doi.org/10.1257/aer.104.12.4205

Andre, P., Pizzinelli, C., Roth, C., & Wohlfart, J. (2022). Subjective models of the macroeconomy: Evidence from experts and representative samples. *The Review of Economic Studies*, *89*(6), 2958–2991. https://ideas.repec.org/a/oup/restud/v89y2022i6p2958-2991..html

Angeletos, G.-M., Huo, Z., & Sastry, K. A. (2021). Imperfect macroeconomic expectations: Evidence and theory. *NBER Macroeconomics Annual*, *35*(1), 1–86. https://doi.org/10.1086/712313

Angeletos, G.-M., & La'O, J. (2020). Optimal Monetary Policy with Informational Frictions. *Journal of Political Economy*, *128*(3), 1027–1064. https://doi.org/10.1086/704758

Attanasio, O. P., & Weber, G. (1995). Is consumption growth consistent with intertemporal optimization? evidence from the consumer expenditure survey. *Journal of Political Economy*, *103*(6), 1121–1157. Retrieved August 29, 2026, from http://www.jstor.org/stable/2138706

Auclert, A., Monnery, H., Rognlie, M., & Straub, L. (2026, July). *Spend What You (L)earn* [Presentation slides, NBER Summer Institute, Monetary Economics]. https://conference.nber.org/conf_papers/f246767/f246767.slides.pdf

Auclert, A., Rognlie, M., & Straub, L. (2020). *Micro jumps, macro humps: Monetary policy and business cycles in an estimated hank model* (NBER Working Paper No. 26647) (R&R, American Economic Review). National Bureau of Economic Research. https://doi.org/10.3386/w26647

Bachmann, R., Bayer, C., & Kornejew, M. (2022). Kinderbonuskonsum. *Perspektiven der Wirtschaftspolitik*, *23*(4), 281–298. https://doi.org/10.1515/pwp-2022-0013

Bai, Y., Ríos-Rull, J.-V., & Storesletten, K. (2026). Demand shocks as technology shocks. *The Review of Economic Studies*, *93*(2), 798–832. https://doi.org/10.1093/restud/rdaf045

Bayer, C., Born, B., Luetticke, R., & Müller, G. J. (2023). The coronavirus stimulus package: How large is the transfer multiplier. *The Economic Journal*, *133*(652), 1318–1347. https://ideas.repec.org/a/oup/econjl/v133y2023i652p1318-1347..html

Boppart, T., Krusell, P., & Mitman, K. (2018). Exploiting MIT shocks in heterogeneous-agent economies: The impulse response as a numerical derivative. *Journal of Economic Dynamics and Control*, *89*, 68–92. https://doi.org/10.1016/j.jedc.2018.01.002

Boppart, T., Krusell, P., & Olsson, J. (2024, September). Who should work how much? https://doi.org/10.3386/w32977

Bordalo, P., Gennaioli, N., & Shleifer, A. (2018). Diagnostic expectations and credit cycles. *Journal of Finance*, *73*(1), 199–227. https://doi.org/10.1111/jofi.12586

Broer, T., Kohlhas, A., Mitman, K., & Schlafmann, K. (2026). Expectation and Wealth Heterogeneity in the Macroeconomy. *Journal of Political Economy*.

Caldwell, S., Nelson, S., & Waldinger, D. (2023). Tax refund uncertainty: Evidence and welfare implications. *American Economic Journal: Applied Economics*, *15*(2), 352–76. https://doi.org/10.1257/app.20210383

Carroll, C. D. (2003). Macroeconomic Expectations of Households and Professional Forecasters. *The Quarterly Journal of Economics*, *118*(1), 269–298. https://doi.org/10.1162/00335530360535207

Carroll, C. D., Crawley, E., Slacalek, J., Tokuoka, K., & White, M. N. (2020). Sticky expectations and consumption dynamics. *American Economic Journal: Macroeconomics*, *12*(3), 40–76. https://doi.org/10.1257/mac.20180286

Cavallo, A., Cruces, G., & Perez-Truglia, R. (2017). Inflation Expectations, Learning, and Supermarket Prices: Evidence from Survey Experiments. *American Economic Journal: Macroeconomics*, *9*(3), 1–35. https://doi.org/10.1257/mac.20150147

Coibion, O., Georgarakos, D., Gorodnichenko, Y., & van Rooij, M. (2023). How does consumption respond to news about inflation? field evidence from a randomized control trial. *American Economic Journal: Macroeconomics*, *15*(3), 109–152. https://doi.org/10.1257/mac.20200445

Coibion, O., Gorodnichenko, Y., & Weber, M. (2022). Does policy communication during COVID work? *International Journal of Central Banking*, *18*(1), 3–39.

D'Acunto, F., Hoang, D., & Weber, M. (2022). Managing households' expectations with unconventional policies. *The Review of Financial Studies*, *35*(4), 1597–1642. https://doi.org/10.1093/rfs/hhab083

D'Acunto, F., Malmendier, U., Ospina, J., & Weber, M. (2021). Exposure to Grocery Prices and Inflation Expectations. *Journal of Political Economy*, *129*(5), 1615–1639. https://doi.org/10.1086/713192

Deutsche Bundesbank. (2020, June 23). *Questionnaire for the survey on consumer expectations (bop-hh), wave 4 – april 2020*. Retrieved September 20, 2026, from https://www.bundesbank.de/en/bundesbank/research/survey-on-consumer-expectations-bop-hh/questionnaires-850746

Deutsche Bundesbank. (2025). Bundesbank online panel – households (bop-hh) [Scientific Use File (SUF), version 2025Q4]. https://doi.org/10.12757/bbk.bophh2025q4.01

Evans, G. W., & Honkapohja, S. (2001). *Learning and expectations in macroeconomics*. Princeton University Press. Retrieved June 10, 2026, from http://www.jstor.org/stable/j.ctt7s6t9

Fagereng, A., Holm, M. B., & Natvik, G. J. (2021). Mpc heterogeneity and household balance sheets. *American Economic Journal: Macroeconomics*, *13*(4), 1–54. https://doi.org/10.1257/mac.20190211

Fève, P., & Pietrunti, M. (2016). Noisy fiscal policy. *European Economic Review*, *85*, 144–164. https://doi.org/10.1016/j.euroecorev.2016.02.013

Gallegos, J.-E., García-Miralles, E., Kataryniuk, I., & Párraga Rodríguez, S. (2025). *Fiscal announcements and households' beliefs: Evidence from the euro area* (Working Paper Series No. 3139). European Central Bank. https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp3139~dc84785340.en.pdf

Georgarakos, D., & Kenny, G. (2022). Household spending and fiscal support during the covid-19 pandemic: Insights from a new consumer survey. *Journal of Monetary Economics*, *129*(S), S1–S14. https://doi.org/10.1016/j.jmoneco.2022.02.007

Goldfayn-Frank, O., Lewis, V., & Wehrhöfer, N. (2022). *Spending effects of child-related fiscal transfers* (Discussion Papers No. 26/2022). Deutsche Bundesbank. https://ideas.repec.org/p/zbw/bubdps/262022.html

Gross, T., Notowidigdo, M. J., & Wang, J. (2020). The marginal propensity to consume over the business cycle. *American Economic Journal: Macroeconomics*, *12*(2), 351–84. https://doi.org/10.1257/mac.20160287

Guarda, S. (2026). Narrow and Short Beliefs in Macroeconomics with Heterogeneous Agents. *Working Paper*.

Guo, J., & Yin, P. (2026). *Signaling effects of government spending: The financing schemes matter* [Working paper]. https://ssrn.com/abstract=6432318

Guvenen, F. (2009). An empirical investigation of labor income processes. *Review of Economic Dynamics*, *12*(1), 58–79. https://doi.org/10.1016/j.red.2008.06.004

Han, Z. (2021). Low-frequency fiscal uncertainty. *Journal of Monetary Economics*, *117*, 639–657. https://doi.org/10.1016/j.jmoneco.2020.03.017

Hellwig, C., & Venkateswaran, V. (2011, September). *Hayek vs. Keynes: Dispersed information and market prices in a price-setting model* [Working Paper]. https://www.aeaweb.org/conference/2012/retrieve.php?pdfid=370

Hellwig, C., & Venkateswaran, V. (2025). Dispersed information, nominal rigidities and monetary business cycles: A hayekian perspective. *Journal of Monetary Economics*, *155*(S), Article 103843. https://doi.org/10.1016/j.jmoneco.2025.103843

Huo, Z., & Takayama, N. (2025). Rational expectations models with higher-order beliefs. *Review of Economic Studies*, *92*(5), 3138–3173. https://doi.org/10.1093/restud/rdae096

Kaplan, G., & Violante, G. L. (2022, May). The Marginal Propensity to Consume in Heterogeneous Agent Models. https://doi.org/10.3386/w30013

Kindberg-Hanlon, G. (2024). Transfers, Excess Savings, and Large Fiscal Multipliers. *IMF Working Papers*, *2024*(208), 1. https://doi.org/10.5089/9798400289354.001

Kohlhas, A. N. (2022). Learning by Sharing: Monetary Policy and Common Knowledge. *American Economic Journal: Macroeconomics*, *14*(3), 324–364. https://doi.org/10.1257/mac.20190311

Kohlhas, A. N., & Walther, A. (2021). Asymmetric Attention. *American Economic Review*, *111*(9), 2879–2925. https://doi.org/10.1257/aer.20191432

Krueger, D., Mitman, K., & Perri, F. (2016). Macroeconomics and household heterogeneity. In J. B. Taylor & H. Uhlig (Eds.), *Handbook of macroeconomics* (1st ed., pp. 843–921, Vol. 2). Elsevier. https://doi.org/10.1016/bs.hesmac.2016.04.003

Krusell, P., & Smith, A. A., Jr. (1998). Income and wealth heterogeneity in the macroeconomy. *Journal of Political Economy*, *106*(5), 867–896. https://doi.org/10.1086/250034

Kuchler, T., & Zafar, B. (2019). Personal Experiences and Expectations about Aggregate Outcomes. *The Journal of Finance*, *74*(5), 2491–2542. https://doi.org/10.1111/jofi.12819

Kueng, L. (2018). Excess sensitivity of high-income consumers. *The Quarterly Journal of Economics*, *133*(4), 1693–1751. https://doi.org/10.1093/qje/qjy014

Kurz, M., Piccillo, G., & Wu, H. (2013). Modeling diverse expectations in an aggregated new keynesian model. *Journal of Economic Dynamics and Control*, *37*(8), 1403–1433. https://doi.org/10.1016/j.jedc.2013.01.016

Lahiri, K., & Sheng, X. (2010). Measuring forecast uncertainty by disagreement: The missing link. *Journal of Applied Econometrics*, *25*(4), 514–538. https://doi.org/10.1002/jae.1167

Laibson, D., Maxted, P., & Moll, B. (2022, January). *A simple mapping from MPCs to MPXs* (NBER Working Paper No. 29664). National Bureau of Economic Research. https://doi.org/10.3386/w29664

Leeper, E. M., Plante, M., & Traum, N. (2010). Dynamics of fiscal financing in the united states. *Journal of Econometrics*, *156*(2), 304–321. https://doi.org/10.1016/j.jeconom.2009.11.001

Lieb, L., & Schuffels, J. (2022). Inflation expectations and consumer spending: The role of household balance sheets. *Empirical Economics*, *63*(5), 2479–2512. https://doi.org/10.1007/s00181-022-02222-8

Link, S., Peichl, A., Pfäuti, O., Roth, C., & Wohlfart, J. (2026). Attention to the macroeconomy. *The Quarterly Journal of Economics*, qjag047. https://doi.org/10.1093/qje/qjag047

Lorenzoni, G. (2009). A Theory of Demand Shocks. *American Economic Review*, *99*(5), 2050–2084. https://doi.org/10.1257/aer.99.5.2050

Lucas, R. E. (1972). Expectations and the neutrality of money. *Journal of Economic Theory*, *4*(2), 103–124. https://doi.org/10.1016/0022-0531(72)90142-1

Ludolph, M., Nghiem, G., & Tonzer, L. (2026). Fiscal expansion and households' income inequality expectations: A survey experiment. *Review of Income and Wealth*, *72*(4), e70093. https://doi.org/10.1111/roiw.70093

Maćkowiak, B., & Wiederholt, M. (2015). Business cycle dynamics under rational inattention. *The Review of Economic Studies*, *82*(4), 1502–1532. https://doi.org/10.1093/restud/rdv027

Mankiw, N. G., & Reis, R. (2002). Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve. *The Quarterly Journal of Economics*, *117*(4), 1295–1328. https://doi.org/10.1162/003355302320935034

Marcet, A., & Sargent, T. J. (1989). Convergence of least-squares learning in environments with hidden state variables and private information. *Journal of Political Economy*, *97*(6), 1306–1322. Retrieved April 29, 2026, from http://www.jstor.org/stable/1833240

McKay, A., & Reis, R. (2016). The role of automatic stabilizers in the u.s. business cycle. *Econometrica*, *84*(1), 141–194. https://doi.org/10.3982/ECTA11574

McKay, A., & Reis, R. (2021). Optimal automatic stabilizers. *The Review of Economic Studies*, *88*(5), 2375–2406. https://doi.org/10.1093/restud/rdaa038

