Heterogeneity in what?
Cognitive Skills, Beliefs and the Liquid Wealth Distribution

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March 22, 2023

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Abstract

We show that households with lower cognitive skills are persistently: (i) overconfident about their abilities, (ii) overly optimistic about their future financial situations, and (iii) more likely to be hand-to-mouth. We introduce permanent heterogeneity in households' cognitive skills and beliefs about their skills in a heterogeneous-agent New Keynesian model to match these findings. Our model jointly matches the average marginal propensities to consume and the average wealth in the U.S. even when all wealth is liquid. Heterogeneity in skills and overconfidence matters for fiscal policy: providing liquidity is less effective in bringing households away from the borrowing constraint and the optimal level of public debt is substantially lower than in standard models.

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1 Introduction

A growing body of work is showing that heterogeneity in household savings behavior and financial situations can have significant implications for macroeconomic fluctuations and policy design.[1] However, this literature typically assumes ex-ante identical households, abstracting from fundamental and persistent dimensions of heterogeneity that may shape households' savings behavior and financial situations and improve models' predictive and prescriptive power (Auclert et al. (2020), Aguiar et al. (2021)). A key technical challenge is that heterogeneity in many fundamental inputs has been empirically linked to micro decisions and macro outcomes (e.g., Stango and Zinman (forthcoming), Andre et al. (2022), Roth et al. (2023), Weber et al. (2022), Coibion et al. (2022)). This raises the question summarized in our paper title: which margin(s) of consumer heterogeneity can help us better explain macroeconomic outcomes and guide policy design?

One seemingly promising starting point is heterogeneity in cognitive skills, which has been shown to play a crucial role in explaining economic growth (Hanushek and Woessmann (2008)), and in shaping households' expectations about the macroeconomy and how they respond to changes in these expectations (D'Acunto et al. (2019, 2020)). Moreover, heterogeneity in cognitive skills has been empirically linked to heterogeneity in behavioral biases and income (e.g., Stango and Zinman (forthcoming), Chapman et al. (forthcoming)), suggesting a potential margin for bridging heterogeneous-agent macro modeling and behavioral macro, which typically models a homogeneous behavioral bias (e.g., Farhi and Werning (2019), Angeletos and Huo (2021), Laibson et al. (2021) or Pfäuti and Seyrich (2022)).[2]

The problem with focusing on heterogeneity in cognitive skills alone is that it delivers counterfactual predictions for variables that are key to understanding macroeconomic fluctuations. Specifically, we show formally that adding persistent heterogeneity in cognitive skills—modeled as differences in average idiosyncratic productivity levels leading to differences in average income levels—to an otherwise standard, general equilibrium heterogeneous-agent New Keynesian (HANK) incomplete-markets model generates predictions that lower-skilled households are less likely to be *Hand-to-Mouth* (HtM) and exhibit lower marginal propensities to consume (MPC). Empirical evidence runs counter to these predictions. For example, in Parker (2017) low liquidity is a strong predictor of high MPCs and this in turn is a "persistent characteristic of low-income households lasting years" (pp. 155). Similarly, Johnson et al. (2006) and Jappelli and Pistaferri (2014) find that low liquid wealth and low income levels are strongly tied to higher MPCs. Consistent with these patterns and the strong positive correlation between cognitive skills and income, we provide new empirical evidence that households with lower cognitive skills are substantially

[1] See, e.g., Werning (2015), Kaplan et al. (2018), Auclert (2019), Bayer et al. (2022), Luetticke (2021), Hagedorn et al. (2019), Patterson (forthcoming), Almgren et al. (2022), Holm et al. (2021) on shock transmission and policy efficacy, and Dávila and Schaab (2023), McKay and Wolf (2022), Bhandari et al. (2021), Bilbiie (2021) on optimal policy design.

[2] An important exception that we discuss later is Ilut and Valchev (2023).

more likely to be HtM.[3]

Although adding heterogeneity in cognitive skills alone does not help fit the data better, we show that adding one additional and related source of consumer heterogeneity does: overconfidence about one's cognitive skills. Specifically, we extend our model—in which households self-insure their idiosyncratic income risk by accumulating wealth—by introducing both permanent heterogeneity in cognitive skills and permanent heterogeneity in perceptions of one's own skills (modeled as differences in forecasts of one's own idiosyncratic productivity). The key assumption required is that lower-skilled consumers persistently overestimate their future productivity (they are "overconfident"), while the higher-skilled are well-calibrated (they are "rational").[4]

This and other key elements of our model are disciplined using consensus estimates from prior work and our new analysis of rich micro-level data on U.S. consumers from the American Life Panel. We start by describing persistent overconfidence about cognitive skills, finding e.g., an estimated population share in the same ballpark as the share of persistently overconfident managers in Huffman et al. (2022). We next show, in keeping with prior work (e.g., Chapman et al. (forthcoming); Stango and Zinman (forthcoming)) that overconfidence in cognitive skills is strongly negatively correlated with the level of cognitive skills. Then we show that persistent overconfidence is strongly correlated with households' actual and expected financial situations: overconfident households are 1.5 times more likely than rational ones to hold persistently overly optimistic views about their future financial situation. Additionally, overconfident households are substantially more likely to be persistently financially constrained per our eight complementary measures of HtM status.

