Expectation and Wealth Heterogeneity in the Macroeconomy*

Tobias Broer Alexandre Kohlhas Kurt Mitman Kathrin Schlafmann

February 2026

Abstract

We document systematic differences in macroeconomic expectations across U.S. households and rationalize our findings with a theory of information choice. We embed this theory into an incomplete-markets model with aggregate risk. Our model is quantitatively consistent with the pattern of expectation heterogeneity in the data. In comparison to a full-information counterpart, our model suggests substantially increased macroeconomic volatility and inequality. We show through a series of examples that neglecting the information channel can lead to misleading conclusions about the effects of macroeconomic policies. Increasing unemployment insurance or introducing a wealth tax, for example, reduces information acquisition, leading to increases in macroeconomic volatility an order of magnitude larger than in an otherwise identical model without information choice.

JEL codes: D84, E21, E27, E63

Keywords: Expectations, heterogeneity, information

*Broer: PSE (tobias.broer@psemail.eu). Kohlhas: University of Oxford (alexandre.kohlhas@economics.ox.ac.uk). Mitman: IIES, Stockholm University, CEMFI (kurt.mitman@iies.su.se). Schlafmann: Copenhagen Business School (ksc.fi@cbs.dk). For comments and useful suggestions, we thank Adrien Auclert, Zhen Huo, Per Krusell, Tommaso Monacelli, Kristoffer Nimark, Alessandra Peter, Morten Ravn, Matthew Rognlie, Kjetil Storesletten, Laura Veldkamp, Gianluca Violante, Mirko Wiederholt, and seminar and conference participants at various locations. A previous version of this paper was circulated under the title "Heterogeneous Information Choice in General Equilibrium". This research received financial support from Ragnar Soderberg Stiftelsen and the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (Grant agreement No. 759482). Broer and Kohlhas thank the Institut Universitaire de France and the John Felt Fund for financial support, respectively. Mitman gratefully acknowledges the support of the Riksbankens Jubileumsfond, the Ministerio de Ciencia, Innovación y Universidades Grant IneqEx, and the Swedish Research Council Project Grant 2023-01635. Schlafmann acknowledges financial support from the Danish Finance Institute (DFI).

1 Introduction

Expectations have been part of the bedrock of modern macroeconomics since the "rational expectations revolution" pioneered by Robert E. Lucas, Jr., in the 1970s. The prevailing paradigm—the full-information and rational expectations framework—posits that all households, at all moments in time, have the same expectations about the macroeconomy. Building on the work of Muth (1961) and several others, Mankiw *et al.* (2003) contrast this prediction with survey data on expectations, showing instead the profound dispersion of expectations that exists among households. Recent empirical work has stressed that household expectations are not only heterogeneous but also correlate systematically with household characteristics. This creates systematic heterogeneity in both the level and accuracy of expectations across the distribution of households (e.g., Carroll, 2003; Lusardi and Mitchell, 2014; Coibion *et al.*, 2018; Weber *et al.*, 2022). Given the importance of expectations to macroeconomics, it seems central to have a theory of expectation formation that is consistent with the data.

In this paper, we develop a theory of information choice that we embed into a standard heterogeneous-agent model with aggregate risk. Our main contribution is to provide the first, to our knowledge, heterogeneous-agent model that allows for the study of the macroeconomic consequences of systematic differences in expectations. Our quantitative-theoretical framework can capture both the rich differences in expectations, observed in the data, as well as those that exist in wealth, income, and employment status. Heterogeneity in income, wealth, and employment status on its own significantly impacts the response of the economy to shocks (e.g., Krueger *et al.*, 2016; Kaplan and Violante, 2018). We use our framework—disciplined by survey data—to assess the consequences of the expectation-wealth nexus for understanding aggregate fluctuations and the distribution of wealth. We then explore how the presence of heterogeneous expectations can also modify the efficacy of macroeconomic policies.

We first provide new evidence on the heterogeneity in household expectations using U.S. micro-level data. We show that in a leading household survey (the New York Fed's Survey of Consumer Expectations) both the mean and self-reported uncertainty of stated forecasts of key macroeconomic variables differ substantially across households. Importantly, we document that the accuracy of household expectations is systematically related to household wealth: All else equal, wealthier households have more accurate expectations; however, unlike the evidence in Carroll (2003) and Vissing-Jorgensen (2003), this relationship is far from clearly monotone—especially at the lower-end of the wealth distribution, where the accuracy of household expectations appears to decline with financial wealth.[1]

[1] A burgeoning literature has begun to document the various ways in which household and firm expectations differ from one another and within groups (e.g., Coibion *et al.*, 2018; Coibion *et al.*, 2020; Reis, 2020; Andrade *et al.*, 2022; and Macaulay and Moberly, 2022). We contribute to this line of research by providing new evidence on the systematic (non-monotone) relationship between the accuracy of expectations and household wealth. Our estimates of the effects of other characteristics (e.g., education and sex) are consistent with those

Next, we embed dynamic information choice into an otherwise standard business-cycle model with idiosyncratic risk and incomplete markets, to explore households' heterogeneous incentives to acquire information. In the model, households form expectations about future returns, wages, and unemployment risk, to determine their optimal consumption-savings choices, and acquire costly information about the state of the economy to do so. The information that households can acquire approximates the optimal signal that households would choose to design. The gains to acquiring this information depend on household wealth, employment status, and prior beliefs, leading to systematic heterogeneity in expectations.

While prior work has examined the financial and macroeconomic consequences of costly information choices, it has primarily focused on once-and-for-all information choices that are identical across time and decision-makers (Grossman and Stiglitz, 1980; Sims, 2003; Hellwig and Veldkamp, 2009; Veldkamp, 2011; and Maćkowiak *et al.*, 2021). In contrast, in our model, households make *dynamic information choices* that depend on *individual characteristics* at any point in time. We refer to our synthesis of a heterogeneous-agent economy with a model of dynamic information choice—and hence heterogeneous expectations—as `HetExp`.

We show how to adapt results from the heterogeneous-agent literature to provide a novel solution method for GE frameworks with dynamic information choices and non-linear decision rules. Solving heterogeneous-agent models with aggregate risk and non-linear decision rules is challenging. Our framework adds a further layer of complexity by allowing for heterogeneity also in expectations. We develop a tractable method to tackle these challenges. In closely-related work, Auclert *et al.* (2020) and Carroll *et al.* (2020) analyze a heterogeneous-agent economy with *exogenous* information, based on Mankiw and Reis (2002) and Carroll (2003), and (partially) linearized policy rules. We document how the endogeneity of information and a fully non-linear approach profoundly alter the macro consequences of incomplete information.

Using our solution method, we calibrate our model framework to match key features of U.S. macro and micro data. The model-generated distribution of household expectations rationalizes the survey evidence. Heterogeneous information choices—consistent with the data—naturally arise from differences in wealth and employment status that are the fundamental characteristics of heterogeneous-agent economies. To understand households' heterogeneous incentives to acquire information—and to highlight how they can profoundly shape macroeconomic outcomes—it is instructive to understand households' savings decisions.

Consider first *unemployed households,* who dissave to smooth consumption. The poorest—those at the borrowing constraint for all states in the next period—have no benefit from acquiring information. By contrast, unemployed households with modest wealth have substantial benefits, as savings mistakes are costly near the borrowing constraint. This is due to

found in the literature (e.g., Lusardi and Mitchell, 2014), lending further support to our findings.

the curvature of both the utility and policy functions being high. As wealth then increases, the value of information initially declines. In this region, errors about future labor-market prospects and capital returns push saving in opposite directions: Optimistic expectations about the job-finding rate reduce precautionary savings, while expecting a higher return on capital raise savings through intertemporal substitution. In the middle of the distribution, these two effects partially offset each other, temporarily lowering the value of information. At even higher wealth levels, financial assets eventually comprise the bulk of household resources and return risk, as a result, dominates, leading to increasing information acquisition.

The value of information for *employed households* is similar to that of wealthy unemployed households: Employed households always have (relatively) higher income, and thus cash-at-hand, compared to unemployed, and separation rates are small. The value of additional information about the state of the economy, as a result, starts low and then rises with wealth.

We show that such heterogeneity in information choices substantially alters the equilibrium properties of the economy relative to the full-information benchmark, in which all households have full information (and hence common expectations) about the state of the economy.

On *the micro level*, heterogeneous information choices feed back into wealth and income inequality, as differently informed households make disparate savings choices. Indeed, the introduction of heterogeneous information moderately exacerbates inequality. In particular, poor households with incomplete information are unable to exploit periods of good labor market prospects and high returns to build up financial wealth; wealthy households with incomplete information are likewise unable to effectively increase consumption and run down savings when higher future returns increase their permanent income. Both groups in response acquire information at higher rates than average, yet still face substantial information frictions in equilibrium. The introduction of heterogeneous incomplete information, as such, modestly (but non-trivially) mitigates the lack of wealth inequality that exists in standard frameworks.

On *the macro level*, the presence of uninformed households leads to an increase in business-cycle volatility, due to a stronger endogenous propagation of shocks. Under full information, household savings are procyclical; but as the aggregate capital stock rises in booms, the return on savings falls, dampening the procyclicality of the savings response. By contrast, uninformed households' expectations about returns are sluggish to adjust, which makes household savings more procyclical and the economy more volatile than under full information. This mechanism is itself somewhat dampened by increased information acquisition, due to the benefits of information about the economy being higher when the economy is more volatile. In equilibrium, not all households acquire information in every period, leading to 5-11 percent larger fluctuations in consumption and output relative to the full-information case.

Importantly, we show that these micro and macro results—and the mechanisms behind them—extend to alternative versions of our model that, for example, consider alternative information cost structures and features of U.S. labor-income taxes. A prominent issue with the Aiyagari-Bewley-Huggett-Imrohoroglu class of models that we depart from is that it does not generate realistic wealth heterogeneity: The data display significantly more skewness in wealth than the models. Using an extension that builds on Bayer *et al.* (2024), in which a fixed share of wealthy entrepreneurs receive all pure profits in the economy, we show that our results nevertheless carry over to a framework that better matches the wealth distribution.

A key implication of our framework is that the interaction between wealth and information choice alters the endogenous propagation of aggregate shocks. Because households with different wealth levels respond differently to information frictions, incomplete information changes the cyclicality of savings and the persistence of the capital stock, thereby amplifying business-cycle fluctuations. Policies that reshape the wealth distribution therefore also reshape the economy's information structure and can meaningfully modify aggregate dynamics relative to standard full-information heterogeneous-agent models. To demonstrate this, in the final part of the paper, we consider two popular policies to reduce inequality that directly affect the wealth-expectation nexus: (i) a wealth tax, modeled on the French tax system and the recent proposal in the U.S. Congress;[2] and (ii) an increase in unemployment benefits.[3] Both policies disproportionately affect the resources available to one of two groups—the rich and the poor, respectively—that we find acquire information at higher rates than average.[4]

The direct impact of *the wealth tax* is to decrease household wealth; its indirect effect is to reduce information acquisition, as information on average rises with wealth. By reducing the information in the economy, business-cycle volatility rises by 6 percent. In contrast, in the full-information case, the wealth tax has virtually no impact on aggregate volatility, despite a similar fall in aggregate wealth. The effect of the wealth tax on inequality is similarly surprising: A one percent tax hardly changes the Gini coefficient. As in the full-information case, the lump-sum rebate of the wealth tax, and the disincentive effect from lower after-tax returns, reduce savings across the wealth distribution—and hence inequality. However, in the `HetExp`-economy, this decline is countered by the increased "randomness" of savings, as information acquisitions fall. This, in turn, leads to larger over-accumulation of savings for uninformed, high-wealth households and more savings mistakes by the poor. Our framework,

[2] For a description of the French wealth tax that used to operate, see, for example, `https://www.service-public.fr/particuliers/vosdroits/N20074`. The "Warren 2021 proposal" can be found here: `https://www.congress.gov/bill/senate-bill/510`.

[3] Specifically, we consider a 1 percent per annum wealth tax and an increase in the replacement rate from 40 to 50 percent of current wages.

[4] Notice that the policy reforms considered here are stylized and we focus more on the qualitative impacts than the quantitative numbers, as a proper treatment of these first-order public finance questions would require a more comprehensive model framework. Our focus is mainly on illustrating how taking into account heterogeneity in information choice can fundamentally alter, or even reverse, the consequences of policies that have a first-order impact on the wealth distribution.

thus, provides one rationale for why several countries did not see increases in wealth inequality following the abolition of wealth taxes (e.g., Jakobsen *et al.*, 2020)

The impact of *increased unemployment benefits* on the aggregate economy is akin to the effect of the wealth tax: Average wealth in the economy decreases—caused, in this case, by a reduced need for precautionary savings by poor households—and information acquisitions falls. In equilibrium, this fall in information once more substantially raises aggregate volatility (by 4 percent) and inequality also rises. While both our benchmark economy and the full-information economy generates an increase in inequality and a fall in wealth, only the HetExp economy generates additional business-cycle amplification through the information channel.

Overall, both policy experiments suggest that the consequences of dynamic, heterogeneous information choices may substantially alter the relative costs and benefits of macroeconomic policies. Our findings, thus, imply a Lucas-style critique (Lucas, 1976) of policy evaluations in full-information heterogeneous-agent models: Policies that reshape the wealth distribution also reshape an economy's information structure and thereby substantially modify economy-wide dynamics relative to the predictions standard full-information heterogeneous-agent models.

Finally, three wider implications of our framework are worth noting. First, in our analysis we for simplicity abstract from any behavioral drivers of information choices (e.g., Bordalo *et al.*, 2016; Bordalo *et al.*, 2017; and Gabaix, 2019), as well as any relationship between, for example, education, gender, and household information (e.g., Lusardi and Mitchell, 2014 and Reiche, 2025). Notwithstanding such alternative drivers, we show that households' rational incentives to systematically acquire different information, depending on their wealth and employment status, fundamentally alter business-cycle dynamics and the consequences of redistributive macroeconomic policies. We conjecture that behavioral heuristics, salience effects, and other household drivers of information choices would only increase the gap between the predictions of standard models and those relevant for macroeconomic policy.

Second, our emphasis on households' rational information choices, highlighting that wealth-poor households produce forecasts of close-to commensurable accuracy to wealth-rich, connects with the small-scale surveys in Harrington (1997), Shipler (2005), Newman (2009), Morduch and Schneider (2017), and others, showing that poor and working-class households are often substantially more aware of local conditions, prices, and opportunities, and devote more mental resources to tracking economic conditions, than wealthier households. We surmise that accounting for the full scale of such effects would only lead to a richer relationship between household informativeness and wealth than that detailed below. Our work is similarly closely related to that in finance, documenting that informed, wealthier investors often earn higher returns, which contributes to inequality among traders (e.g., Peress, 2004; Kacperczyk *et al.*, 2019; and Mihet, 2022). Our work, in part, accounts for a similar mechanism.

Lastly, because of the complexity of computing rational expectations equilibria in neoclassical heterogeneous-agent economies, several authors have proposed dimensionality reduction methods (e.g., Moll, 2024). Most notably, Krusell and Smith (1998) propose constraining households to only form their expectations based on a limited set of moments. Through this lens, our approach is to allow households themselves to decide which variables (or moments) to use to forecast the future state of the economy. In this sense, our framework presents a natural evolution of the Krusell and Smith (1998) computational approach.

2 Motivating Evidence

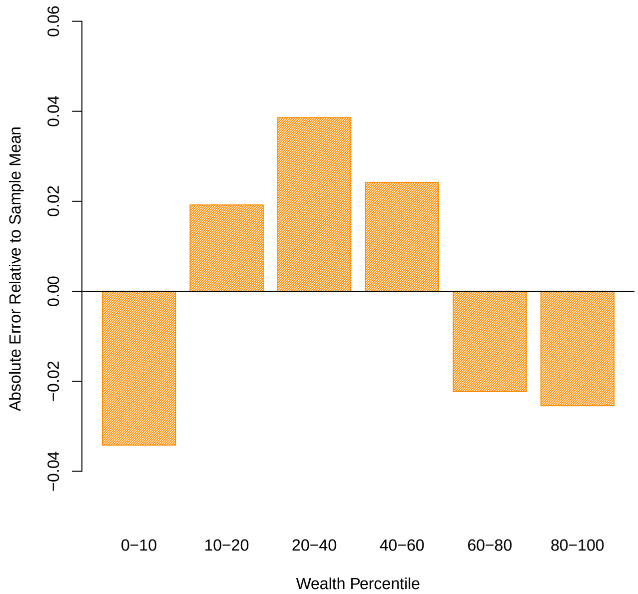
We present new evidence on the relationship between household wealth and the accuracy of household expectations. To do so, we use micro data on household expectations from the *Survey of Consumer Expectations (SCE).* The SCE is a monthly panel of point and density forecasts for several macroeconomic and financial variables. In addition, the survey contains detailed data on household economic characteristics.[5] We link the monthly SCE expectation survey with the SCE's supplemental survey of household finances, which includes detailed data on household wealth and its composition. The merged SCE sample covers the period 2013M8-2020M1. Appendix A provides more information on the sample construction.

We explore the relationship between the accuracy of household expectations and their wealth. To do so, we first focus on household forecasts of the one-year-ahead unemployment rate, as unemployment represents the main source of income risk for many households. As such, perceived unemployment risk is a main driver of households' consumption and savings choices. We later include unemployment into our structural framework. We define a respondent's forecast error as the difference between the actual outcome and the respondent's forecast. A negative error thus corresponds to an over-estimate of the variable. The SCE ask respondents for the "probability that the unemployment rate is higher 12-months from now". Unlike other variables (e.g., inflation) for which we can observe realized outcomes, the probability of unemployment rising is not objectively known. We proxy the true-but-unobserved probability of rising unemployment with the average probability computed from the *Survey of Professional Forecasters.* We make this choice because professional forecasters often provide more accurate predictions than even those from modern statistical and economic models.[6] We later show how our results are robust to other proxies of the probability of rising unemployment and extend to variables for which realized outcomes are objectively known.

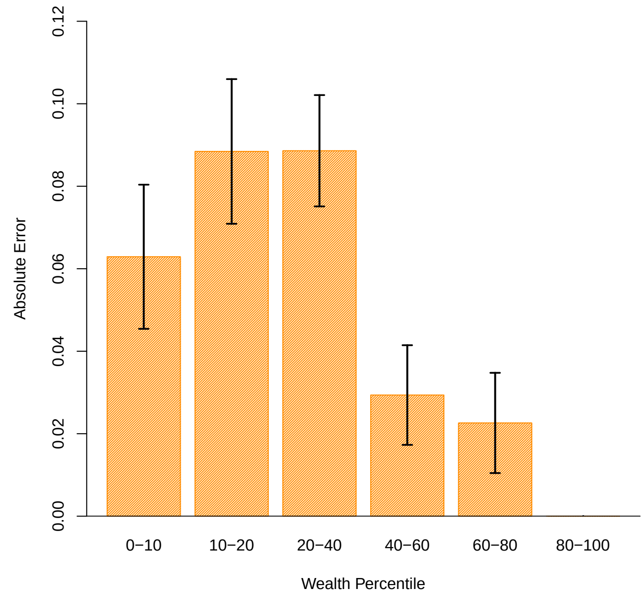
[5] Armantier *et al.* (2017) provide an overview of the construction and scope of the Survey of Consumer Expectations, administered monthly by the Federal Reserve Bank of New York.

[6] See, for example, Stark *et al.* (2010), Faust and Wright (2013), and Bhandari *et al.* (2025). For interpretability reasons, we also scale the value of unemployment forecast errors in the data with the average proxied probability of rising unemployment, to approximate the "Brier score" (Appendix A).

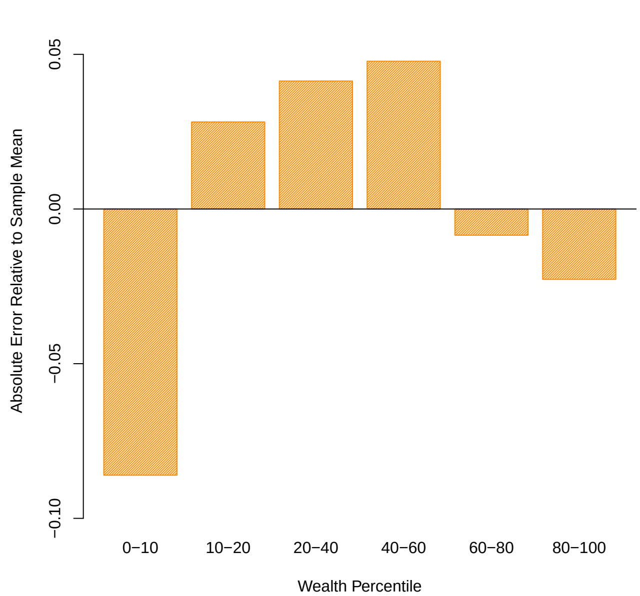
Figure 1: Unemployment Expectations Across the Wealth Distribution



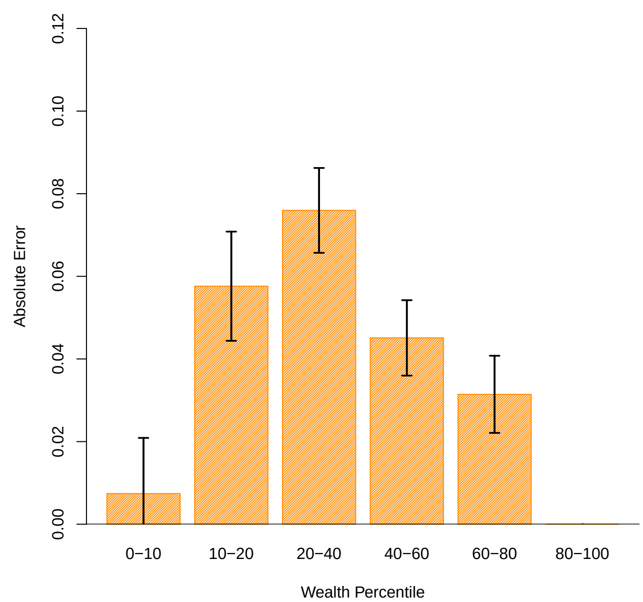
Panel (a): Relative Accuracy (SPF)



Panel (b): Coefficient on Wealth (SPF)



Panel (c): Relative Accuracy (BVAR)



Panel (d): Coefficient on Wealth (BVAR)

Note: Panel (a) plots the difference between the average one-year-ahead accuracy of unemployment forecasts within wealth deciles/quintiles and the overall average taken across all wealth levels. The true probability is proxied by the average probability of rising unemployment from the SPF (Appendix A.2). Panel (b) plots the coefficient estimates on wealth from a regression of the absolute value of individual errors on the wealth decile/quintile the respondent belongs to, controlling for the age, education level, labor market status, and sex of the respondent, as well as time fixed effects. Estimates are relative to the wealthiest households, those in the 80-100 percentile of the wealth distribution. Whisker-intervals correspond to one-standard deviation robust confidence bounds (Table A.8). Panel (c) and (d) proxy the true probability of rising unemployment with that from a standard forecasting VAR (Online Appendix A.3). Sample: 2013M10-2020M1.

We begin by documenting a systematic correlation between household forecast errors and household wealth. Panel (a) in Figure 1 shows a marked, non-monotone relationship between household wealth and the accuracy of household expectations in the raw data. All else equal, wealthier households produce more accurate forecasts; however, in contrast to the findings of Carroll (2003) and Vissing-Jorgensen (2003), this pattern is only discernible for households that are above the 20th percentile of the wealth distribution. The poorest households—those between the 0-10th percentile of the wealth distribution—produce unemployment forecasts that are of comparable accuracy to those of the wealthiest households. All else equal, this suggests that household expectations are *heterogeneous* across the wealth distribution.

The relationship in Panel (a) in Figure 1 may be contaminated by idiosyncratic factors, such as labor-market status, or aggregate shocks that can simultaneously affect household wealth and the accuracy of expectations. To address this issue, Panel (b) in Figure 1 plots the coefficient estimates from a regression of the accuracy of individual expectations on the household wealth-decile/quintile controlling for household characteristics and time fixed effects. The regression coefficients exhibit a similar non-monotonic relationship to that in the raw data. All else equal, wealthier households make more accurate unemployment forecasts; yet the accuracy of households in the bottom decile is higher than those between the 20-40th percentile, although the difference is not statistically significant at conventional levels. The magnitudes are also meaningful: Considering a household in the 30th percentile of the wealth distribution instead of the 90th percentile, all else equal, decreases the accuracy of the household's expectations by around 9 percent. To benchmark the magnitude, having a university degree is estimated to only increase accuracy by 7 percent (Table A.8).[7] Crucially, Panel (c) and (d) in Figure 1 show that our results also extend to cases where we proxy the probability of rising unemployment with that computed from a standard forecasting VAR (Christiano *et al.*, 2005; Del Negro *et al.*, 2007), while Table A.10 in the Appendix shows that our results further extend to the case in which we directly control for the percentile rank of respondents in the wealth distribution. This illustrates the robustness of our findings.

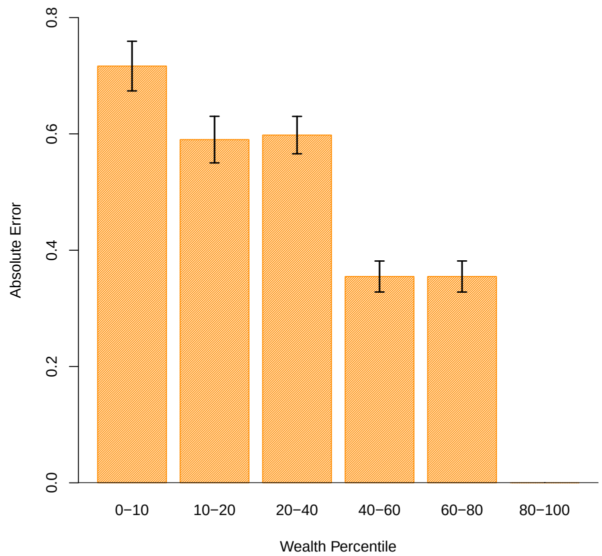
Clearly, the estimates in Figure 1 cannot be interpreted as causal, as a household's wealth and the accuracy of its expectations are determined jointly (e.g., Section 3). That said, the evidence is clearly at odds with the assumption of common expectations embedded at the heart of the full-information rational expectations framework, showing instead that the state of household finances is closely tied to households' economic expectations.