Melosi, L. (2017). Signalling effects of monetary policy. *The Review of Economic Studies*, *84*(2), 853–884. https://ideas.repec.org/a/oup/restud/v84y2017i2p853-884..html
Melosi, L., Morita, H., Rogantini Picco, A., & Zanetti, F. (2025, September). The Signaling Effects of Fiscal Announcements. https://doi.org/10.2139/ssrn.5492801
Metiu, N., & Stockerl, V. (2024). *What moves households' expectations during a crisis? evidence from a randomized information experiment* (Deutsche Bundesbank Discussion Paper No. 42/2024). Frankfurt a. M., Deutsche Bundesbank. https://hdl.handle.net/10419/311843
Minka, T. P. (2001). Expectation propagation for approximate bayesian inference. *Proceedings of the Seventeenth Conference on Uncertainty in Artificial Intelligence*, 362–369.
Moll, B. (2026). The trouble with rational expectations in heterogeneous agent models: A challenge for macroeconomics. *The Economic Journal*, *136*(676), 1173–1216. https://doi.org/10.1093/ej/ueaf104
Müller, G. J., Wolf, M., & Hettig, T. (2024). Delayed overshooting: The case for information rigidities. *American Economic Journal: Macroeconomics*, *16*(3), 310–42. https://doi.org/10.1257/mac.20210212
Nakamura, E., & Steinsson, J. (2018). High-frequency identification of monetary non-neutrality: The information effect. *The Quarterly Journal of Economics*, *133*(3), 1283–1330. https://ideas.repec.org/a/oup/qjecon/v133y2018i3p1283-1330..html
Nimark, K. P. (2017). Dynamic Higher Order Expectations. *Working Paper*.
Oh, H., & Reis, R. (2012). Targeted transfers and the fiscal response to the great recession. *Journal of Monetary Economics*, *59*, S50–S64. https://doi.org/10.1016/j.jmoneco.2012.10.025
Orchard, J., Ramey, V., & Wieland, J. (2025). Micro mpcs and macro counterfactuals: The case of the 2008 rebates. *The Quarterly Journal of Economics*, *140*, 2001–2052. https://doi.org/10.1093/qje/qjaf015
Orchard, J., Ramey, V., & Wieland, J. (2026). Using macro counterfactuals to assess plausibility: An illustration using the 2001 rebate mpcs. *The Economic Journal*, *136*(673), 1–25. https://ideas.repec.org/a/oup/econjl/v136y2026i673p1-25..html
Overhage, J. (2026). Solving heterogeneous agent models with dispersed information in sequence space. *Working Paper*.
Parker, J. A., Schild, J., Erhard, L., & Johnson, D. (2022, October). *Economic impact payments and household spending during the pandemic* (Working Paper No. 30596). National Bureau of Economic Research. https://doi.org/10.3386/w30596
Pischke, J.-S. (1995). Individual income, incomplete information, and aggregate consumption. *Econometrica*, *63*(4), 805–840. Retrieved September 7, 2026, from http://www.jstor.org/stable/2171801
Porapakkarm, P., & Young, E. R. (2008). *Information heterogeneity in the macroeconomy* (2008 Meeting Papers No. 67). Society for Economic Dynamics. https://ideas.repec.org/p/red/sed008/67.html
Ramey, V. A. (2026). Do Temporary Cash Transfers Stimulate the Macroeconomy? Evidence from Four Case Studies. *IMF Economic Review*, *74*(1), 1–35. https://doi.org/10.1057/s41308-025-00274-1

Reicher, C. P. (2011). *An estimated fiscal taylor rule for the postwar united states* (Kiel Working Papers No. 1705). Kiel Institute for the World Economy. https://ideas.repec.org/p/zbw/ifwkwp/1705.html

Roth, C., & Wohlfart, J. (2020). How do expectations about the macroeconomy affect personal expectations and behavior? *The Review of Economics and Statistics*, *102*(4), 731–748. https://ideas.repec.org/a/tpr/restat/v102y2020i4p731-748.html

Sokolova, A. (2023). Marginal propensity to consume and unemployment: A meta-analysis. *Review of Economic Dynamics*, *51*, 813–846. https://doi.org/10.1016/j.red.2023.08.005

Souleles, N. S. (1999). The response of household consumption to income tax refunds. *American Economic Review*, *89*(4), 947–958. https://doi.org/10.1257/aer.89.4.947

Statistisches Bundesamt. (2020, May). *Einkommens- und Verbrauchsstichprobe: Konsumausgaben privater Haushalte 2018* (Fachserie 15 No. Heft 5). Statistisches Bundesamt. https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Einkommen-Konsum-Lebensbedingungen/Konsumausgaben-Lebenshaltungskosten/Publikationen/Downloads-Konsumausgaben/evs-aufwendung-privater-haushalte-2152605189004.html

Tallis, G. M. (1961). The moment generating function of the truncated multi-normal distribution. *Journal of the Royal Statistical Society. Series B (Methodological)*, *23*(1), 223–229. Retrieved October 13, 2026, from http://www.jstor.org/stable/2983860

Taubinsky, D., Butera, L., Saccarola, M., & Lian, C. (2026). Beliefs about the economy are excessively sensitive to household-level shocks: Evidence from linked survey and administrative data. *The Quarterly Journal of Economics*, *141*(4), 2803–2873. https://doi.org/10.1093/qje/qjag032

Taylor, J. B. (2009). The lack of an empirical rationale for a revival of discretionary fiscal policy. *American Economic Review*, *99*(2), 550–55. https://doi.org/10.1257/aer.99.2.550

Taylor, J. B. (2022). The effect of the rescue plans and the need for policies to increase economic growth. *Journal of Policy Modeling*, *44*(4), 768–779. https://doi.org/10.1016/j.jpolmod.2022.09.004

U.S. Bureau of Economic Analysis. (n.d.-a). Real disposable personal income [DPIC96]. https://fred.stlouisfed.org/series/DPIC96

U.S. Bureau of Economic Analysis. (n.d.-b). Real personal consumption expenditures [PCECC96]. https://fred.stlouisfed.org/series/PCECC96

U.S. Bureau of Economic Analysis. (2026). Real personal consumption expenditures [DPCERA3A086NBEA]. https://fred.stlouisfed.org/series/DPCERA3A086NBEA

van Deuverden, K. (2022). Steuereinnahmen haben sich von Corona bereits erholt: In der finanzkrise hat es länger gedauert. *DIW Wochenbericht*, *89*(11), 171–179. https://doi.org/10.18723/diw_wb:2022-11-1

Weber, M., D'Acunto, F., Gorodnichenko, Y., & Coibion, O. (2022). The Subjective Inflation Expectations of Households and Firms: Measurement, Determinants, and Implications. *Journal of Economic Perspectives*, *36*(3), 157–184. https://doi.org/10.1257/jep.36.3.157

Yin, X. (2026). Learning in the limit: Income inference from credit extensions. *The Journal of Finance*, *81*(5), 2729–2772. https://doi.org/10.1111/jofi.70040

# A Responses to fiscal transfers: empirical benchmarks

This appendix collects micro- and macro-level consumption benchmarks to complement the empirical evidence and model results.

## A.1 Household MPCs and the policy context

Figure 19 compares selected quarterly MPC estimates from U.S. studies. Responses to regular tax refunds and Alaska dividends exceed the estimates for three countercyclical episodes. Due to differences in settings and underlying data, this comparison is suggestive rather than causal.

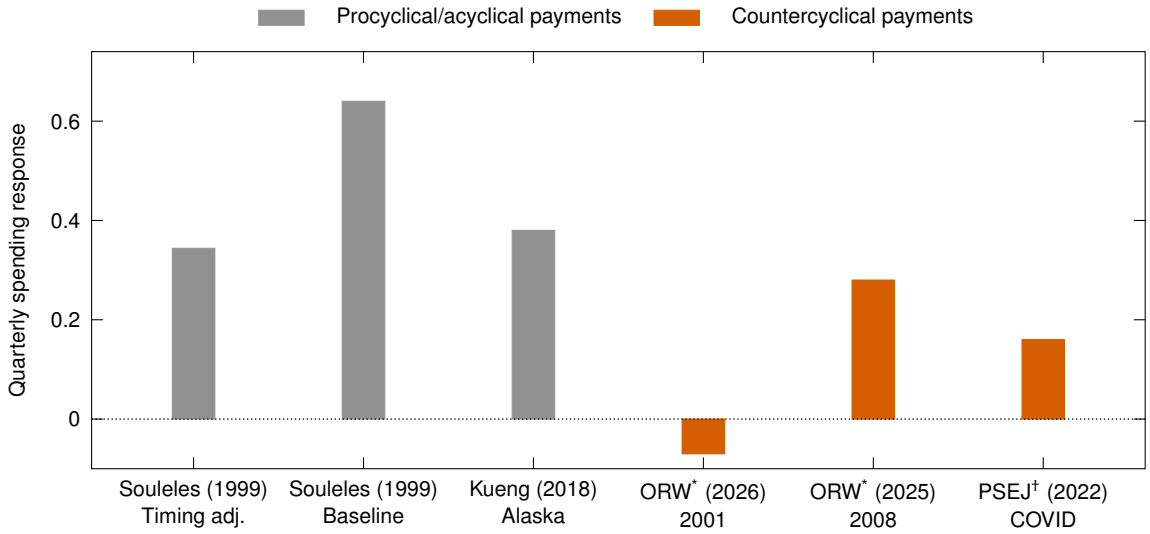



**Figure 19:** Selected quarterly household MPC estimates by policy context

Notes: Bars show selected point estimates. All estimates are total spending responses including durables. Souleles values are alternative specifications from the same study. The Kueng value combines the quarterly responses of nondurable and service spending (0.25) and classified durable purchases (0.13). The negative 2001 point estimate does not establish a significantly negative response. *ORW denotes Orchard, Ramey, and Wieland; †PSEJ denotes Parker, Schild, Erhard, and Johnson. The PSEJ estimate averages over the coefficients for the three EIP rounds they consider. Cyclicality labels refer to the policy context and design, rather than an estimated correlation between payments and output.

Related evidence comes from Goldfayn-Frank et al. (2022), who estimate an overall low MPC of 5.4% across the three countercyclical *Kinderbonus* payments in Germany during COVID, although Bachmann et al. (2022) find much larger responses for the first two installments. Conversely, Agarwal and Qian (2014) find a large spending response of about 0.80 per dollar from Singapore's procyclical Growth Dividend. These non-U.S. studies are excluded from the figure because they concern different settings and non-quarterly horizons: the Kinderbonus estimates use spending within the payment months, while

Singapore's ten-month estimate starts at the announcement, even including spending before disbursement.

The earlier rebates' lower MPCs are not explained by payment size. Fagereng et al. (2021) document that MPCs decline with lottery prize size. Yet Souleles (1999) reports a mean household refund of $874 in 1982–1984 dollars, and Kueng (2018) reports average Alaska dividends of $1,650 per person, or $4,600 per household, in 2014 dollars. The 2001 rebates were generally $300–$600 per household, and the 2008 payments averaged about $1,000 per household. In essence, if anything, differences in payment size would bias the procyclical or acyclical MPCs downward.

The pattern is noteworthy given that there is evidence of state dependence in MPCs. Sokolova (2023) finds that MPC estimates increase with unemployment rates, while Gross et al. (2020) find higher MPCs out of additional credit availability during recessions and in areas with higher unemployment. The information channel pushes the other way: countercyclical payments can convey negative news that can offset stronger spending responses associated with weak economic conditions.

There are additional concerns on how the empirical MPCs are estimated. The countercyclical-payment estimates in Figure 19 exploit household-level differences in payment receipt, timings or amounts. If policy announcements or other common information convey information about weak aggregate conditions before receipt, households in the comparison group may already have lowered their consumption. To the extent that recipients and comparison households share this negative information effect, it is differenced out of the estimated spending response; only additional information conveyed by receipt can contribute to that response. These estimates may therefore miss part of the consumption decline generated by the information channel.

## A.2 Aggregate income and consumption around stimulus payments

Figure 20 plots real disposable income and consumption around the 2001 and 2008 U.S. tax rebates. Temporary income spikes do not necessarily come with consumption increases. This is suggestive, rather than causal evidence. Nevertheless, these patterns motivate examining why stimulus payments can generate modest aggregate consumption responses, as done by Taylor (2009, 2022), Orchard, Ramey, and Wieland (2025, 2026), and Ramey (2026).

The divergence is even more pronounced during the COVID-19 pandemic (Figure 21). Restrictions, health risks, and other contemporaneous policies directly affected spending, however. The figure illustrates the divergence between aggregate income and consumption. It does not establish that the payments themselves had a small or negative effect on consumption.