Our model endogenously generates that overconfident households tend to be (i) overly optimistic about their future financial situations and (ii) more likely to be HtM.[5] The reason is that an overconfident household underestimates her future income risk and, thus, has a lower incentive to self-insure. In other words, for any given real interest rate, an overconfident household accumulates less wealth than a rational household would.

The same mechanism allows us to match the U.S. average marginal propensity to consume while simultaneously matching the average wealth level in the economy. Typically, this is not possible in one-asset HANK models: if the supply of assets is large enough to match the average wealth in the economy, the price of assets is so low that almost all of the households have accumulated a sufficient buffer stock to be away from the borrowing constraint (Auclert et al. (2018), Kaplan and Violante

[3]We measure HtM status per various standard definitions, including ones based on the household's net worth, whether they live paycheck-to-paycheck, whether they could cover unexpected expenses of $2000, or whether they report to be in severe financial distress.

[4]Relatedly, Balleer et al. (2022) and Mueller et al. (2021) study the role of households' potentially mis-calibrated) beliefs about future income situations, but focus on implications for labor markets, and Rozsypal and Schlafmann (forthcoming) introduce an overpersistence bias in individual income expectations in a partial equilibrium setting. Wang (2023) shows how calibrating a standard-incomplete markets model to consumers' perceived rather than actual income risk is better able to account for the observed wealth inequality.

[5]Sergeyev et al. (2022) study the reverse effects, namely, how financial stress affects cognitive abilities and productivity.

(2022)). This implies that almost all households should have relatively low MPCs. In our model, in contrast, overconfident households underestimate their insurance needs and consequently perceive the price of the assets as too high to merit accumulating a sufficient buffer stock. Consequently, although the supply of assets is high, a large share of overconfident households still lives near or at the borrowing constraint and thus exhibits high marginal propensities to consume, pushing up the average MPC. The rational households, on the other hand, fully understand their insurance needs and happily absorb the supply of assets. As a result, almost all rational households are well-insured and not at or close to the borrowing constraint.

The joint distribution of cognitive skills, overconfidence, and financial constraints matters greatly for the model's policy implications—both positively and normatively. Consider a fiscal policy that injects liquidity into the economy. In a standard HANK model that abstracts from overconfidence, this liquidity provision is highly effective in reducing the share of HtM households. As households at or close to the borrowing constraint have the highest incentives to save in liquid assets, these households benefit from the additional liquidity. Thus, the wealth share of the bottom 50% increases substantially. In our model with overconfidence, however, a large share of the households that are HtM—the overconfident households—are borrowing constrained because they underestimate their income risk. Thus, even when the government provides more liquidity, these households do not substantially increase their liquid-asset holdings. The result is that the wealth share of the bottom 50% increases only mildly. The wealth share of the top 10%, on the other hand, decreases in a similar fashion in both models, as in both models the asset-rich households are (mostly) rational and thus behave similarly across models.

We then show that the heterogeneous savings behavior also matters for *optimal* fiscal policy. Our model's estimated optimal amount of government debt is about one-third of that in a standard HANK model (roughly 100% vs. 300% of annual GDP). Higher public debt increases the self-insurance possibilities of households (Woodford (1990), Aiyagari and McGrattan (1998)), but when some households are over-confident, they do not make enough use of these possibilities. Consequently, a large share of households remains badly insured even when liquidity supply is high, diminishing the average benefits of higher government debt. At the same time, the marginal cost of public debt is higher in our model, due to the higher equilibrium interest rate required to induce saving. Thus both sides of the benefit-cost ledger push toward lowering the optimal amount of government debt in our model compared to standard models.

We next extend our analysis to a two-asset HANK model with permanent skill heterogeneity and overconfidence. A standard practice to reconcile the high average MPC with the average wealth level is to introduce a second "illiquid" asset that can be adjusted only infrequently (Kaplan and Violante (2014), Kaplan et al. (2018), Auclert et al. (2018), Bayer et al. (2019)). This introduces "wealthy HtM" households who are rich in illiquid assets but still have high MPCs as they hold only little liquid assets. These models typically require a high return gap between the liquid and the illiquid asset to match the average MPC in the data (Kaplan and Violante (2022)).

Our two-asset model, in contrast, can account for the average MPC in the data with a return gap between liquid and illiquid assets that is about one-third of the return gap required in the rational model. The intuition is that overconfident households underestimate their individual income risk and, hence, require a smaller return premium to invest in the illiquid asset.