We show that the systematic relationship between household wealth and the accuracy of

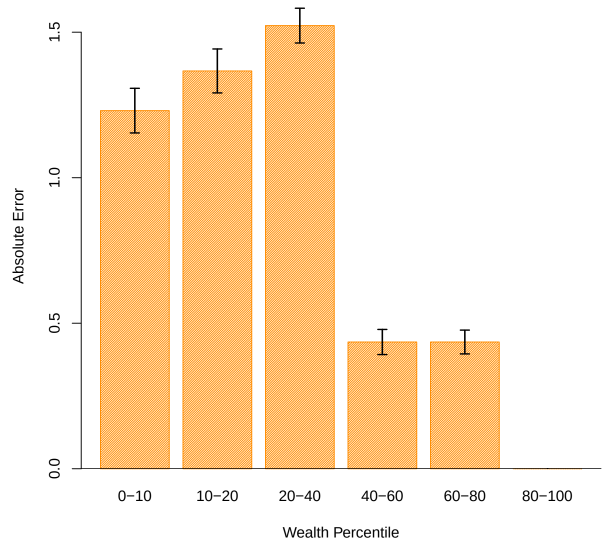
[7] Our results on education are consistent with the findings of Lusardi and Mitchell (2014), among others, who show that education, in part, through its impact on financial literacy improves households' forecast accuracy. The focus of our analysis is on the three-way relationship between wealth, unemployment, and information, which is why we abstract from the influence of education in what follows.

Figure 2: Inflation and House Prices Expectations Across the Wealth Distribution

Panel (a): Inflation Forecasts

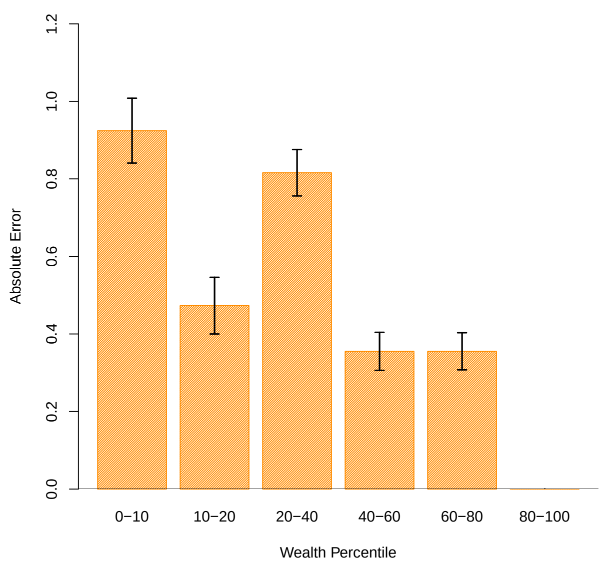


Actual Accuracy

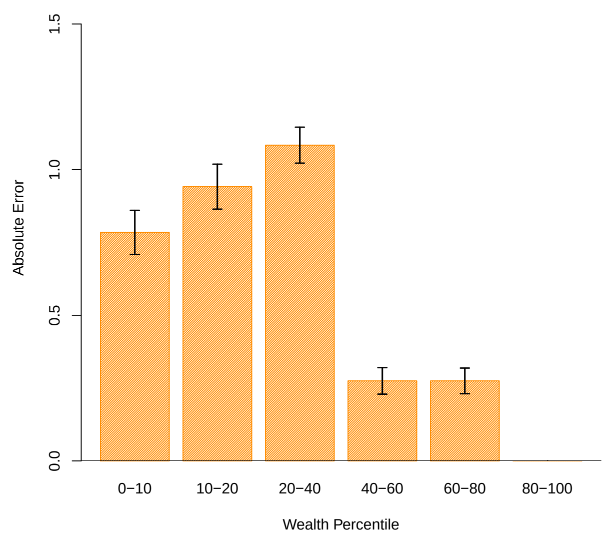


Perceived Accuracy

Panel (b): House Price Forecasts



Actual Accuracy



Perceived Accuracy

Note: Panels (a) to (d) show the *actual* and *perceived* accuracy of individual forecasts of one-year ahead CPI inflation and the annual growth rate of U.S. house prices, respectively. All panels plot estimates from regressions of individual (actual or perceived) accuracy on the wealth decile/quintile the respondent belongs to, controlling for the age, education level, labor market status, and sex of the respondent, as well as time fixed effects. All estimates are relative to the wealthiest households, those in the 80-100 percentile of the wealth distribution. "Actual accuracy" corresponds to the absolute value of individual forecast errors, while "perceived accuracy" corresponds to the interquartile range of the reported probability distribution of the future outcome. Whisker-intervals are one-standard deviation robust confidence bounds. Sample: 2013M10-2020M1.

expectations extends to other macroeconomic variables. We perform the same analysis for household forecasts of one-year-ahead inflation and the growth rate of house prices. We use real-time data to measure the realizations of inflation and house prices, to capture the precise definition of the variable being forecasted. Figure 2 summarizes the estimates. For both variables, Figure 2 also includes the *perceived accuracy* of individual forecasts, as measured by respondents' interquartile range of their stated probability distribution of future outcomes. All estimates show that wealthier households make more accurate forecasts and perceive themselves to be less uncertain. Apart from inflation, all measures of uncertainty are also higher for households near the 20-40th percentile of the distribution than for poorest households.

Table A.9 in the Appendix uses the "worst-case" Likelihood Ratio test developed by Silvapulle and Sen (2005) to explicitly test for the monotonicity of the regression coefficients in Figure 1 and 2.[8] As evident, 6 of the 8 tests reject the null hypothesis at the 10 percent level, providing instead evidence in favor of an inverse-u-shaped relationship between wealth and the accuracy of expectations. Finally, in Appendix A.2 we perform additional robustness exercises. There, we furthermore show that, compared to professional forecasters, household expectations are more dispersed, less accurate, and perceived to be more uncertain. We will later leverage these additional moments to discipline our structural framework.

In summary, the results in this section provide evidence for systematic heterogeneity in the accuracy of household expectations. The data clearly reject the common-expectation assumption embedded in the full-information rational expectations framework. Motivated by these findings, in the next section, we extend a workhorse incomplete-markets economy to allow for heterogeneity in the accuracy of household expectations. We then proceed to quantify the impact of heterogeneous expectations for positive and normative questions.

3 Model Framework

In this section, we describe a workhorse incomplete-markets model with idiosyncratic and aggregate risk. The model extends the environment in Krusell and Smith (1998) with a modified information structure. In particular, we assume that every period households have the option to acquire information about the state of the economy.

[8] Note that, because the regression coefficients are only set-identified under the null hypothesis, the LR test corresponds to a "worst-case test"—it uses the coefficients most in line with the null hypothesis. This makes any rejection of the null difficult, but conversely also implies that any rejection provides strong evidence against the null, which we interpret as evidence in favor of a humped-shaped relationship.

3.1 Households

The economy consists of a continuum of heterogeneous households $i \in [0, 1]$, whose preferences over streams of consumption and information are described by the utility function:

$$\mathcal{U}_i = \mathbb{E}_{i0} \sum_{t=0}^{\infty} \beta^t \left[\frac{c_{it}^{1-\gamma} - 1}{1-\gamma} - \kappa_{it} \left(\mathcal{I}_{it} \right) \right], \tag{3.1}$$

where $\mathbb{E}_{i0} [\cdot] \equiv \mathbb{E} [\cdot \mid \Omega_{i0}]$ denotes household i's expectations conditional on its period-0 information set Ω_{i0}, β the effective discount factor between two periods, c_{it} non-durable consumption at time $t = \{0, 1, 2, \ldots\}$, κ_{it} the utility cost of acquiring information $\mathcal{I}_{it}$, and $\gamma > 0$. The effective discount factor $\beta = \rho b$, where $1 - \rho \in (0, 1)$ and $b \in (0, 1)$ are the per-period probability of death and the per-period discount factor, respectively.[9] The household's information set Ω_{it} accumulates according to $\Omega_{it} = \{\mathcal{I}_{it}, \Omega_{it-1}\}$.[10] The utility cost κ_{it} follows a type-I extreme value distribution with scale parameter α_κ, and is i.i.d. across households, time, and signals acquired. We introduce the extreme value shocks to account for unobserved heterogeneity in the survey data and to account for any utility costs of information processing.

Each household is endowed with $\bar{l}$ units of time, which it supplies inelastically to the labor market. Labor productivity ϵ_{it} is stochastic and can take on two values, $\epsilon_{it} \in \{0, 1\}$, which we interpret as unemployment and employment, respectively. We assume that ϵ_{it} follows a two-state, first-order Markov process $\Pi_{z_{t+1}, \epsilon_{it+1} | z_t, \epsilon_{it}}$, which depends on ϵ_{it} and aggregate total factor productivity z_t (described below). A household earns wage w_t when employed and receives unemployment benefits μw_t when unemployed, where the replacement rate equals $\mu \in (0, 1)$. We assume that households cannot borrow but can save in physical capital k_{it}, whose net return equals $r_t - \delta$, where r_t denotes the stochastic rental rate and $\delta \in (0, 1)$ the depreciation rate of capital. Households have access to perfect annuity markets.[11]

In addition to the borrowing constraint and a non-negativity constraint on consumption, household consumption-saving choices are restricted by the per-period budget constraint:

$$c_{it} + k_{it+1} = (1 + r_t - \delta) \rho^{-1} k_{it} + (1 - \tau_t) \left[\epsilon_{it} w_t \bar{l} + (1 - \epsilon_{it}) \mu w_t \right] - \eta(\mathcal{I}_{it}), \tag{3.2}$$

where $\eta(\mathcal{I}_{it})$ denotes the resource cost of acquiring $\mathcal{I}_{it}$, and τ_t is the tax rate on income. We refer to the right-hand side of (3.2) as a household's *cash-at-hand after choosing to acquire information*, and denote it by m_{it} in what follows. A household maximizes utility (3.1) subject to the budget constraint (3.2) and non-negativity constraints on c_{it} and k_{it+1}.

[9] Consistent with this, a fraction $1 - \rho$ of households are born every period with zero initial wealth.

[10] We will, ultimately, analyze the model beginning at $t >> 0$, such that the economy has settled into its ergodic distribution and any effects of initial conditions have washed out.

[11] The capital of the deceased is, thus, used to pay an extra proportional return on capital of ρ^{-1} .

3.2 Technology and Markets

The production sector consists of a representative competitive firm, which maximizes profits. Output Y_t is produced using a Cobb-Douglas technology,

$$Y_t = z_t K_t^{\alpha} \left(L_t \bar{l} \right)^{1-\alpha}, \tag{3.3}$$

where K_t and L_t denote aggregate capital and employment in period t, respectively. Aggregate productivity z_t is stochastic and follows a first-order Markov process that takes two values, $z_t \in \{z_l, z_h\}$ with $z_h > z_l$. The firm rents capital and labor in competitive markets, so that factor prices for labor w_t and capital r_t are given by their respective marginal products:

$$w_t = (1-\alpha) z_t \left(\frac{K_t}{\bar{l} L_t} \right)^{\alpha}, \quad r_t = \alpha z_t \left(\frac{K_t}{\bar{l} L_t} \right)^{\alpha - 1}. \tag{3.4}$$

Finally, we assume that the share of households in a given idiosyncratic employment state only depends on the current value of productivity z_t. Hence, the unemployment rate u_t is a function only of z_t, and thus only takes on two values, u_h and u_l with $u_h < u_l$.

3.3 Government Policy

In our baseline analysis, the government runs a balanced-budget unemployment insurance scheme, such that $\tau_t = \frac{\mu u_t}{\bar{l} L_t}$. Appendix C.4 and Section 5.4 discuss an alternative setup with acyclical income taxes. We consider a tax on household wealth and the response of the economy to changes in the replacement rate μ in Section 6.

3.4 Timeline and Information Structure

At the start of each period, idiosyncratic $(\epsilon_{it}, \kappa_{it})_i$ and aggregate shocks (z_t) realize. Firms rent capital and labor, production takes place, and factor prices are determined. Households, who do not observe the realization of aggregate shocks but know the savings they brought into the period and their employment status, then choose which signals $\mathcal{I}_{it}$ to acquire about the current state of the economy from a maximum signal set $\mathcal{I}^{\max}$.[12] We assume that $\mathcal{I}^{\max}$ does not contain sufficient information for households to perfectly learn the current state of the economy, but that it does include elements of the state-space relevant for future prices (see below).[13] Finally, conditional on information choices and factor payments, households

[12] We assume a household that is born in period t inherits the information set of its "parent" (i.e., the corresponding household that died in period t). We experimented with different assumptions about the informativeness of recently born households and found that it makes little difference to our results below.

[13] An alternative approach is to instead allow households to flexibly design their optimal signal subject to a utility cost (e.g., Maćkowiak *et al.*, 2018). Such an optimal signal can, however, always be reduced to a

make consumption and savings choices (c_{it} and k_{it+1}, respectively) and the period ends.

3.5 Recursive Formulation of the Household Problem

Given the timeline and informational assumptions, we develop a recursive formulation of the household problem. Let $S = (\Gamma, z)$, where Γ denotes the cross-sectional distribution of capital and employment status. We denote an individual household's first-order belief about S by $\mathcal{P}_i(S)$.[14] Household i's second-order belief about household $j \neq i$'s belief is referred to as $\mathcal{P}_{ij}(S)$, and so on *ad infinitum*. Individual household beliefs are summarized by the object p_i, which includes the infinite-set of household (higher-order) beliefs. Let $\mathcal{P}$ denote the cross-sectional distribution of all such beliefs.[15] The *aggregate state* of the economy can then be described by $\Sigma = (S, \mathcal{P})$, while the *individual state* variables at the stage in which consumption and savings choices are made (*Stage 2*) are described by $\sigma_{i,2} = (m_i, \epsilon_i, p_i)$, where m_i is household i's cash-at-hand *net* of information costs. We denote next period's realization of variable x by x' and previous period's realization by x_{-1}. The individual state variables at the stage where information choices are made (*Stage 1*) are $\sigma_{i,1} = (k_i, \epsilon_i, p_{i,-1})$.

Stage 2: At the end of the period, after making its information choices, a household chooses consumption c_i and savings k_i' out of cash-at-hand net of information acquisition costs:

$$\begin{aligned} \mathcal{W}(m_i, \epsilon_i, p_i) &= \max_{c_i, k_i' \geq 0} \frac{c_i^{1-\gamma} - 1}{1-\gamma} + \beta \mathbb{E}\left[\mathcal{V}(k_i', \epsilon_i', p_i) \mid \Omega_i\right] \\ \text{subj. to} & \\ c_i + k_i' &= m_i \end{aligned} \tag{3.5}$$

where $\mathcal{W}(\sigma_{i,2})$ and $\mathcal{V}(\sigma_{i,1})$ are a household's value functions *after* and *before* information acquisition, respectively, and the expectation is taken using today's updated information set Ω_i. We let $g(\cdot)$ denote the function that characterizes a household's savings choice (i.e., $k_i' = g(\sigma_{i,2})$), while $h(\cdot)$ characterizes its consumption choice (i.e., $c_i = h(\sigma_{i,2})$). We assume that households rationally use the equilibrium law of motion for the aggregate state, which we denote by H (i.e., $\Sigma' = H(\Sigma)$), to form their prior expectation about tomorrow's state—and hence wealth k_i' embedded in $\sigma_{i,1}'$—from today's posterior beliefs. *Stage 2* posterior beliefs

signal of some combination of state variables, which the above approach in principle allows for. Furthermore, although the information-design approach has several advantages, it is computationally intractable for the non-linear, non-quadratic model that we study (see also Sections 3.5 and 3.7).

[14] Not to be confused with the Powerset, $\mathcal{P}_i$ here has a distribution with $\hat{\Gamma}_i$ and $\hat{z}_i$ as its typical elements, representing household i's first-order belief about the mass of capital and employment status at some point, as well as the household's beliefs about productivity, respectively. $\mathcal{P}_i$ is hence a distribution over distributions.

[15] More formally, we can describe $p_i = \left\{\mathcal{P}_i, (\mathcal{P}_{ij})_{j\in[0,1]}, ..., (\mathcal{P}_{ij...k})_{j,...,k\in[0,1]^{n-1}}, ...\right\}$, while the cross-sectional distribution of such beliefs $\mathcal{P} = \left\{(\mathcal{P}_i)_{i\in[0,1]}, (\mathcal{P}_{ij})_{i,j\in[0,1]^2}, ..., (\mathcal{P}_{ij...k})_{i,j,...,k\in[0,1]^n}, ...\right\}$.

p_i are linked to *Stage 1* priors $p_{i,-1}$ through Bayes' Rule and the information choice $\mathcal{I}_i$ the household makes in *Stage 1*.

Stage 1: At the beginning of the period, households choose what information to acquire:

$$\begin{aligned}\mathcal{V}\left(k_i, \epsilon_i, p_{i,-1}\right) &= \max_{\mathcal{I}_i \subseteq \{\emptyset \cup \mathcal{I}^{\max}\}} \mathbb{E}\left[\mathcal{W}\left(m_i, \epsilon_i, p_i\left(\mathcal{I}_i\right)\right) - \kappa_i(\mathcal{I}_i) \mid \Omega_{i,-1}\right] \\ \text{subj. to} & \\ m_i &= \left[1 + r\left(\Sigma\right) - \delta\right]\rho^{-1} k_i + \left(1 - \tau\right)\left[\epsilon_i w\left(\Sigma\right)\bar{l} + \left(1 - \epsilon_i\right)\mu w\left(\Sigma\right)\right] - \eta\left(\mathcal{I}_i\right).\end{aligned} \tag{3.6}$$

Recall that information acquisition entails *both* a utility cost $\kappa\left(\mathcal{I}_i\right)$ and a resource cost $\eta\left(\mathcal{I}_i\right)$—and that individual states and expectations themselves also depend on the information choice $\mathcal{I}_i$. A household's expectation in the first stage is computed using previous period's posterior belief $p_{i,-1}$ (and hence information). We let $\iota\left(\cdot\right)$ denote the function that characterizes the household's optimal information choice (i.e., $\mathcal{I}_i = \iota(\sigma_{i,1})$).

The assumption of type-I extreme value shocks for the utility cost of information implies a parsimonious logistic choice function for the probability of acquiring $\mathcal{I}_i \subseteq \{\emptyset \cup \mathcal{I}^{\max}\}$:

$$\text{Prob}\left(\mathcal{I}_i \mid \sigma_{i,1}\right) = \frac{e^{\mathbb{E}\left[\alpha_\kappa \mathcal{W}\left(m_i(\mathcal{I}_i), \epsilon_i, p_i(\mathcal{I}_i)\right) - \kappa_i(\mathcal{I}_i) \mid \Omega_{i,-1}\right]}}{\sum_{\tilde{\mathcal{I}} \subseteq \{\emptyset \cup \mathcal{I}^{\max}\}} e^{\mathbb{E}\left[\alpha_\kappa \mathcal{W}\left(m_i(\tilde{\mathcal{I}}), \epsilon_i, p_i(\tilde{\mathcal{I}})\right) - \kappa_i(\tilde{\mathcal{I}}) \mid \Omega_{i,-1}\right]}}, \tag{3.7}$$

where we suppress arguments other than $\mathcal{I}$ in the policy functions, yielding the value function:

$$\mathcal{V}\left(\sigma_{i,1}\right) = \frac{\gamma_E}{\alpha_\kappa} + \frac{1}{\alpha_\kappa}\log\left(\sum_{\tilde{\mathcal{I}} \subseteq \{\emptyset \cup \mathcal{I}^{\max}\}} e^{\mathbb{E}\left[\alpha_\kappa \mathcal{W}\left(m_i(\tilde{\mathcal{I}}), \epsilon_i, p_i(\tilde{\mathcal{I}})\right) - \kappa_i(\tilde{\mathcal{I}}) \mid \Omega_{i,-1}\right]}\right), \tag{3.8}$$

where γ_E is the Euler-Mascheroni constant (McFadden *et al.*, 1973).

3.6 Recursive Incomplete Information Competitive Equilibrium

The definition of a *Recursive Incomplete Information Competitive Equilibrium* (RIICE) extends the standard definition of a Recursive Competitive Equilibrium to the case with incomplete information: A RIICE is a law of motion $H\left(\cdot\right)$, a pair of individual value functions $\{\mathcal{V}\left(\cdot\right), \mathcal{W}\left(\cdot\right)\}$, policy functions $\{g\left(\cdot\right), h\left(\cdot\right), \iota\left(\cdot\right),\}$, as well as pricing functions $\{r\left(\cdot\right), w\left(\cdot\right)\}$ such that: (i) $\{\mathcal{V}\left(\cdot\right), \mathcal{W}\left(\cdot\right), g\left(\cdot\right), h\left(\cdot\right), \iota\left(\cdot\right)\}$ solve the household's optimization problem (i.e., Equations 3.5-3.6) given $H\left(\cdot\right)$; (ii) $r\left(\cdot\right)$ and $w\left(\cdot\right)$ satisfy firm maximization (i.e. Equation 3.4), (iii) $H\left(\cdot\right)$ is generated by policy functions $g\left(\cdot\right)$, $h\left(\cdot\right)$, and $\iota\left(\cdot\right)$, the Markov process $\Pi_{z',\epsilon'|z,\varepsilon}$, as well as Bayes' Rule, using the information contained in $\left(\mathcal{I}_i\right)_i$ and current beliefs described in $\mathcal{P}$;[16] and (iv) market-clearing conditions hold for capital and goods markets (e.g., for the goods market: $Y(\Sigma) + (1-\delta)K = \int (g(\sigma_{i,2}) + h(\sigma_{i,2}) + \eta [\iota(\sigma_{i,1})])\, di)$.[17]

3.7 Remarks on Modeling Assumptions

The above recursive formulation helps clarify the nature of the two-sided relationship between wealth and information that exists in our model. On the one hand, a household's capital holdings and employment status, in addition to its prior expectation, help determine the extent of the household's information acquisition at the first stage of any period (Equation 3.6). Yet, on the other hand, a household's information choice also helps determine the household's consumption-savings choice in the second stage, through its expectations, and hence the household's future wealth level (Equation 3.5). This two-sided interaction, which we label the *expectation-wealth nexus*, will be central for the aggregate consequences of the accuracy-wealth relationship documented in the data (Section 2).

The recursive formulation further illustrates that our framework falls within the broader class of "noisy rational expectations" models. For example, although households are uncertain about the current state of the economy, they rationally use the law of motion to form their expectations about future productivity conditional on current information—and hence the likelihood of, for instance, future information purchases. As such, our framework is closely related to the work on "costly information acquisition" within rational expectations frameworks (e.g., Grossman and Stiglitz, 1980; Veldkamp, 2011) and its extension to "rational inattention" (e.g., Sims, 2003; Maćkowiak *et al.*, 2021). This literature has primarily restricted itself to studying the implications of once-and-for-all information choices that are identical across time and decision-makers. The contribution of our framework, in this context, is to highlight the macroeconomic consequences of *dynamic, heterogeneous information choices.*[18]

Finally, notice that our benchmark model allows for both a resource cost of information

[16] For example, we can construct the part of $H(\cdot)$ that pertains to the marginal distribution of capital, $H_k(\cdot)$, conditional on employment states and productivity, as follows. For all measurable sets Δk:

$$H_k(\Sigma)(\Delta k, \epsilon, z) = \sum_{\tilde{\epsilon}} \Pi_{\epsilon, z|\tilde{\epsilon}, \tilde{z}} \cdot \int \mathbf{1}\{g[m(k, \tilde{\epsilon}; \Sigma), \tilde{\epsilon}, p] \in \Delta k\} \cdot d\Phi(k, \tilde{\epsilon}, p),$$

where $\Phi(\cdot)$ denotes the joint cross-sectional distribution of (k, ϵ, p).

[17] Notice that the information cost $\eta(\mathcal{I})$ is paid in terms of the numéraire. Thus, the goods-market clearing condition accounts for total information expenditures, $\int \eta(\mathcal{I}_i)\, di$. Baley and Veldkamp (2025) discuss the different assumptions possible for information costs (i.e., whether costs are paid in goods, labor, or capital).

[18] In our framework, we deliberately abstract from the "non-instrumental value" of information and focus only on the consequences that information has on utility through improving decision-making. Brunnermeier and Parker (2005) and Caplin and Leahy (2019), among others, consider the consumption-saving biases that arise when households engage in "wishful thinking", in which expectations maximize average felicity, optimally balancing the benefit of optimism against the costs of worse decision-making.

$\eta(\mathcal{I}_i)$ (Equation 3.6) as well as a utility cost $\kappa_i(\mathcal{I}_i)$ (Equation 3.6). The former captures the physical costs associated with the acquisition of information, while the latter captures the (cognitive) utility costs associated with its processing (e.g., Veldkamp, 2011), in addition to accounting for unobserved heterogeneity in the survey data.[19] Crucially, the latter, for example, also captures the utility costs associated with the processing of market-based information (see below for further discussion). Our calibrated framework in Section 5 highlights the distinctive footprint that each of these information costs has at the aggregate level.

4 Solution Method and Calibration

In this section, we first outline our procedure for computing RIICE equilibria. Our description here is deliberately non-technical. We include it in the main text because our description is intimately linked to the three-way relationship between information choices, consumption-savings decisions, and the macroeconomy that is at the heart of our analysis—and because it illustrates the underlying methodology behind our framework. We then proceed to discuss the specification of the information structure and the calibration of the model.

4.1 Computational Strategy

The endogenous aggregate state variables of our economy, Γ and $\mathcal{P}$, are infinite-dimensional objects. Even the *full-information* version of our incomplete-markets economy therefore presents a computational challenge, because of the high dimensionality of Γ (the endogenous state variable of that model). Our *incomplete-information* framework has a *double-infinity problem*—the additional complexity arising from the entire set of (higher-order) beliefs $\mathcal{P}$ in principle mattering for equilibrium dynamics, depending on the specification of $\mathcal{I}^{\max}$.

The standard strategy for computing incomplete-markets models *without* incomplete information involves approximating the distribution Γ with a finite set of moments $\mathbf{m} \equiv (m_1, m_2, \cdots, m_n)$ (Krusell and Smith, 1998). Accurately forecasting those moments enables households to forecast future prices, which are necessary for solving the household problem. One interpretation of the Krusell-Smith solution method is one of "boundedly rational" expectations, as households only keep track of a limited set of moments of the distribution. Importantly, in this solution method, the information that households use to base their expectations on is *exogenously predetermined* by the researcher—containing productivity z and the moments in $\mathbf{m}$. By contrast, in our model, households *optimally choose* the information on which to form their "boundedly rational" expectations. Thus, one can view our model as

[19] Veldkamp (2011) discusses how a resource cost of information, for example, also captures the costs associated with "getting advice from experts" or out-sourcing decisions. Boccanfuso and Neri (2025) document how a random utility component to attention choices are necessary to match expectations in the SCE.

a natural extension of the Krusell-Smith approach to study incomplete-markets models with aggregate risk, since we provide a micro-foundation for the boundedly-rational solution based on costly information choice. In particular, the Krusell-Smith solution can be seen as the special case in which the cost of information is zero, and $\mathcal{I}_{it} = \mathcal{I}_t^{\max} = \{z_t, \mathbf{m}_t\}$ for all i and t, as a consequence.