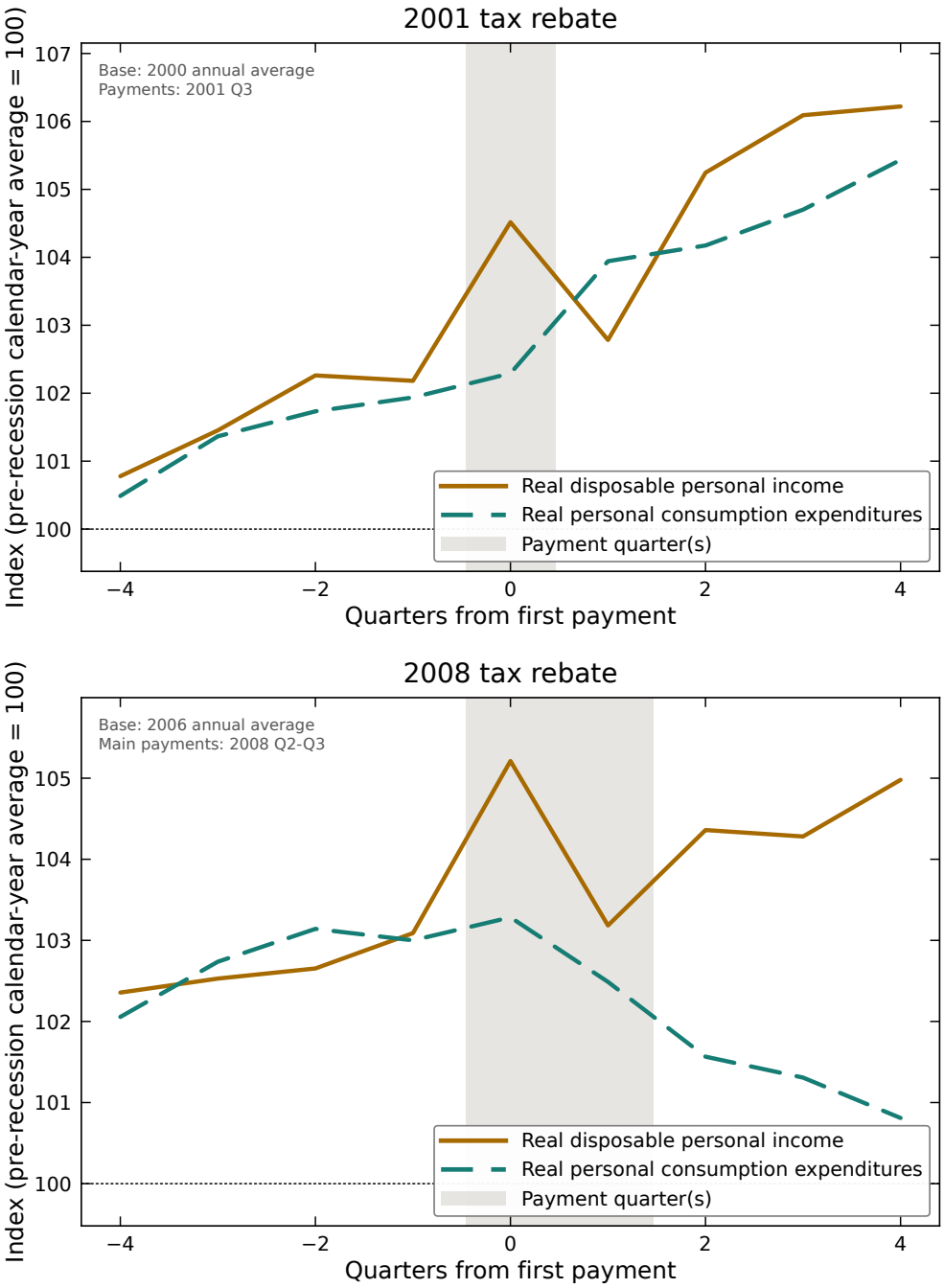



**Figure 20:** Real disposable income and consumption around the 2001 and 2008 tax rebates

Notes: Quarterly real disposable personal income (DPIC96, BEA account code A067RX) and real personal consumption expenditures (PCECC96, DPCERX), from the BEA National Income and Product Accounts, retrieved through FRED (U.S. Bureau of Economic Analysis, n.d.-a; U.S. Bureau of Economic Analysis, n.d.-b). The underlying series are seasonally adjusted annual rates in billions of chained 2017 dollars. Each series is indexed to its own calendar-year average: 2000 for the 2001 episode and 2006 for the 2008 episode. Quarter zero is 2001 Q3 and 2008 Q2, respectively. Shading marks payment quarters. Vertical scales differ across panels.

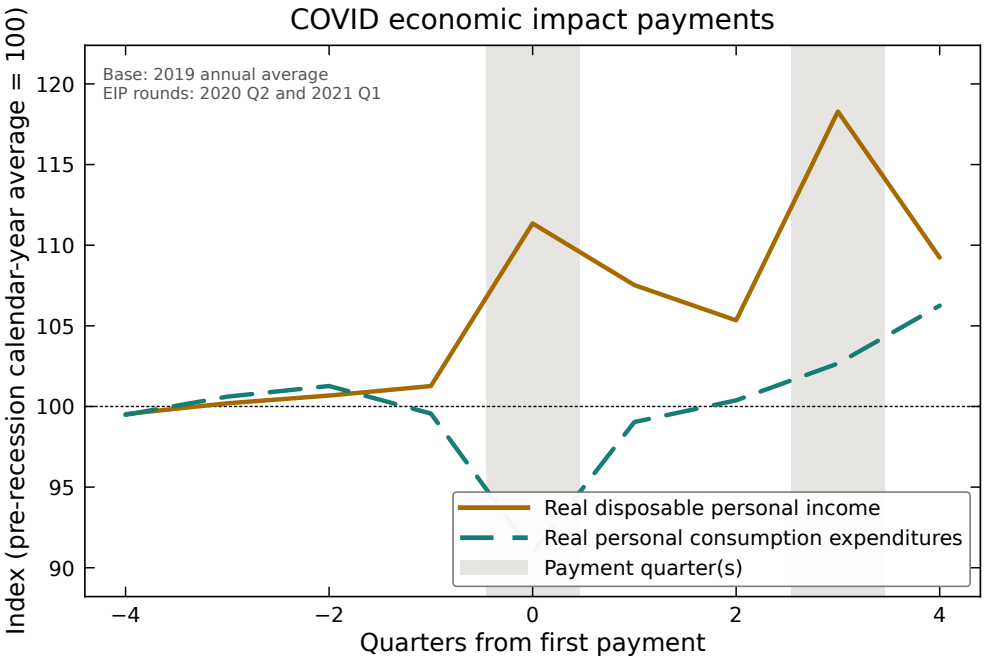



**Figure 21:** Real disposable income and consumption around COVID economic impact payments

Notes: Data sources and units are as in Figure 20 (U.S. Bureau of Economic Analysis, n.d.-a; U.S. Bureau of Economic Analysis, n.d.-b). Each series is indexed to its own 2019 calendar-year average. Quarter zero is 2020 Q2. Shading marks the payment quarters shown in the figure: 2020 Q2 and 2021 Q1.

# B Additional empirical results

This appendix provides additional information on the construction of the SCE and BOP-HH samples and reports supplementary results supporting the empirical analysis in the main text. The experience-effects appendix documents the full specifications behind the SCE core-panel results and the household-income evidence from the BOP-HH. The experimental appendix reports validity checks, raw purchase-probability responses, income heterogeneity, the persistence of the fiscal-package treatment effect, and savings-related outcomes. Appendix D describes the model validation, including the conversion of durable-purchase intentions into consumption revisions and the household-income comparison.

## B.1 Data and measurement

### B.1.1 SCE core panel

I use the SCE core panel between June 2013 and September 2025 to study the relationship between households' financial circumstances and their expectations about aggregate unemployment. The household financial-situation variable is question Q1, which asks

whether the household is financially better or worse off than twelve months earlier on a five-point scale from 1, much worse, to 5, much better. Aggregate unemployment expectations are measured by Q4new, the reported percent chance that the US unemployment rate will be higher twelve months later.

The analysis sample retains observations with nonmissing Q1, Q4new, and positive survey weights. The main fixed-effects regressions use SCE survey weights and cluster standard errors by respondent.

For the rationality exercise, I define the forecast as

$$F_{it} = Q4new_{it}/100. \tag{89}$$

The realization is

$$R_{it} = \mathbb{1}\{u_{t+12} > u_t\}, \tag{90}$$

where $u_t$ is the US unemployment rate in the interview month. The forecast error is

$$FE_{it} = R_{it} - F_{it}. \tag{91}$$

The rationality sample excludes interviews for which the unemployment rate twelve months later is unavailable. The primary covariance estimator clusters by both survey month and respondent. This accounts for the fact that the realization is common to all respondents interviewed in the same month, while forecast and reporting errors may also be correlated within respondents.

### B.1.2 BOP-HH experience panel

The BOP-HH experience sample uses the Scientific Use File (SUF), version 2025Q4 (Deutsche Bundesbank, 2025), and covers waves 4 through 69, corresponding to April 2020 through September 2025. Aggregate beliefs are measured using qualitative questions about whether German unemployment and economic growth will decrease, remain approximately unchanged, or increase over the following twelve months.

Household income is reported in brackets and converted to the midpoint supplied with the scientific-use file. Nominal household-income growth is the log change in this midpoint between consecutive interviews. Real income growth subtracts German HICP inflation over the corresponding interval. Both nominal and real growth are winsorized at their respective first and ninety-ninth percentiles.

The BOP-HH variable refers to total household income and remains defined following a job change or job loss, making it well suited to measuring adverse changes in household resources. One significant issue is that the survey is mostly only available during a time with high (expected) inflation. This together with the measurement of income

through brackets or midpoints means many wage increases likely go unmeasured, while movements crossing brackets that are recorded might simply reflect inflation adjustments, possibly even decreases in real wages.

The SCE and BOP-HH aggregate-unemployment variables measure similar but not identical objects. The SCE asks for the probability that unemployment will be higher, while the BOP-HH asks for the direction of change on a qualitative scale. In the shared experience-effect specifications, belief outcomes are scaled by their full-sample standard deviations.

### B.1.3 BOP-HH randomized experiment

The randomized information experiment was conducted in wave 4 of the BOP-HH in April 2020 (Deutsche Bundesbank, 2020). Respondents were assigned to one of six treatment arms:

1. placebo information about European human rights;
2. recession news;
3. uncertainty news;
4. information about the ECB Pandemic Emergency Purchase Programme;
5. information about the German federal fiscal package;
6. government reassurance.

The empirical analysis in the paper compares respondents assigned to the federal fiscal-package treatment, arm 5, with respondents assigned to the placebo treatment, arm 1. Arms 2, 3, 4, and 6 are excluded from the main treatment regressions. The treatment indicator is therefore

$$fp_i = \mathbf{1}\{\text{respondent } i \text{ is assigned to arm } 5\}, \tag{92}$$

within the sample consisting of arms 1 and 5.

Post-treatment GDP expectations are constructed from the eight-bin probability distribution in question 419. The mean forecast uses the bin midpoints and is expressed in percentage points of expected GDP growth. Spending outcomes are stated propensities from 0 to 100 to purchase a house, purchase a car, purchase another large durable good, or build up additional financial reserves over the following twelve months. Appendix B.7 discusses the interpretation of the reserves question.

All experimental regressions use BOP-HH survey weights and heteroskedasticity-robust standard errors. The standard control set includes gender, age, household size, employment status, and pre-treatment qualitative growth expectations. Treatment also affects several other indicators for expectations about aggregate and individual conditions going forward. Table 10 collects these expectations. Broadly, these support a pessimistic revision of expectations due to the fiscal policy information, although many indicators are noisy. For some, this is due to being reported one wave later, with attrition in the panel cutting the number of respondents roughly by half.

**Table 10:** Treatment effect on other expectations

| Outcome | Item / wave | Units | ATE | SE | p-value | N |
|---|---|---|---|---|---|---|
| Economy as a serious problem | Q515e May 2020 | score points | +0.447 | 0.189 | 0.0187 | 329 |
| Concern about the German economy | Q518a May 2020 | score points | +0.238 | 0.236 | 0.3135 | 331 |
| Concern about the EU economy | Q518b May 2020 | score points | +0.288 | 0.277 | 0.2988 | 331 |
| Concern about own future finances | Q518d May 2020 | score points | +0.622 | 0.391 | 0.1121 | 331 |
| Expected stock-market return | Q422 April 2020 | pp | -1.051 | 1.663 | 0.5275 | 593 |
| Expected local house-price growth | Q420 April 2020 | pp | +1.579 | 1.074 | 0.1419 | 636 |

Notes: Problem and concern outcomes are measured on 1–10 scales; their effects are changes in mean ratings. Reported $p$-values are nominal and the outcomes are exploratory. The economy-as-a-problem estimate has $p = 0.019$ before adjustment and $p = 0.112$ after a Holm correction across the six outcomes in this table.

The four May outcomes in Table 10 additionally control for the April rating of the economy as a serious problem (Q410e). The income-expectation regressions use the post-treatment forecast as the dependent variable and additionally control for the corresponding pre-treatment forecast. Expected monthly euro changes are constructed from the twelve probability bins, divided by the midpoint of current monthly household net income, and multiplied by 100. The main income sample is untrimmed. Open income-change tails are represented by $\pm$2,250 euros and the two bins adjacent to zero by $\pm$125 euros; there is no separate zero-change bin. Respondents are instructed to assume unchanged taxes and social contributions. For the GDP density, the open tails are represented by $\pm$17.5%.

## B.2 Experience effects and forecast efficiency

### B.2.1 Financial conditions and unemployment expectations

The following table reports the full set of specifications relating respondents' household financial situation to their aggregate unemployment expectations. It includes the pooled specification, month fixed effects, respondent fixed effects, and both sets of fixed effects, with weighted and unweighted estimates.

**Table 11:** Own financial situation and aggregate unemployment expectations (SCE)

| | Unweighted | Survey-weighted |
|---|---|---|
| No fixed effects | -4.128*** | -3.943*** |
| | (0.121) | (0.160) |
| Month fixed effects | -3.893*** | -3.759*** |
| | (0.122) | (0.161) |
| Respondent fixed effects | -1.858*** | -1.884*** |
| | (0.097) | (0.132) |
| Respondent and month fixed effects | -1.577*** | -1.600*** |
| | (0.095) | (0.128) |
| Observations | 185,086 | |

Notes: Coefficients relate the reported probability that US unemployment will be higher twelve months ahead, on a 0–100 scale, to household financial conditions, coded from 1 (much worse) to 5 (much better) relative to twelve months earlier. Rows vary the included fixed effects; columns report unweighted and survey-weighted estimates. Respondent-clustered standard errors are in parentheses. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The relationship between household financial conditions and aggregate unemployment expectations is negative across specifications. The month-fixed-effects estimates compare respondents interviewed under the same aggregate conditions, while the respondent-fixed-effects estimates use changes within respondents during their SCE panel spells.

### B.2.2 Forecasts, realizations, and forecast errors

The following table reports the full rationality exercise. In addition to the preferred two-way-clustered standard errors, it includes specifications clustering only by survey month and only by respondent.

The estimated financial-situation slopes for forecasts and realizations are quantitatively similar. The corresponding forecast-error slope is close to zero and is not statistically distinguishable from zero under two-way clustering. Respondent-only clustering understates uncertainty in the realization equation because the realized aggregate outcome varies only across survey months.

### B.2.3 BOP-HH household-income changes

Figure 22 reports the asymmetric relationship between real household-income changes and revisions in aggregate expectations. Positive and negative income changes enter the same regression with a shared intercept, wave fixed effects, and a control for the number of waves since the previous interview.