Overall, our model accommodates richer consumer heterogeneity in behavioral decision inputs than related work to-date. Ilut and Valchev (2023) is similar in spirit in introducing deviations from full information rational expectations in a model with household heterogeneity. They show that imperfect knowledge of one's optimal policy function can fit the data on persistent HtM shares. We show that our empirically-grounded heterogeneity in cognitive skills and overconfidence thereon matches the data on savings behavior of households and their financial situations. We further show that accounting for heterogeneity in skills and overconfidence has important implications for fiscal policy—both positive and normative. Broadly, we build on other prior work in behavioral macroeconomics by allowing for heterogeneity in beliefs rather than imposing a representative behavioral decision maker (for example, Woodford (2013), Gabaix (2014), Woodford (2019), Gabaix (2020), Bordalo et al. (2020), and Lian (2023) focus on a representative behavioral decision maker, and see, e.g., Farhi and Werning (2019), Auclert et al. (2020), Angeletos and Huo (2021), Laibson et al. (2021) or Pfäuti and Seyrich (2022) for HANK models with a homogeneous behavioral or information friction about an aggregate variable only).

We also relate to prior work showing that persistent sources of consumer heterogeneity can help explain systematic patterns in savings behavior and financial situations, and affect policy implications as e.g., in Krueger et al. (2016), Aguiar et al. (2021) and Auclert et al. (2020). Aguiar et al. (2021) introduce heterogeneity in preferences and patience to match a number of empirical facts about the behavior of HtM households and suggest that behavioral models might provide a potential micro-foundation for their modelling choices. Krueger et al. (2016) and Auclert et al. (2020) introduce permanent heterogeneity in patience and—in the case of Auclert et al. (2020)—in average skills to better match the wealth inequality in the data.

Most starkly, the fact that our consumers at the borrowing constraint *systematically* differ from asset-rich households offers a sharp contrast to models with rational expectations ("RE") and to behavioral HANK models where the only deviation from RE regards some aggregate variable. In those models, households become borrowing constrained because they are unlucky and are hit by negative productivity shocks. In our model, households are borrowing constrained because they overestimate their own abilities, leading to a systematic relationship between cognitive skills, overconfidence and financial constraints. Thus, it holds true in our model that liquidity is the main predictor of MPCs (as empirically reported, e.g., in Fagereng et al. (2021), Jappelli and Pistaferri (2014)). And it turns out that accounting for the underlying reason why some households are systematically less willing to hold liquidity matters greatly for policy.

2 Data and Empirical Results

This section provides empirical evidence that we use to help discipline the model in Section 3. As previewed in the Introduction, persistent cross-consumer heterogeneity in overconfidence about cognitive skills plays a central and fundamental role in our model, generating persistent forecast errors and financial constraints as emergent phenomena with important implications for macroeconomic aggregates and policies.

As such we focus here on documenting heterogeneity in persistent overconfidence (Table 1), including its relationship to heterogeneity in cognitive skills themselves (also in Table 1), and its relationships with forecast errors (Table 3) and financial constraints (Tables 4a and 4b). Several Appendix Tables provide additional motivation and details for the key parameters in our model.

In estimating empirical relationships between variables we focus on pairwise correlations, for two reasons. One is empirical: pairwise correlations are easier to interpret when all of the variables of interest are correlated with each other; conversely, multi-variate estimates are likely subject to confounds from over-controlling and multi-collinearity. The other is conceptual: for modeling purposes, we are interested in identifying a proxy for persistent and relatively fundamental consumer heterogeneity (like overconfidence about cognitive skills) that can reproduce key empirical patterns in the aggregate (like patterns of forecast errors and financial constraints). The proxy can be useful, for modeling purposes, whether or not it has a causal relationship with the other variables of interest. Following Solon et al. (2015), we show both unweighted and sampling probability-weighted estimates.

Our data source is the American Life Panel, a long-running online panel that goes to great lengths to obtain a nationally representative sample of U.S. adults. We measure overconfidence about cognitive skills using data from the modules in Stango and Zinman (2022, forthcoming), henceforth SZ, which administered the same behavioral and cognitive elicitations, together with questions about household financial condition, to the same 845 panelists in two survey rounds administered in 2014 and 2017. The SZ modules sample only working-age adults (aged 18-60 in 2014), which maps well into our model's focus on labor-market productivity. Cognitive skills are measured with standard tests for general or fluid intelligence (McArdle et al. (2007)), numeracy (Banks and Oldfield (2007)), cognitive control/executive function (MacLeod (1991), Miyake and Friedman (2012)), and financial literacy (Lusardi and Mitchell (2014)).