In addition to predetermined information, notice that the Krusell-Smith approach also imposes *common knowledge* over both z and $\mathbf{m}_t$, as all households form expectations using the same information. Our framework, by contrast, relaxes the common knowledge assumption by allowing for heterogeneous information choices.[20] The RIICE framework, as a result, allows for the study of the three-way interaction between incomplete common knowledge, aggregate dynamics, and inequality that we focus on below—in contrast to Krusell-Smith.

Our computational strategy can be summarized as follows: Households form priors over the contemporaneous realization of productivity z and over a set of moments of Γ given by $\mathbf{m}$. Given those priors, using Bayes' Rule and the equilibrium law of motion $H(\cdot)$, households form expectations about the future path of wages and the return on capital, necessary to solve their maximization problem. Households then choose what information to acquire about any combination of productivity z and the moments in $\mathbf{m}$, which we include in $\mathcal{I}^{\max}$. If all households acquire information about all elements in $\mathcal{I}^{\max} = \{z, \mathbf{m}\}$ in every period, our equilibrium coincides with the equilibrium concept from Krusell and Smith (1998).[21]

4.2 The Specification of Moments

For the set of moments households can choose between, we follow Krusell and Smith (1998) and consider only the first moment of the cross-sectional distribution of capital, $\mathbf{m} = \int g(\sigma_{i,2})\, d\sigma_{i,2} = K_t$. Even with this restricted set, the model in principle suffers from the problem of "*infinite regress of expectations*", described in e.g., Townsend (1983), which is induced by the public observation of an endogenous market-outcome. To solve this problem, we exploit a feature of Krusell-Smith-like economies: The sequence of shocks $\{z_s\}_{s=0}^t$ alone allows for extremely

[20] Both our framework and the Krusell-Smith framework assume common knowledge over the underlying structure of the economy—in particular, the law of motion $H(\cdot)$. Thus, if households knew the current state of the economy, they would correctly forecast tomorrow's state. That is why the Krusell-Smith solution can be seen as a special case of our equilibrium concept when the cost of information is zero.

[21] Our assumption that households know the law of motion $H(\cdot)$ and use it to form expectations is in line with a large literature on noisy rational expectations, going back to at least Lucas (1972). In all of this work, agents observe signals about unobserved fundamentals, characterizing the state of the economy, but crucially know the mapping between the signals they observe and the underlying fundamentals, as well as all other equilibrium relationships (e.g., Woodford, 2002; Sims, 2003; Lorenzoni, 2009; Maćkowiak and Wiederholt, 2009; Coibion and Gorodnichenko, 2012, 2015; and Angeletos *et al.*, 2021 among others). This allows us to focus on the implications of uncertainty about the state of the economy and not conflate any effects with those that also arise from uncertainty about the structure of the economy.

accurate predictions about the future capital stock K_{t+1} (Den Haan *et al.*, 2010). We therefore set $\mathcal{I}^{\max} = \{z_t\}$, so that households simply decide each period whether or not to acquire information about the exogenous value of productivity z_t. Importantly, we check *ex post* that this assumption allows households to form accurate posteriors about K_t, and thereby make accurate predictions about future wages and rates of returns (Appendix B.3).

A main result in the literature on optimal signal design is that optimal signals can be reduced to signals about (some combination of) state variables (e.g., Maćkowiak *et al.*, 2018). Because the history of aggregate productivity z_t accurately approximates the relevant state variables for prices in our economy (Appendix B.3), our assumption can be viewed as allowing households to choose to observe elements of the optimal signal.[22] Finally, in previous work (Broer *et al.*, 2022), we have shown that the utility benefits of acquiring information about the capital stock K_t (or equivalent past productivity) conditional on current productivity, z_t, assuming a Markov process for z_t, are small—in the order of \$3-30 at 2020 prices.

4.3 Approximated Problem and Equilibrium

Given our assumptions, we can state the approximated household problem that households solve: Households enter the period with capital k_i, their employment status ϵ_i, their prior over whether the economy is in the high productivity state $p^z_{i,-1} \equiv \text{Prob}\,(z = z_h \mid \Omega_{i,-1})$, and their prior over the capital stock $p^K_{i,-1}$. Households then choose whether to observe contemporaneous productivity z.[23] In line with the above notation, let $\tilde{\sigma}_{i,2} \equiv \left(m_i, \epsilon_i, p^z_i, p^K_i\right)$ and $\tilde{\sigma}_{i,1} \equiv \left(k_i, \epsilon_i, p^z_{i,-1}, p^K_{i,-1}\right)$. The two-stage optimization problem can then be stated as:

Stage 2: Consumption-savings choice

$$\begin{aligned}
\tilde{\mathcal{W}}\left(\tilde{\sigma}_{i,2}\right) &= \max_{c_i, k'_i \geq 0} \frac{c_i^{1-\gamma} - 1}{1-\gamma} + \beta \mathbb{E}\left[\tilde{\mathcal{V}}\left(\tilde{\sigma}'_{i,1}\right) \mid p^z_i, p^{K\prime}_i\right] \\
\text{subj. } & \text{ to} \\
c_i + k'_i &= m_i \\
K' &= \tilde{H}(z, K) \\
p^z_i &= \text{Prob}\,(z = z_h \mid \Omega_i)\,, \quad p^{K\prime}_i = \mathbb{E}\left[\tilde{H}(z, p^K_i) | \Omega_i\right].
\end{aligned} \tag{4.1}$$

[22] We thank Mirko Wiederholt for this comment.

[23] For computational tractability, we assume households have a point prior on capital, $p^{K\prime}_i = \mathbb{E}\left[\tilde{H}(z, p^K_i)|\Omega_i\right]$. Appendix C.7 shows that our results are extremely similar when households internalize uncertainty in their forecasts about capital, analogous to the findings in Den Haan *et al.* (2010) and Broer *et al.* (2022).

Stage 1: Information choice

$$\begin{aligned}
\tilde{\mathcal{V}}\left(\tilde{\sigma}_{i,1}\right) &= \max_{\mathcal{I}_i \in \{\emptyset, z\}} \mathbb{E}\left[\tilde{\mathcal{W}}\left(\tilde{\sigma}_{i,2}\right) - \kappa_i(\mathcal{I}_i) \mid p^z_{i,-1}, p^K_i\right] \qquad (4.2)\\
\text{subj. to} & \\
m_i &= \left[1 + r\left(z, K\right) - \delta\right] \rho^{-1} k_i + (1-\tau)\left[\epsilon_i w\left(z, K\right) \bar{l} + (1-\epsilon_i)\,\mu w\left(z, K\right)\right] - \eta\left(\mathcal{I}_i\right)
\end{aligned}$$

Notice that $\tilde{H}(z, K)$ in Equation (4.1) is the law of motion for the aggregate capital stock, which replaces $H(\cdot)$ as the aggregate law of motion in the approximated problem. Thus, in addition to their individual cash-at-hand and employment status, households forecast the probability of being in the high-productivity state and the aggregate capital stock. Households update their priors after their information acquisition choice using Bayes' rule. Consistent with the notation above, we let $\tilde{h}(\cdot)$, $\tilde{g}(\cdot)$, and $\tilde{\imath}(\cdot)$ denote the policy functions for consumption, capital, and information, respectively (i.e., $c_i = \tilde{h}(\tilde{\sigma}_{i,2})$, $k_i' = \tilde{g}(\tilde{\sigma}_{i,2})$, and $\mathcal{I}_i = \tilde{\imath}(\tilde{\sigma}_{i,1})$). The aggregate state variable is denoted by $\tilde{\Sigma} = (z, K)$ in what follows.

We provide a brief overview of the numerical procedure that we use to solve for the approximated RIICE equilibrium. To solve for the equilibrium fixed point, we use an iterative procedure: First, we postulate a law of motion $\tilde{H}(\cdot)$ for the aggregate state variables. As in Krusell and Smith (1998), we assume a log-linear relationship between K' and K, whose coefficients depend on the (boom or bust) realization of z. Second, we solve the household's two-stage problem in (4.2) and (4.1) conditional on $\tilde{H}(\cdot)$. We use Equation (3.7) and the EGM-algorithm from Carroll (2006) to solve for the policy functions and value function iteration to solve the value functions. Third, using the resulting individual decision rules, we simulate a large number of households for a long number of periods. From this simulation, we then calculate a time-series for K, and estimate a new law of motion $\tilde{H}'(\cdot)$ (i.e., new log-linear relationships). We iterate until convergence on $\tilde{H}(\cdot)$.

4.4 Calibration

The aim of our calibration exercise is to ensure that the model can account for salient business-cycle and cross-sectional facts, as well as capture the rich heterogeneity in household expectations documented in Section 2. We assume that a model period corresponds to one quarter.

Externally Calibrated Parameters: We choose standard parameters for the capital share α (0.36) and the depreciation rate δ (0.025). Following Krueger *et al.* (2016), we calibrate the structure of aggregate and idiosyncratic risk to capture key features of the unemployment and job-finding rates in the post-World War II U.S. economy. We define "booms" and "busts" based on the observed unemployment dynamics, as those more closely align to our model framework than traditional NBER-dated recessions. We define a boom as a period with a below-trend unemployment rate.[24] The productivity variable z_t is calibrated to match the difference in average U.S. total factor productivity during booms and busts. We estimate the persistence of booms and busts to be 0.88 and 0.82, respectively, and the ratio of productivity values $z_h/z_l = 1.027$. The individual transition probabilities in labor productivity ϵ_{it} are set to match U.S. labor market transitions calculated from the Current Population Survey. We choose an unemployment rate in booms and busts equal to 6 and 10 percent, respectively. Monthly job-finding rates are set to match unemployment-to-employment flows in the CPS, and are equal to 55 and 45 percent in boom and busts, respectively. The remaining transition probabilities are then pinned down by the requirement that the unemployment rate depends only on current productivity z_t. Finally, we set the UI replacement rate μ to 0.40.

Internally Calibrated Parameters: We calibrate the discount factor $b = 0.987$ and the probability of death $1 - \rho = 0.005$ to generate a quarterly capital-output ratio of 10 (Carroll *et al.*, 2017) and to be consistent with an expected work-life of 45 years. We calibrate the degree of relative risk aversion γ and the information cost parameters α_κ and η to quantitatively capture key features of the micro-data on expectations discussed in Section 2. We set $\gamma = 5$ and the monetary cost per signal equal to $\eta = 0.0028$ (equivalent roughly to 0.1 percent of quarterly pre-tax wages) to match our empirical finding that forecast accuracy increases in wealth for richer households (Section 5.3).[25] We set the scale parameter α_κ equal to $1/15 \times 10^{-4}$ to capture the dispersion in unemployment expectations observed in the SCE (even for households with similar observable characteristics). To check how household expectations compare to those in the SCE, we concentrate on expectations of future unemployment. Table I compares the accuracy and standard deviation of households' one-year ahead unemployment rate errors in the model and the data. Recall that the SCE elicits expectations of future unemployment in the form of the "percent chance that 12-months from now the unemployment rate in the U.S. will be higher than it is now". For households in the model, we therefore compute the difference between a household's perceived probability conditional on its current information $\text{Prob}(u_{t+4} > u_t|\Omega_{it})$ and the true probability $\text{Prob}(u_{t+4} > u_t|z_t)$, which depends on current productivity z_t. We then compare the resulting errors with the corresponding errors in the survey data. Table I shows that the dispersion of errors is somewhat larger in the data, but that overall the model replicates both the accuracy and volatility of expectation errors in the

[24] We use an HP filter with smoothing parameter λ equal to 14.400 to construct the trend in the unemployment rate from monthly unemployment data (Ravn and Uhlig, 2002).

[25] The benefit of additional information for wealthy households arises mainly from improved predictions about the future rate of return on capital. Yet when relative risk aversion is close to one, income and substitution effects largely cancel one another, and wealthy households do not value those improved predictions.

Table I: Unemployment Expectations: Model vs. Data

	Mean Abs. Error	Std. Dev. of Abs. Error
Survey of Consumer Expectations	1.24	0.68
Model Simulated Data	1.28	0.52

Note: The table shows the mean and standard deviation of the absolute value of errors in the probability that the unemployment rate four quarters ahead is higher than at time t. The table compares the simulated moments from the calibrated model to those from the Survey of Consumer Expectations (see Section 2 for a description). For interpretability reasons, we scale the absolute value of unemployment errors in the model and in the data with the average true probability of rising unemployment, proxied in the data with average probability of rising unemployment from the Survey of Professional Forecasters (Section 2).

data well. Table B.1 in the Appendix summarizes the parameters.

5 Quantitative Results

In order to understand the drivers and consequences of households' information choices, we proceed in four steps. First, we analyze how different information choices affect household savings decision—the intertemporal decision variable in the model. Second, we characterize how household information choices depend on individual state variables, such as wealth. Third, we combine the insights from the first two steps to show how the interaction between information and savings choices allows us to match the micro data on expectations. Finally, we explain the impact of the wealth-expectations nexus on aggregate dynamics and inequality, and show that our results carry over to several alternative versions of our benchmark model.

5.1 Savings Choices and Information

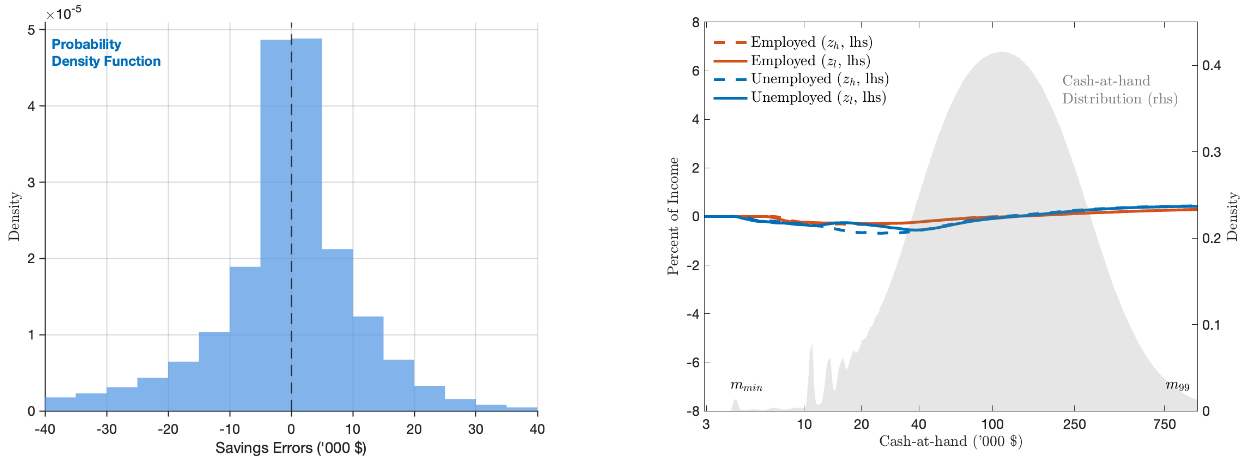
We start by describing how information affects households' savings choices, k_i'. These micro-level effects are central for understanding the aggregate amplification we later document. In the model, households save to smooth consumption in the face of volatile income and to intertemporally substitute consumption in response to movements in the interest rate. The state of the economy that households can acquire information about affects these both through *exogenous fluctuations* in productivity and employment, and through *endogenous fluctuations* in capital—all of which matter for households' labor income and future rates of return.

Comparison to Full-information. Panel (a) in Figure 3 plots the distribution of differences in savings choices between the benchmark (heterogeneous incomplete-information) HetExp economy and the economy in which all households exogenously acquire information every period. We refer to this counterfactual economy as the "full-information economy"; it

Figure 3: Savings Choices Compared to Full-information Model

(a) Distribution of Savings Differences

(b) Informed vs. Full Information



Note: The figure compares savings choices in the benchmark economy to those from the full-information economy. Panel (a) shows the distribution of savings differences using the same sequence of aggregate and idiosyncratic shocks. Panel (b) plots the differences between the savings choice of "an informed household", who has just acquired information about z, in our benchmark ecoonmy and the savings choice of a household in the full-information economy as a percent of household income. We plot this difference in a recession (solid lines, $z = z_l$) and a boom (dashed lines, $z = z_h$) for both an unemployed (in blue) and employed (in red) household, and overlay the distribution of cash-at-hand in the benchmark economy in gray. The figure also depicts the minimum of cash-at-hand (m_{min}) and its 99th percentile value (m_{99}). We plot savings differences as a function of cash-at-hand and use 2020 values of U.S. household income to convert into USD ($) amounts.

corresponds to the workhorse full-information (Krusell-Smith) analog of our benchmark economy.[26] For comparison, on average, only around 10 percent of households choose to acquire information in any given period in our benchmark economy.[27] We plot differences in quarterly savings choices based on a simulated panel of households with identical idiosyncratic and aggregate shocks across the two economies. Differences in savings choices are often considerable—approx. 20% of them exceed $20,000 in absolute value. Clearly, such large differences have the potential to matter for macroeconomic outcomes, and arise due to a combination of the presence of incomplete information and its implications for the dynamics of the economy.

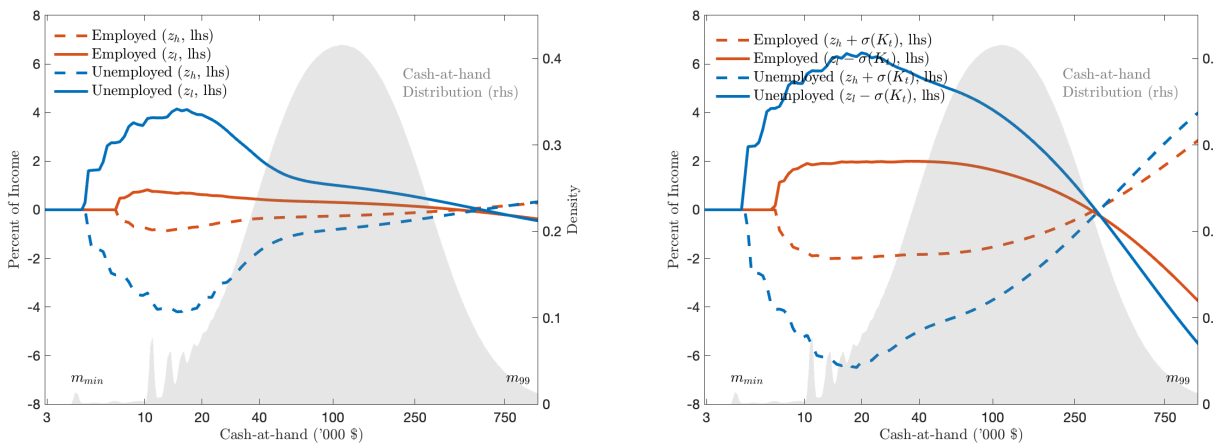
Panel (b) in Figure 3 starts to break down the drivers of these differences by showing that they are *not driven by the behavior of informed households*. It does so by comparing the savings choices of a household who has just acquired information in our benchmark model and a household in the full-information version of the model. We plot differences in savings

[26] Notice that we assume households still pay the resource and utility cost of information acquisition in the full-information economy. Section 5.8 compares our results to the case in which households do not pay these costs. We re-calibrate the discount factor to target the same $K/Y-$ratio as in our benchmark economy and use the same sequence of aggregate and idiosyncratic shocks in all model simulations.

[27] The probabilities of information acquisition in the benchmark economy are 0.122 and 0.097 for the unemployed and employed, respectively. The average rate of unemployment is 7.6 percent.

Figure 4: Savings Choices, Information, and Wealth

(a) Informed vs. Uninformed (b) Informed $\pm\sigma(K_t)$ vs. Uninformed



Note: The figure plots the difference between the savings choice of "an informed household", who has just acquired information about z, and "an uninformed household" in our benchmark economy as a percent of household income. An uninformed household has a 50-50 prior over productivity z. We plot this difference in a recession (solid lines, $z = z_l$) and a boom (dashed lines, $z = z_h$) for both an unemployed (in blue) and employed (in red) household, and overlay the distribution of cash-at-hand in the benchmark economy in gray. Panel (a) plots the difference evaluated at the mean prior for capital, while Panel (b) instead evaluates the savings choice of the informed household at a prior over the capital stock that is 1 standard deviation higher (lower) than the mean in a boom (bust). We plot savings differences as a function of cash-at-hand and use 2020 values of U.S. household income to convert values into USD ($) amounts.

choices ("benchmark informed minus full-information") as a function of a household's cash-at-hand and assume both households have the same expectation about capital. The figure further conditions on the same perceived law-of-motion (from the benchmark economy), which embodies the aggregate dynamics of the economy. Any differences in savings choices thus result from informed households in the benchmark economy *anticipating being uninformed in the future*. The resulting differences are small—often less than 1% of income—and do not vary much with either the individual employment state (employed or unemployed) or the aggregate state of the economy (boom z_h or bust z_l). The large differences in Panel (a) clearly do not arise from differences in informed households' savings choices.

Comparison of Informed to Uninformed. Instead, what drives the often substantial differences *is the different savings behavior of uninformed households*. We contrast these to informed households' savings choices in Figure 4, where we plot savings differences ("informed minus uninformed") in the benchmark economy as a function of a household's cash-at-hand. Panel (a) assumes both households share the same expectation of the capital stock, while Panel (b) internalizes that an informed household's expectation of capital will also be different. Combined, the two panels show large differences in savings—up to around 6% of income—across much of the cash-at-hand distribution, especially for unemployed households and after one accounts for how information also alters household expectations of capital. The presence of incomplete information matters for the bulk of households.

Crucially, Figure 4 documents substantial variation in savings differences across the cash-at-hand distribution. *Below around the 85th percentile, uninformed households save more procyclically than informed ones.* While informed households save more in recessions (z_l) and less in booms (z_h), uninformed households do the opposite; they save comparatively less in recessions and more in booms. However, unlike this majority of households, above the 90th percentile the pattern instead reverses: *Uninformed rich households save more in recessions and less in booms; their savings are are instead more countercyclical.* Taken together, this shows how the wealth distribution can shape the overall cyclicality of savings. We return in Section 5.4 to how the net-effect of these countervailing forces amplifies business cycles.

Information about Productivity: To understand this varying cyclicality, start with Panel (a) in Figure 4 that shows the savings differences caused by information about productivity alone. The poorest households optimally reduce capital holdings to zero independent of the state of the economy. As such, information does not change their savings behavior. Savings rates of informed households, by contrast, differ strongly from those of the uninformed households at low-but-positive levels of cash-at-hand, where the non-linearity of the savings policy function is pronounced near the kink at the borrowing constraint. Information about productivity helps such households better predict the probability of employment and future wages, and thus future labor income, which is the main determinant of future consumption for low-wealth households. Informed households, as a consequence, save more in recessions and less in booms. This difference between informed and uninformed savings is especially pronounced for unemployed households, whose job-finding rate differs strongly across booms and busts.

As cash-at-hand increases, the difference between informed and uninformed savings initially declines. In this region, errors about future labor-market prospects and capital returns push savings in opposite directions. Optimistic expectations about the job-finding rate in a bust, for example, reduces precautionary savings, while expecting a higher return on capital raises savings through intertemporal substitution. As one moves towards the middle of the wealth distribution, these effects partially offset each other, lowering savings differences between informed and uninformed households.[28] At even higher wealth levels—above around the 90th percentile—the savings differences eventually flip sign, as financial assets comprise the bulk of household resources. Variations in returns here dominate household savings choices, leading to increasing savings differences, as intertermporal substitution makes informed households

[28]The moderate persistence of productivity shocks entails only ever weak income effects. This decline is further reinforced by the savings function becoming increasingly linear.

save more in booms and less in recessions.

Information about Capital: While knowing the current productivity state is important, acquiring information also causes households to perceive the economy's endogenous dynamics more accurately—particularly the evolution of the capital stock. Recall that in Panel (a) of Figure 4 informed and uninformed households have the same expectation of capital. Any perceived differences in wages and rates of return from being informed stem only from perceived differences in productivity and hence employment prospects. With incomplete information, however, uninformed households also perceive less accurately the dynamics of capital (that rises in booms and falls in recessions). Their expectations about future capital, returns and wages, are less cyclical and biased towards the unconditional mean. We illustrate how such mean-biased capital expectations change savings behavior in Panel (b) of Figure 4.

Compared to Panel (a), having mean-biased capital expectations increases the magnitude of savings mistakes that the vast majority of households make. The additional effect is especially pronounced for low-wealth households and households above the 90th percentile, whose savings mistakes are amplified by a factor between 1.5 and 4.0. These savings mistakes are explained by errors in households' expectations of future wages and returns, crucial for low- and high-wealth households' savings choices, respectively. Both now combine errors due to (i) mistaken *exogenous components* of labor income and returns (i.e., productivity and employment transitions); and (ii) a mistaken *endogenous component* (i.e., capital accumulation). Since a higher capital stock in booms, for example, provides an additional, persistent boost to future labor income through higher wages, informed savings by the poor are reduced by more relative to the savings of the uninformed—both components compound each other. Similarly, income effects from reduced returns at a higher aggregate capital stock boost savings of the informed rich further relative to those of the uninformed.[29]

Combined, Figures 3 and 4 show that an absence of information about exogenous and endogenous components substantially alters household savings, with the direction and magnitude of distortions varying across the wealth distribution. These individual-level distortions have the potential to significantly affect macroeconomic outcomes, depending on which households are uninformed in equilibrium. We next explore how the above forces interact to shape households' information choices. This will cast further light on the wealth-expectations nexus.

[29]Note the compounding effects of information about productivity and the capital stock on rich households' informed savings: Higher returns during moderately persistent productivity booms have weak income effects, and thus increase savings through a substitution effect (Panel a of Figure 4). Diminishing returns from highly persistent increases in the capital stock have strong income effects, further boosting savings as capital accumulates (Panel b of Figure 4).

5.2 Household Information Choices

Information choices are most easily described by the probability of acquiring information. Figure 5 plots this probability as a function of a household's state variables—cash-at-hand and the prior over productivity—separately for the employed and unemployed, and for a low and a high prior over the capital stock. Combined, the results in Figure 5 showcase the rich heterogeneity that exists in incentives to acquire information. Unsurprisingly, households with less informative prior expectations (closer to one half) are more likely to acquire information for all wealth levels, except those at the borrowing constraint.