**Table 12:** Forecast efficiency: stated probability versus realized outcome

| | Coefficient | Two-way SE | Month SE | Respondent SE |
|---|---|---|---|---|
| Forecast | -0.0391*** | (0.0021) | (0.0016) | (0.0016) |
| Realization | -0.0362*** | (0.0105) | (0.0100) | (0.0034) |
| Forecast error | 0.0029 | (0.0108) | (0.0102) | (0.0038) |
| Observations | | 180,863 | | |
| Survey months | | 144 | | |
| Respondents | | 24,049 | | |

Notes: Each row reports a survey-weighted linear regression on household financial conditions, coded from 1 (much worse) to 5 (much better). The forecast is the probability, on a 0–1 scale, that US unemployment will be higher twelve months ahead. The realization equals one if the US unemployment rate twelve months after the interview exceeds its interview-month level, and zero otherwise. Forecast errors equal realizations minus forecasts. Standard errors use the clustering indicated by each column. Stars refer to two-way clustering by survey month and respondent: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

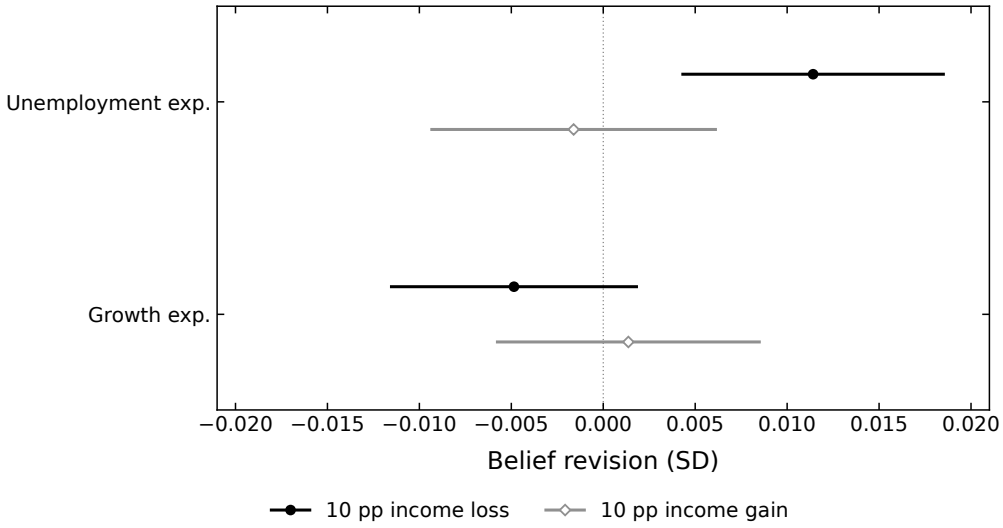



**Figure 22:** Real household-income changes and aggregate expectations in the BOP-HH

Notes: Associations between real household-income gains or losses of 10 log percentage points and revisions in twelve-month unemployment and growth expectations, measured in standard deviations of the respective belief outcome. Gains and losses enter the same survey-weighted regression, with wave fixed effects and a control for the interview gap. Error bars show 95% confidence intervals based on respondent-clustered standard errors.

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Bundesbank Online Panel – Households (BOP-HH), April 2020–September 2025, own calculations.

The point estimates imply larger responses to real-income losses than to gains. Tests of equality between the gain and loss slopes yield $p = 0.063$ for unemployment expectations and $p = 0.492$ for growth expectations. The growth response to income losses is itself imprecisely estimated ($p = 0.158$). The evidence for asymmetry is therefore suggestive for unemployment and weak for growth.

## B.3 Experimental validity

### B.3.1 Covariate balance

Table 13 reports balance in pre-treatment covariates between respondents assigned to the fiscal-package treatment and respondents assigned to the placebo treatment.

**Table 13:** Randomization balance: placebo versus fiscal treatment

| Covariate | Placebo | Fiscal package | Difference | p-value | N |
|---|---|---|---|---|---|
| *Panel A: Full analysis sample* | | | | | |
| Age | 53.358 | 54.088 | 0.730 | 0.557 | 681 |
| Household size | 2.248 | 2.232 | -0.015 | 0.854 | 679 |
| Gender | 1.510 | 1.444 | -0.066* | 0.084 | 681 |
| Employed | 0.571 | 0.566 | -0.004 | 0.912 | 679 |
| Homeowner | 0.683 | 0.641 | -0.042 | 0.246 | 681 |
| Income bracket | 2.868 | 2.811 | -0.057 | 0.584 | 647 |
| Prior growth outlook | 1.707 | 1.605 | -0.102 | 0.173 | 680 |
| Credit constrained | 0.091 | 0.135 | 0.044* | 0.070 | 680 |
| Joint F-test (Unweighted) | – | – | 1.398 | 0.194 | 645 |
| Joint F-test (Weighted) | – | – | 1.902 | 0.057 | 645 |
| *Panel B: Top-income group* | | | | | |
| Age | 48.800 | 52.873 | 4.073 | 0.202 | 100 |
| Household size | 3.022 | 2.745 | -0.277 | 0.173 | 100 |
| Gender | 1.356 | 1.309 | -0.046 | 0.628 | 100 |
| Employed | 0.689 | 0.673 | -0.016 | 0.865 | 100 |
| Homeowner | 0.822 | 0.764 | -0.059 | 0.475 | 100 |
| Income bracket | 5.000 | 5.000 | 0.000 | – | 100 |
| Prior growth outlook | 1.756 | 1.582 | -0.174 | 0.397 | 100 |
| Credit constrained | 0.067 | 0.109 | 0.042 | 0.456 | 100 |
| Joint F-test (Unweighted) | – | – | 0.869 | 0.534 | 100 |
| Joint F-test (Weighted) | – | – | 1.062 | 0.395 | 100 |

Notes: Pre-treatment covariate means for the fiscal-package and placebo arms, with differences defined as fiscal package minus placebo. Individual comparisons are unweighted and use the available observations for each covariate. Panel B restricts the sample to monthly household income of at least EUR 5,000. Joint rows report F-statistics and p-values for covariate balance, with and without survey weights. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Bundesbank Online Panel – Households (BOP-HH), April 2020, own calculations.

The unweighted balance tests evaluate whether random assignment generated comparable groups in the arm-5-versus-arm-1 sample. The weighted tests provide a corresponding

diagnostic for the weighted estimation sample. Survey weights were not used in treatment assignment, so differences between weighted and unweighted balance tests do not imply a failure of randomization.

### B.3.2 GDP expectations across experimental arms

Figure 23 reports mean post-treatment GDP expectations in all six experimental arms.

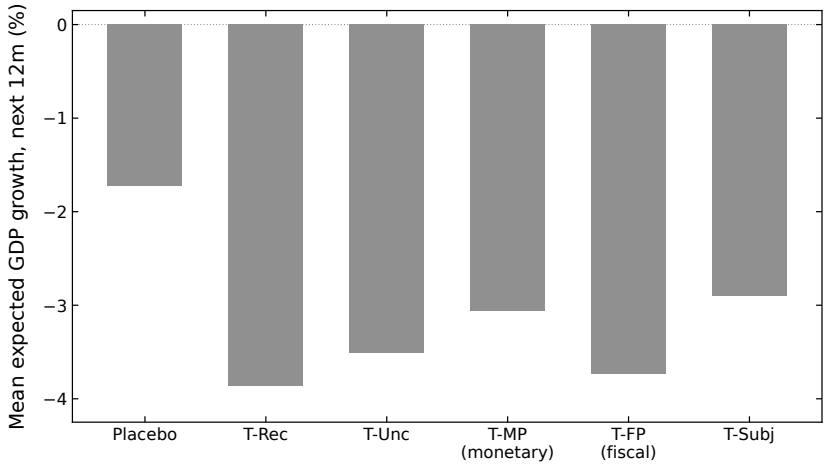



**Figure 23:** Post-treatment GDP expectations by experimental arm

Notes: Survey-weighted means of expected German GDP growth over the next twelve months, constructed from respondents' post-treatment probability distributions. The six arms provide placebo information, recession news, uncertainty news, monetary-policy information, fiscal-package information, and government reassurance, respectively. Bars show forecast levels rather than treatment effects relative to placebo.

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Bundesbank Online Panel – Households (BOP-HH), April 2020, own calculations.

Although the main regressions compare only the fiscal-package and placebo arms, the six-arm figure provides a transparent overview of the experimental variation. It also validates the construction of the post-treatment GDP-growth forecast from the probability bins.

## B.4 Spending heterogeneity

### B.4.1 Income-bracket profiles

Figure 24 reports the effects of the fiscal-package treatment on expected GDP growth and intended durable purchases separately across the five household-income groups. Each coefficient compares arm 5 with placebo arm 1.

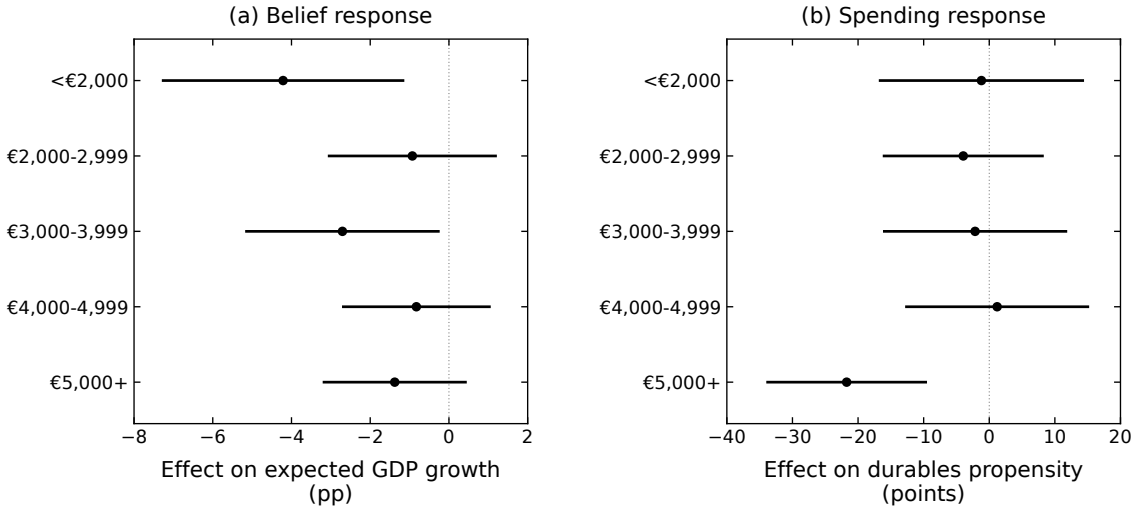



**Figure 24:** Fiscal-package information, GDP expectations, and intended durable spending by household income

Notes: Treatment effects of fiscal-package information relative to placebo on expected German GDP growth and the stated probability of another large durable purchase over the next twelve months, both in percentage points. Separate survey-weighted linear regressions within each monthly household-income group control for gender, age, household size, employment status, and pre-treatment growth expectations. Both panels use the same complete-case sample. Error bars show 95% confidence intervals based on heteroskedasticity-robust standard errors.

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Bundesbank Online Panel – Households (BOP-HH), April 2020, own calculations.

### B.4.2 Purchase-probability responses

Table 14 reports the raw durable-purchase-probability responses underlying the spending comparison. These outcomes are stated intentions rather than expenditure amounts. Section 5.1 reports consumption revisions constructed using the category-specific purchase-probability responses, control-group probabilities, and expenditure weights described in Appendix D.5.

## B.5 Persistence of the fiscal-package belief effect

Figure 25 reports the effect of the fiscal-package information treatment on qualitative growth expectations in the months following the experiment.

The figure shows whether the initial effect of the fiscal-package treatment remains visible in the subsequent BOP-HH waves. Precision declines over the follow-up period because of rapid panel attrition and because the analysis is restricted to the fiscal-package and placebo arms.

**Table 14:** Raw durable-purchase-probability responses

| | Effect | Standard error |
|---|---|---|
| Average treatment effect | −6.15 | 3.09 |
| Slope across income brackets | −2.27 | 2.22 |
| Slope across prior categories | −4.53 | 2.97 |

Notes: Entries are treatment effects on stated durable-purchase propensity, in percentage points. Slope rows report the change in the treatment effect per one-category increase in household income or prior optimism about growth. Estimates compare the fiscal-package treatment with the placebo and use survey weights and the experimental control set described in Appendix B.1.3.

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Bundesbank Online Panel – Households (BOP-HH), April 2020, own calculations.

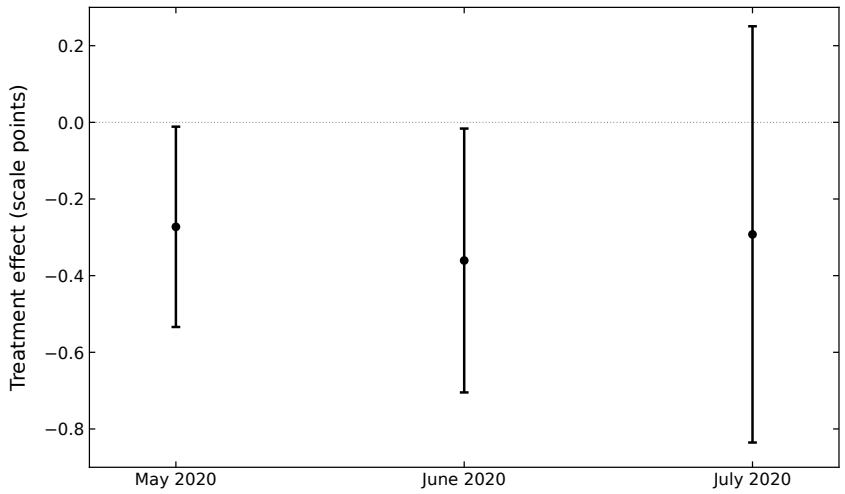



**Figure 25:** Persistence of the fiscal-package treatment effect on growth expectations

Notes: Effects of the April fiscal-package information treatment relative to placebo on subsequent twelve-month growth expectations. Outcomes use a five-category scale from decline sharply to rise sharply; effects are in scale points. Survey-weighted linear regressions use April covariates and weights. Error bars show 95% confidence intervals based on heteroskedasticity-robust standard errors. Follow-up samples contain 331, 160, and 111 respondents in May, June, and July, respectively.

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Bundesbank Online Panel – Households (BOP-HH), April–July 2020, own calculations.

The follow-up outcome is the qualitative five-category growth-expectations question from the regular BOP-HH module. It is not the original post-treatment GDP-density forecast, which was not repeatedly elicited for the surviving experimental households. The persistence exercise therefore examines whether the treatment continues to affect a closely related measure of aggregate growth expectations rather than the exact original outcome. The large standard errors are partly due to attrition: between treatment and control group, there are only 331 respondents left in wave 5, 160 in wave 6 and 111 in wave 7.