We focus on overconfidence in relative performance (i.e. in placement) because it has the most granular measure among the three varieties of overconfidence elicited in the SZ modules (see Table 1 in Stango and Zinman (forthcoming)). Panelists are asked "... what you think about your intelligence as it would be measured by a standard test. How do you think your performance would rank, relative to all of the other ALP members who have taken the test?", elicited as an integer percentile, and later in that survey take a standard 15-question "number series" test of fluid intelligence (McArdle et al. (2007)). We then define the degree of overconfidence as the

the self-assessed rank minus the actual rank and a greater value indicates more overconfidence (we refer to this as "oc percentile rank"). This cross-sectional ranking is correlated, for the most part strongly, with the SZ rank measures of overconfidence in level (a.k.a. absolute) performance and precision, perceptual biases regarding probability and exponential growth, and cognitive skills (Stango and Zinman (forthcoming)).[6]

A key model input is the population share with persistent overconfidence, so we also measure persistent overconfidence on the extensive margin, defined as being above-median rank in both 2014 and 2017. This measure of "oc in both rounds" provides a roughly estimated population share of 38 percent, with a standard error of 4 pp (see upper panel in Table 1).[7] We are not aware of any other quantitative estimate of the share of consumers who are persistently overconfident about their ability, or some closely related object, in a plausibly representative national sample of the working-age population. Huffman et al. (2022) estimates that 45 to 48 percent of managers are over-confident about their performance in a repeated high-stakes workplace tournament held by a single employer. Balleer et al. (2022) infer that working-age individuals in the U.S. are "vastly over-optimistic about their own labor market prospects" (p. 1). Mueller et al. (2021) find optimistic bias about job-finding rates, especially for the long-term unemployed and little evidence for downward revision of these beliefs when remaining unemployed. Caplin et al. (2023) document that the subjective earnings risk is substantially lower than earnings risk estimated from administrative data. Moschini et al. (2023) find widespread over-optimism about college completion among 18 year-olds in the 1997 NLSY. Given the persistence in overconfidence, we later model overconfidence as a form of permanent heterogeneity. Various theories can explain how overconfidence persists in the presence of feedback (e.g., Heidhues et al. (2018) or Zimmermann (2020)).

Another key input to the model is a negative relationship between overconfidence about cognitive skills and the level of skills (Section 4 shows that this is required to produce empirically realistic levels of financial constraints among the low-skilled, who would otherwise save their way out of HtM status in the absence of overconfidence). The lower part of Table 1 shows the requisite strong correlations between each of our extensive margin and rank measures of overconfidence and our summary and component measures of cognitive skills.[8]

[6]Chapman et al. (forthcoming) also finds positive correlations among the three overconfidence varieties, and negative correlations between overconfidence and cognitive skills.

[7]Here we use ALP's raked sample probability weight for the last of the four SZ modules. Our measures of the other two overconfidence varieties are arguably less suited for estimated population shares, but for completeness we report them and their limitations here. 26 percent of the sample exhibits overconfidence in precision in both rounds, but we can identify overconfidence only for those expressing complete certainty about objects that are at least a bit uncertain. 42 percent that could reveal overconfidence in level performance does so in both rounds, but that share is estimable only for a lower cognitive skills sub-sample because those with the highest score on the quiz used to measure confidence in level performance mechanically cannot exhibit over-confidence. (The measure of level performance belief simply asks "How many of the last 3 questions... do you think you got correct?")

[8]The correlations with rank fluid intelligence have point estimates $> |1|$ because the IV estimator does not restrict the coefficient. (Note however that the confidence intervals here contain values <1.) These correlations are remarkably and relatively strong, likely for two reasons. One is mechanical, since our measure of overconfidence is

Table 1: Persistent overconfidence: Population share, and correlations with cognitive skills

	1 = oc both rounds		oc percentile rank	
	Unweighted	Weighted	Unweighted	Weighted
	(1)	(2)	(3)	(4)
Population share	0.340	0.377		
s.e.	0.017	0.035		
N	817	817		
Cognitive skill measures				
Summary: 1st principal component	-0.546	-0.542	-0.818	-0.830
s.e.	0.030	0.045	0.032	0.049
N	733	733	733	733
Component: Fluid intelligence	-0.718	-0.734	-1.049	-1.065
s.e.	0.026	0.047	0.026	0.055
N	817	817	817	817
Component: Numeracy	-0.362	-0.453	-0.573	-0.656
s.e.	0.040	0.068	0.046	0.077
N	798	798	798	798
Component: Financial literacy	-0.321	-0.242	-0.467	-0.362
s.e.	0.038	0.087	0.041	0.087
N	813	813	813	813
Component: Executive function	-0.316	-0.407	-0.444	-0.600
s.e.	0.045	0.072	0.052	0.090
N	749	749	749	749

Note: Overconfidence re: relative performance in a cognitive skills test (see Section 2 for details). All cognitive skills measures are percentile ranks. Cognitive skills summary measure is the first principal component of each of the component measures shown in the table (see Stango and Zinman (forthcoming) for details on component measures). Weighted estimates use the sampling probability for the last SZ module. All cognitive skills measures, and overconfidence percentile rank, use Obviously Related Instrumental Variables to account for measurement error by having the two rank measures (taken in 2014 and 2017) instrument for each other (Gillen et al. (2019), Stango and Zinman (forthcoming)). We do not take the same approach to the overconfidence indicator in Columns 1 and 2, because measurement error-IV does not work well on misclassification error.