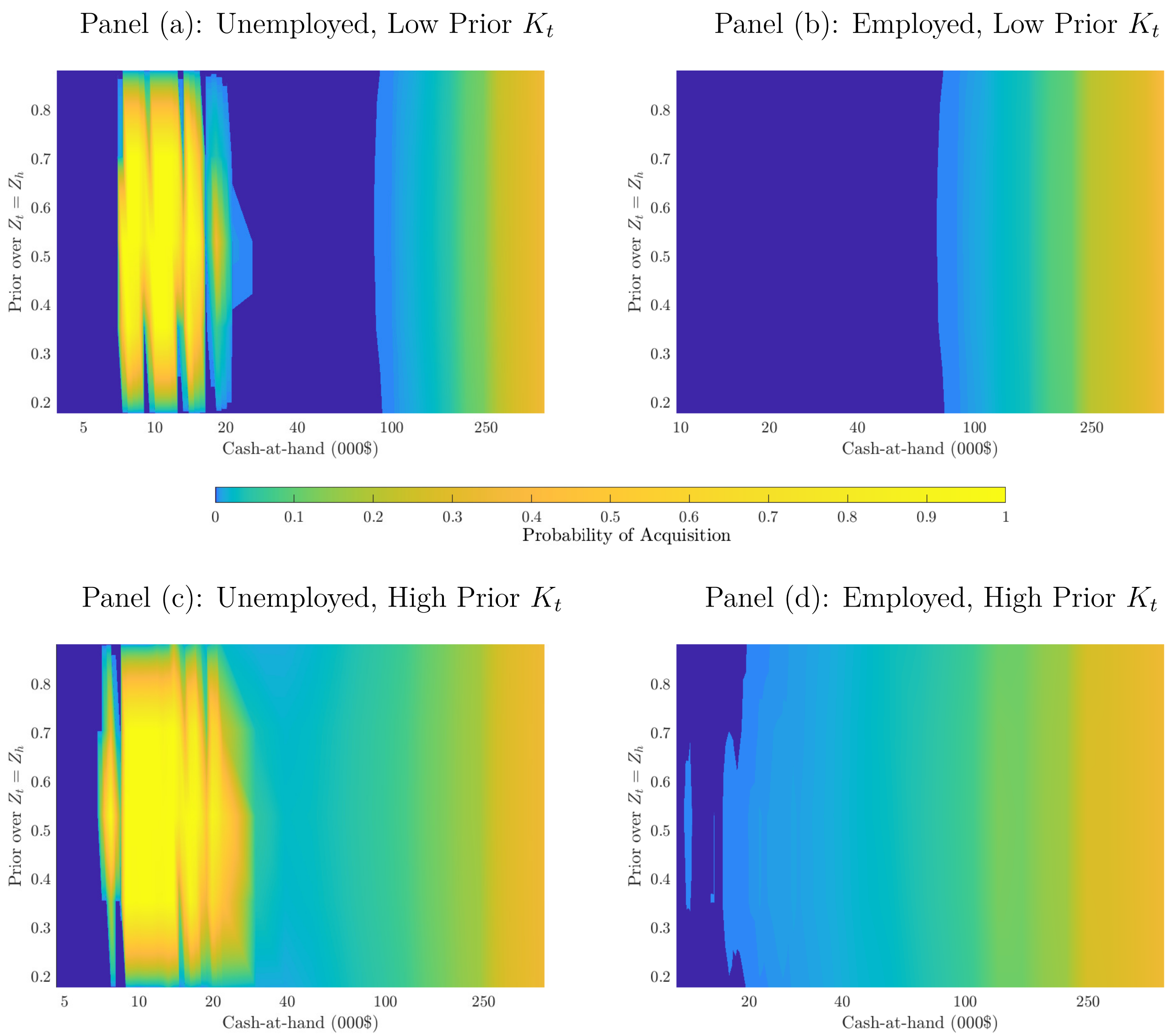
Employed households—the savers in the economy—are less likely to acquire information, especially at low levels of wealth. Because separation rates are only mildly cyclical (5.0 percent in recessions and 3.5 percent in booms), their optimal savings change comparatively little across boom-bust states (Figure 4). With low unemployment risk and a moderate persistence of boom-busts, they are further unlikely to hit the borrowing constraint soon. Thus, they expect to continue to accumulate assets over time, so that the average savings error from remaining uninformed is relatively small, as discussed in the previous section. The option to acquire information after a future job loss further lowers the value of doing so today. As wealth rises, however, the benefit of predicting returns on increasing financial wealth rises and the cost of acquiring information relative to wealth falls, increasing the probability of information acquisition. Indeed, households with more than $300,000 in cash-at-hand acquire information close to 50 percent of the time (Panel (b) and (d) in Figure 5). This compares to an overall average rate of information acquisition of 10 percent.

Now, consider instead *unemployed households*. The unemployed are dissavers, as they attempt to smooth consumption. At low enough values of cash-at-hand, they consume their resources and end up at the borrowing constraint. Thus, at sufficiently low values, unemployed households almost never acquire information. These households are at the borrowing constraint for all states that realize tomorrow, and hence have no benefit from acquiring information today (Figure 4). However, at slightly higher values of cash-at-hand, unemployed households start to acquire information with high probability—to avoid large savings mistakes from not knowing the state of the economy (Figure 4). Savings mistakes from being uninformed are costly near the borrowing constraint where the curvature of both the utility function and policy functions is high. In this range of the wealth distribution, unemployed households thus almost uniformly acquire information (Panel (a) and (c) in Figure 5).[30]

As wealth rises further, marginal utility eventually falls, and the value of information

[30]The same incentives raise information-acquisition probabilities of uninformed employed households, who face a smaller but positive probability of becoming unemployed, at moderate levels of cash-at-hand, as seen in Panel (d) in Figure 5.

Figure 5: Information Acquisition Probabilities



Note: The figure plots the probability of information acquisition (from 0 to 1) for different values of the prior belief that current productivity z_t is high and for different values of household cash-at-hand. The figure uses our baseline calibration to depict the probabilities and evaluates them at a "low" (i.e., 25% below the mean) and "high" (i.e. 25% above the mean) prior over the aggregate capital stock K_t. The left-hand (right-hand) panels show the probabilities for an unemployment (employed) household. We use 2020 values of U.S. household income to convert cash-at-hand in our model to USD ($) amounts.

initially declines. The household is no longer at risk of imminently hitting the constraint, and expectation errors about the labor market and capital returns have opposing effects on savings, lowering savings differences due to information (Figure 4). This temporarily lowers the value of information. The value of information, nevertheless, then slowly starts to rise again with wealth for the same reasons as discussed for the case of the employed.

Finally, notice that households with low-levels of wealth are, on balance, more likely to acquire information when their prior about the current capital stock is high (Panel (c) and (d) in Figure 5). This is because higher wages implied by abundant capital increase the dispersion of incomes across employment states. This increases the value of accurately predicting employment prospects, and thus the probability of information acquisition.

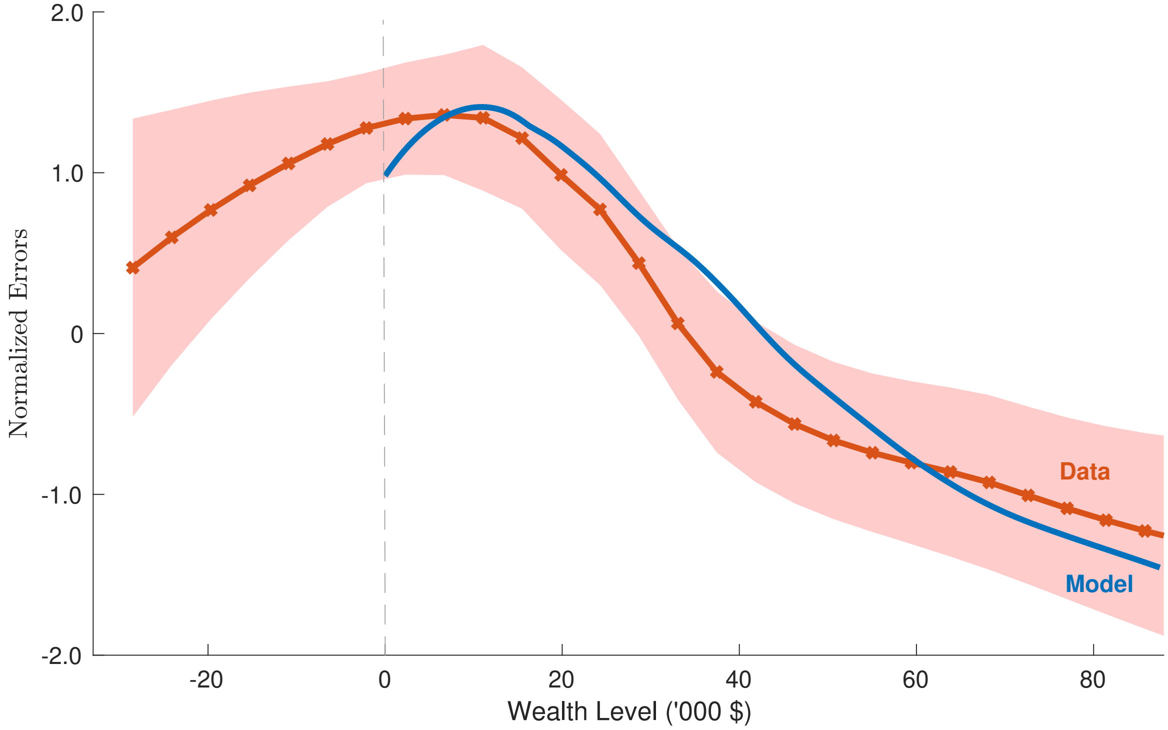
5.3 Accuracy of Expectations

We have described how wealth and employment status affect a household's decision to acquire information, and how a household's savings decision is in turn affected by the accuracy of its information. Before we turn to the macroeconomic consequences of the two-sided interaction between household heterogeneity and information choice, we study how these forces interact to shape the accuracy of household expectations across the wealth distribution. This will also allow us to confront our model with the empirical evidence discussed in Section 2.

Figure 6 shows how households' information acquisition probabilities in equilibrium translate into a systematic relationship between the accuracy of household expectations and their wealth level. Because the model matches the mean and standard deviation of absolute errors, Figure 6 plots normalized errors in both the model and in the data (Figure B.2 shows errors relative to the top quintile and extends the horizontal axis). For compatibility with the SCE data, we plot errors as a function of household wealth k_i instead of cash-at-hand m_i. Although our model cannot speak to the positive slope that exists in the data for households with negative wealth—recall that we assume a simple no-borrowing limit $k_i' \geq 0$ for households—the model generates an inverse-u shape, which on balance resembles that in the survey data.

The inverse-u shape in the model is a result of two opposing forces: First, the upward sloping part is driven by the unemployed. The poorer households in the model are, on average, the unemployed, who at low levels of wealth acquire information with high probability. As those households find jobs, their wealth increases but they also stop acquiring information, leading to the observable decline in accuracy at low levels of wealth. Second, as wealth increases, the probability of acquiring information eventually becomes monotonic in wealth (Figure 5). As wealth rises, the benefits of information about its return increases and the relative cost falls—both of which increase a household's information acquisition probability and thus accuracy. We conclude that the model, on balance, successfully replicates the salient

Figure 6: Accuracy of Forecasts: Model vs. Data



Note: The figure shows the estimated relationship between (the absolute value of) normalized errors of the one-year ahead probability of the unemployment rate increasing and household wealth. We plot this relationship both in the SCE data and in the calibrated model (see also Section 2). We use a local polynomial regression (the LOESS regression) to estimate the non-linear relationship between the accuracy of household expectations and household wealth. Error bands correspond to one-standard deviation confidence bounds. We use 2020 values of quarterly U.S. household income to convert values in the data and in the model to $ (USD) amounts.

features of the empirical wealth-expectations relationship, making it a suitable laboratory to explore the effects of expectation heterogeneity on the macroeconomy.

5.4 Aggregate Implications

Our analysis so far has centered on the savings and information choices of an individual household. In this subsection, we document how the heterogeneity in savings and information choices depicted in Figures 4 and 5 accumulate to amplify business-cycle fluctuations.

In Table II, we contrast the dynamics of our benchmark economy with those that arise in the full-information economy, where all households exogenously acquire information every period. Recall that, on average, only around 10 percent of households choose to acquire information in any given period under our baseline calibration. We also compare the dynamics from our model with those that arise from an economy in which all households face the same

Table II: Business Cycle Moments

	$\sigma(K)$	$\sigma(Y)$	$\sigma(I)$	$\sigma(C)$	$\text{Cor}(C,Y)$
	Panel (a): Level of Moments				
Benchmark Model	5.05	3.38	11.98	1.25	0.70
Exogenous Information	4.19	3.22	11.56	1.19	0.67
Full Information	3.07	3.04	10.54	1.19	0.72
	Panel (b): Percent Difference w.r.t. Full Information				
	$\sigma(K)$	$\sigma(Y)$	$\sigma(I)$	$\sigma(C)$	$\text{Cor}(C,Y)$
Benchmark Model	64.24	11.03	13.61	5.08	-3.08
Exogenous Information	36.43	5.84	9.63	0.29	-7.24

Note: The table shows the standard deviation $\sigma(\cdot)$ of the logarithms of economy-wide capital (K), output (Y), investment (I), and consumption (C). In addition, the table shows the correlation between log. consumption and output, $Cor(C,Y)$. The table computes these moments in the calibrated economy ("Benchmark Model"), the associated full-information economy ("Full Information"), as well as in a model with an exogenously specified probability of acquiring information ("Exogenous Information"). The probabilities of information acquisition in the benchmark model are 0.122 and 0.097, respectively, for the unemployed and employed. This probability is set equal to 0.10 in the exogenous information case.

(exogenous) 10 percent probability of information acquisition in every period à la Mankiw and Reis (2002). In a slight abuse of terminology, we refer to this economy as the "exogenous-information economy".[31] In both cases, we assume households pay the resource and utility cost of information upon acquisition, and recalibrate the discount factor to target the same capital-to-output ratio. Section 5.8 compares our results to the case where households do not pay these costs. Table B.2 further compares the business-cycle dynamics to those in the U.S.[32]

Relative to the full-information case, fluctuations in all aggregate variables are substantially more pronounced in our benchmark economy. The standard deviation of capital is around 2/3 higher, and output and consumption are, as a result, 5-11 percent more volatile than in the full-information economy. These stark differences are caused by the increased procyclicalty

[31] Notice that the full-information economy is merely an exogenous-information economy with the probability of information acquisition fixed at 1. We keep the "full-information'" and "exogenous-information" labels in what follows to clarify that any comparison between the two focuses on the *incompleteness* of information. A comparison between our benchmark economy and the exogenous-information economy, by contrast, focuses on the consequences of *heterogeneity* in information.

[32] Compared to the data (Table B.2), our model features the same deficiencies synonymous with workhorse RBC or Krusell and Smith (1998) economies: Investment is too volatile, consumption too smooth, and output is, as a result of employment and investment dynamics, too volatile. We abstract from these deficiencies in what follows below, as our focus is squarely on the consequences of the wealth-expectation nexus.

and persistence of capital, driven by heterogeneous incomplete information.

As discussed in Section 5.1, the central difference between the savings choices in the benchmark economy and its full-information counterpart is the different savings behavior of *uninformed households*. Households who choose *not* to acquire information—who comprise 90 percent of the population—have expectations that are tilted towards the long-run average of the economy. In booms, such households systematically underpredict productivity and the capital stock, and hence future labor income, and vice versa in recessions.[33] Consequently, households below the 85th percentile save more in booms and less in recessions than if they had full information—their savings are more procyclical (Figure 4). Wealthy households above 90th percentile, by contrast, make the opposite mistake, but because these households acquire information more frequently and control less of the capital stock (Figure 4 and 5), they do not not offset the procyclical forces from the majority. In equilibrium, the economy thus systematically "overaccumulates" capital in booms and "underaccumulates" in recessions, leading to much larger fluctuations in output and investment than under full-information.

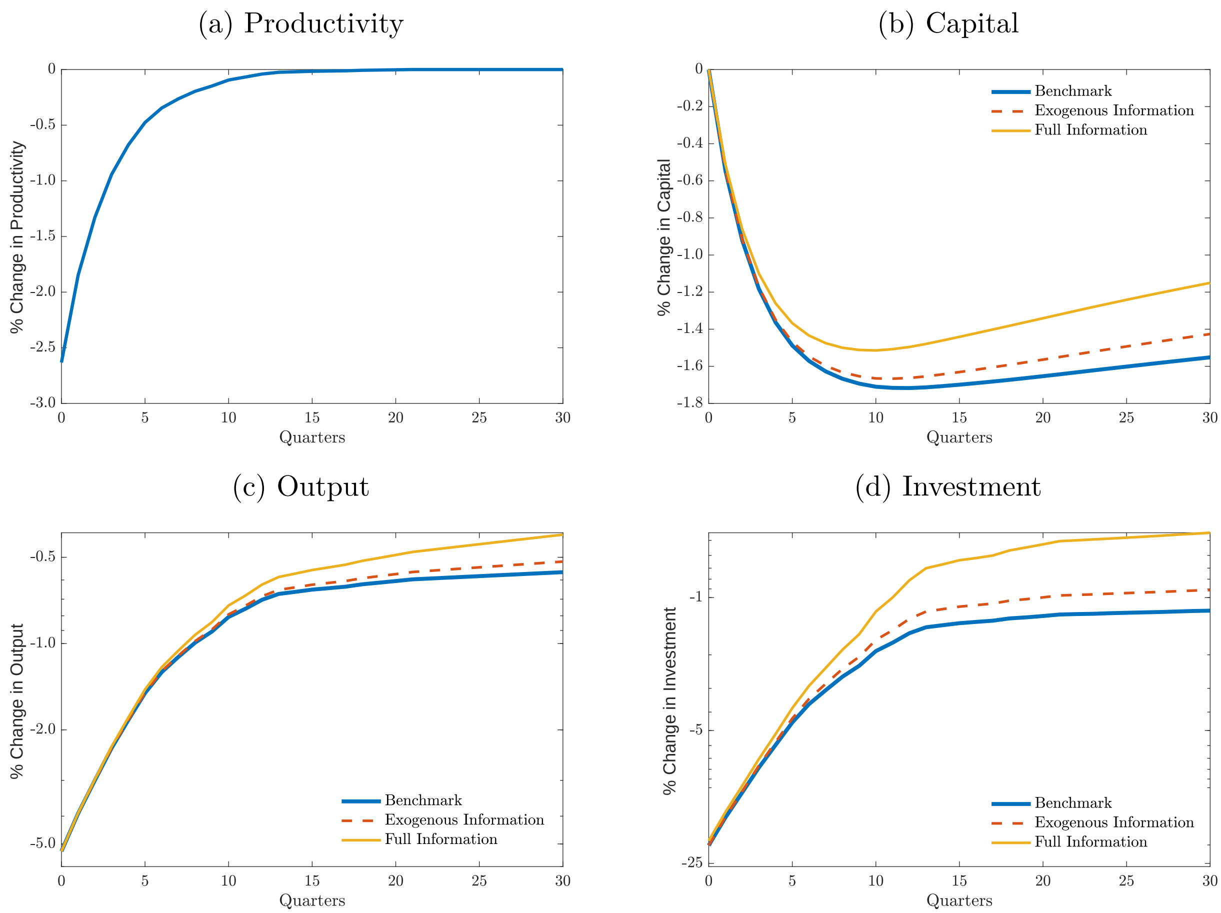
Figure 7 illustrates the weakened mean-reversion and amplification; it does so by plotting the economy's response to a negative productivity shock (a transition from z_h to z_l). Consistent with Table II, the impulse responses are substantially larger and more persistent in the benchmark economy. Panel (b) shows that capital decreases in all cases and that even after several years the shock has yet to die out; however, importantly, the speed of recovery is substantially slower in our benchmark economy, due to the increased procyclicality of savings. There is *substantially more internal propagation*. Panel (d) shows the investment response behind this difference. Panel (c) mirrors these results and shows that output, as a consequence, falls by similar amounts on impact but that the recovery is substantially more protracted in the benchmark economy. Because of heterogeneous incomplete information, business cycles are amplified and more protracted—and the IRFs directly illustrate the mechanism.

Compared to the exogenous-information case, where all households have the same probability of acquiring information, the endogeneity of information that is a feature of our benchmark economy further amplifies the increase in aggregate volatility (Table II; Figure 7). This occurs because middle-wealth households who combine to hold most of the capital stock acquire information with less than average frequency (Figure 5). This further dampens the mean-reversion of capital in our benchmark economy relative to an economy in which all households have the *same probability* of acquiring information. The *heterogeneity in information choices* amplifies the consequences of incomplete information.

Finally, Appendix C.1 illustrates the non-linear relationship between aggregate volatility

[33] We should note, however, that a hypothetical household that acquires information in every period would have an accurate estimate of the true capital stock and make negligible forecast errors (Appendix B.3).

Figure 7: Impulse Response Functions



Note: The figure shows impulse response functions to a negative productivity shock (transitioning from z_h to z_l). Panels (b)-(d) show the responses of capital K_t, output Y_t, and investment I_t, respectively, while Panel (a) shows the underlying shock to the economy (productivity z_t). The horizontal axis refers to quarters after the initial shock, t. We plot the dynamics of our benchmark economy (solid blue line), the exogenous-information economy (dashed red line), and the full-information economy (solid yellow line).

and the accuracy of expectations about capital. Recall that a main driver of savings differences caused by incomplete information was the resulting lack of information about capital (Figure 4). To do so, we compare the business-cycle dynamics of the benchmark economy with those from two additional economies, where households *exogenously* learn the current capital stock with a fixed probability every period, in addition to their *endogenous* decision to acquire information about productivity. Our results document strong non-linearities in the effects of incomplete information: In the case in which household learn capital every period—and thus for which only *static effects* of incomplete information about productivity exists—the volatility of capital increases by around 5 percent relative to the full-information case. By contrast, if households learn capital every 10 quarters, this difference is more than 2.5 as large—while, in our benchmark model, where households are never exogenously told about the capital stock, volatilities increase by close to a factor of 4. Our results, thus, highlight the important role of dynamic information accumulation about the capital stock, and the strong non-linearities inherent in the business-cycle effects of mean-biased capital expectations.

We conclude that the presence of heterogeneous information serves as an amplifying force—it induces weaker mean-reversion of the capital stock relative to the full-information case. This amplification acts as a powerful propagation mechanism, making the economy respond more to shocks than standard full-information models would otherwise predict.[34]

5.5 Amplification and the Wealth Distribution

In the previous section, we showed that heterogeneous information amplifies business cycles. The strength of resulting amplification yet depends centrally on the shape of the wealth distribution. Because uninformed savings are more procyclical for the bottom 80 percent of the wealth distribution but countercyclical for the rich, the distribution of capital holdings determines the strength of the amplification. The more of the capital stock that is held by households whose uninformed savings are more procyclical, the larger the amplification.

Table III addresses the empirical validity of our results. The table shows the wealth distribution in the data and in our benchmark economy, as well as the associated consumption expenditure shares, the flip-side of savings. Although there are well-known issues related to the lack of skewness in wealth with the Aiyagari-Bewley-Huggett-Imrohoroglu class of models that we depart from (see Section 5.8), on balance, the benchmark model does well at capturing the salient dimensions of the joint distribution of consumption and wealth.

The table shows that a sizable share of consumption occurs for households for which the presence of incomplete information has bite. In the benchmark model, 52% of consumption expenditures are made by households in the bottom 60% of wealth, whose uninformed savings are more procyclical. Another 27% occur for households above the 80th percentile, where countercyclical forces operate for the wealthiest. A substantial share of consumption expenditures thus occur for households in the region of the distribution for which the presence of incomplete information has bite on their consumption-savings choices (Figure 4).

Crucially, the net effect—business-cycle amplification—here arises because (i) households with little or moderate wealth, whose uninformed savings are more procyclical, control a large share of consumption-savings; and (ii) rich households acquire information frequently enough to neutralize most of their potential dampening effect. This insight has important implica-

[34] These dynamics elucidate a more general feature of our framework: Information acquisition choices are *strategic substitutes.* The individual benefits of information rise with the volatility of the capital stock. But, when the average share of information in the economy increases, the volatility of the capital stock falls, and so does the incentive to acquire information. In previous work, Broer *et al.* (2022), we show how this may imply non-existence of homogeneous-information (representative-agent) equilibria in neoclassical economies.

Table III: Selected Variables by Wealth: Data vs Model (% share of)

	Benchmark Model				Entrepreneur Model			
	Wealth		Expend.		Wealth		Expend.	
NW	Data	Mod	Data	Mod	Data	Mod	Data	Mod
$D1$	-0.8	0.9	6.9	7.6	-0.8	-0.2	6.9	7.4
$D2$	0.0	2.1	4.3	8.3	0.0	0.5	4.3	7.8
$Q2$	1.1	7.4	13.7	17.5	1.1	2.8	13.7	16.0
$Q3$	5.2	12.9	17.8	18.7	5.2	5.5	17.8	16.8
$Q4$	14.6	21.0	22.5	20.6	14.6	10.5	22.5	17.9
$Q5$	79.9	55.8	34.7	27.3	79.9	80.8	34.7	34.2

Note: The table shows the distribution of wealth and expenditures from the U.S. Panel Study of Income Dynamics (PSID). The wealth shares in the SCE (2014-2022) are similar to those in the PSID.

tions: In Section 5.7, we document that even when we extend our model framework to better match wealth concentration at the top, business-cycle amplification remains the dominant feature, as the poor and middle class still control substantial resources and acquire information infrequently. We conclude that the amplification documented in Section 5.4 provides a suitable first-pass guide to the business-cycle consequences of heterogeneous information.