## B.6 Prior belief relevance for the effect

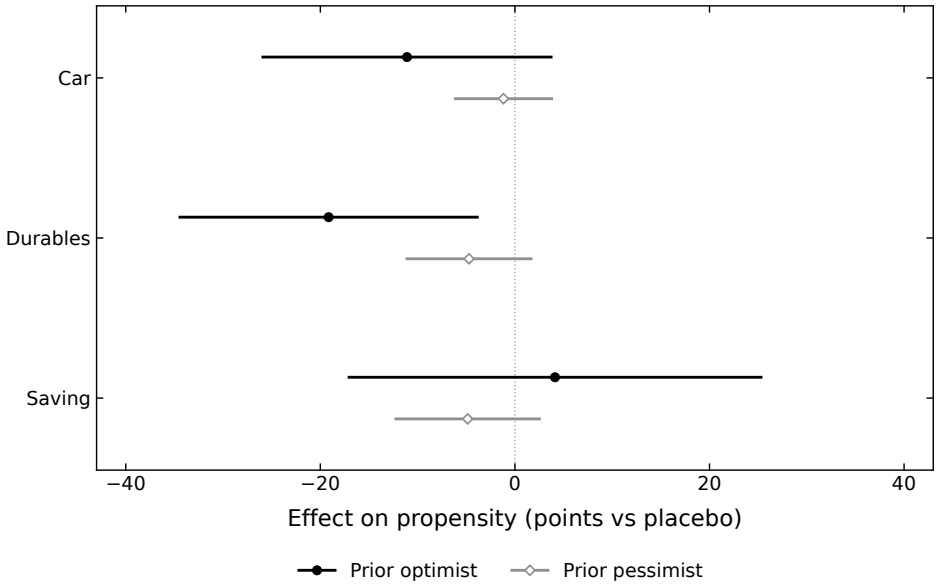



**Figure 26:** Spending and saving responses by prior growth expectations

Notes: Treatment effects of fiscal-package information relative to placebo on stated probabilities of purchasing a car, purchasing another large durable good, and building additional financial reserves over the next twelve months, in percentage points. Groups are defined using pre-treatment growth expectations: categories 1–2 are prior pessimists, while categories 3–5 include neutral and optimistic respondents. Estimates use separate survey-weighted linear regressions within each prior group, with demographic controls and pre-treatment growth expectations. Error bars show 95% confidence intervals based on heteroskedasticity-robust standard errors. Saving refers to reserve-building intentions.

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Bundesbank Online Panel – Households (BOP-HH), April 2020, own calculations.

Figure 26 shows that the reduction in intended spending is concentrated among respondents who were relatively optimistic before receiving the fiscal-package information. For these respondents, the announcement represents more information relative to their prior beliefs. The saving-intention estimates are imprecise and do not provide clear evidence of increased precautionary saving. Appendix B.7 discusses the measurement and interpretation of this outcome.

## B.7 Savings intentions and financial constraints

The April 2020 survey asks respondents for the probability that they will "build up additional financial reserves" over the following twelve months. The estimated treatment effect is negative, at $-3.58$ percentage points, but statistically insignificant. The income gradients are also imprecisely estimated. This question does not distinguish longer-term asset accumulation from the accumulation of liquid funds available to cover near-term expenses.

The May 2020 survey instead asks whether respondents have or anticipate difficulty covering current expenditure in the near future because of the coronavirus pandemic. Table 15 reports effects on the probability of financial constraints over one- and three-month horizons. The point estimates are negative, indicating less anticipated difficulty financing expenditure. The one-month estimates are more precise; the three-month results are more sensitive to the control specification. The smaller samples reflect attrition between the April experiment and the May follow-up.

**Table 15:** Savings intentions and anticipated financial constraints

| Estimand / specification | Effect | SE | $p$-value | $N$ |
|---|---|---|---|---|
| *Build additional financial reserves: April 2020* | | | | |
| Average treatment effect | −3.58 | 3.61 | 0.322 | 637 |
| Slope per EUR 1,000 of income | 1.20 | 1.86 | 0.520 | 611 |
| Slope per pooled income bracket | 2.22 | 2.74 | 0.419 | 611 |
| *Probability of financial constraints: May 2020* | | | | |
| One month: core controls | −5.70 | 3.34 | 0.0885 | 329 |
| One month: add April liquidity and income | −8.00 | 3.23 | 0.0138 | 318 |
| Three months: core controls | −1.71 | 4.37 | 0.6962 | 329 |
| Three months: add April liquidity and income | −7.17 | 3.72 | 0.0551 | 318 |

Notes: Effects are in percentage points; income slopes are per EUR 1,000 or per one-category increase, as indicated. Estimates compare the fiscal-package treatment with the placebo and use survey weights. The extended financial-constraints specifications additionally control for April liquidity and income. SE denotes standard error.

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Bundesbank Online Panel – Households (BOP-HH), April–May 2020, own calculations.

These outcomes concern different aspects of household finances. Respondents may interpret building reserves as longer-term saving, while near-term financing capacity depends on income and liquid funds already available. A lower reported probability of building reserves can therefore coexist with an improved ability to cover expenses. The follow-up responses do not establish that households increased realized saving. I consequently report both outcomes but do not use either as a quantitative counterpart to saving in the model.

## B.8 Construction of untargeted belief moments

This appendix describes the construction of the belief moments reported in Table 7. The empirical moments are calculated using wave 68 of the Bundesbank Online Panel – Households (BOP-HH), conducted in August 2025. The corresponding model moments are calculated without changing the baseline calibration.

*Survey measurement.* Question P6809 asks respondents to assess the percentage change in German real GDP in Q2 2025 relative to Q1 2025. The question is asked before respondents are shown the published GDP figure in the subsequent question. The response therefore provides a measure of respondents' assessments of past aggregate growth, rather than a forecast of future growth.

Responses are recorded in seven categories, distinguishing declines and increases of different magnitudes, as well as approximately unchanged output. To recover a measure of cross-sectional dispersion, I fit an interval-normal model to these categorical responses. The three categories closest to zero are combined into an interval from $-0.25\%$ to $0.25\%$. The remaining categories distinguish changes between $0.25\%$ and $0.50\%$, with open-ended tails beyond $0.50\%$. Category boundaries are transformed from percentage changes $g$ into log percentage points using $100 \log(1 + g/100)$.

To measure the relationship between household income and aggregate beliefs, I link respondents to their household-income reports in wave 62, conducted in February 2025. Household income is reported in brackets, which I represent by their assigned midpoints. The resulting six-month change in log household net income is denoted by $x_i$. The baseline sample contains households whose reported income changed by at most a factor of two, $|x_i| \leq \log 2$; households with unchanged income remain in the sample. I estimate the conditional mean of the latent GDP-growth assessment as

$$\mu_i = \alpha + \beta x_i + \gamma \log I_{i,62} + Z_i' \delta, \tag{93}$$

where $I_{i,62}$ denotes the initial household-income midpoint. The controls $Z_i$ include age, age squared, gender, household size, children, and education. The latent GDP-growth assessment is assumed normally distributed around $\mu_i$, with residual variance $\sigma_B^2$.

I estimate the model by maximizing the survey-weighted interval-normal likelihood, using the reported GDP-growth categories as interval observations. Confidence intervals are based on heteroskedasticity-robust standard errors. The estimated slope is $\hat{\beta} = 0.283$, with a 95% confidence interval of $[0.123, 0.443]$.

The corresponding estimate of total cross-sectional belief dispersion is

$$\widehat{\mathrm{SD}}(B_i) = \sqrt{\hat{\sigma}_B^2 + \mathrm{Var}_w(\hat{\mu}_i)}, \tag{94}$$

where $\mathrm{Var}_w$ denotes the survey-weighted cross-sectional variance. This yields a standard deviation of 0.274 log percentage points in the six-month matched sample.

Importantly, this estimate is based on a parametric reconstruction of latent assessments from categorical responses. It may contain reporting variation in addition to genuine disagreement about aggregate conditions. These components cannot be separately identified from the observed responses.

*Model counterparts.* Let $\hat{y}_{i,t-k|t}$ denote household $i$'s posterior estimate of log aggregate output in quarter $t-k$, conditional on all information available through quarter $t$. The model belief object is

$$m_{it} = 100\hat{y}_{it|t}. \tag{95}$$

I treat the survey's growth assessment as a proxy for beliefs about the level of output and apply this interpretation to both moments: I report the cross-sectional standard deviation of $m_{it}$ as the model disagreement moment, and use $m_{it}$ to construct the income-belief slope. The interview quarter corresponds to $t$. Posterior estimates are obtained using the model's linear-Gaussian filtering system, incorporating information received through quarter $t$. No additional public GDP signal is imposed.

To approximate the survey's measure of household income, I calculate model household net income $I_{it}$ as labour income plus transfers, minus taxes, plus interest income, treating each model household as one survey household. I convert quarterly income into a monthly flow, scale it so that median income equals EUR 3,750, close to the empirical median, and assign it to the survey's thirteen income brackets and their midpoints, denoted $J_{it}$. I then regress $m_{it}$ on the six-month change $\log J_{it} - \log J_{i,t-2}$, controlling for $\log J_{i,t-2}$, in the sample with $|\log J_{it} - \log J_{i,t-2}| \leq \log 2$. The resulting slope is 0.374. Varying the median between EUR 2,500 and EUR 5,500 changes the slope by less than 0.01.

The model moments are computed across 200,000 simulated households, conditional on a common aggregate state at its reference level. Under dispersed information, the cross-sectional standard deviation of current-output beliefs is 0.195 log percentage points. Under full information, both belief disagreement and the income-belief slope are zero.

*Measurement sensitivity.* Table 16 reports alternative survey measurements together with the corresponding model slopes. The first alternative removes the restriction on the size of income changes. The second additionally requires unchanged household size and number of children at both interviews; since household composition does not change in the model, its model slope equals the baseline.

I also report estimates obtained by assigning representative values to the categorical GDP-growth responses and estimating the regression by weighted least squares, assigning $\pm 0.75$ percent to the open-ended response categories. The model counterpart assigns the same representative values to the model beliefs, centred at zero. This specification illustrates sensitivity to the measurement of categorical beliefs and should not be interpreted as a confidence bound on underlying disagreement.

**Table 16:** Sensitivity of untargeted survey belief moments

| Specification | $N$ | SD | Slope | 95% CI | Model slope |
|---|---|---|---|---|---|
| Six-month income change, baseline | 2,299 | 0.274 | 0.283 | [0.123, 0.443] | 0.374 |
| All income changes | 2,306 | 0.274 | 0.181 | [0.067, 0.294] | 0.375 |
| Stable household composition | 2,292 | 0.274 | 0.270 | [0.106, 0.435] | 0.374 |
| Midpoint coding ($\pm$0.75) | 2,299 | 0.302 | 0.231 | [0.054, 0.408] | 0.385 |

Notes: GDP beliefs are in log percentage points. Survey specifications control for starting household income, age, age squared, gender, household size, children, and education. All rows except "All income changes" restrict the sample to households whose reported income changed by at most a factor of two. The first three rows use the survey-weighted interval-normal estimator; the midpoint row uses weighted least squares with representative values, in percent, for the categorical GDP-growth responses. Confidence intervals are heteroskedasticity-robust. Model slopes regress current-output beliefs on the six-month change in bracketed log household income and starting log income; the model has no demographic controls. The model SD is 0.195 (0.214 under midpoint coding).

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH waves 62 and 68, own calculations. Model calculations by author.

The positive income-belief relationship is broadly robust to these alternative measurements, although its magnitude varies. Removing the restriction on the size of income changes lowers the empirical slope, while the model slope is unaffected, as the model generates few such large income changes. The level of measured disagreement also depends on assumptions used to reconstruct beliefs from categorical responses. The dispersion moment should therefore be interpreted as a descriptive benchmark, rather than a precise target for the model's information structure.

# C Machine-learning signal-extraction counterfactuals

This appendix describes the alternative forecasting rules used in the ex-post signal-extraction exercise. All methods forecast current aggregate log output $y_t$ from household-observable variables. Define the current observation vector as

$$o_{it} = (w_{it}, \widetilde{T}_t, D_t)'. \tag{96}$$

Here, $D_t$ is observed exactly through the tax rule. All standardization parameters and forecasting coefficients are estimated using the training sample only. Hyperparameters are selected using expanding-window cross-validation over time blocks.

## C.1 Ridge regression

The Ridge specification uses the most recent $L$ observations of all three observable series. Define

$$\mathbf{s}_{it} = \left(o_{it}', o_{i,t-1}', \ldots, o_{i,t-L+1}'\right)' \in \mathbb{R}^{3L}, \qquad L = 12. \tag{97}$$

Equivalently, $\mathbf{s}_{it}$ contains the current and lagged values of $w_{it}$, $\widetilde{T}_t$, and $D_t$. The inputs are standardized using training-sample means $m_s$ and standard deviations $d_s$:

$$\widetilde{\mathbf{s}}_{it} = (\mathbf{s}_{it} - m_s) \oslash d_s. \tag{98}$$

The Ridge forecast is

$$\widehat{y}_{it}^{\text{ridge}} = \alpha + \beta' \widetilde{\mathbf{s}}_{it}. \tag{99}$$

The parameters solve

$$(\widehat{\alpha}, \widehat{\beta}) = \arg\min_{\alpha,\beta} \sum_{(i,t)\in\mathcal{T}} \left(y_t - \alpha - \beta' \widetilde{\mathbf{s}}_{it}\right)^2 + n_{\mathcal{T}} \lambda \|\beta\|^2, \tag{100}$$

where $\mathcal{T}$ denotes the training sample and $n_{\mathcal{T}}$ is its number of observations. The penalty parameter $\lambda$ is selected by expanding-window cross-validation.

The current observation vector is an input rather than a predetermined household state. The recursive state required to carry the forecasting rule forward therefore consists of the preceding $L-1$ observations of each series, for a total of

$$3(L-1) = 33 \tag{101}$$

state variables per household.