A key output of the model is that persistent overconfidence about cognitive skills endogenously generates persistent overoptimism about one's own household financial condition. Tables 2 and 3 show that this is empirically realistic, as we detail below. Tables A1-A3 provide details on financial condition forecasts and forecast errors. We measure these with questions that have long been used in the Michigan Survey of Consumers, and many other national household surveys across the world, to help measure consumer sentiment (Souleles (2004)). Forecasts are elicited with "... do you think that a year from now you will be better off financially, or worse off, or just

based on the difference between perceived and actual scores on this test: the higher one's test score, the smaller the range of potential values for overconfidence. The second is that the fluid intelligence measure, which is based on responses to 15 questions, is more granular than the numeracy and financial literacy measures, which are each based on 3 questions.

about the same as now?", and realizations a year later with "We are interested in how people are getting along financially these days. Would you say that you are better off or worse off financially than you were a year ago?" We consider 17,266 forecast-realization pairs, provided by 3,401 ALP panelists across fourteen surveys administered in January and July from July 2010-January 2016.

Table 2: Pairwise correlations between persistent overconfidence about cognitive skills and persistent optimistic forecast errors

	1 = oc both rounds		oc percentile rank		Mean(row var)	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
	(1)	(2)	(3)	(4)	(5)	(6)
1=(Consec. opt. FEs)	0.163	0.082	0.107	0.029	0.147	0.124
s.e.	0.095	0.123	0.056	0.066		
N	409	409	409	409		
1=(Prop. opt. FEs ≥ 0.5)	0.219	0.197	0.155	0.149	0.130	0.140
s.e.	0.097	0.145	0.055	0.091		
N	409	409	409	409		
Prop. opt. FEs	0.096	0.108	0.134	0.159	0.174	0.181
s.e.	0.056	0.084	0.057	0.073		
N	409	409	409	409		

Note: Overconfidence re: relative performance in a cognitive skills test (see Section 2 for details). Forecast errors re: household financial condition (see Appendix Table A1 for details). Weighted estimates use the mean of each panelist's: (sample probably weight from the last SZ module, mean sampling weight across the survey(s) with the realization component of the forecast error(s) used here). In Columns 3 and 4, we use Obviously Related Instrumental Variables to account for measurement error by having the two measurements of o/c rank (taken in 2014 and 2017) instrument for each other (Gillen et al. (2019), Stango and Zinman (forthcoming)). We do not take the same approach to the overconfidence indicator in Columns 1 and 2, because measurement error-IV does not work well on misclassification error. Fully non-IV correlations estimated using tetrachoric or Pearson.

Financial condition forecasts and forecast errors tilt both optimistic in the aggregate (see Appendix Table A1).[9] 28 percent of forecasts are for improvement while only 12 percent forecast worsening, and approximately 72 percent of forecast errors are in the optimistic direction.[10] Panels B-E show that these estimates are quite similar over time and whether or not we weight by sampling probability.

Appendix Table A2 shows that these financial condition forecast errors (or lack thereof) are persistent: overall about 75 percent of probability mass is on the diagonal, and 45 percent of panelists who make an optimistic forecast error in the previous period make the same error in the next period. Forecast errors persist and learning seems modest.[11] Nor is there evidence of

[9] Souleles (2004) also finds evidence of optimistic forecast errors about one's own financial condition in the aggregate, for the U.S. during 1978-1996. Using similar questions in Finland, Hyytinen and Putkuri (2018) find symmetric forecast errors during 1994-2013.

[10] When estimating forecast errors from these measures we focus on realizations in the middle ("about the same") category, to allow for potential errors in either direction. So in Appendix Table 1, $18/63 = 28$ percent of the sample makes a forecast error, and $13/18 = 72$ percent of those errors are in the optimistic direction.

[11] Comparing the first to last forecast-realization pair we observe for those with multiple pairs, A3 shows that

substantial overcorrection: Appendix Table A2 shows that optimists are about $0.095/0.003 = 32$ times more likely to get better-calibrated than to over-correct with a pessimistic forecast error. This, together with our allowance for consumer heterogeneity, distinguishes our model from those with diagnostic expectations or other sources of overreaction (Bordalo et al. (2022), Bianchi et al. (2022), L'Huillier et al. (2022)).