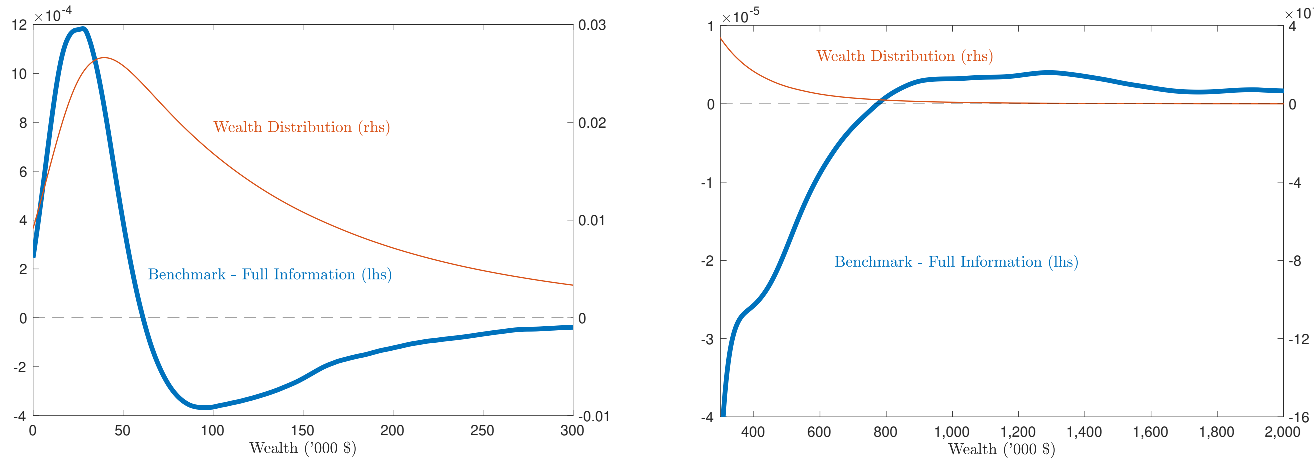
5.6 Distributional Implications

We next turn to the distributional implications of heterogeneous incomplete information. The wealth distribution does not only affect the consequences of heterogeneous information but is itself also affected by its presence. Figure 8 and Table IV compare the wealth distribution in our calibrated benchmark economy—averaged across a long simulation—with those from the equivalent full-information and exogenous-information economies.

The introduction of heterogeneous incomplete information increases wealth dispersion relative to the full-information case—with more mass placed at the bottom and at the top of the wealth distribution (Panel (a) and (b) in Figure 8). Conversely, there are fewer households with intermediate wealth levels (between $65,000-750,000). Consistent with the widening of the wealth distribution, all measures of inequality (Gini coefficient, the 90/10-ratio, as well as the 99/1-ratio) increase modestly between 2-5 percent (Table IV). Finally, comparing instead to the exogenous-information case, the widening of the wealth distribution is also somewhat amplified: Households' endogenous information choices increase the widening of the wealth distribution, especially near the top.[35]

[35] The introduction of heterogeneous information also causes the dynamics of inequality to change, increasing

Figure 8: Information and the Wealth Distribution



Panel (a): Distribution Differences (I/II) Panel (b): Distribution Differences (II/II)

Note: The figure shows differences in the wealth distribution relative to the full-information economy (left-hand side axis) and plots the underlying wealth distribution in the benchmark economy (right-hand side axis). The horizontal axis is household wealth (capital levels) in USD '000 ($). We use 2020 values of U.S. household income to convert values in the model to $ amounts. Probability density functions are estimated from a simulated panel of households, using a kernel density estimator with the Epanechnikov kernel.

Underlying these modest overall increases in inequality are *substantially larger but offsetting* gross effects. In Appendix C.3, we decompose the overall change in the wealth distribution into three separate forces: (i) the presence of incomplete information; (ii) the heterogeneity that exists in information choices; and (iii) the change in the equilibrium law of motion. Combined, these three forces capture the partial and general equilibrium channels by which heterogeneous incomplete information itself alters the wealth distribution.

The main driver of the overall increase in inequality is the presence of *incomplete information*. Uninformed households make savings errors that, while individually rational, introduce dispersion in wealth accumulation. The more procyclical savings of low-to-medium wealth uninformed households—combined with the more countercyclical savings of rich uninformed households—amplify inequality: Poor uninformed households save less precisely when returns are high, while wealthy households are unable to effectively run down wealth to increase consumption. In effect, the presence of incomplete information increases the "randomness" of savings choices across the wealth distribution. This parallels the mechanism in Piketty and Saez (2003), who show that random savings rates combined with linear policy functions can generate Pareto tails in the wealth distribution. In our framework, however, this randomness is micro-founded through rational information choice rather than assumed exogenously.[36]

its volatility over time. We analyze the dynamics of inequality in depth in Appendix C.2.

[36]That said, because the magnitude of the errors are comparatively small relative to what is needed, in the

Table IV: Wealth Distribution

	Panel (a): Level of Moments				
	Gini G	90/10	99/1	90/50	Cor(K, Y)
Benchmark Model	0.51	14.53	345.3	3.51	0.62
Exogenous Information	0.51	14.51	339.4	3.45	0.56
Full Information	0.50	14.16	329.0	3.39	0.49
	Panel (b): Percent Difference w.r.t. Full Information				
	Gini G	90/10	99/1	90/50	Cor(K, Y)
Benchmark Model	1.60	2.66	4.96	3.58	24.66
Exogenous Information	1.07	2.51	3.20	1.66	14.38

Note: The table shows the mean of the logarithm of capital (K), the Gini coefficient of the capital distribution (G), as well as the 90/10, 99/1, and 90/50 percentile ratios of the wealth distribution. In addition, the table shows the correlation between the logarithm of capital and log. output (Y) (Cor(K, Y)). The table computes these moments in the calibrated model ("Benchmark Model"), the associated full-information economy ("Full Information"), as well as in the model with an exogenously specified probability of acquiring information ("Exogenous Information"). The probabilities of information acquisition in the benchmark model are, on average, 0.122 and 0.097, respectively, for the unemployed and employed. This probability is set equal to 0.10 in the exogenous-information case for all households and for all moments in time.

While the presence of incomplete information widens the distribution, the other two forces dampen the increase. First, the *heterogeneity in information choices* allows the most exposed households—the poor unemployed and the wealthy—to acquire information at higher rates, reducing their savings errors, all else equal. Second, the *weakened mean-reversion of capital* (apparent in the change in the equilibrium law of motion) increases the persistence of wages and returns, strengthening income effects that compress the distribution. On balance, we find that the former effect quantitatively dominates the latter, leading to a modest overall increase in inequality (Table IV). The combined effects of heterogeneous information are subtle—and, crucially, affect different parts of the distribution differentially.[37]

5.7 Matching the Wealth Distribution

A prominent issue with the Aiyagari-Bewley-Huggett-Imrohoroglu class of models that we depart from is that it does not generate realistic wealth heterogeneity: The data display

benchmark model this force is not sufficiently potent to generate a thick Pareto tail of wealth (cf. Section 5.7).

[37]Notice that while heterogeneity in information acquisition by itself decreases inequality, our benchmark economy features more inequality than its exogenous information counterpart (Table IV). This is due to the weaker general equilibrium dynamics in our benchmark model with heterogeneous information.

significantly more skewness than the models. Although the presence of stochastic death helps match the lower-tail of the wealth distribution, the concentration of wealth among the richest is likewise too small in our benchmark framework. The Gini coefficient is as a result too low: On the basis of the 2022 SCF, the Gini coefficient on wealth in the U.S. is around 0.80. In the benchmark model, by contrast, the equivalent number is only 0.51. The presence of heterogeneous information, as argued above, modestly increases wealth concentration among the rich—and thus the Gini coefficient—but does not do so by enough to match the data.

One of the main purposes of our line of research is to extend heterogeneous-agent frameworks to simultaneously allow for heterogeneity in wealth and expectations. It therefore seems important to ensure that the forces we highlight extend to models that roughly match the observed wealth distribution—especially given how the amplification that we document depends on it. To analyze such an environment, Appendix C.7 follows Bayer *et al.* (2024) and extends our baseline framework with a CES-structure for final production and a share of entrepreneurs in the population, who do not work but earn all pure rents in the economy. We set the share of entrepreneurs to 1 percent and the elasticity of substitution to target the top 10 percent wealth share. We also allow households to borrow (up to $k_{\min} < 0$), so as to match the negative wealth share held by the bottom of the distribution; and follow Bayer *et al.* (2024) and set the transition matrix governing switches between worker and entrepreneur states to the estimated values in Guvenen *et al.* (2014). Finally, we recalibrate the information cost parameters to target the same forecast error moments as our benchmark framework. Table III shows that the extended model matches closely the wealth distribution in the data.[38]

Figure C.4 compares the accuracy of unemployment forecasts across the wealth distribution with that in the benchmark model. Although the inverse u-shaped relationship is slightly shallower compared to that in the benchmark model, the overall strength of the relationship is similar to before. Consistent with this similarity, Table V and C.10 show that the presence of heterogeneous information once more amplifies business cycles: The standard deviation of capital and output, for example, increases by 71 percent and 9 percent, respectively. This compares to 64 percent and 11 percent, respectively, in the benchmark model. This resemblance is not obvious ex ante. With more wealth concentrated at the top, one might expect wealthy uninformed households' countercyclical savings to *dampen* rather than *amplify* fluctuations. Table III helps explain why this does not occur. Despite greater concentration, the bottom 60 percent still account for a substantial share of consumption expenditures (and exhibit the strongest procyclical bias when uninformed). Additionally, wealthy households still acquire information at high rates, and the extended model further introduces negative-wealth

[38]While the model better matches the Gini coefficient on wealth, it is, however, not able to match the Pareto tail of wealth in the data, as the wealth distribution merely inherits the tail of entrepreneurial earnings (Benhabib and Bisin, 2018). We also modestly increase μ to 0.45, to better target recent U.S. values.

households whose procyclical uninformed savings counters those from wealthy entrepreneurs.

Finally, Table V and C.10 show that, as in our benchmark framework, the presence of incomplete information once more widens the wealth distribution, especially the right tail, while the modified general equilibrium dynamics, all else equal, dampens the increase. The presence of heterogeneous incomplete information, as such, causes the Gini to increase by 8.6 percent.[39] The increased randomness in savings choices caused by incomplete information operates on a more skewed distribution, amplifying the dispersion of wealth at both tails.

Overall, we conclude that the consequences of heterogeneous incomplete information that we highlighted above extend to a framework which better matches the top and bottom of the wealth distribution. Clearly, the addition of another source of heterogeneity—whether households are workers or entrepreneurs—further complicates the already intricate consequences of heterogeneous incomplete information. Yet, the overall consequences that we find are qualitatively and quantitatively similar and akin to those in our benchmark framework.

5.8 Discussions and Robustness

Before ending with two policy exercises that target the wealth-expectation nexus, we briefly turn to several alternative versions of our benchmark framework. The overall aim is to demonstrate that our main findings—amplified business cycles and modest increases in inequality—are robust to alternative assumptions about information costs and the cyclicality of taxes. We recalibrate all alternative models to target the same capital-output ratio and (where appropriate) average errors as our benchmark model. Table V summarizes the results.

Angels and Demons: The frameworks considered so far with a fixed probability of information acquisition keep the costs of information acquisition from the benchmark model unchanged. Thus, while households have no choice about information acquisition in these alternative models, they still have to pay the resource and utility cost of information upon becoming informed. This focuses any comparison between the different models on the *endogeneity* and *incompleteness* of information itself—rather than the size of costs associated with it. We relax this assumption in Appendix C.5, where we instead make information freely (but randomly) available. We note that the exogenous-information economy without information costs is similar to the "Mankiw-Reis"-style economy studied in Auclert *et al.* (2020) and Carroll *et al.* (2020). Table C.6 and C.7 show that key moments change little irrespective of

[39]One noteworthy difference between our benchmark framework and the entrepreneur extension is that, while in the former case heterogeneity in information choices dampened the overall increase inequality, in the latter case it contributes to the widening of the wealth distribution (Table C.11). This once more shows that the details of who acquires information matters for inequality.

Table V: Summary of Robustness Exercises

	Panel (a): Difference % to Alternative Model			
	$\sigma(K)$	$\sigma(Y)$	Gini	Reference
Full Information w/o Costs	-0.04	-0.01	-0.20	Tables C.6, C.7
Exo. Information w/o Costs	-0.02	0.00	-0.31	Tables C.6, C.7
Scaled Utility Cost	-1.77	-0.52	-0.19	Table C.8
No Resource Cost	-18.49	-5.10	-1.50	Table C.9
	Panel (b): Difference % to Full Information Model			
	$\sigma(K)$	$\sigma(Y)$	Gini	Reference
Benchmark Model	64.2	11.0	1.6	Tables II, IV
Acyclical Taxes	66.1	7.7	2.3	Tables C.4, C.5
Entrepreneur Model	71.0	9.0	8.6	Table C.10

Note: Panel (a) reports the difference in moments relative to the relevant alternative economy, isolating the effect of each assumption; Panel (b) instead shows the change relative to a specifications full-information counterpart. $\sigma(K)$ and $\sigma(Y)$ denote the standard deviations of the log. of capital K and output Y, respectively. "W/o Costs" refers to the alternative economies in which information is freely available (Appendix C.5).

whether the given information is from a "Calvo-Angel" or a "Calvo-Demon".[40] Business cycle moments are next to unaffected: The maximum difference is less than a quarter of 1 percent (Table C.6). Inequality measures are slightly more affected, because the absence of a resource cost affects the disposable income of the poor (Table C.7). Nevertheless, the maximum difference in inequality measures is still below 1 percent. We conclude that assumptions about the information costs themselves matter little for the above comparisons between our benchmark economy and the alternative informational environments.

Homotheticity of Information Costs: Our benchmark model features both a resource cost η and a utility cost κ of information acquisition. Appendix C.6 explores the consequences that the non-homotheticity embedded in both have for our results. First, making the utility cost homothetic—by scaling it with the utility value of cash-at-hand—has only negligible effects. Figure C.2 shows that the relationship between the accuracy of unemployment expectations and wealth is nearly identical to that in the benchmark model—with only a small

[40] An anonymous referee provided the labeling for these alternative economies: When we make information freely available in the alternative frameworks with an (exogenously) pre-specified probability of information acquisition it is as-if households are touched by a "Calvo-Angel" upon becoming informed. By contrast, in the alternative frameworks that we studied above, where households still have to pay the costs of information upon becoming informed, it is as-if households are instead touched by a "Calvo-Demon".

increase in the size of the inverse u-shape noticeable. Consistent with these findings, Table C.8 shows that the business-cycle and inequality statistics also do not depend much on the non-homotheticity of the utility cost. The maximum difference between our benchmark model and the moments of the model with the scaled utility cost is less than 2 percent. By contrast, the resource cost matters more. Removing it entirely dampens both the amplification and the increase in inequality (Table C.9) documented above, and—importantly—eliminates the inverse u-shaped relationship between accuracy and wealth in the model (Figure C.3). Although the information policy function still shows non-monotonicities similar to those in the benchmark model, the resource cost, though small (roughly 0.1 percent of average quarterly earnings), acts as a barrier for wealth-poor households' information acquisition. We conclude that the non-homotheticity embedded in the resource cost of information is an important feature for matching the survey data—and for the consequences of heterogeneous information highlighted above—unlike the non-homotheticity implied by the utility cost.

Cyclicality of Taxes: Following Krusell and Smith (1998) and others, our baseline framework assumes a balanced government budget in every period (Section 3.3). Because the labor endowment falls and government outlays for unemployment insurance rise in recessions, a balanced budget, however, implies *countercyclical tax rates*. To analyze the importance of these for our results, Appendix C.4 studies an alternative tax scheme in which the government perfectly smoothes taxes through an implicit insurance scheme with (unmodelled) financial intermediaries from the rest of the world. This follows the approach taken in Mitman and Rabinovich (2015), among others. In particular, the government charges a constant tax rate $\tau^\star$ such that the present value of labor-income taxes equals that of unemployment-benefit payments when appropriately discounted.[41] As expected, aggregate volatility is lower with acyclical taxes (Table V and C.4); however, crucially, relative to the full-information case, the increase that arises due to heterogeneous incomplete information is similar to before. The standard deviation of output, for example, increases by 8 percent compared to 11 percent previously. While the equilibrium level of inequality is similarly slightly smaller, the increase that arises is, if anything, now somewhat larger—with a similar decomposition of the overall increase to that from before. The 99/1-ratio, for example, now rises by 7 percent versus 5 percent previously (Table C.5). We conclude that our main business-cycle and inequality implications are robust to changes in assumptions about the cyclicality of income taxes.

Across all extensions, a consistent pattern emerges: Heterogeneous information amplifies business-cycle volatility and modestly increase inequality. The specific magnitudes vary—the

[41]The exact formula for the constant tax rate is $\tau = \mathbb{P}[z = z_l]\frac{\mu u_l}{u_l\mu + (1-u_l)} + \mathbb{P}[z = z_h]\frac{\mu u_h}{u_h\mu + (1-u_h)}$, where $\mathbb{P}[z = z_l]$and $\mathbb{P}[z = z_h]$ are the unconditional probabilities of a bust and a boom, respectively.

resource cost of information matters more for matching the empirical expectation patterns, while the cyclicality of taxes and the homotheticity of utility costs less—but the core mechanisms persist. Whether households face cyclical or constant taxes, or operate in economies with utility or resource costs for information, the fundamental two-way relationship between wealth and information systematically alters macroeconomic dynamics. Combined with the entrepreneur extension, this robustness strengthens confidence that our conclusions reflect genuine features of the wealth-expectation nexus rather than artifacts of particular modeling choices. The next section shows how the interplay between information choice, (precautionary) savings, and the aggregate economy similarly modifies the effects of simple economic policies that target different dimensions of inequality but have uninteded consequences due to the expectation-wealth nexus.

6 Two Policy Experiments

The previous section documented the macroeconomic consequences of the wealth-expectation nexus. Our findings raise a natural question: Do macroeconomic policies have important additional effects via the wealth–expectation link through endogenous information acquisition? We close the paper by illustrating the potential for such consequences using two policy experiments that directly affect groups with high information acquisition rates: (i) a wealth tax, which primarily impacts wealthy households; and (ii) increased unemployment benefits, which primarily affects the poor. Both policies reduce information acquisition but operate through different channels and with different economy-wide outcomes.

6.1 A Wealth Tax

For our first policy experiment, we consider a 1 percent per annum wealth tax, modeled on France's pre-2017 wealth tax and recent U.S. Congressional proposals (e.g., Guvenen *et al.*, 2019; Saez and Zucman, 2022).[42] One of the main arguments of the proponents of the tax is that it will reduce inequality and be an equitable way to finance increased government spending and transfers. We assume the government imposes the linear wealth tax $\tau_k > 0$ on beginning-of-period capital holdings and rebates all proceeds to households as lump-sum transfers.[43] Household cash-at-hand m_i is therefore given by the expression:

$$m_i = (1 + r - \delta - \tau_k)k_i + (1 - \tau)\left[\epsilon_i w\bar{l} + (1 - \epsilon_i)\,\mu w\right] + T, \tag{6.1}$$

[42] The "Warren 2021 proposal" can be found here: https://www.congress.gov/bill/senate-bill/510

[43] We have experimented with an alternative setup in which the proceeds are not rebated but instead treated as unvalued spending. This alternative specification only captures part of the effects that we present here—it only effects the right tail of the distribution since without the rebate there is no direct effect on the wealth-poor. The results from this specification (unreported) are in line with the detailed results we present below.

Table VI: Quantitative Effects of a Wealth Tax

	$\mu(K)$	$\sigma(Y)$	Gini(K)	90/10	99/1	90/50	Info U.	Info E.
Benchmark Model	-8.57	6.35	-0.17	-3.54	-1.90	-1.86	-6.83	-8.53
Exogenous Information	-8.24	3.00	-1.23	-3.59	-5.19	-2.28	.	.
Full Information	-7.73	0.66	-3.05	-4.55	-10.26	-4.12	.	.

Note: The table shows the effects of a one percent per annum wealth tax on moments of the average cross-sectional capital distribution and the logarithm of economy-wide output in percent. $\mu(K)$ denotes the mean of the capital stock, while $\sigma(Y)$ denotes the standard deviation of (log-)economy-wide output. The table computes the moments for both the calibrated model ("Benchmark Model") and the associated full-information and exogenous-information economies ("Full Information" and "Exogenous Information", respectively). The final two columns measure the percent difference in the average number of households who acquire information. We compute this probability separately for the employed and unemployed.

where the transfer T equals the average proceeds of the tax τ_k. Table VI and Figure D.1 in the Appendix report the macroeconomic consequences of the wealth tax.[44]

The direct effect of the wealth tax is—unsurprisingly—to reduce aggregate savings across all informational environments considered, as seen by the 5-6 percent drop in the capital stock in all cases (Table VI). The wealth tax reduces after-tax returns, which discourages savings across the wealth distribution. Because the probability of information acquisition is heterogeneous across the wealth distribution, the wealth tax, nevertheless, also changes the level and incidence of information in the benchmark economy.

While wealthy households see their resources reduced by the tax, the lump-sum transfers increase cash-at-hand for households at the bottom of the distribution. Because both of these groups acquire information at higher rates than average (Section 5.2), the introduction of the wealth tax thus strongly reduces information acquisition—by more than 8 percent, on average. This reduction, in turn, has countervailing effects on the volatility of output: The reduction in information acquisition by the poor increases the procyclicality of savings (and hence capital), while the reduction of the rich dampens it. On balance, Table VI shows that the former effect dominates the latter. The wealth tax and the associated reduction in information acquisition dampens the mean-reversion of capital and raises output volatility (by 6.4 percent). This compares to an only 0.7 percent increase under full-information.

Perhaps more surprisingly, the wealth tax barely reduces inequality in the benchmark economy. The Gini coefficient falls by less than 0.2 percent after the wealth tax, while it declines by more than 3 percent under full information (Table VI). We plot the change in the

[44] The French wealth tax was called the "Impôt de solidarité sur la fortune" (ISF). The IFS was an annual tax, with rates from 0.5 percent to 1.0 percent per annum, depending on your wealth.

wealth distribution following the wealth tax in Figure D.1 in the Appendix. There are three contrasting forces that explain the effects of the wealth tax on inequality.

First, the lump-sum transfer financed by the tax, all else equal, reduces income volatility, and thus households' precautionary wealth. Second, this left-ward shift in the wealth distribution is, in turn, reinforced by the "disincentive effect" from a lower after-tax return on capital, which further reduces savings for all households, including the rich. Combined, these effects reduce inequality—as in the full-information case. However, because information increases with wealth for rich households, the tax-induced reduction in wealth also decreases their information acquisition. Wealthy households' savings become more "random". Similar to the results in Piketty and Saez (2003), and for the same reasons as discussed in Section 5.4, this dampens the reduction in top-wealth holdings. The mass of households with more than \$1 million in wealth in Figure D.1 is almost unchanged—despite the wealth tax—and the 99/1-ratio barely budges. Counterintuitively, introducing a wealth tax does not *substantially* decrease the share of wealth held by the most wealthy in the economy.[45]

Finally, we also study the introduction of a wealth tax in the entrepreneur model, which better matches the wealth distribution. The results, presented in Appendix D.3, show that the effect of a wealth tax on aggregate volatility is somewhat smaller and more alike across different informational environments than before. The volatility of output rises by 2 percent with endogenous information. The decreased information acquisition of the rich and the poor cancel each other more in terms of their effects on the overall cyclicality of savings, as more of the stock of wealth is now held by the rich. However, crucially, the presence of heterogeneous information once more counters any equalizing effects of a wealth tax. Indeed, in the extended model, the Gini coefficient increases by 2.2 percentage points due to heterogeneous information. This compares to 2.8 percentage points in the benchmark model.[46]

6.2 An Increase in Unemployment Benefits

We close the paper with our second policy counterfactual that instead considers a 10 percentage points increase in the replacement rate μ (from 40 to 50 percent of wages). The unemployed are

[45] Although our model is not meant to capture all the dimensions of a wealth tax, we note that several studies, often building on data from Swiss Cantons (e.g., Marti *et al.*, 2023) or Norwegian regions (e.g., Iacono and Smedsvik, 2024), show that a *decrease* in wealth taxes can lead to an *increase* in *measured inequality*. However, as argued in Seim (2017), among others, the lion's share of the estimated effect often reflect changes in "evasion and avoidance rather than changes in actual savings behavior" (Seim, 2017).

[46] We note that introducing the wealth tax changes the Gini in the full-information entrepreneur extension only slightly (it rises by 0.6%; Appendix D.3). The wealthiest households—entrepreneurs—save at high rates and adjust savings little when after-tax returns change. By contrast, the tax still lowers both the mean and the dispersion of workers' capital holdings, as in the benchmark full-information model. As a result, within-worker inequality falls, but wealth becomes slightly more concentrated between workers and entrepreneurs; this between-group effect dominates, such that inequality rises by a small amount under full information.

the second category of households that we identified as acquiring information at higher rates than the average (Section 5.2). This increase—combined with the increase in labor-income taxes required to finance it—reduces the income risk from unemployment, and thus both the incentive to accumulate precautionary savings and to acquire information about the current state of the economy. Table VII and Figure D.2 in the Appendix report the macroeconomic consequences of the 10 percentage points increase in unemployment benefits.

When the replacement rate is increased, the unemployed especially reduce both their savings and their rate of information acquisition, the latter by about 13 percent.[47] As in the case of the wealth tax, this reduction in information acquisition probabilities once more decreases the accuracy of expectations, dampens the mean-reversion of capital by increasing the procyclicality of savings, and increases the volatility of output (by 3.5 percent). In contrast, in the full-information case, the volatility of output hardly changes (rises only by 0.4 percent).

Inequality is further affected: The Gini coefficient on wealth rises by 5.7 percent due to the increase in unemployment benefits, nearly twice the increase under full information. The savings and information behavior of the rich—for whom post-tax labor or replacement incomes account only for a small share of total wealth—is nearly unaffected *directly* by the policy. Yet, because the reduced precautionary savings by the poor increases returns to capital, it increases the average savings of the rich. As the reduction in information acquisition is further concentrated among the poor, their reduction in savings is worsened by their inability to save when future returns are high. The poor make larger errors precisely when opportunities for wealth accumulation are greatest. This explains why the rise in inequality documented in Table VII and Figure D.2 is substantially more pronounced in the benchmark economy compared to the economies with full and (to a lesser extent) exogenous information.

The same results carry over to the extended environment of Section 5.7, which more closely matches the wealth distribution (Appendix C.7 and D.3). An increase in unemployment benefits (i) *increases* the volatility of output, albeit slightly less so than in the benchmark model, due to less wealth being held by the poor; and (ii) *increases* inequality by *more* after one accounts for households' endogenous information choices. A policy designed to strengthen the safety net for the unemployed, in essence, inadvertently reduces their incentive to be informed, leading them to make larger savings errors that ultimately increase inequality.

While we above have abstained from making welfare statements about the policies that we analyze, our positive findings indicate that policymakers should proceed cautiously when evaluating the consequences of tax and transfer policies. The effects on households' information choices may lead to implications that run counter to the stated objectives—for example,

[47] Since there are fewer unemployed than employed households, the average probability of information acquisition across all households falls by almost 3 percentage points.

Table VII: Quantitative Effects of Increased Unemployment Benefits

	$\mu(K)$	$\sigma(Y)$	Gini(K)	90/10	99/1	90/50	Info U.	Info E.
Benchmark Model	-1.63	3.52	5.66	24.85	44.53	7.50	-12.63	-1.77
Exogenous Information	-1.32	1.06	4.64	23.71	40.17	6.46	.	.
Full Information	-0.95	0.36	3.13	22.37	33.37	4.54	.	.