## C.2 Gated recurrent unit

The GRU replaces the finite observation window with a nonlinear recursive state $h_{it} \in \mathbb{R}^H$. Let $\widetilde{o}_{it}$ denote the standardized current observation vector and initialize $h_{i0} = 0$. The recursion is

$$r_{it} = \Lambda\left(W_r \widetilde{o}_{it} + U_r h_{i,t-1} + b_r\right), \tag{102}$$

$$g_{it} = \Lambda\left(W_g \widetilde{o}_{it} + U_g h_{i,t-1} + b_g\right), \tag{103}$$

$$\widetilde{h}_{it} = \tanh\left(W_h \widetilde{o}_{it} + r_{it} \odot \left(U_h h_{i,t-1}\right) + b_h\right), \tag{104}$$

$$h_{it} = (1 - g_{it}) \odot \widetilde{h}_{it} + g_{it} \odot h_{i,t-1}. \tag{105}$$

Here, $\Lambda(v) = 1/(1+\exp(-v))$ is applied element by element and $\odot$ denotes elementwise multiplication. The output forecast is

$$\widehat{y}_{it}^{\text{GRU}} = \mu_y + \sigma_y\left(a' h_{it} + c\right), \tag{106}$$

where $\mu_y$ and $\sigma_y$ are computed from the training sample.

The parameters minimize training-sample mean squared error using truncated backpropagation through time. The hidden-state dimension is selected by validation from

$$H \in \{8, 16\}. \tag{107}$$

Validation selects $H = 16$. The forecasting rule therefore requires sixteen recursively updated state variables per household.

### C.3 $k$-nearest neighbors

The $k$NN estimator uses the same standardized $L$-period vector $\widetilde{\mathbf{s}}_{it}$ as the Ridge specification. Let the reference sample be

$$\mathcal{R} = \left\{ \left( \widetilde{\mathbf{s}}_j, y_j \right) \right\}_{j=1}^{N}, \qquad N = 25{,}000. \tag{108}$$

For a household-period observation $\widetilde{\mathbf{s}}_{it}$, define the distance to reference observation $j$ as

$$d_j = \left\| \widetilde{\mathbf{s}}_{it} - \widetilde{\mathbf{s}}_j \right\|_2. \tag{109}$$

Let $\mathcal{N}_k(\widetilde{\mathbf{s}}_{it})$ contain the indices of the $k$ smallest distances. The inverse-distance weights and output forecast are

$$\omega_j = \frac{1}{d_j + \epsilon_d}, \qquad \widehat{y}_{it}^{k\mathrm{NN}} = \frac{\sum_{j \in \mathcal{N}_k(\widetilde{\mathbf{s}}_{it})} \omega_j y_j}{\sum_{j \in \mathcal{N}_k(\widetilde{\mathbf{s}}_{it})} \omega_j}. \tag{110}$$

The constant $\epsilon_d > 0$ prevents division by zero. The number of neighbors is selected by expanding-window cross-validation, which yields $k = 160$.

As with Ridge, the household must retain $3(L-1) = 33$ lagged observations. In addition, implementation of the forecasting rule requires storing and searching the reference sample $\mathcal{R}$.

## D Design of the fiscal-announcement validation

This appendix describes how households interpret the cumulative fiscal announcement used in Section 5.1. For this validation exercise, $Y^{\mathrm{ref}}$ is Q1 2020 output. The announcement covers Q2 2020 through Q1 2021 and reveals the planned normalized four-quarter total

$$s = \mathbb{E}_t^G \left[ \sum_{j=0}^{3} \widetilde{T}_{t+j} \right] = 0.1696, \tag{111}$$

where $\mathbb{E}_t^G$ denotes the government's expectation given the current aggregate state and its own planned fiscal innovations. The announcement does not reveal separate quarterly transfers. Because the countercyclical component of transfers continues to respond to output, realized transfers over the window can differ from the announced total.

## D.1 The announcement as a signal

For this exercise, it is convenient to use the augmented household state

$$q_{it}^a = (\widetilde{y}_t, e_{it}, \nu_t, D_t)'. \tag{112}$$

Let its perceived transition be

$$q_{i,t+1}^a = a_q + A^a q_{it}^a + G^a \boldsymbol{\varepsilon}_{i,t+1}. \tag{113}$$

Here $a_q$, $A^a$, and $G^a$ are the augmented counterparts of $d_q$, $A_q$, $D_q$, and $G_q$ in Section 4, obtained by replacing $y_t$ with $\widetilde{y}_t$ and appending the debt transition. Normalized transfers are selected from this state by

$$\widetilde{T}_t = c' q_{it}^a, \qquad c = (-\psi_y, 0, 1, 0)'. \tag{114}$$

Under the perceived law, the announced total consists of the observed current transfer, expected rule-implied future transfers, and planned future fiscal innovations:

$$s = c' q_{it}^a + \sum_{j=1}^{3} \mathbb{E}_t^G \left[ c' q_{i,t+j}^a \right] = c' q_{it}^a + \alpha_s + \bar{\theta}' q_{it}^a + \sum_{k=1}^{3} \omega_k \varepsilon_{t+k}^{\nu}. \tag{115}$$

The loading on the current state and the deterministic intercept are

$$\bar{\theta}' = \sum_{j=1}^{3} c' (A^a)^j, \qquad \alpha_s = \sum_{j=1}^{3} c' a^{(j)}, \tag{116}$$

where $a^{(j)}$ is the $j$-step transition intercept. The loading of the fiscal innovation in quarter $t+k$ on the cumulative package is

$$\omega_k = \left[ (G^a)' \sum_{j=k}^{3} \left( (A^a)^{j-k} \right)' c \right]_{\nu}. \tag{117}$$

The government knows the current state and its own fiscal plan, but not future productivity innovations. The announced total is therefore an expectation over future productivity. Realized transfers over the window satisfy

$$\sum_{j=0}^{3} \widetilde{T}_{t+j} = s + \sum_{k=1}^{3} \omega_k^{\mu} \mu_{t+k}, \qquad \omega_k^{\mu} = \left[ (G^a)' \sum_{j=k}^{3} \left( (A^a)^{j-k} \right)' c \right]_{\mu}, \tag{118}$$

where $\omega_k^{\mu} < 0$ under the calibration: positive future productivity innovations reduce countercyclical transfers. Future productivity innovations are independent of the current state and the fiscal plan, so the gap between realized and announced transfers has conditional mean zero. These innovations do not enter (115), and the announcement contains no information about them. Every posterior state and fiscal plan satisfies the announced expected-total constraint. Consequently, $E_{it}[\sum_{j=0}^{3} \widetilde{T}_{t+j} \mid s] = s$, while realized cumulative transfers remain uncertain. Revisions to future output expectations reflect revised beliefs about the current state and the fiscal plan.

$$\omega = (2.701, 1.895, 0.998), \tag{119}$$

close to $(1 + \rho_\nu + \rho_\nu^2, 1 + \rho_\nu, 1)$. An innovation at $t+1$ affects all three future quarters, an innovation at $t+2$ affects two quarters, and an innovation at $t+3$ affects only the final quarter. These are persistence loadings, not an exogenous quarterly allocation of the announced package.

Households already know the current transfer. Household $i$'s announcement surprise is therefore

$$u_i = s - \widetilde{T}_t - \alpha_s - \bar{\theta}' m_{i,t|t}^a = s - E_{it} \left[ \sum_{j=0}^{3} \widetilde{T}_{t+j} \right], \tag{120}$$

where $m_{i,t|t}^a$ denotes the posterior mean after observing the current wage, transfer, and tax payment but before receiving the cumulative announcement. The prior expectation $E_{it}[\cdot]$ sets future fiscal and productivity innovations to their zero means, so $u_i$ is the difference between the announced total and the household's prior expectation of the same object.

## D.2 Joint Bayesian update

Collect the current state and the three future fiscal innovations in

$$x_i = \left( (q_{it}^a)', \varepsilon_{t+1}^{\nu}, \varepsilon_{t+2}^{\nu}, \varepsilon_{t+3}^{\nu} \right)'. \tag{121}$$

The prior mean and covariance are

$$E_{it}[x_i] = \begin{pmatrix} m_{i,t|t}^a \\ 0_3 \end{pmatrix}, \qquad \mathrm{Var}_{it}(x_i) = \begin{pmatrix} P & 0 \\ 0 & \sigma_\nu^2 I_3 \end{pmatrix}. \tag{122}$$

The future fiscal innovations are independent before the announcement. Define

$$S = \bar{\theta}' P \bar{\theta} + \sigma_\nu^2 \omega' \omega. \tag{123}$$

The posterior means are

$$E_{it}[q_{it}^a \mid s] = m_{i,t|t}^a + \frac{P\bar{\theta}}{S}u_i, \qquad E_{it}[\varepsilon_{t+k}^v \mid s] = \frac{\sigma_v^2 \omega_k}{S}u_i. \tag{124}$$

After the current signals, uncertainty about the state is rank one:

$$P = p_y dd', \qquad d = (1, -1, \psi_y, 0)'. \tag{125}$$

The current transfer is constant along this remaining uncertainty direction because $c'd = 0$. Let

$$\lambda = \bar{\theta}'d = -0.0639. \tag{126}$$

The signal variance becomes

$$S = p_y\lambda^2 + \sigma_v^2\omega'\omega = 2.2 \times 10^{-6} + 1.54 \times 10^{-4} = 1.56 \times 10^{-4}. \tag{127}$$

The share of the announcement surprise attributed to uncertainty about the current state is

$$\varphi = \frac{p_y\lambda^2}{S} = 0.014, \qquad 1 - \varphi = 0.986. \tag{128}$$

Thus, households attribute 1.4% of the surprise to worse current conditions and 98.6% to the fiscal plan.

The output-belief update is

$$\Delta\widehat{\bar{y}}_{it} = \frac{p_y\lambda}{S}u_i = -0.225u_i. \tag{129}$$

The posterior gains on the future fiscal innovations are

$$\big(E_{it}[\varepsilon_{t+1}^v \mid s], E_{it}[\varepsilon_{t+2}^v \mid s], E_{it}[\varepsilon_{t+3}^v \mid s]\big) = (0.224, 0.157, 0.083)u_i. \tag{130}$$

The inferred plan is front-loaded because an early innovation is more effective at generating a large cumulative package. Equivalently, the household selects the least statistically surprising sequence of future fiscal innovations consistent with the announced total. Table 17 displays the contributions to the cumulative surprise.

The contribution assigned to the $t+1$ innovation includes its persistent effects on transfers in $t+1$, $t+2$, and $t+3$. It should not be interpreted as the share paid in quarter $t+1$.

**Table 17:** Posterior decomposition of the announcement surprise

| Explanation | Share of announcement surprise |
|---|---|
| Worse current economic state | 1.4% |
| Planned innovation at $t+1$ and its persistent effects | 60.5% |
| Planned innovation at $t+2$ and its persistent effects | 29.8% |
| Planned innovation at $t+3$ | 8.3% |

Notes: Decomposition of the difference between the announced planned total of transfers over four quarters and the household's prior expectation of that total. Entries are components' shares of the surprise variance, which also determine their shares of posterior attribution under the linear-Gaussian update. Shares are common across households and independent of the surprise's size. Future-innovation contributions include their persistent effects on subsequent transfers within the announcement window.

## D.3 Mapping the update into GDP expectations

The model counterpart of the survey outcome is average expected output over the four-quarter window relative to Q1 2020:

$$G_i = \frac{100}{4} \sum_{j=0}^{3} E_{it}[\widetilde{y}_{t+j} \mid s]. \tag{131}$$

The treatment effect is linear in the household-specific surprise:

$$\Delta G_i = 100 \left( \Gamma_{\text{state}} + \Gamma_{\text{plan}} \right) u_i. \tag{132}$$

The current-state component is

$$\Gamma_{\text{state}} = \frac{1}{4} \sum_{j=0}^{3} \left[ (A^a)^j \frac{P\bar{\theta}}{S} \right]_1 = -0.21237, \tag{133}$$

and the fiscal-plan component is

$$\Gamma_{\text{plan}} = \frac{1}{4} \sum_{j=1}^{3} \sum_{k=1}^{j} \left[ (A^a)^{j-k} G_\nu^a \right]_1 \frac{\sigma_\nu^2 \omega_k}{S} = 0.00375. \tag{134}$$

Consequently,

$$\Delta G_i = -20.862 u_i. \tag{135}$$

At the mean model surprise, $\bar{u} = 0.1082$, the model predicts

$$\overline{\Delta G} = -20.862 \times 0.1082 = -2.258 \text{ percentage points.} \tag{136}$$

The empirical effect of $-1.755$ percentage points corresponds to a surprise of approximately $u = 0.084$. At this surprise,

$$\Delta\widehat{\widetilde{y}}_{it} = -0.225 \times 0.084 = -0.019, \tag{137}$$

and

$$\Delta G_{\text{state}} \approx -1.79 \text{ pp}, \qquad \Delta G_{\text{plan}} \approx 0.03 \text{ pp}, \qquad \Delta G \approx -1.76 \text{ pp}. \tag{138}$$

The bad-state inference lowers expected output in every quarter because the revision to current output is persistent. This does not represent news about additional future productivity shocks. The plan component raises expected output, but only slightly because fiscal innovations enter the perceived output law with a small coefficient. Under full information, the current state is already known, so the state component is absent and the announcement produces only the positive plan effect.

The announcement fixes only one expected cumulative total. It does not identify the three future fiscal innovations separately. Let $\Sigma_x$ denote the prior covariance of $x_i$ and define $g = (\bar{\theta}', \omega')'$, so that $s - \widetilde{T}_t - \alpha_s = g'x_i$, with $\widetilde{T}_t$ already observed. The posterior covariance is

$$\text{Var}_{it}(x_i \mid s) = \Sigma_x - \frac{\Sigma_x g g' \Sigma_x}{g' \Sigma_x g}. \tag{139}$$

The individual quarterly fiscal innovations therefore remain uncertain and become negatively correlated after conditioning on the announced expected total.