Focusing on the model output described above, Tables 2 and 3 suggest that there is indeed a positive correlation between persistent overconfidence about one's own cognitive abilities and persistent optimism about one's own financial condition. Here we use the sub-sample of the forecasting panel that completed the SZ surveys as well, and construct three panelist-level measures of persistent optimism: 1=(has consecutive optimistic forecast errors); 1=(proportion of optimistic forecast errors ≥ 0.5); proportion of pairs that are optimistic forecast errors. The denominator for the proportions is the count of all forecast-realization pairs observed for the panelist.

Table 3: Optimistic forecast errors are more prevalent among the overconfident

$\frac{\text{(Optimist share} \mid \text{overconfident)}}{\text{(Optimist share} \mid \text{not oc)}}$	Optimism measure	
	1 = (Consec. Opt. FEs)	1 = (Prop. Opt. FEs $\geq$ 0.5)
Unweighted	1.51	1.77
Weighted	1.17	1.63

Note: Sample is the 409 Stango-Zinman panelists who also provide the requisite data, in other ALP modules, on financial condition forecasts and realizations. Overconfidence re: relative peformance in a cognitive skills test (see Section 2 for details). Forecast errors re: household financial condition (see Table A1 for details). Weighted estimates use the mean of each panelist's: (sample probably weight from the last Stango-Zinman module, mean sampling weight across the survey(s) with the realization component of the forecast error(s) used here).

Table 2 then correlates each of these three measures with our two measures of persistent overconfidence about cognitive skills: the extensive margin in Columns 1 and 2 (unweighted and weighted), and the persistent component of cross-sectional rank in Columns 3 and 4.[12] The six unweighted estimates each suggest a positive correlation between persistent overconfidence and persistent optimistic forecast errors. The magnitude of the estimated correlations is modest–the range is 0.10 to 0.22, with t-stats of 1.7 to 2.3–but this strikes us as unsurprising given the measures' coarseness. The weighted estimates have larger standard errors but are still uniformly positively-signed and with similar point estimates in four of six cases.

Table 3 provides a complementary perspective on magnitude of the relationship between overconfidence and optimism, in an empirical form that maps more directly into our model. Here we see that persistent optimism about one's future financial condition—as measured by the two

the accuracy rate increases from 55 to 62 percent and the optimistic slant decreases from $16/21 = 77$ percent to $13/18 = 72$ percent.

[12]Specifically, we use our two measures of cross-sectional rank, taken three years apart, to instrument for each other (Gillen et al. (2019), Stango and Zinman (forthcoming)). This measurement error IV strategy does not work well for the extensive margin measures in Columns 1 and 2 because those have non-classical misclassificaton error.

indicators used in Table 2—is about 1.5 times more prevalent among the persistently overconfident households than in the rest of the population.

Our model will show that being persistently too optimistic about one's own future financial situation can lead to less precautionary savings and persistently binding liquidity constraints. Tables 4a and 4b show that this is empirically realistic. These tables present estimates of weighted and unweighted correlations between our two persistent overconfidence measures and eight measures of persistent financial constraints or HtM status. We find a positive sign on 30 of the 32 point estimates here. Twenty-six of them fall within the 0.10 to 0.36 range, and 22 have t-stats >2. Only the persistent "Wishes saved more" measure of HtM status seems uncorrelated with persistent overconfidence, while the other seven measures (including "Wishes saved a lot more") are positively correlated.

The HtM measures in Table 4a are based on data from the SZ modules. The HtM measures in Table 4b are pulled in from other ALP modules completed by a subset of the SZ panelists at various times. Note that although seven of these eight measures are based on data from relatively placid economic times (2012-2018), the COVID-era measure in Table 4b is based on 9 surveys administered from May 2020-July 2022. The last column in Tables 4a and 4b provides a point of comparison to prior work estimating population shares per different HtM definitions. One example is the estimate in Kaplan and Violante (2022) of 41 percent (based on net worth and liquid asset data from the 2019 SCF). This is similar to our estimated shares based on net worth in 2014 and 2017 (47 percent), and on living paycheck-to-paycheck during 2020-2022 (44 percent). Another example is the Sergeyev et al. (2022) estimate, from the Dynata panel, that 54 percent of U.S. households would have difficulty covering an unexpected 2,000 dollar emergency expense in 2022. We also estimate 54 percent, based on data from 2011, 2012, and 2018.

To summarize, we find that consumers who are persistently overconfident about their cognitive skills tend to be lower-skilled, persistently too optimistic about their future financial situation, and persistently more likely to be HtM. We next develop a model that can explain these findings and analyze how they matter for macroeconomic policy.

3 Model

In this section, we show how we introduce permanent heterogeneity in cognitive skills and overconfidence about these cognitive skills into an otherwise standard HANK model. The model features incomplete markets in the spirit of Bewley (1986), Huggett (1993), and Aiyagari (1994), and nominal rigidities in the form of sticky wages. Time is discrete and denoted by $t = 1, 2, \ldots$. We first focus on the case in which households can only save in one asset; a liquid bond issued by the government. In Section 6, we introduce a second asset in the form of illiquid productive capital.