Note: The table shows the effects of a ten percentage-point increase in the replacement rate on moments of the average cross-sectional capital distribution and the logarithm of economy-wide output in percent. $\mu(K)$ denotes the mean of the capital stock, while $\sigma(Y)$ denotes the standard deviation of (log-)economy-wide output. The table computes the moments for the both benchmark economy ("Benchmark Model") and the associated full-information and exogenous-information economies ("Full Information" and "Exogenous Information", respectively). The final two columns measure the percent difference in the average number of households who acquire information. We compute this probability separately for the employed and unemployed.

their implications on wealth inequality. For both the case of a wealth tax and an increase in benefits, the endogeneity of household information choices acts to increase inequality relative to standard full-information environments. More generally, the above policy experiments illustrate that macroeconomic policies may have important additional effects through changes in the distribution of expectations: By changing the wealth distribution, and hence distribution of agents' information, macroeconomic policies fundamentally alter an economy's responsiveness to shocks. These additional effects, absent from standard full-information environments, may be quantitatively important—both from a positive and a normative perspective.

7 Conclusion

The frontier of macroeconomics continues to incorporate salient dimensions of household and firm heterogeneity to provide a more complete and accurate description of the macroeconomy. In this paper, we have illustrated how the interaction between two important dimensions of household heterogeneity—heterogeneity in expectations and heterogeneity in wealth—gives rise to new qualitative and quantitative insights about macroeconomic dynamics and the effects of macroeconomic policies. In particular, we have demonstrated how the wealth-expectation nexus increases the endogenous propagation of shocks and partially accounts for the lack of inequality in standard frameworks with incomplete markets. We have showed how the wealth-expectation nexus further fundamentally alters the predictions of government policies such as wealth taxes or unemployment benefits—and in unexpected ways.

Our findings have important implications for both the heterogeneous-agent macro literature and the literature on models with dispersed information. For the former, our policy experiments provide a "Lucas-style" criticism (Lucas, 1976) to policy analysis in incomplete-markets models: Any policy that has a substantial impact on the wealth distribution will systematically affect household information choices and their expectations, with associated consequences for macroeconomics dynamics and the cross-section.[48] For the latter, studying the consequence of dispersed information in models with linear policy rules misses the important two-way interaction between the distribution of agent wealth and the non-linearity of the value of additional information. Our framework provides a laboratory to push both strands of the literature forward to explore new questions in macroeconomics.

Our analysis has been positive in nature but raises interesting normative questions. In particular, information choices have obvious externalities in our environment through the implied change in the dynamic properties of prices and quantities. Does this mean policymakers should subsidize information or alter the manner in which they condition their policy instruments? Should such subsidies or policy instruments target a particular subset of the population? And how close do market-based or institutional solutions, which collect information on behalf of households and distribute it to them, come to the constrained efficient allocation? We leave these exciting questions for future research.

[48] In this sense, our results provide a Lucas-style criticism (Lucas, 1976) of Lucas' own comments about the response of an economy with incomplete information to shocks; that "It seems safe and, for my purposes, sensible to abstract here from the fact that in reality this situation can be slightly mitigated by the purchase of additional information" (p. 1121, Lucas, 1975).

References

Andrade, P., Coibion, O., Gautier, E. and Gorodnichenko, Y. (2022). No firm is an island? how industry conditions shape firms expectations. *Journal of Monetary Economics*, **125**, 40–56.

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

Armantier, O., Topa, G., Van der Klaauw, W. and Zafar, B. (2017). An overview of the survey of consumer expectations. *Economic Policy Review*, (23-2), 51–72.

Auclert, A., Rognlie, M. and Straub, L. (2020). Micro jumps, macro humps: Monetary policy and business cycles in an estimated hank model. *National Bureau of Economic Research*.

Baley, I. and Veldkamp, L. L. (2025). *The Data Economy: Tools and Applications*. Princeton University Press.

Bayer, C., Born, B. and Luetticke, R. (2024). Shocks, frictions, and inequality in us business cycles. *American Economic Review*, **114** (5), 1211–1247.

Benhabib, J. and Bisin, A. (2018). Skewed wealth distributions: Theory and empirics. *Journal of Economic Literature*, **56** (4), 1261–1291.

Bhandari, A., Borovička, J. and Ho, P. (2025). Survey data and subjective beliefs in business cycle models. *Review of Economic Studies*, **92** (3), 1375–1437.

Bordalo, P., Coffman, K., Gennaioli, N. and Shleifer, A. (2016). Stereotypes. *The Quarterly Journal of Economics*, **131** (4), 1753–1794.

—, Gennaioli, N. and Shleifer, A. (2017). Memory, attention, and choice. *The Quarterly journal of economics*.

Broer, T., Kohlhas, A., Mitman, K. and Schlafmann, K. (2022). On the possibility of krusell-smith equilibria. *Journal of Economic Dynamics and Control*.

Brunnermeier, M. K. and Parker, J. A. (2005). Optimal expectations. *American Economic Review*, **95** (4), 1092–1118.

Caplin, A. and Leahy, J. V. (2019). Wishful thinking. *National Bureau of Economic Research*.

Carroll, C., Slacalek, J., Tokuoka, K. and White, M. N. (2017). The distribution of wealth and the marginal propensity to consume. *Quantitative Economics*, **8** (3), 977–1020.

Carroll, C. D. (2003). Macroeconomic expectations of households and professional forecasters. *the Quarterly Journal of economics*, **118** (1), 269–298.

— (2006). The method of endogenous gridpoints for solving dynamic stochastic optimization problems. *Economics letters*, **91** (3), 312–320.

—, Crawley, E., Slacalek, J., Tokuoka, K. and White, M. N. (2020). Sticky expectations and consumption dynamics. *American economic journal: macroeconomics*, **12** (3), 40–76.

Christiano, L. J., Eichenbaum, M. and Evans, C. L. (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of political Economy*, **113** (1), 1–45.

—, Eichenbaum, M. S. and Trabandt, M. (2016). Unemployment and business cycles. *Econometrica*, **84** (4), 1523–1569.

—, Trabandt, M. and Walentin, K. (2010). Dynamic stochastic general equilibrium models for monetary policy analysis. **3**, 285–367.

Coibion, O. and Gorodnichenko, Y. (2012). What can survey forecasts tell us about information rigidities? *Journal of Political Economy*, **120** (1), 116–159.

— and — (2015). Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review*, **105** (8), 2644–2678.

—, — and Kamdar, R. (2018). The formation of expectations, inflation, and the phillips curve. *Journal of Economic Literature*, **56** (4), 1447–91.

—, — and Ropele, T. (2020). Inflation expectations and firm decisions: New causal evidence. *The Quarterly Journal of Economics*, **135** (1), 165–219.

Del Negro, M., Schorfheide, F., Smets, F. and Wouters, R. (2007). On the fit of new keynesian models. *Journal of Business & Economic Statistics*, **25** (2), 123–143.

Den Haan, W. J., Judd, K. L. and Juillard, M. (2010). Computational suite of models with heterogeneous agents: Incomplete markets and aggregate uncertainty. *Journal of Economic Dynamics and Control*, **34**.

Faust, J. and Wright, J. H. (2013). Forecasting inflation. *Handbook of economic forecasting*, **2**, 2–56.

Gabaix, X. (2019). Behavioral inattention. In *Handbook of Behavioral Economics: Applications and Foundations 1*, vol. 2, Elsevier, pp. 261–343.

Grossman, S. J. and Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *The American economic review*, **70** (3), 393–408.

Guvenen, F., Kambourov, G., Kuruscu, B., Ocampo-Diaz, S. and Chen, D. (2019). Use it or lose it: Efficiency gains from wealth taxation.

—, Kaplan, G. and Song, J. (2014). How risky are recessions for top earners? *American Economic Review*, **104** (5), 148–153.

Harrington, M. (1997). *The other america*. Simon and Schuster.

Hellwig, C. and Veldkamp, L. (2009). Knowing what others know: Coordination motives in information acquisition. *The Review of Economic Studies*, **76** (1), 223–251.

Iacono, R. and Smedsvik, B. (2024). Behavioral responses to wealth taxation: evidence from a norwegian reform.

Jakobsen, K., Jakobsen, K., Kleven, H. and Zucman, G. (2020). Wealth taxation and wealth accumulation: Theory and evidence from denmark. *The Quarterly Journal of Economics*, **135** (1), 329–388.

Kacperczyk, M., Nosal, J. and Stevens, L. (2019). Investor sophistication and capital income inequality. *Journal of Monetary Economics*, **107**, 18–31.

Kaplan, G. and Violante, G. L. (2018). Microeconomic heterogeneity and macroeconomic shocks. *Journal of Economic Perspectives*, **32** (3), 167–194.

Krueger, D., Mitman, K. and Perri, F. (2016). Macroeconomics and household heterogeneity. In *Handbook of Macroeconomics*, vol. 2, Elsevier, pp. 843–921.

Krusell, P. and Smith, A. (1998). Income and Wealth Heterogeneity in the Macroeconomy. *Journal of Political Economy*, **106** (5).

Lorenzoni, G. (2009). A theory of demand shocks. *American economic review*, **99** (5), 2050–2084.

Lucas, R. E. (1972). Expectations and the neutrality of money. *Journal of economic theory*, **4** (2), 103–124.

— (1975). An equilibrium model of the business cycle. *Journal of political economy*, **83** (6), 1113–1144.

— (1976). Econometric policy evaluation: a critique,. *The Phillips Curve and Labour Markets, Carnegie-Rochester Conference Series on Public Policy*, **1**.

Lusardi, A. and Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *American Economic Journal: Journal of Economic Literature*, **52** (1), 5–44.

Macaulay, A. and Moberly, J. (2022). Heterogeneity in imperfect inflation expectations: theory and evidence from a novel survey. *Oxford University mimeo.*

Maćkowiak, B., Matějka, F. and Wiederholt, M. (2018). Dynamic rational inattention: Analytical results. *Journal of Economic Theory*, **176**, 650–692.

—, — and Wiederholt, M. (2021). Rational inattention: A review. *Journal of Economic Perspectives.*

— and Wiederholt, M. (2009). Optimal sticky prices under rational inattention. *American Economic Review*, **99** (3), 769–803.

Mankiw, N. G. and 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.

—, — and Wolfers, J. (2003). Disagreement about inflation expectations. *NBER macroeconomics annual*, **18**, 209–248.

Marti, S., Martínez, I. Z. and Scheuer, F. (2023). Does a progressive wealth tax reduce top wealth inequality? evidence from switzerland. *Oxford Review of Economic Policy*, **39** (3), 513–529.

McFadden, D. *et al.* (1973). Conditional logit analysis of qualitative choice behavior. *Institute of Urban and Regional Development, University of California Berkeley.*

Mihet, R. (2022). Who benefits from innovations in financial technology? *University of Lausanne mimeo.*

Mitman, K. and Rabinovich, S. (2015). Optimal unemployment insurance in an equilibrium business-cycle model. *Journal of Monetary Economics*, **71**, 99–118.

Moll, B. (2024). The trouble with rational expectations in heterogeneous agent models: A challenge for macroeconomics. *London School of Economics, mimeo, available at https://benjaminmoll. com.*

Morduch, J. and Schneider, R. (2017). *The financial diaries: How American families cope in a world of uncertainty*. Princeton University Press.

Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica: Journal of the Econometric Society*, pp. 315–335.

Newman, K. S. (2009). *No shame in my game: The working poor in the inner city*. Vintage.

Peress, J. (2004). Wealth, information acquisition, and portfolio choice. *The Review of Financial Studies*, **17** (3), 879–914.

Piketty, T. and Saez, E. (2003). Income inequality in the united states, 1913–1998. *The Quarterly journal of economics*, **118** (1), 1–41.

Ravn, M. O. and Uhlig, H. (2002). On adjusting the hodrick-prescott filter for the frequency of observations. *Review of economics and statistics*, **84** (2), 371–376.

Reiche, L. (2025). That's what she said: an empirical investigation on the gender gap in inflation expectations. *University of Oxford mimeo.*

Reis, R. (2020). The people versus the markets: A parsimonious model of inflation expectations. *LSE Working Paper*.

Saez, E. and Zucman, G. (2022). Wealth taxation: Lessons from history and recent developments. **112**, 58–62.

Seim, D. (2017). Behavioral responses to wealth taxes: Evidence from sweden. *American Economic Journal: Economic Policy*, **9** (4), 395–421.

Shipler, D. K. (2005). *The working poor: Invisible in America*. Vintage.

Silvapulle, M. J. and Sen, P. K. (2005). *Constrained statistical inference: Inequality, order and shape restrictions*. John Wiley & Sons.

Sims, C. A. (2003). Implications of rational inattention. *Journal of monetary Economics*, **50** (3), 665–690.

Stark, T. *et al.* (2010). Realistic evaluation of real-time forecasts in the survey of professional forecasters. *Federal Reserve Bank of Philadelphia Research Rap, Special Report*, **1**.

Townsend, R. M. (1983). Forecasting the forecasts of others. *Journal of Political Economy*, **91** (4), 546–588.

Veldkamp, L. L. (2011). *Information choice in macroeconomics and finance*. Princeton University Press.

Vissing-Jorgensen, A. (2003). Perspectives on behavioral finance: Does" irrationality" disappear with wealth? evidence from expectations and actions. *NBER macroeconomics annual*, **18**, 139–194.

Weber, M., DAcunto, F., Gorodnichenko, Y. and Coibion, O. (2022). The subjective inflation expectations of households and firms: Measurement, determinants, and implications. *National Bureau of Economic Research*.

Woodford, M. (2002). *Imperfect common knowledge and the effects of monetary policy*. Tech. rep., National Bureau of Economic Research.

Online Appendix for
"Expectation and Wealth Heterogeneity in the Macroeconomy"

Tobias Broer Alexandre Kohlhas Kurt Mitman Kathrin Schlafmann

February 2026

Contents

A Motivating Evidence

A.1 Additional Estimates

Table A.8: Unemployment Expectations Across the Wealth Distribution

	Absolute Error		
	(1)	(2)	(3)
Wealth Percentile (0-10)	-0.009	0.063***	0.060***
	(0.020)	(0.017)	(0.017)
Wealth Percentile (10-20)	0.045**	0.088***	0.082***
	(0.020)	(0.018)	(0.017)
Wealth Percentile (20-40)	0.064***	0.089***	0.084***
	(0.016)	(0.013)	(0.013)
Wealth Percentile (40-60)	0.050***	0.029**	0.026**
	(0.015)	(0.012)	(0.012)
Wealth Percentile (60-80)	0.003	0.023*	0.020
	(0.015)	(0.012)	(0.012)
Wealth Percentile (80-100)	–	–	–
Male	–	-0.004	-0.004
		(0.008)	(0.008)
Education	–	-0.072***	-0.072***
		(0.010)	(0.010)
Non-participation	–	0.019*	0.020*
		(0.011)	(0.011)
Age	–	0.013***	0.013***
		(0.002)	(0.002)
Age^2	–	-0.0001***	-0.0001***
		(0.00002)	(0.00002)
Time Fixed Effects	×	✓	✓
Pre-2020Q1	×	×	✓
Observations	40,998	37,163	36,408
F Statistic	6.12	409.57	355.05
R^2	0.01	0.44	0.40

Note: Column (1) shows estimates from a regression of the absolute value of individual unemployment errors on the wealth bucket (decile/quintile) that the individual respondent belongs to. Estimates are relative to the wealthiest households, those in the 80-100 percentile of the wealth distribution. Column (2) adds controls to the regression specification: the age, education (college or not), labor market status, and sex of the respondent, as well as time fixed effects. Column (3) shows estimates "pre-covid"; that is, before January 2020. Robust standard errors in parentheses. Sample: 2013M10-2020M3. $*$ p<.1, $**$ p<.05, $***$ p<.01

Table A.9: Test for the Monotonicity of Regression Coefficients

	Unemployment Forecasts	
	Left-hand side	Right-hand side
Figure 1 (Panel a and b)	0.01	0.32
Figure 1 (Panel c and d)	<0.01	<0.01
	Inflation Forecasts	
	Panel a (lhs)	Panel a (rhs)
Figure 2	0.89	0.01
	House Price Forecasts	
	Panel a (lhs)	Panel a (rhs)
Figure 2	0.09	0.03

Note: The table reports p-values from the Likelihood Ratio test by Silvapulle and Sen (2005) of monotonically declining regression coefficients (H_0 : monotonic decline) against the alternative (H_A : non-monotinicty) using the SCE data discussed in Section 2. Results are reported using 10,000 draws from a semi-nonparametric Bollen-Stine bootstrap procedure. The figure and panel labels correspond to those used in the main text.

Table A.10: Unemployment Expectations and Wealth Percentiles

	Dependent variable:
	Absolute Error
Wealth Percentile	0.113^{*}
	(0.059)
Wealth Percentile Squared	-0.162^{**}
	(0.067)
Constant	1.237^{***}
	(0.015)
Controls	✓
Observations	40,998
F Statistic	6.876^{***} (df = 2; 40995)

Note: The table shows estimates from a regression of the absolute value of individual unemployment errors on the wealth percentile that the individual respondent belongs to, in addition to controls: the age, education (college or not), labor market status, and sex of the respondent, as well as time fixed effects. Robust standard errors in parentheses. Sample: 2013M10-2020M3. $*$ p<.1, $**$ p<.05, $***$ p<.01

A.2 Data Construction

The SCE is a monthly internet survey of c. 1,300 "household heads", defined as the person in a household who owns, is buying, or rents the home. Subjects are chosen from the respondents to the Consumer Confidence Survey (CCS), itself based on the universe of U.S. postal addresses, to match demographic targets from the American Community Survey, and remain in the survey for up to 12 months. The SCE core module contains monthly information about households' expectations about key macroeconomic and individual variables. Importantly, a yearly module also asks the survey respondents for key financial variables, including their financial wealth.[49]

A.2.1 Variable Definitions

We focus on expectations of three variables: inflation, house prices, and the unemployment rate. The former two ask respondents for their best guess of a variable's outcome, in addition to the probability of it falling into a number of bins. The exact questions are:

- Inflation:
  "*What do you expect the rate of (CPI) inflation to be over the next 12 months? Please give your best guess*", followed by *"In your view, what would you say is the percent chance that, over the next 12 months the rate of inflation will be...* ".

- House prices:
  "*By about what percent do you expect the average home price to [increase/decrease]? Please give your best guess.*", followed by "*And in your view, what would you say is the percent chance that, over the next 12 months, the average home price nationwide will...*".

We calculate forecast errors as the difference between individual best estimates and the actual (12-month-ahead) outcomes of U.S. consumer price index inflation and inflation in the S&P Case-Shiller 20-City Composite Home Price Index, respectively. We use the measures of interquartile ranges of individual forecasts provided by the SCE.

For unemployment expectations, the survey does not ask for point forecasts but instead elicits beliefs about the probability that the national unemployment rate will rise:

- Unemployment: "*What do you think is the percent chance that 12 months from now the unemployment rate in the U.S. will be higher than it is now?*"

To construct errors ν_{it} of individual unemployment forecasts $P_{it}(u_{t+12} > u_t)$, we would ideally compare household $i \in [0,1]$'s response to the true-but-unobserved probability $P_t(u_{t+12} > u_t)$.

[49] We match wealth observations with the household's monthly expectations using the household's id variable.

Consistent with ample evidence that professional forecasters provide more accurate predictions than even those from modern statistical and economic models (Stark *et al.*, 2010; Faust and Wright, 2013; and Bhandari *et al.*, 2025), we proxy the true probability by the consensus forecast from the SPF, which we denote $P_{SPF,t}(u_{t+12} > u_t)$. In particular, we calculate each forecaster's belief about the probability of rising unemployment (using the probabilistic answers in the variable PRUNEMP), and then average over forecasters. Finally, since the data was collected during a time of steadily falling unemployment, we scale the difference between a household's expectations and the consensus forecast of professional forecasters by the average consensus forecast to make the measure comparable to the model-implied probabilities that are calibrated to a different time period. We also multiply our measure by 2 to make it consistent with the "Brier score". We thus compute the errors in unemployment forecasts as:

$$\nu_{it} = 2 \times \frac{P_{it}(u_{t+12} > u_t) - P_{SPF,t}(u_{t+12} > u_t)}{T^{-1}\sum_t P_{SPF,t}(u_{t+12} > u_t)}, \tag{A1}$$

where the average is computed across all observations in our sample.

In addition to survey estimates, we use the following household characteristics: sex, age, dummies that take values of one if the household head reports to have a college degree or to participate in the labor market (in the sense that she / he is either employed or unemployed), respectively. We also use a measure of household net-financial wealth, which we construct as the difference between a household's total financial assets and non-mortgage debt.[50] We construct wealth deciles/quintiles based on the initial two years of data (2013 and 2014). We deflate the resulting quantities by the level of the U.S. consumer price index.

We do not perform any sample selection other than dropping households whose median inflation expectations lie in the extreme bins (higher than $+/-12$ percent) respectively.

A.2.2 Summary Statistics

Table A.11 illustrates that households' 12-month unemployment and inflation expectations from the SCE are on average *less accurate* than professional forecasts. Households attach on average a higher probability to rising unemployment than professional forecasters, implying larger forecast errors during a sample period where unemployment declined steadily. We find a similar picture for CPI inflation: the median of household point forecast errors are substan-

[50] The question about financial assets is "*Approximately what is the total current value of your [and your spouse's/partner's] savings and investments (such as checking and savings accounts, CDs, stocks, bonds, mutual funds, Treasury bonds), excluding those in retirement accounts*?". The question about mortgage debt is *"Approximately, what is the total amount of outstanding loans against your home(s), including all mortgages and home equity loans?"*, while that for total debt is *"Approximately, what is the total amount of your [and your spouses/partners] current outstanding debt?"*.

Table A.11: Macroeconomic Expectations in the SCE and SPF

	Panel a: Unemployment Rate			
		Median Forecast	Std. Dev. of Forecast	
SCE		39.00	22.98	
SPF		32.13	17.80	
		Panel b: Inflation		
	Median Abs. Error	Std. Dev. of Error	Median IQR	Std. Dev. of IQR
SCE	1.61	2.93	2.00	4.48
SPF	0.72	0.65	0.56	0.25

Note: The table shows moments of the individual probability distributions from the Survey of Consumer Expectations (SCE) and the Survey of Professional Forecasters (SPF). Panel a shows the median and standard deviation of individual unemployment forecasts. Panel b shows the median error of individual inflation forecasts (column 2), the standard deviation of these errors (column 3), the median interquartile ranges derived from individual distributions (column 4), and their standard deviation (column 5).

tially larger for households than for professional forecasters—equal to 1.6 and 0.7 percentage points (pp), respectively. Furthermore, Table A.11 demonstrates that household expectations are also substantially *more uncertain* than professional forecasts. When elicited for their probability distribution over possible inflation realizations, households report substantially wider distributions. The median of the interquartile ranges of individual forecast distributions is more than triple that of professional forecasters—2.0pp vs. 0.6pp, respectively. Finally, Table A.11 shows that household expectations are also substantially *more heterogeneous* than SPF forecasts. Specifically, household unemployment expectations and point forecasts for CPI inflation have a much higher cross-sectional standard deviation than the forecasts of professionals. The standard deviation of forecast errors for CPI inflation across households is, for example, about three times larger than across professional forecasters.

A.3 Forecasting VAR

We use a standard quarterly forecasting VAR to compute forecasts of the probability of a rising unemployment rate under the data-generating measure. All time series are downloaded from FRED for the period 1960Q1– 2019Q4: CPI inflation (CPIAUCSL, percentage change from a year ago), real GDP (GDPC1, percentage change from a year ago), unemployment rate (UNRATE), log hours worked per capita (average hours per worker PRS85006023 multiplied by the employment-population ratio CE16OV/CNP16OV), and the federal funds rate (FEDFUNDS). The VAR is estimated with two lags and we use an AR(1)-Minnesota prior for all variables. These choices for the VAR are similar to those made in Christiano *et al.* (2005), Del Negro *et al.* (2007), Christiano *et al.* (2010), and Christiano *et al.* (2016). We sample 100,000 observations at each moment in time from the posterior distribution, to estimate the probability of a rising unemployment rate. We experimented with increasing the number of lags used and including additional forecasting variables (e.g., consumption of non-durables, wages, and capacity utilization). This did not materially affect our results.