For a draw $x_i^0$ from the prior distribution, let $m_i^0 = E_{it}[x_i]$ denote its mean before the announcement. The simulation constructs a treated draw by adding a projected, centered prior draw to the posterior mean:

$$x_i^T = E_{it}[x_i \mid s] + (x_i^0 - m_i^0) - \frac{\Sigma_x g}{g' \Sigma_x g} g'(x_i^0 - m_i^0). \tag{140}$$

Every treated draw satisfies $g'x_i^T = s - \widetilde{T}_t - \alpha_s$ and is therefore consistent with the same announced expected cumulative total. The quarterly fiscal plan varies across draws. Each draw is combined with future productivity and efficiency innovations drawn from their unconditional distributions, which the announcement does not inform. Along a draw, realized cumulative transfers can therefore differ from $s$ as in (118). The household propagates the drawn state forward under the perceived law, observes future wages, transfers, and taxes, updates its beliefs, and applies its consumption policy. Treated and control households use common random draws.

## D.4 Conditional output path

Figure 7 in Section 5.1 compares the model's conditional output distribution with realized German GDP. The productivity shock is chosen to reproduce the observed contraction between Q1 and Q2 2020. The realized recovery was substantially faster than the model's conditional path. The subsequent realized output path provides context for the exercise, while the validation targets households' expectations at the time of the announcement.

## D.5 Mapping durable-purchase intentions into consumption revisions

This subsection describes the consumption-equivalent measure used in Section 5.1. Let $\Delta Z_h$ denote the treated-minus-untreated revision in expected $Z_h$. The horizon is $H = 4$ quarters, with $h = 1$ corresponding to Q2 2020 and $h = 4$ to Q1 2021. The inherited durable stock at the start of this window is fixed.

### D.5.1 Purchase probabilities and net durable expenditure

For each category $j$, cars and other durables, let $P_{0j}$ be the control-group purchase probability and $G_{0j}$ baseline annual gross expenditure. Probabilities are expressed as fractions. Holding expenditure conditional on purchase fixed gives

$$Q_j = \frac{G_{0j}}{P_{0j}}, \qquad \Delta G_j = Q_j \Delta P_j. \tag{141}$$

Let $\eta_j$ be the net-to-gross expenditure ratio, which deducts resale proceeds. Baseline net expenditure and its revision are

$$N_{0j} = \eta_j G_{0j}, \qquad \Delta N_j = \eta_j \Delta G_j. \tag{142}$$

The proportional revision in total net durable expenditure is therefore

$$R_B = \frac{\sum_j \Delta N_j}{\sum_j N_{0j}} = \sum_j w_j \frac{\Delta P_j}{P_{0j}}, \qquad w_j = \frac{N_{0j}}{\sum_k N_{0k}}. \tag{143}$$

The purchase probabilities and treatment effects are taken from the same BOP-HH estimation sample. Baseline expenditure inputs are from the German EVS 2018 reported by Destatis (2020).

### D.5.2 Durable-stock accounting

Following the durable mapping in Laibson et al. (2022, Appendix B), let $D_h$ denote the durable stock and $x_h$ net durable purchases. The stock evolves according to

$$D_h = (1-\delta)D_{h-1} + x_h, \qquad D_h = \kappa_D c_h, \qquad \kappa_D = \frac{s_D}{r+\delta}, \tag{144}$$

where $c_h$ is notional consumption, $s_D$ the durable share, and $r+\delta$ the user cost. Prices, shares, and user costs are held fixed. With $\Delta D_0 = 0$, the revision in cumulative net durable purchases satisfies

$$\Delta X_H^D = \sum_{h=1}^{H} \Delta x_h = \Delta D_H + \delta \sum_{h=1}^{H-1} \Delta D_h = \kappa_D \left( \Delta c_H + \delta \sum_{h=1}^{H-1} \Delta c_h \right). \tag{145}$$

Thus, expenditure over the window reflects both the terminal stock adjustment and replacement purchases associated with the intervening stock revisions.

### D.5.3 Consumption-equivalent revision

Let $\Delta c_h^M$ be the model's quarterly consumption revision and $\bar{c}_0^M$ mean untreated consumption over the four quarters. Define

$$g_h^M = \frac{\Delta c_h^M}{\bar{c}_0^M}, \qquad \bar{g}^M = \frac{1}{H} \sum_{h=1}^{H} g_h^M. \tag{146}$$

Under stationary replacement and proportional stock adjustment by category,

$$N_{0j} = H\delta D_{0j}, \qquad \Delta D_{jh} = D_{0j} g_h^M. \tag{147}$$

The model-implied proportional revision in durable expenditure is

$$R_M = \frac{g_H^M + \delta \sum_{h=1}^{H-1} g_h^M}{H\delta}, \qquad \Delta P_j^M = P_{0j} R_M. \tag{148}$$

The empirical consumption-equivalent path assumes a flat quarterly profile. Matching its implied durable-expenditure revision to $R_B$ gives

$$g_h^{\mathrm{eq}} = \bar{g}^{\mathrm{eq}} = \frac{H\delta}{1+(H-1)\delta} R_B, \qquad h = 1, \ldots, H. \tag{149}$$

The main table reports $100\bar{g}^{\mathrm{eq}}$ for the empirical consumption revision and $100\bar{g}^M$ for the model revision. The same conversion is applied to the heterogeneity comparisons.

**Table 18:** Calibration of the durable-to-consumption mapping

| Parameter | Value |
|---|---|
| Horizon $H$ | Four quarters |
| Quarterly depreciation $\delta$ | 0.05 |
| Annual gross expenditure on cars $G_{0,\text{car}}$ | EUR 1,452 |
| Annual gross expenditure on other durables $G_{0,\text{other}}$ | EUR 876 |
| Net-to-gross ratio for cars $\eta_{\text{car}}$ | 0.8 |
| Net-to-gross ratio for other durables $\eta_{\text{other}}$ | 1 |
| Net expenditure weights $(w_{\text{car}}, w_{\text{other}})$ | $(0.570, 0.430)$ |

Notes: Expenditure inputs are from EVS 2018, Destatis (2020). The car adjustment deducts resale proceeds. Depreciation is a rounded benchmark from Laibson et al. (2022); housing is excluded from the mapping.

## D.6 Household-income expectations

The survey elicits probabilities over brackets describing changes in monthly net household income over the following twelve months. The income concept includes after-tax labor income, pensions, and transfers. Table 19 reports the treatment effect on expected household net income, the model decomposition into labor income and transfers, and heterogeneity by current household income.

**Table 19:** Household-income expectations in the experiment and model

| | Data | Dispersed information | Full information |
|---|---|---|---|
| Expected net-income revision | 2.21 | 2.98 | 3.39 |
| | (2.73) | | |
| Of which: labor income | – | −0.29 | 0.35 |
| Of which: transfers | – | 3.28 | 3.04 |
| Slope per EUR 1,000 of income | −1.23 | −0.76 | −0.75 |
| | (2.00) | | |
| Slope per income group | −0.74 | −0.71 | −0.70 |
| | (2.07) | | |

Notes: The first row reports treatment effects on expected household net income, in percent. The decomposition gives contributions in percentage points. Slope rows report the change in the income revision, in percentage points, per EUR 1,000 or per one-category increase in current household income. Empirical standard errors are in parentheses. Components may differ from totals because of rounding.

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Bundesbank Online Panel – Households (BOP-HH), April 2020, own calculations. Model calculations by author.

The positive but imprecise empirical income revision is consistent with both information structures. In the dispersed-information model, the contribution of expected labor income

is negative, while expected transfers contribute positively and more than offset this decline. Under full information, both components are positive. The negative income gradients are similar across the two models and are imprecisely estimated in the data, so they do not distinguish between the information structures.

# E Extension: Idiosyncratic noise in fiscal receipts

The baseline model specifies that transfers and taxes are identical across households and reveal their aggregate counterparts exactly. I relax this assumption by introducing idiosyncratic components into both fiscal payments:

$$T_{it} = T_t + Y^{\text{ref}}\chi_{it}, \qquad \chi_{it} \sim \mathcal{N}(0, \sigma_\chi^2), \tag{150}$$

$$\tau_{it} = \tau_t + \xi_{it}^\tau, \qquad \xi_{it}^\tau \sim \mathcal{N}(0, \sigma_{\xi^\tau}^2). \tag{151}$$

These components are independent across households and time, independent of all other shocks, and integrate to zero across households. Aggregate fiscal policy and government debt dynamics thus remain unchanged.

Households observe their fiscal receipts, which enter budget constraints, but can no longer infer aggregate transfers and taxes exactly. In particular, government debt is no longer directly observed. The hidden state is therefore expanded to

$$q_{it} = (y_t, e_{it}, \nu_t, D_t)'. \tag{152}$$

The perceived state transition continues to follow the aggregate output law and fiscal rules used in the baseline model. Households continue to apply the Kalman filter, now with idiosyncratic observation noise in transfers and taxes. Since labor income remains an exact observation of $y_t + e_{it}$, the independent posterior belief state consists of $(\hat{y}_{it|t}, \hat{\nu}_{it|t}, \hat{D}_{it|t})$. The model is otherwise solved as in the baseline.

This model extension introduces two new parameters to be calibrated. Because the purpose of this extension is to verify whether the information channel survives when fiscal receipts contain additional idiosyncratic noise, I calibrate both parameters to measures of the information content and precision. Fève and Pietrunti (2016) estimate quarterly fiscal-signal precision across Canada, the UK, and the US, with an average of $\alpha = 0.37$. Matching this precision in an auxiliary scalar Kalman filter for the persistent fiscal state implies $\sigma_\chi = 1.86\sigma_\nu$.[6] For taxes, Caldwell et al. (2023) report a median coefficient of variation of subjective tax-refund uncertainty of 0.27 and an estimated updating coefficient of 0.597.

[6] For a signal $s_{it} = \nu_t + \chi_{it}$, the stationary Kalman gain $\alpha$ implies $\sigma_\chi/\sigma_\nu = \sqrt{(1-\alpha)/[\alpha(1-\rho_\nu^2(1-\alpha))]}$.

Interpreting the latter as a scalar Kalman gain and scaling posterior uncertainty by an approximate reference tax payment of 0.02 gives $\sigma_{\xi^\tau} = 0.02 \times 0.27/\sqrt{0.597} \approx 0.007$.[7]

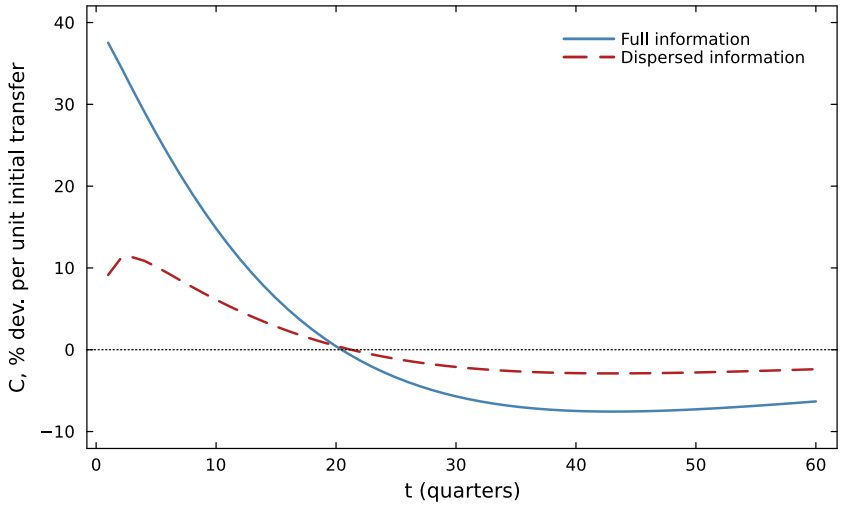



**Figure 27:** Aggregate consumption response, with noise in transfers and taxes

Notes: Responses to a one-standard-deviation positive discretionary fiscal innovation, starting from the stationary distribution. Consumption responses are normalized by the initial aggregate transfer and multiplied by 100, giving cents per dollar; periods are quarters. The dispersed-information economy is re-solved with independent idiosyncratic noise in transfer receipts and tax payments, with standard deviations $\sigma_\chi = 1.86\sigma_\nu$ and $\sigma_{\xi^\tau} \approx 0.007$, respectively. Noise averages to zero across households.

Figure 27 shows the aggregate response with noise in both transfers and taxes, calibrated as described above. Compared with the baseline results in Figure 10, the responses change only slightly. The change to the impact consumption response under dispersed information is slightly larger, but only increases it from 8 to 9 cents per dollar transferred. The shape of the response alters slightly: in addition to the attribution of the shock to countercyclical and discretionary components, households now only see a noisy representation of the aggregate transfer. This makes the consumption response more hump-shaped than in the baseline model. Relative to the baseline model, the additional noise introduces more disagreement about output movements. The cross-sectional standard deviation of beliefs about current output rises from 0.19 in the baseline model to about 0.46, exceeding the empirical benchmark reported in Section 5.

# F Extension: Additional output signal

This section describes a setup in which households receive an additional signal about contemporaneous output $y$. It demonstrates that an additional signal about output can

[7]The tax benchmark approximates the reference debt-service payment using a quarterly interest rate of 1% and $\bar{B} = 2$. The exact reference payment under the model calibration is 0.0148.

move the dispersed-information economy closer to its full information equivalent. The case with an additional signal is reserved for an extension, as moving closer to the full-information economy substantially weakens the model's performance in the validation exercise described in Section 5.1. Let each household receive an additional private, noisy signal about current output:

$$s_{it} = y_t + \iota_{it}, \qquad \iota_{it} \sim \mathcal{N}(0, \sigma_\iota^2), \tag{153}$$

where $\iota_{it}$ is independent across households and over time and independent of all other shocks. The signal enters only beliefs, not budget constraints. Since $\iota_{it}$ is serially uncorrelated, no additional state variables are required. The belief state and the household problem keep their dimensions. The model is otherwise re-solved as in the baseline, including the perceived law of motion. Full information is unaffected by construction.

Figure 28 reports aggregate responses for $\sigma_\iota = 0.12$, 0.056 and 0.028, that is 4.2, 2.0 and 1.0 times the standard deviation of $y_t$. Because the signal noise is independent over time while output is persistent, averaging over successive signals makes it considerably more informative than its single-period noise suggests. A more precise signal moves the dispersed-information economy closer to full information. The impact consumption response rises from 8 cents per dollar transferred in the baseline to 11, 16 and 22 cents, compared with 38 cents under full information.