Households. There is a unit mass of households that are subject to idiosyncratic risk, incomplete markets, and borrowing constraints. We allow for permanent heterogeneity in households'

Table 4a: Pairwise correlations between persistent overconfidence about cognitive skills and persistent HtM measures from SZ modules

	1=O/c both rounds		O/c pctile rank		Row variable, unw.	Row variable, w.
	Unweighted	Weighted	Unweighted	Weighted	Pop. share	Pop. share
	(1)	(2)	(3)	(4)	(5)	(6)
1=(Severe financial distress)	0.176	0.273	0.194	0.180	0.277	0.305
s.e.	0.059	0.119	0.039	0.078	0.016	0.035
N	813	813	813	813		
1=(Low net worth)	0.250	0.198	0.226	0.086	0.397	0.468
s.e.	0.057	0.097	0.041	0.073	0.018	0.018
0.032	0.032					
N	760	760	760	760		
1=(Wishes saved more)	-0.003	0.080	0.025	-0.041	0.611	0.615
s.e.	0.058	0.111	0.041	0.075	0.017	0.033
N	813	813	813	813		
1=(Wishes saved a lot more)	0.172	0.359	0.131	0.183	0.156	0.156
0.213	0.213					
s.e.	0.066	0.127	0.041	0.084	0.013	0.035
N	813	813	813	813		

Note: Overconfidence re: relative performance in a cognitive skills test (see Section 2 for details). SZ modules: the same modules containing the oc measures. Weighted estimates use the sampling probability for the last SZ module. In Columns 3 and 4, we use Obviously Related Instrumental Variables to account for measurement error by having the two measurements of o/c rank (taken in 2014 and 2017) instrument for each other (Gillen et al. (2019), Stango and Zinman (forthcoming)). We do not take the same approach to the oc indicator in Columns 1 and 2, because measurement error-IV does not work well on misclassification error. Fully non-IV correlations estimated using tetrachoric or Pearson. Severe financial distress=1 if panelist reported any of four events (forced move, late payments, hunger, foregone medical care) in past 12 months. Low net worth is defined as $< 1/2$ total monthly household income, with net worth measured coarsely in the SZ data and probably excluding most illiquid assets and retirement accounts. Savings wish indicators based on the question: 'Now, apart from retirement savings, please think about how your household typically uses the money you have: how much is spent and how much is saved or invested. Now choose which statement best describes your household: 1 I wish my household saved a lot less and spent a lot more; 2 I wish my household saved somewhat less and spent somewhat more; 3 My household saving and spending levels are about right; 4 I wish my household saved somewhat more and spent somewhat less; 5 I wish my household saved a lot more and spent a lot less'. These =1 if panelists answered ≥ 4, or 5, in both 2014 and 2017.

Table 4b: Pairwise correlations between persistent overconfidence about cognitive skills and persistent HtM measures from other modules

	1=O/c both rounds		O/c pctile rank		Row variable, unw.	Row variable, w.
	Unweighted	Weighted	Unweighted	Weighted	Pop. share	Pop. share
	(1)	(2)	(3)	(4)	(5)	(6)
1=(paycheck-to-paycheck c. 2012)	0.151	0.023	0.154	0.155	0.588	0.561
s.e.	0.099	0.181	0.074	0.099	0.031	0.056
N	255	255	255	255		
paycheck-to-paycheck, COVID era	0.224	0.220	0.301	0.290	0.404	0.440
s.e.	0.053	0.085	0.049	0.077		
N	516	516	516	516		
1=(Lacks prec. savings in 2012 & 2018)	0.112	0.104	0.181	0.205	0.634	0.691
s.e.	0.101	0.133	0.071	0.086	0.030	0.037
N	262	262	262	262		
Difficult covering 2k$ emergency expense	0.230	0.314	0.222	0.281	0.513	0.543
s.e.	0.065	0.078	0.050	0.058		
N	485	485	485	485		

Note: Overconfidence re: relative performance in a cognitive skills test (see Section 2 for details). Weighted estimates use the mean of the SZ module sampling weight and other module sampling weights for other correlations. Paycheck-to-paycheck c. 2012 survey =1 if panelist strongly agrees with: 'I live from paycheck to paycheck'. Paycheck-to-paycheck for COVID era is the proportion of up to 9 surveys, from May 2020-July 2022, where panelist responds 'Very difficult' or 'Somewhat difficult' to 'In the past month, how difficult has it been for you to cover your expenses and pay all your bills?' OR if on the followup q. 'Suppose now you have an emergency expense that costs $400. Based on your current financial situation, how would you pay this expense?' they report one or more expensive options: credit card revolving, small-dollar credit, wouldn't be able to pay for it. Lacks precautionary savings=1 if panelist does not have emerg/rainy day funds set side to cover 3-months' expenses. Difficulty covering expense is the proportion of 3 surveys from 2011, 2012, and 2018 where panelist does not express the highest confidence or certainty that they could cover an unexpected $2,000 need arising in the next month. Population shares for the non-indicator variables estimated by taking the mean of the estimated population shares for each survey used in creating that variable.

cognitive skills and overconfidence about these cognitive skills, consistent with our empirical measure of overconfidence in Section 2. Permanent heterogeneity is denoted by g and μ_g denotes the mass of agents of type g.