B Calibration and Model Fit

B.1 Calibration Parameters

Table B.1: Parameterization

Parameter	Value
Externally calibrated parameters	
Capital share (α)	0.36
Depreciation rate (δ)	0.025
Persistence of booms	0.88
Persistence of busts	0.82
Ratio of productivity between booms and bust (z_h/z_l)	1.027
Unemployment rate in booms	0.06
Unemployment rate in busts	0.10
Monthly job-finding rate in booms	0.55
Monthly job-finding rate in busts	0.45
Unemployment insurance replacement rate(μ)	0.40
Internally calibrated parameters	
Discount factor (b)	0.987
Death probability ($1-\rho$)	0.0045
Relative risk aversion (γ)	5.00
Resource cost of information (η)	0.0028
Scale parameter of utility cost of information (α^{κ})	$1/15e^{-4}$

B.2 Business Cycle Moments: Data Comparison

Table B.2: Comparison of Business Cycle Moments

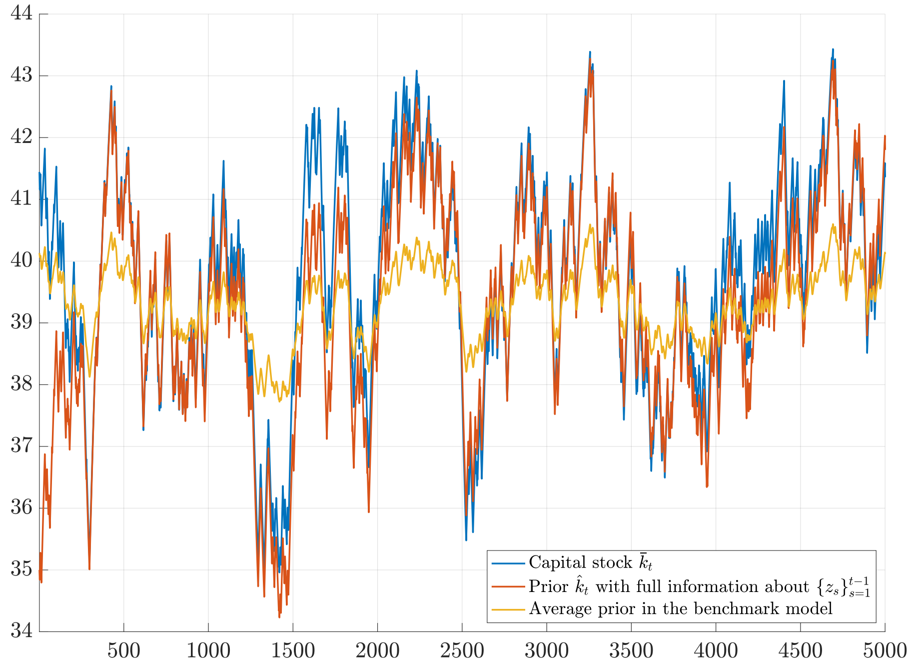
Variable (x)	σ_x	σ_x/σ_y	Corr(x_t, x_{t-1})	Corr(x_t, y_t)	Corr(x_t, y_{t-1})
			Panel (a): U.S. Data (1947Q1-2024Q4)		
Output (y)	1.64	1.00	0.79	1.00	0.79
Investment	7.26	4.42	0.78	0.82	0.61
Consumption.	1.39	0.85	0.72	0.79	0.54
			Panel (b): Benchmark Model		
Variable (x)	σ_x	σ_x/σ_y	Corr(x_t, x_{t-1})	Corr(x_t, y_t)	Corr(x_t, y_{t-1})
Output (y)	3.38	1,00	0.83	1.00	0.83
Investment	11.93	3.53	0.76	0.97	0.75
Consumption	1.25	0.37	0.99	0.70	0.72
			Panel (c): Full Information		
Variable (x)	σ_x	σ_x/σ_y	Corr(x_t, x_{t-1})	Corr(x_t, y_t)	Corr(x_t, y_{t-1})
Output (y)	3.04	1.00	0.78	1.00	0.78
Investment	10.53	3.46	0.72	0.97	0.70
Consumption	1.19	0.39	0.98	0.72	0.72

Note: The table reports the comparison of business cycle moments in different versions of our baseline model to that in the U.S. data. The data on output, consumption, and investment come from FRED (code: `A939RX0Q048SBEA`, `A939RX0Q048SBEA`, $NFIRSAXDCUSQ$). We cumulate capital from investment using a 2.5% depreciation rate. All data variables are expressed in per capita terms and in logs. The data are at a quarterly frequency, and all cyclical components are extracted using an HP filter with $\lambda = 1{,}600$.

B.3 Time-series for Capital and Priors

Incomplete information makes individual expectations about the current capital stock move more slowly than the actual capital stock. In particular, households who choose not to acquire information will have priors about the capital stock that are more tilted towards the long-run average level of aggregate capital. Hence, in booms, they will systematically underpredict the capital stock (and overpredict the return r), and vice-versa in recessions. Importantly, however, this sluggishness is not a consequence of our maintained assumption that households estimate the current capital stock only from the information they acquire about productivity. In fact, for economies with full information, Den Haan *et al.* (2010) show that the history of shocks z^t alone allows for very accurate predictions about the future capital stock K_{t+h}, $h \geq 1$. We verify that this holds also in our setup: Figure B.1 depicts the time series of the actual

Figure B.1: Mean Capital K_t: Realization and Priors



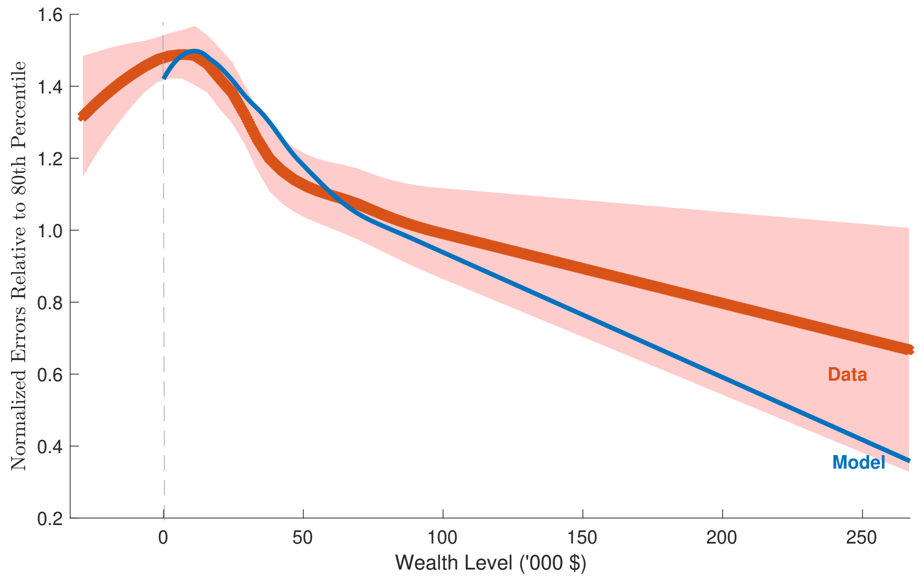
Note: Based on a simulation of the calibrated benchmark model, the figure shows time series of the mean (aggregate) capital stock $K_t = \bar{k}_t$ (blue line), the prior expectation of current aggregate capital $\hat{K}_t = \hat{k}_t$ of households who acquire information about the current productivity state every period (red line), and the average prior expectation in the benchmark economy (yellow line).

capital stock (blue line) and the prior expectation of an individual that has an arbitrary belief about capital in period 0 but then acquires information in every period (red line). We also, for comparison, plot the average prior expectation in our benchmark economy (yellow line). An individual that always acquires information would have prior expectations that closely track the realized value (with a correlation above 0.95).[51]

[51] In the figure, we start the prior at an arbitrary value of 35, and discard the initial 200 periods to calculate the correlation, to demonstrate that the strong correlation does not depend on an accurate initial point prior.

B.4 Extended Error-wealth Plot

Figure B.2: Accuracy of Forecasts: Model vs. Data



Note: The figure shows the estimated relationship between (the absolute value of) errors of the one-year ahead probability of the unemployment rate increasing and household wealth. We plot this relationship both in the SCE data and in the calibrated model (see also Section 2). We use a local polynomial regression (the LOESS regression) to estimate the non-linear relationship between the accuracy of household expectations and household wealth. Error bands correspond to one-standard deviation confidence bounds. We use 2020 values of quarterly U.S. household income to convert values in the data and in the model to $ (USD) amounts.

C Extensions and Robustness

C.1 Mean-biased Capital Expectations

Table C.1: Mean-biased Capital Expectations—% Relative to Full Information

	Panel (a): Business Cycle Moments				
	$\sigma(K)$	$\sigma(Y)$	$\sigma(I)$	$\sigma(C)$	Cor(C,Y)
Endog. Info (P(learn K)=1.0)	5.49	1.03	6.40	-0.34	-15.15
Endog. Info (P(learn K)=0.1)	11.47	1.89	8.43	-0.90	-17.90
Benchmark model	64.24	11.03	13.61	5.08	-3.08

	Panel (b): Inequality Moments				
	Gini(G)	90/10	99/1	90/50	Cor(K,Y)
Endog. Info (P(learn K)=1.0)	-0.60	0.82	-2.21	-0.41	3.16
Endog. Info (P(learn K)=0.1)	-0.53	0.92	-2.46	-0.26	5.25
Benchmark model	1.60	2.66	4.98	3.58	24.66

Note: The table shows model moments in the calibrated model ("Benchmark Model"), as well as in models in which households exogenously obtain information about the level of the aggregate capital stock with a fixed probability $p \in [0,1]$ ("Endogenous Information (P(learn K)=p)"). The table reports the percentage difference relative to the full-information version for the same moments as those computed in Table II and Table IV.

C.2 Dynamics of the Wealth Distribution

Section 5.6 studied the *average consequences* of heterogeneous information for inequality. Table C.2 identifies the forces that also make inequality volatile over time. It does so by comparing the dynamics of different parts of the wealth distribution in the benchmark economy to its full- and exogenous-information counterparts. The main feature that stands out are the substantially larger swings that occur in the benchmark economy. Relative to the case with full information, the standard deviations of both the Gini coefficient and, for example, the 99/50 percentile ratio are about 4–4.5 times higher in the benchmark economy—with inequality moments that are, further, substantially larger than in the exogenous-information case.

The key to understanding this increase in the volatility of wealth dispersion lies, once more, in the impact that incomplete information has on savings choices across the wealth distribution. With full information, low-to-medium wealth households save less in booms, making their wealth accumulation *countercyclical*. The rich, by contrast, save more when capital is

Table C.2: Dynamics of the Wealth Distribution

	σ(Gini)	σ(90/50)	σ(99/50)	Cor(90th,10th)	Cor(99th,10th)
Benchmark Model	0.04	0.63	2.68	0.24	-0.24
Exogenous Information	0.03	0.42	1.93	0.40	-0.20
Full Information	0.01	0.15	0.57	0.72	0.26

Note: Based on a long simulation of the benchmark economy and the versions with exogenous and full information, the table shows the standard deviations (σ) over time of the Gini, the 90/50, and the 99/50 percentile ratios of the wealth distribution (k), as well as the correlations (Cor) of, respectively, the 90th and 99th percentiles with the 10th percentile of the wealth distribution.

high and returns low, but their overall wealth accumulation remains *countercyclical*—driven by countercyclical returns to their stock of wealth. Taken together, the two imply that the whole wealth distribution moves up and down in tandem, limiting variations in inequality.

The presence of incomplete information, by contrast, makes savings, and thus wealth, at the bottom of the distribution *more procyclical (i.e. less* countercyclical*)*, while *increasing* the countercyclicality at the top of the wealth distribution. Both arise due to an increase in savings errors that households make due to the presence of incomplete information. Combined, the two explain the increased volatility of inequality measures in Table C.2. Finally, notice that—relative to the economies with *exogenous information*—the endogeneity of information in our benchmark economy dampens the cyclicality of savings by medium-wealth households (who have less-than-average information and own the bulk of the capital stock) further. This, in turn, causes the volatility of wealth inequality to be larger in our benchmark economy than in its exogenous-information counterpart.[52]

C.3 Decomposition of Changes in the Wealth Distribution

In this Appendix, we decompose the overall change in the wealth distribution into three separate forces: (i) the change in the equilibrium law of motion for capital; (ii) the presence of incomplete information; and (iii) the heterogeneity that exists in information choices. Figure C.1 provides a breakdown of the overall change into these three components.

[52] Because unemployment is countercyclical, individual earnings volatility is generally higher in busts than in booms. As we mention above, this increases the value of information for unemployed households, causing their information acquisitions to be weakly countercyclical—more information is bought by unemployed households in a bust. Overall, however, information purchases are weakly procyclical, driven by the behavior of the employed. This modulates the above discussed effects.

1. General Equilibrium: To isolate the general-equilibrium component, we conduct the following experiment: We solve for household policy functions in the full-information economy taking the benchmark economy*'s* law of motion for capital, $\tilde{H}(z, K)$, as given. We then simulate the economy with the same sequence of shocks as in the full-information case and compare the two wealth distributions. This experiment isolates the channel by which the weakening of the mean-reversion of capital affects the wealth distribution.[53]

Panel (b) in Figure C.1 shows that the change in the *equilibrium law of motion for capital* in-and-of itself *dampens inequality.* All else equal, the weaker mean-reversion in the benchmark economy causes a substantially more persistent law of motion for capital, and thus increases the persistence of wages and the rate of return on capital. This, in turn, causes stronger income effects on savings, all else equal. Relative to the full-information economy with its own law of motion, a stronger correlation between returns and savings at the bottom—and a lower correlation at the top—of the distribution thus arises, reducing wealth inequality. Recall that income effects reduce savings for low-to-medium wealth households when the capital stock (and hence wages) are high, while the opposite is the case for wealthy households as returns (and hence financial income) decline with capital.[54] General-equilibrium dynamics—through these mechanisms—partially offset the widening of the wealth distribution.

2. Incomplete Information: Our next experiment isolates the consequences that the *incompleteness of information* itself has on the wealth distribution. We solve for the policy functions and simulate the distribution when households have exogenously incomplete information but believe the law of motion for capital is the one from the benchmark economy. By comparing the distribution under this experiment to the previous one (full-information with benchmark law of motion), we can quantify the effects of household incomplete information on inequality. Panel (c) in Figure C.1 plots the difference between the two distributions.

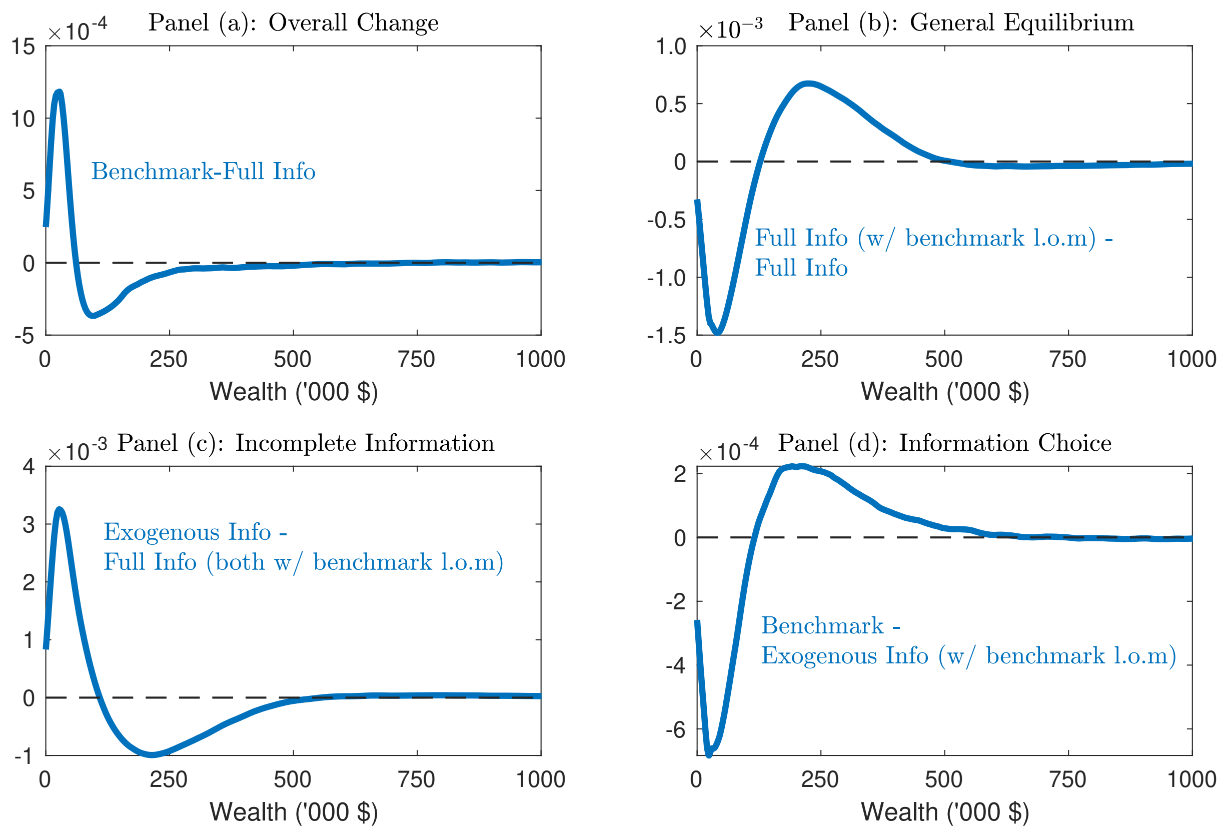
The presence of incomplete information *per se* explains the lion's share of the widening of the wealth distribution. The dampened correlation between savings and returns—caused by the incompleteness of information—implies a widening of the wealth distribution that is qualitatively similar but stronger than that in our benchmark economy (Panel (a)).

For low-to-medium wealth households, the presence of incomplete information weakens

[53] To be clear, households still optimize in this experiment and markets clear in every period. Household expectations are simply inconsistent with the true aggregate dynamics.

[54] This mechanism is further amplified by the widening of the difference between the income of employed and unemployed. The cross-sectional dispersion of labor-market income increases with the volatility of wages, and hence with the volatility of the capital stock. In equilibrium, the difference between wages and unemployment benefits equal $(1-\mu)w_t = (1-\mu)(1-\alpha)z_t K_t^{\alpha}\bar{l}^{-\alpha}$, whose average is increasing in the volatility of the capital stock K_t. This, in turn, causes pre-cautionary savings to also increase, especially near the bottom of the distribution, further reducing inequality.

Figure C.1: Decomposition of Changes to the Wealth Distribution



Note: The figure decomposes the change in the average wealth distribution relative to the full-information version of the benchmark economy (Panel (a)). Panel (b) shows the difference in the average probability density function of the wealth distribution between the full-information economy and the full-information economy in which the law of motion for the capital stock equals that in our benchmark economy. Panel (c) shows the difference between the exogenous-information economy and the full-information economy, where we equip both economies with a law of motion for the capital stock equal to that in our benchmark economy. Finally, Panel (d) shows the differences between our benchmark (endogenous-information) economy and exogenous-information economy equipped with the law of motion from our benchmark economy. The horizontal axis in all panels is household wealth (capital levels) in '000 USD ($). We use 2020 values of U.S. household income to convert values in the model to $ amounts. Probability density functions are estimated from a simulated panel of household capital holdings, using a kernel density estimator with the Epanechnikov kernel.

the positive correlation that exists between returns and savings in response to fluctuations in capital (Figure 4). This, in turn, reduces their average wealth accumulation. In effect, these households make more "mistakes" with their savings choices—as they are unable to effectively exploit periods of high returns on capital—and end up poorer, as a result.

The increased randomness by which households make savings choices, by contrast, increases the share of wealthy households. These households' informed savings policies, as mentioned in the main text, correlate negatively with fluctuations in the return on capital (Figure 4). The presence of incomplete information thus increases the average correlation between their savings and returns, increasing the average wealth of high-wealth households.

In essence, high-wealth households in our model—who also feature close to linear policy functions, as they are far away from the borrowing constraint—are akin to the households described in Piketty and Saez (2003): The authors show that the combination of exogenous random savings rates and linear policy functions can generate Pareto tails in the wealth distribution. In our case, however, the presence of incomplete information provides a micro-foundation for this type of "random savings behavior", as opposed to other models that either assume exogenously stochastic savings rates or random returns on savings.[55]

3. Information Choice: Our final decomposition compares the distribution from the previous experiment (exogenous, incomplete information with benchmark law of motion) with the benchmark distribution. This difference isolates the effects that *heterogeneous information choices* have on the wealth distribution. We plot differences in Panel (d) in Figure C.1.

All else equal, the more informed households in our benchmark economy are the poor, unemployed households and the rich households with substantial amounts of wealth (Figure 5). These households, who are better informed than their exogenous-information counterparts, make fewer savings mistakes—they are, on average, better able to exploit differences in rates of return on capital. As a result, the existence of *heterogeneous information* causes fewer wealth-poor ($0-50,000) as well as wealth-rich (above $750,000) households. The decline in "random savings" caused by the presence of additional information allows households near the bottom-end of the wealth distribution to better correlate their savings with its rate of return, allowing these households to better accumulate wealth. By contrast, the decline in "random savings" of the wealthy drives down their realized saving.

Summary and Quantification: In sum, the presence of heterogeneous, incomplete information leads to rich and complex changes in the wealth distribution. On the one hand, the

[55] That said, because the magnitude of the errors are comparatively small relative to what is needed, in the benchmark model this force is not sufficiently potent to generate a thick Pareto tail of wealth (cf. Section 5.7).

presence of incomplete information widens the wealth distribution by leading to "random savings behavior". On the other hand, the existence of heterogeneity in information choices, all else equal, dampens this increase by allowing the more exposed households—the poor and the wealthy—to acquire information to make better savings choices. This dampening effect is then further amplified by the weakening of the mean-reversion of capital further lessening any increase in inequality.[56] On balance, we find that the former effect dominates, leading to a modest overall increase in inequality (Table IV). Table C.3 decomposes the overall increase in different summary measures of inequality (e.g., the Gini) and shows that the *modest net increase* in inequality is comprised of *large, offsetting gross effects*. The 2 percent increase in the Gini is, for example, comprised of an 8 percent increase due to incomplete information counteracted by 4 and 2 percent decreases, respectively, due to general equilibrium dynamics and heterogeneity in information choices. The combined effects of heterogeneous information are subtle—and, crucially, affect different parts of the distribution differentially.

Table C.3: Decomposition of Wealth Distribution Changes—% Relative to Full Information

	Overall	GE	Incomplete Info.	Heterogenous Info.	Interaction
Gini Statistic	1.50	-4.04	7.54	-1.65	-0.35
90/10−ratio	2.64	-2.99	7.31	-1.40	-0.28
99/1−ratio	4.67	-13.92	20.67	-3.73	1.65

Note: This table decomposes the overall change in the wealth distribution (relative to the full-information case) into the forces highlighted in Section 5.6. We focus, for concreteness, on the Gini, the 90/10-ratio, and the 99/1-ratio. Similar results hold for other summary inequality measures.

[56]Notice that while heterogeneity in information acquisition by itself decreases inequality, our benchmark economy features more inequality than its exogenous information counterpart (Table IV). This is due to the weaker general equilibrium dynamics in our benchmark model with heterogeneous information.

C.4 Acyclical Income Taxes

Table C.4: Business Cycle Moments—Acyclical Income Taxes

	Panel (a): Level of Moments					
	$\sigma(K)$	$\sigma(Y)$	$\sigma(I)$	$\sigma(C)$	$\mathrm{Cor}(C, Y)$	$\mathrm{Cor}(I, Y)$
Benchmark Model	3.98	3.15	9.33	0.98	0.64	0.99
Exogenous Information	3.30	3.05	9.00	0.94	0.61	0.99
Full Information	2.40	2.93	8.14	0.93	0.69	0.98
	Panel (b): Percent Difference w.r.t. Full Information					
	$\sigma(K)$	$\sigma(Y)$	$\sigma(I)$	$\sigma(C)$	$\mathrm{Cor}(C, Y)$	$\mathrm{Cor}(I, Y)$
Benchmark Model	66.08	7.72	14.68	4.86	-8.20	0.55
Exogenous Information	37.88	4.13	10.59	0.10	-11.79	0.29

Note: This table shows the standard deviation σ of the logarithm of economy-wide capital (K), output (Y), investment (I), and consumption (C). In addition, the table shows the correlation between aggregate consumption, investment, and output, respectively (e.g., $\mathrm{Cor}(I, Y)$). The table depicts these moments for the benchmark model ("Benchmark Model") as well as the two comparison models with full and exogenous information ("Full Information" and "Exogenous Information", respectively).

Table C.5: Inequality Moments—Acyclical Income Taxes

	Panel (a): Level of Moments				
	Gini G	90/10	99/1	90/50	$\mathrm{Cor}(K, Y)$
Benchmark Model	0.51	14.48	337.3	3.47	0.54
Exogenous Information	0.51	14.45	331.8	3.42	0.49
Full Information	0.50	14.04	315.9	3.34	0.43
	Panel (b): Percent Difference w.r.t. Full Information				
	Gini G	90/10	99/1	90/50	$\mathrm{Cor}(K, Y)$
Benchmark Model	2.33	3.18	6.80	4.00	25.11
Exogenous Information	1.74	2.97	5.05	2.38	14.42

Note: The table shows the Gini coefficient of the capital distribution (G), as well as the 90/10, 99/1, and 90/50 percentile ratios of the wealth distribution. In addition, the table shows the correlation between the logarithm of capital and log. output (Y) ($Cor(K, Y)$). The table depicts these moments for the benchmark model ("Benchmark Model") as well as the two comparison models.

C.5 Costs of Information and Alternative Models

Table C.6: Business Cycle Moments—No Costs of Information

	$\sigma(K)$	$\sigma(Y)$	$\sigma(I)$	$\sigma(C)$	$\mathrm{Cor}(C, Y)$
Benchmark Model	5.05	3.38	11.98	1.25	0.7
	Panel (a): With Costs of Information				
Exogenous Information	4.19	3.22	11.56	1.19	0.67
Full Information	3.07	3.04	10.54	1.19	0.72
	Panel (b): Without Costs of Information				
Exogenous Information	4.19	3.22	11.55	1.19	0.67
Full Information	3.07	3.04	10.54	1.19	0.72
	Panel (c): Percentage Difference due to Costs				
Exogenous Information	-0.04	-0.01	-0.04	-0.08	-0.03
Full Information	-0.02	0.00	0.00	-0.21	-0.03

Note: The table shows the standard deviation σ of the logarithm of capital (K), output (Y), investment (I), and consumption (C). In addition, the table shows the correlation between consumption and output ($\mathrm{Cor}(C, Y)$). The table shows these moments for the benchmark model ("Benchmark Model"), the two comparison models with full and exogenously limited information ("Full Information" and "Exogenous Information", respectively), as well as versions of the comparison models in which all costs of information are set equal to zero.

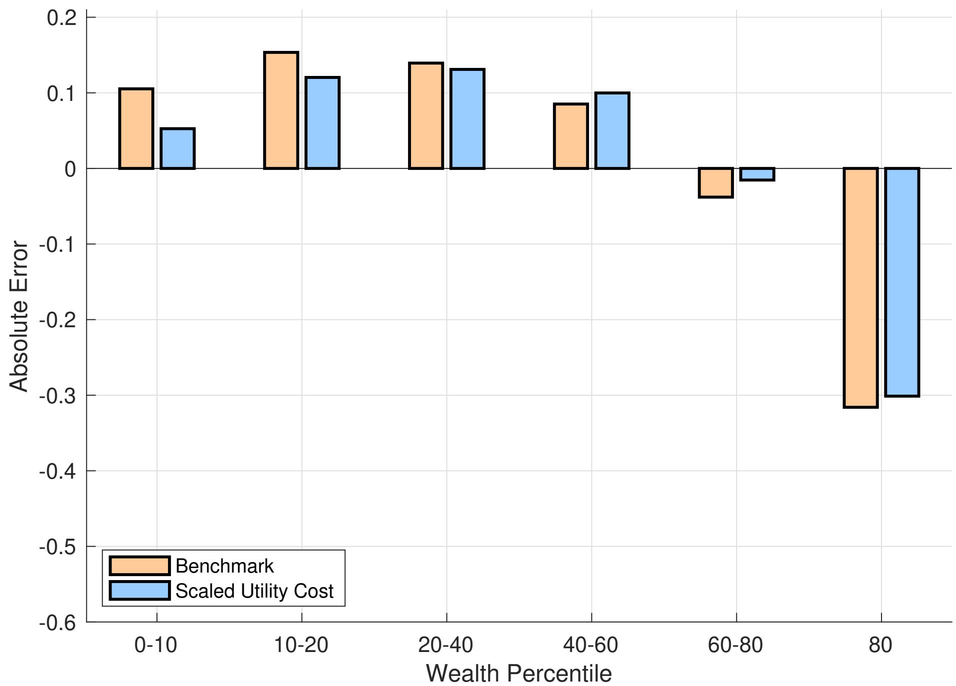
Table C.7: Inequality Moments—No Costs of Information

	$\mathrm{Gini}(K)$	90/10	99/1	90/50	$\mathrm{Cor}(K, Y)$
Benchmark Model	0.51	14.53	345.3	3.51	0.62
	Panel (a): With Costs of Information				
Exogenous Information	0.51	14.51	339.4	3.45	0.56
Full Information	0.50	14.16	329.0	3.39	0.49
	Panel (b): Without Costs of Information				
Exogenous Information	0.51	14.49	337.6	3.44	0.56
Full Information	0.50	14.13	326.0	3.38	0.49
	Panel (c): Percentage Difference due to Costs				
Exogenous Information	-0.20	-0.11	-0.53	-0.25	-0.02
Full Information	-0.31	-0.19	-0.89	-0.39	-0.01

Note: The table shows the Gini coefficient of the capital distribution (Gini), as well as the 90/10, 99/1, and 90/50 percentile ratios of the capital distribution. In addition, the table shows the correlation between the logarithm of capital and log. output (Y) ($\mathrm{Corr}(K, Y)$). The table shows these moments for the benchmark model ("Benchmark Model"), the two comparison models, as well as versions of the comparison models in which all costs of information are set equal to zero.