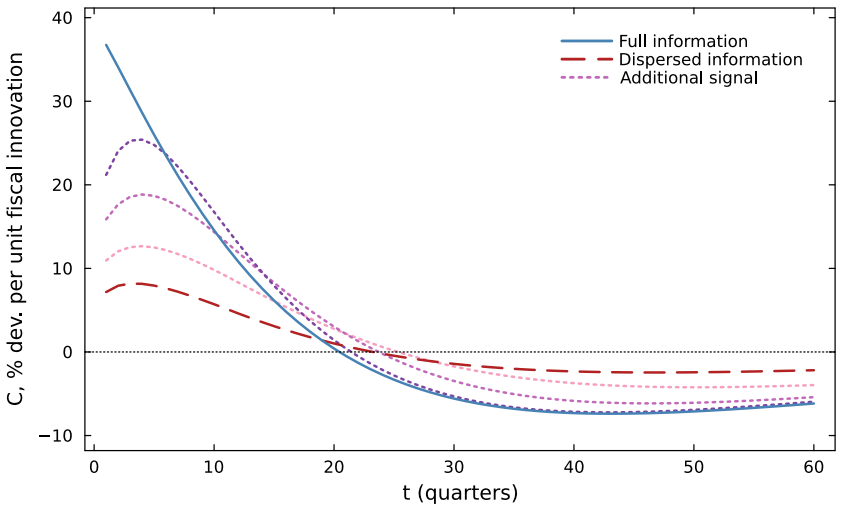



**Figure 28:** Aggregate consumption response, additional output signal

Notes: Responses to a one-standard-deviation positive discretionary fiscal innovation, starting from the stationary distribution. Consumption responses are normalized by the initial aggregate transfer and multiplied by 100, giving cents per dollar; periods are quarters. The full- and dispersed-information economies are exactly as in Section 5. "Additional signal" economies refer to dispersed information setups with an additional signal with standard deviation of noise $\sigma_\iota \in \{0.12, 0.056, 0.028\}$. Darker colors correspond to lower standard deviation of the noise, which implies higher signal precision.

# G Filtering with targeted transfers

This appendix describes the filtering method used to solve the targeted transfer model in Section 6. Targeting changes which continuous signals households observe and adds information through eligibility. The latter generates a non-Gaussian posterior even conditional on the linear perceived aggregate law. I retain a finite-dimensional belief state by projecting this posterior onto a Gaussian distribution with matching first and second moments. This follows assumed density filtering as described by Minka (2001).

## G.1 State transition and continuous observations

For the targeted model, augment the baseline filtering state to include government debt:

$$q_{it} = (y_t, e_{it}, \nu_t, D_t)'. \tag{154}$$

Current debt is observed through taxes. Including it in the filtering state allows the prediction step to account for uncertainty about next-period debt among households that do not observe current aggregate transfers.

Under the perceived output law, the transition equations are

$$D_{t+1} = (R^* - \kappa)D_t + \Upsilon^{\text{ref}}\big[-\psi_y(y_t - y^{\text{ref}}) + \nu_t\big], \tag{155}$$

$$\nu_{t+1} = \rho_\nu \nu_t + \varepsilon^{\nu}_{t+1}, \tag{156}$$

$$e_{i,t+1} = \mu_\zeta + \rho_e e_{it} + \varepsilon^{e}_{i,t+1}, \tag{157}$$

$$y_{t+1} = b_0 + b_y y_t + b_B D_{t+1} + b_\nu \rho_\nu \nu_t + b_\mu \mu_{t+1} + b_\nu \varepsilon^{\nu}_{t+1}. \tag{158}$$

The innovations are mutually independent, with variances $\sigma^2_\nu$, $\sigma^2_\zeta$, and $\sigma^2_\mu$, respectively. The output-law coefficients are estimated in the targeted economy.

Collecting these equations gives the transition equation

$$q_{i,t+1} = a^{\text{tar}} + F^{\text{tar}} q_{it} + G^{\text{tar}} \varepsilon_{i,t+1}, \tag{159}$$

where the matrices follow from equations (155)–(158). Let $Q^{\text{tar}}$ denote the covariance matrix of the transition innovation. Given the previous period's Gaussian approximation, the prediction step is

$$m^-_{it} = a^{\text{tar}} + F^{\text{tar}} \hat{q}_{i,t-1|t-1}, \tag{160}$$

$$P^-_{it} = F^{\text{tar}} P_{i,t-1|t-1} (F^{\text{tar}})' + Q^{\text{tar}}. \tag{161}$$

Recipients observe their wage, the payment amount, and current debt. Since $T_{it} = 2T_t$ for recipients, their continuous observation vector is

$$s_{R,it} = \left( w_{it}, \frac{T_{it}}{2Y^{\text{ref}}}, D_t \right)'. \tag{162}$$

Nonrecipients observe their wage and current debt:

$$s_{N,it} = (w_{it}, D_t)'. \tag{163}$$

For $j \in \{R, N\}$, write the corresponding observation system as

$$s_{j,it} = h_j + H_j q_{it}. \tag{164}$$

The recipient matrices are

$$h_R = \begin{pmatrix} 0 \\ \psi_y y^{\text{ref}} \\ 0 \end{pmatrix}, \qquad H_R = \begin{pmatrix} 1 & 1 & 0 & 0 \\ -\psi_y & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}, \tag{165}$$

while the nonrecipient matrices are

$$h_N = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \qquad H_N = \begin{pmatrix} 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}. \tag{166}$$

First condition on the continuous observations, temporarily setting aside the inequality implied by eligibility. This gives the Gaussian intermediate distribution

$$\pi^G_{j,it} = \mathcal{N}(m^G_{j,it}, P^G_{j,it}), \tag{167}$$

with

$$K_{j,it} = P^-_{it} H_j' \left( H_j P^-_{it} H_j' \right)^\dagger, \tag{168}$$

$$m^G_{j,it} = m^-_{it} + K_{j,it} \left( s_{j,it} - h_j - H_j m^-_{it} \right), \tag{169}$$

$$P^G_{j,it} = P^-_{it} - K_{j,it} H_j P^-_{it}. \tag{170}$$

The generalized inverse allows for redundant observations that are already known exactly from the previous period's information.

This system also incorporates delayed learning from taxes. Once $D_{t+1}$ is observed, the government budget constraint reveals

$$T_t = D_{t+1} - (R^* - \kappa) D_t. \tag{171}$$

Nonrecipients therefore recover the previous aggregate payment even though they do not observe it contemporaneously.

## G.2 Eligibility and truncated posterior moments

Eligibility is determined by $e_{it} \leq \bar{e}$. Since $w_{it} = y_t + e_{it}$, this is equivalent to

$$y_t \geq k_{it}^y, \qquad k_{it}^y = w_{it} - \bar{e} = w_{it} + \frac{\sigma_e^2}{2}. \tag{172}$$

Thus, recipients truncate their intermediate distribution from below in output, while nonrecipients truncate it from above.

Let $a_y = (1, 0, 0, 0)'$ select aggregate output from the state vector. For each intermediate distribution, define

$$m_{y,j,it}^G = a_y' m_{j,it}^G, \tag{173}$$

$$s_{j,it}^2 = a_y' P_{j,it}^G a_y, \tag{174}$$

$$\alpha_{j,it} = \frac{k_{it}^y - m_{y,j,it}^G}{s_{j,it}}. \tag{175}$$

Here and below, $s_{j,it}$ without bold notation denotes the scalar posterior standard deviation of output; the continuous observation vectors are those in equations (162) and (163).

Let $\phi$ and $\Phi$ denote the standard normal density and distribution functions. Conditional on the Gaussian prediction, the posterior incorporating both continuous observations and eligibility is

$$\pi_{it}(dq) = \begin{cases} \dfrac{\mathbf{1}\{a_y' q \geq k_{it}^y\}}{1 - \Phi(\alpha_{R,it})}\, \pi_{R,it}^G(dq), & \text{if } d_{it} = 1, \\ \dfrac{\mathbf{1}\{a_y' q < k_{it}^y\}}{\Phi(\alpha_{N,it})}\, \pi_{N,it}^G(dq), & \text{if } d_{it} = 0. \end{cases} \tag{176}$$

The denominators normalize the distributions after values inconsistent with observed eligibility have been removed.

The moments follow standard truncated-normal formulas (see e.g. Tallis, 1961). Define

$$\ell_{R,it} = \frac{\phi(\alpha_{R,it})}{1 - \Phi(\alpha_{R,it})}, \tag{177}$$

$$\ell_{N,it} = \frac{\phi(\alpha_{N,it})}{\Phi(\alpha_{N,it})}, \tag{178}$$

$$v_{j,it} = P_{j,it}^G a_y. \tag{179}$$

The recipient posterior has mean and covariance

$$\hat{q}_{it}^{R} = m_{R,it}^{G} + \frac{v_{R,it}}{s_{R,it}} \ell_{R,it}, \tag{180}$$

$$P_{it}^{R} = P_{R,it}^{G} - \frac{v_{R,it} v_{R,it}'}{s_{R,it}^{2}} \ell_{R,it} \left( \ell_{R,it} - \alpha_{R,it} \right). \tag{181}$$

For nonrecipients, the corresponding moments are

$$\hat{q}_{it}^{N} = m_{N,it}^{G} - \frac{v_{N,it}}{s_{N,it}} \ell_{N,it}, \tag{182}$$

$$P_{it}^{N} = P_{N,it}^{G} - \frac{v_{N,it} v_{N,it}'}{s_{N,it}^{2}} \ell_{N,it} \left( \ell_{N,it} + \alpha_{N,it} \right). \tag{183}$$

Eligibility shifts beliefs about all states correlated with output and reduces posterior uncertainty. Its informativeness depends on the position of the eligibility threshold relative to the intermediate output distribution. An eligibility outcome that was already very likely changes beliefs little. An outcome that removes a substantial part of the intermediate distribution produces a larger update. If the relevant output variance were zero, eligibility would already be determined and no truncation update needed.

## G.3 Gaussian projection and household decisions

Following the assumed density filtering approach described by Minka (2001), I replace the truncated posterior by a Gaussian distribution with the same mean and covariance:

$$\pi_{it} \approx \mathcal{N}(\hat{q}_{it|t}, P_{it|t}), \tag{184}$$

where $(\hat{q}_{it|t}, P_{it|t})$ are selected from equations (180)–(183) according to eligibility. These moments are exact for the truncated distribution obtained from the incoming Gaussian approximation. The projection discards its higher moments and supplies the Gaussian input for the next prediction step.

Unlike in the baseline model, the covariance recursion depends on household observations through the standardized threshold. Posterior covariance matrices therefore differ across households and histories. Household decisions must account for these differences as well as differences in posterior means.

For example, under the projected posterior, the probability of eligibility next quarter is

$$\Pr_{it}(d_{i,t+1} = 1) = \Phi \left( \frac{\bar{e} - \mu_{\zeta} - \rho_{e} \hat{e}_{it|t}}{\sqrt{\rho_{e}^{2} P_{ee,it|t} + \sigma_{\zeta}^{2}}} \right), \tag{185}$$

where $\hat{e}_{it|t}$ and $P_{ee,it|t}$ are the posterior mean and variance of current log efficiency. Both the mean and uncertainty about efficiency affect anticipated eligibility and thus the value of future support under the targeted rule.

For each candidate perceived output law, I solve household decisions using this filtering recursion. In the simulation, candidate aggregate consumption determines output, wages, aggregate transfers, and individual eligibility. Households observe the resulting signals, update their beliefs, and choose consumption. Aggregate consumption must equal the integral of these choices. The simulated output series then updates the perceived-law coefficients, as in the baseline solution method.

The targeted model therefore introduces two distinct approximations: the perceived law of aggregate output as in the baseline method, and now additionally the Gaussian representation of truncated household posteriors. The latter provides a tractable belief representation when eligibility makes exact conditional distributions non-Gaussian. Without this Gaussian projection or a similar approximation, repeated eligibility signals would generate non-Gaussian posteriors that cannot be summarized by their mean and covariance, requiring the full posterior distribution to enter the household state. This would make solving household consumption functions prohibitively costly under the global solution approach used in this paper.

## G.4 Filtering accuracy

To evaluate the Gaussian approximation, I compare it with a reference Bayesian filter that retains the non-Gaussian distribution. Both filters receive the same simulated histories of wages, eligibility, payments, and debt. The comparison therefore evaluates the filtering approximation for a given simulated equilibrium.

Table 20 reports errors in output beliefs, posterior uncertainty, and predicted eligibility next quarter. Output-belief errors are normalized by the household's posterior standard deviation. The root mean squared error is 4.4% of that standard deviation across all observations, with a bias of 0.2%. Households' uncertainty about current output is approximately 2% of output, so the belief discrepancy is small relative to the uncertainty they face.

**Table 20:** Accuracy of the Gaussian filtering approximation

| | Output belief | | Posterior uncertainty | Eligibility |
|---|---|---|---|---|
| | RMSE | Bias | RMSE | RMSE |
| | (% of posterior s.d.) | | (%) | (pp) |
| All observations | 4.4 | 0.2 | 3.1 | 0.09 |
| Near the cutoff (5%) | 7.0 | 0.2 | 8.2 | 0.13 |

Notes: Gaussian approximation relative to reference Bayesian beliefs in the model targeting the bottom half of the income distribution. RMSE denotes root mean squared error across households and quarters. Output-belief errors and bias are expressed as percentages of the household's posterior standard deviation of output. Errors in posterior uncertainty are reported in percent, and errors in next-quarter eligibility probabilities in percentage points. The near-cutoff group consists of observations for which the eligibility threshold lies within one posterior standard deviation of the household's output belief, approximately 5% of observations.

Errors are larger near the eligibility cutoff, where the binary signal is particularly informative. Even in this group, the root mean squared output-belief error is 7.0% of posterior uncertainty. The error in the probability of eligibility next quarter is 0.09 percentage points overall and 0.13 percentage points near the cutoff.

The reported discrepancies arise from the recursive Gaussian approximation. Matching moments reproduces the mean and covariance of each truncated Gaussian exactly, but subsequent predictions start from the projected distribution rather than the full non-Gaussian history. These checks assess that additional approximation separately from the approximation of aggregate dynamics by the perceived law of motion.