C.6 Homotheticity of Information Costs

Figure C.2: Accuracy Across the Wealth Distribution—Scaled Utility Cost



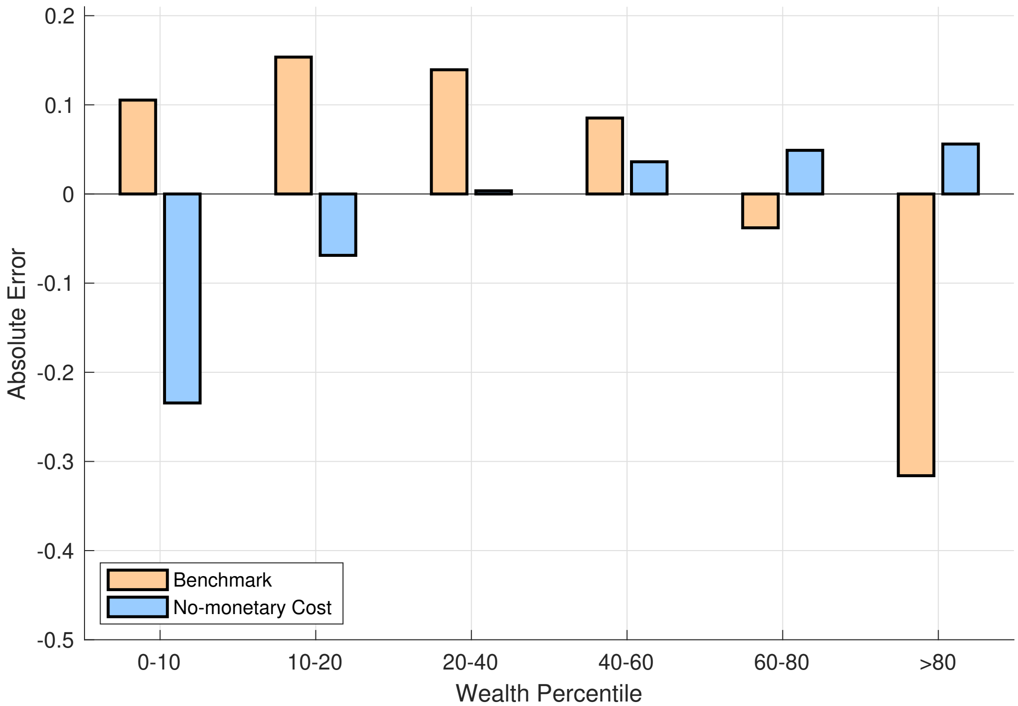
Note: The figure plots the difference between the average one-year-ahead accuracy of unemployment forecasts within wealth deciles/quintiles and the overall average taken across all wealth levels. Accuracy is measured by the absolute value of unemployment errors (Appendix A.2). We plot these accuracies both for the calibrated benchmark model and for the calibrated model with the scaled utility cost.

Table C.8: Model Moments—Scaled Utility Cost

	Panel (a): Business Cycle Moments				
	$\sigma(K)$	$\sigma(Y)$	$\sigma(I)$	$\sigma(C)$	$\text{Cor}(C, Y)$
Benchmark	5.05	3.38	11.98	1.25	0.70
Scaled Utility Cost	4.96	3.36	11.92	1.24	0.70
Difference %	-1.77	-0.52	-0.43	-0.67	-0.37
	Panel (b): Inequality Moments				
	$\text{Gini}(K)$	90/10	99/1	90/50	$\text{Cor}(K, Y)$
Benchmark	0.51	14.53	345.29	3.51	0.62
Scaled Utility Cost	0.51	14.49	343.10	3.50	0.61
Difference %	-0.19	-0.33	-0.64	-0.51	-0.85

Note: The table shows the same model moments as in Section 5 for the benchmark (endogenous information) model ("Benchmark") with and without the scaled utility cost of information κ set equal to zero.

Figure C.3: Accuracy Across the Wealth Distribution—No Resource Cost



Note: The figure plots the difference between the average one-year-ahead accuracy of unemployment forecasts within wealth deciles/quintiles and the overall average taken across all wealth levels. Accuracy is measured by the absolute value of unemployment errors (Appendix A.2). We plot these accuracies both for the calibrated benchmark model and for the calibrated model with no resource cost.

Table C.9: Model Moments—No Resource Costs

	Panel (a): Business Cycle Moments				
	$\sigma(K)$	$\sigma(Y)$	$\sigma(I)$	$\sigma(C)$	Cor(C,Y)
With Resource Cost	5.05	3.38	11.98	1.25	0.70
Without Resource Cost	4.11	3.20	11.48	1.19	0.68
Difference %	-18.49	-5.10	-4.11	-5.01	-3.82
	Panel (b): Inequality Moments				
	Gini(K)	90/10	99/1	90/50	Cor(K,Y)
With Resource Cost	0.51	14.53	345.29	3.51	0.62
Without Resource Cost	0.50	14.11	327.96	3.39	0.56
Difference %	-1.50	-2.88	-5.02	-3.53	-9.08

Note: The table shows the same model moments as in Section 5 for the benchmark (endogenous information) model ("Benchmark Model") with and without the resource cost of information η set equal to zero.

C.7 Matching the Wealth Distribution

C.7.1 Extended Model Framework

A representative final-goods producer bundles varieties $j \in \mathcal{J}$ in accordance with:

$$Y_t = \left(\int y_{jt}^{\frac{\omega-1}{\omega}} d_j \right)^{\frac{\omega}{\omega-1}} \tag{A1}$$

with elasticity of substitution $\omega > 1$. Each of the differentiated goods is sold at price $p_j > 0$, so that the ideal price level equals $P_t = \left(\int p_{jt}^{1-\omega} dj \right)^{\frac{1}{1-\omega}}$, which we normalize to one. Consistent with this structure, the demand for each variety is

$$y_{jt} = p_{jt}^{-\omega} Y_t.$$

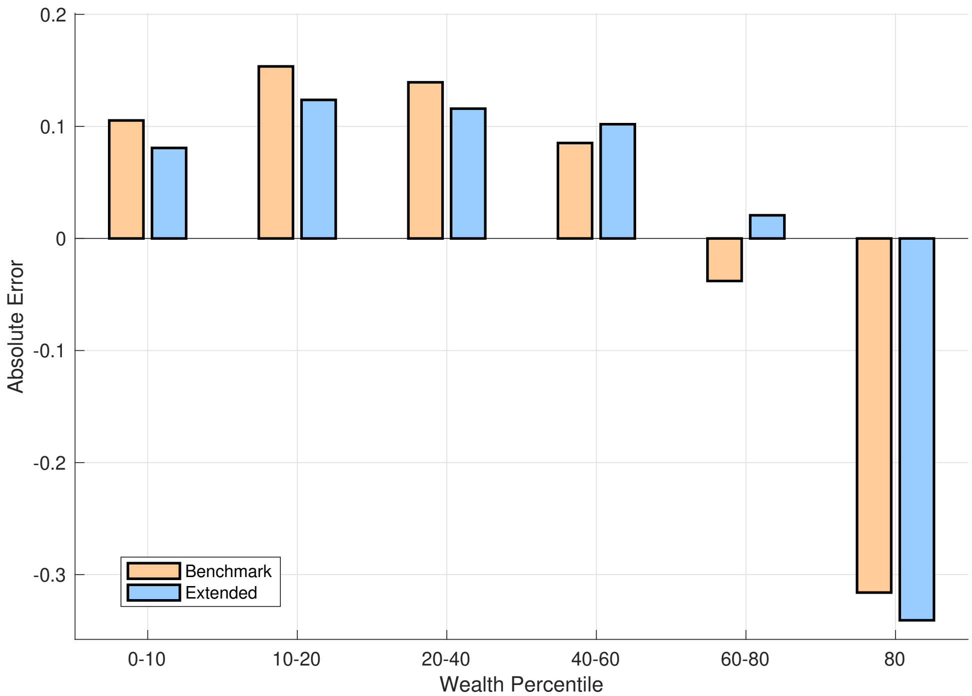
Intermediate goods firms produce using the production technology in (3.3) and are characterized by the same assumptions as firms in our benchmark framework.

There are two types of households: A mass $m \in (0, 1)$ of worker-households and a mass $1-m$ of entrepreneur-households. Worker-households are identical to households in our benchmark model. Entrepreneurs, by contrast, receive all pure rents (i.e., profit income) in the economy but no labor income. Entrepreneurs are across all other dimensions identical to worker-households. We assume the existence of fixed transition probability matrix, Π_T, modeled as in Bayer *et al.* (2024), so that worker-households transition to become entrepreneur-households, and vice versa. We allow for borrowing and assume that $k_i' \geq k_{\min} \in \mathbb{R}_-$. All debts are forgiven upon death. All other model details are as described in Section 3.

C.7.2 Alternative Calibration and Quantification

We follow a similar calibration strategy to that of our benchmark model. To target the bottom of the wealth distribution, we set $k_{\min} = -4$ and increase the replacement rate to 45 percent, in line with the average value for the U.S. in 2022. This ensures that the 10th percentile of the wealth distribution features $k_i = 0$, on average, as in the data. We set the additional parameters—the mass of entrepreneurs and the CES elasticity—to 1 percent and so as to target the top 10 percent wealth share in the data, respectively, consistent with Bayer *et al.* (2024). We set the transition matrix, Π_T, to the values estimated in Guvenen *et al.* (2014), in line with the approach in Bayer *et al.* (2024). Finally, we set resource cost of information and scale parameter for the utility cost of information so as to once more target the mean and cross-sectional standard deviation of forecasts errors in the SCE. We also recalibrate the discount factor to target the same capital-to-output ratio as before. Figure C.4 compares the accuracy of unemployment forecasts across the wealth distribution with that in the benchmark model; Table C.10 shows the business-cycle and inequality moments. We note that because of the possibility of negative wealth, certain percentile ratios of the wealth distributions, such as the 90/10-ratio, are ill-defined, which is why they are excluded from the table.[57]

Figure C.4: Accuracy Across the Wealth Distribution—Extended and Benchmark Model



Note: The figure plots the difference between the average one-year ahead accuracy of unemployment forecasts within wealth deciles/quintiles and the overall average taken across all wealth levels. Accuracy is measured by the absolute value of unemployment errors (Appendix A.2). We plot these accuracies both for the calibrated benchmark model and for the calibrated extended model that matches the wealth distribution.

[57]Indeed, the average value is, for example, ∞ for the 90/10-ratio, as the 10th percentile of the wealth distribution occasionally hits zero in the simulation per its calibration.

Table C.10: Extended Model Moments: Business Cycle and Inequality

	Panel (a): Business Cycle Moments				
	$\sigma(K)$	$\sigma(Y)$	$\sigma(I)$	$\sigma(C)$	Cor(C,Y)
Endogenous Information (A)	4.69	3.22	14.40	1.20	0.64
Exogenous Information (B)	3.45	3.03	13.55	1.08	0.59
Full Information (C)	2.74	2.95	12.14	1.14	0.71
Difference % (A vs C)	71.00	8.99	18.57	5.29	-9.72

	Panel (b): Inequality Moments		
	Gini(K)	90/50	Cor(K,Y)
Endogenous Information (A)	0.76	9.38	0.56
Exogenous Information (B)	0.73	7.37	0.47
Full Information (C)	0.70	6.41	0.44
Difference % (A vs C)	8.61	46.31	27.48

Note: Panel (a) and (b) show the same model moments as in Table II and IV but for the extended benchmark model (endogenous information) as well as its full-information and exogenous-information counterparts.

Table C.11: Decomposition of Wealth Distribution Changes—% Relative to Full Information

	Overall	GE	Incomplete Info.	Heterogenous Info.	Interaction
Gini Statistic	8.61	-18.90	27.38	5.14	-5.00

Note: This table decomposes the overall change in the Gini of the wealth distribution (relative to the full-information case) into the 3 forces highlighted in Section 5.6.

C.8 Internalized Uncertainty about K

The log capital stock evolves according to the posited law of motion:

$$\log K_{t+1} = a_{z_t} + b_{z_t} \log K_t, \qquad z_t \in \{0, 1\}. \tag{A2}$$

Since in practice $b_1 > b_0$ and $a_1 > a_0$, the time series for $\log K_t$ is bounded between:

$$\underline{\log K} = \frac{a_0}{1 - b_0}, \qquad \overline{\log K} = \frac{a_1}{1 - b_1}.$$

Let $\phi_N(\cdot)$ and $\Phi_N(\cdot)$ denote the standard normal pdf. and cdf., respectively. At every t, we assume that the posterior of $\log K_t$ is *approximated* by a truncated normal $\mathcal{TN}\Big(m_t, v_t, [L, U]\Big)$, i.e.:

$$\log K_t \mid \Omega_{it} \overset{\text{approx.}}{\sim} \mathcal{TN}\Big(m_{it}, v_{it}, [\underline{\log K}, \overline{\log K}]\Big).$$

We let μ_{it} and ς_{it}^2 denote the household's mean and variance of $\log K_t$ *before* accounting for truncation. The household then updates its beliefs in accordance with:

Informed Households: Let $\alpha_{it} \equiv \varsigma_{it}^{-1}\left(\underline{\log K} - \mu_{it}\right)$ and $\beta_{it} \equiv \varsigma_{it}^{-1}\left(\overline{\log K} - \mu_{it}\right)$. Then, consistent with Equation (A2), for given (m_{it}, v_{it}) and realized z:

$$\mu_{it} = a_z + b_z\, m_{it}, \qquad \varsigma_{it}^2 = b_z^2 v_{it} \tag{A3}$$

so that

$$m_{it+1} = \mu_{it} + \varsigma_{it} \frac{\phi_N(\alpha_{it}) - \phi_N(\beta_{it})}{\Phi_N(\beta_{it}) - \Phi_N(\alpha_{it})}, \tag{A4}$$

$$v_{it+1} = \varsigma_{it}^2 \left[1 + \frac{\alpha_{it}\phi_N(\alpha_{it}) - \beta_{it}\phi_N(\beta_{it})}{\Phi_N(\beta_{it}) - \Phi_N(\alpha_{it})} - \left(\frac{\phi_N(\alpha_{it}) - \phi_N(\beta_{it})}{\Phi_N(\beta_{it}) - \Phi_N(\alpha_{it})}\right)^2\right]. \tag{A5}$$

Uninformed Households: Let $p_{it,z} = \mathbb{E}(z_t = 1 \mid \Omega_{it})$ denote an uninformed household's expectation of a boom. Given (m_{it}, v_{it}), it follows that:

$$\mu_{it} = (1 - p_{it,z})\Big(a_0 + b_0\, m_{it}\Big) + p_{it,z}\Big(a_1 + b_1\, m_{it}\Big) \tag{A6}$$

$$\varsigma_{it}^2 = (1 - p_{it,z})\, b_0^2 v_{it} + p_{it,z}\, b_1^2 v_{it} + p_{it,z}(1 - p_{it,z})\, \Delta_{it}^2, \tag{A7}$$

where $\Delta_{it} \equiv (a_1 - a_0) + (b_1 - b_0)\, m_{it}$. Truncation is identical to that in (A4) and (A5).

Implementation: The solution algorithm is updated as follows. Instead of assuming households have a point expectation about tomorrow's capital stock, when solving their consumption-savings and information acquisition problem in *Stage 1* and *Stage 2*, households now internalize their uncertainty about tomorrow's capital stock, and that their beliefs evolve in accordance with Equations (A3) to (A7). Beyond how beliefs are updated, all other steps of the solution algorithm are identical to before.

Quantitative Results: We calibrate the model in the same manner as all extensions considered in Section 5. Consistent with the greater uncertainty faced by households, to match the data requires a larger resource and utility cost of information. Specifically, we set $\eta = 0.006$ and the mean of $\kappa = 0.0001$ to match the data. The model-implied errors imply a similar, although slightly milder, inverse-u shape to that in the benchmark model. Table C.12 shows our main results, which on balance confirm the insights from the benchmark specification.

Table C.12: Model Moments: Business Cycle and Inequality

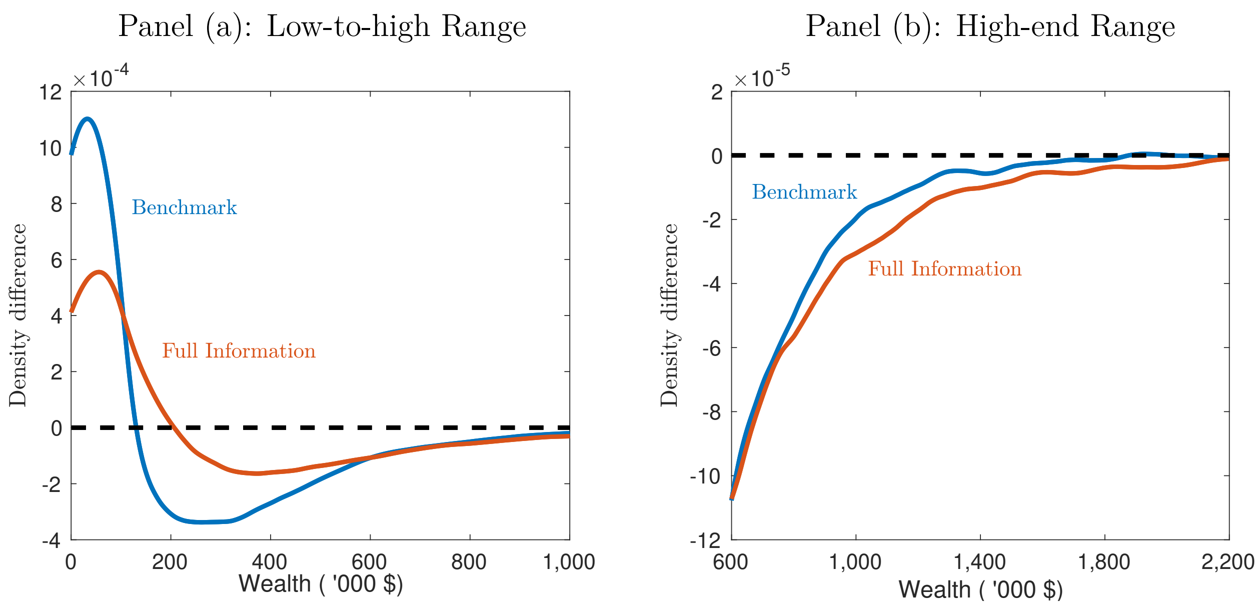
	Panel (a): Business Cycle Moments				
	$\sigma(K)$	$\sigma(Y)$	$\sigma(I)$	$\sigma(C)$	Corr(C, Y)
Endogenous Information (A)	4.12	3.20	11.47	1.17	0.67
Exogenous Information (B)	3.64	3.13	11.16	1.17	0.66
Full Information (C)	3.20	3.05	10.55	1.17	0.71
Difference % (A vs C)	28.75	4.92	8.72	0.05	-5.97
	Panel (b): Inequality Moments				
	Gini(K)	90/10	99/1	90/50	Cor(K, Y)
Endogenous Information (A)	0.49	13.57	318.71	3.24	0.56
Exogenous Information (B)	0.48	13.25	306.44	3.16	0.54
Full Information (C)	0.47	12.84	279.27	3.03	0.50
Difference % (A vs C)	4.26	5.69	14.12	7.10	12.00

Note: Panel (a) and (b) show the model moments as in TableII and IV but for the extended benchmark model (endogenous information) as well as its full-information and exogenous-information counterparts.

D Counterfactual Policy Experiments

D.1 A Wealth Tax

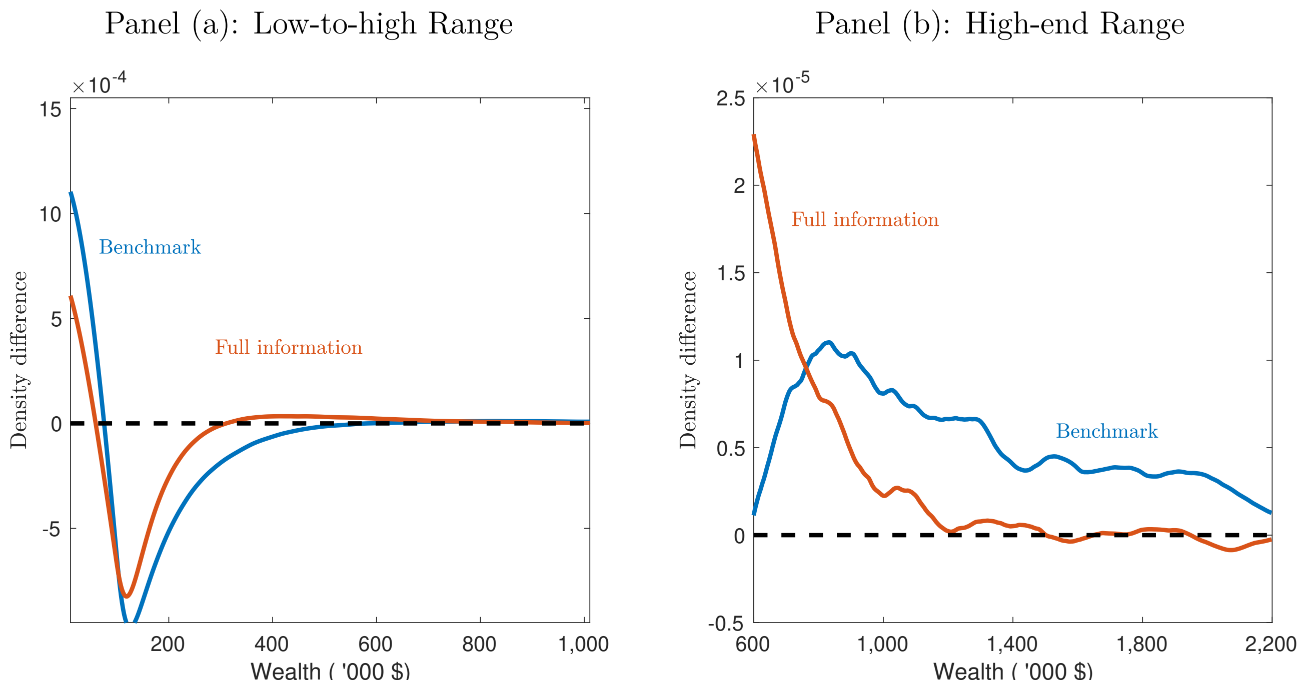
Figure D.1: Wealth Taxes and Changes in the Wealth Distribution



Note: The figure shows changes in the average wealth distribution relative to the zero-wealth tax case. We illustrate these changes for both our calibrated model ("Benchmark Model") and the associated full-information economy ("Full Information"). We use 2020 values of U.S. household income to convert capital-holdings in the model to $ amounts. Probability density functions are estimated from a simulated panel of households, using a kernel density estimator with the Epanechnikov kernel.

D.2 Increased Unemployment Benefits

Figure D.2: Unemployment Benefit Increases and Changes in the Wealth Distribution



Note: The figure shows changes in the average wealth distribution in response to an increase in the replacement rate by 10 percentage points.. We illustrate these changes for both our calibrated model ("Benchmark Model") and the associated full-information economy ("Full Information"). We use 2020 values of U.S. household income to convert capital-holdings in the model to $ amounts. Probability density functions are estimated from a simulated panel of households, using a kernel density estimator with the Epanechnikov kernel.

D.3 Policy Experiments in the Extended Model Framework

Table D.1: Extended Model: Effects of a Wealth Tax

	$\mu(K)$	$\sigma(Y)$	Gini(K)	90/50	Info U.	Info E.
Endogenous Information	-7.55	2.02	2.76	9.40	-0.78	-6.25
Exogenous Information	-7.29	0.83	1.17	1.89	.	.
Full Information	-7.26	0.49	0.58	0.20	.	.

Note: The table shows the effects of a one percent per annum wealth tax on moments of the average cross-sectional capital distribution and the logarithm of economy-wide output in percent. $\mu(K)$ denotes the mean of the capital stock, while $\sigma(Y)$ denotes the standard deviation of (log-)economy-wide output. The table computes the moments for the both calibrated model ("Benchmark Model") and the associated full-information and exogenous-information economies ("Full Information" and "Exogenous Information", respectively). The final two columns measure the percent difference in the average number of households who acquire information. We compute this probability separately for the employed and unemployed.

Table D.2: Extended Model: Effects of Increased Unemployment Benefits

	$\mu(K)$	$\sigma(Y)$	Gini(K)	90/50	Info U.	Info E.
Endogenous Information	-2.05	2.95	7.43	39.21	-21.36	-4.66
Exogenous Information	-1.27	0.70	3.82	15.57	.	.
Full Information	-1.21	0.28	2.82	11.05	.	.

Note: The table shows the effects of a ten percentage-point increase in the replacement rate on moments of the average cross-sectional capital distribution and the logarithm of economy-wide output in percent. $\mu(K)$ denotes the mean of the)capital stock, while $\sigma(Y)$ denotes the standard deviation of (log-)economy-wide output. The table computes the moments for the both benchmark economy ("Benchmark Model") and the associated full-information and exogenous-information economies ("Full Information" and "Exogenous Information", respectively). The final two columns measure the percent difference in the average number of households who acquire information. We compute this probability separately for the employed and unemployed.