An individual household's idiosyncratic skills (or productivity) of permanent type g in period t are denoted by $\bar{e}_g e_t$. Here, $\bar{e}_g$ captures permanent differences across groups in average skill levels, and e_t captures stochastic heterogeneity in skills. The stochastic component e_t follows a Markov process with time-invariant transition matrix $\mathcal{P}$. The process for e_t is the same for all households and the mass of households in state e is always equal to the probability of being in state e in the stationary equilibrium, $p(e)$.

The problem of an individual household of type g in idiosyncratic state e_t, and with liquid asset holdings b_{t-1} is given by

$$V_{g,t}\left(b_{t-1}, e_t\right) = \max_{c_t, b_t} \left\{ \frac{c_t^{1-\gamma}}{1-\gamma} - \frac{n_t^{1+\varphi}}{1+\varphi} + \beta \tilde{\mathbb{E}}_{g,t} V_{g,t+1}\left(b_t, e_{t+1}\right) \right\}$$

subject to

$$c_t + \frac{b_t}{1+r_t} = b_{t-1} + (1-\tau_t) w_t \bar{e}_g e_t n_t \tag{1}$$

$$b_t \geq -\underline{b}, \tag{2}$$

where c_t denotes consumption, n_t hours worked, r_t the net real interest rate, w_t the real wage, and τ_t denotes the income tax rate.

The parameters γ, φ, and β denote relative risk aversion, the inverse Frisch elasticity of labor supply, and the time discount factor, respectively. These parameters are the same for all permanent-heterogeneity types and time invariant.

The expectations operator $\tilde{\mathbb{E}}_{g,t}$ depends on g, which not only captures permanent heterogeneity in cognitive skills but also in overconfidence. Overconfidence affects the perceived future cognitive skills, as we discuss next.

Cognitive skills and overconfidence. We allow for permanent heterogeneity in cognitive skills and overconfidence about these cognitive skills. Heterogeneity in cognitive skills is modelled as different average productivities $\bar{e}_g$.

Consistent with the definition of overconfidence in the data, we introduce overconfidence as overconfidence about one's own cognitive skills. We assume that all households observe their current cognitive skills $\bar{e}_g e_t$ but overconfident households are overly confident about their future cognitive skills. In other words, they have biased beliefs about the transition probabilities $p(e_{t+1}|e_t)$. In particular, households exhibiting overconfidence assign too much probability to reaching (or staying in) relatively high-skill states, and too little probability to reaching (or staying in) relatively low-skill states. As a result, overconfident households are too optimistic about their expected future cognitive skills, relative to a rational household with the same cognitive skills and idiosyncratic risk.

Let $p_{ij} \equiv p(e_{t+1} = e_j | e_t = e_i)$ denote the probability that a household with current skill level $e_i \in \{e_1, e_2, ..., e_J\}$ reaches skill level $e_j \in \{e_1, e_2, ..., e_J\}$ in the following period, and assume that the skill levels are ordered such that $e_1 < e_2 < ... < e_J$. To capture overconfidence by only one additional parameter independent of the number of skill states, we assume that an overconfident household's perceived transition probabilities $\tilde{p}_{ij}$ are given by

$$\tilde{p}_{ij} \equiv \begin{cases} \alpha p_{ij}, & \text{if } i < j \\ \frac{1}{\alpha} p_{ij}, & \text{if } i > j \\ 1 - \sum_{j \neq i} \tilde{p}_{ij}, & \text{if } i = j. \end{cases} \tag{3}$$

The parameter $\alpha \geq 1$ captures overconfidence. If $\alpha > 1$ the household assigns too much weight to reaching a better state (this is the case $i < j$) and too little weight to reaching a worse state ($i > j$). The perceived probability of staying in the same state ($i = j$) ensures that the probabilities sum to 1.[13] This way of modelling overconfidence is consistent with the way Caballero and Simsek (2020) model optimism. They focus, however, on aggregate states and two possible realizations of the state whereas we focus on idiosyncratic states and allow for an arbitrary number of realizations of the state.[14] Note, that in contrast to the overpersistence bias in Rozsypal and Schlafmann (forthcoming), our way of modelling overconfidence is asymmetric. Overconfident households always overestimate the probability of reaching relatively high-skill states, even after being hit by a relatively bad shock, consistent with our empirical results. We nest the rational expectations case by setting $\alpha = 1$.

An immediate implication of overconfidence is that overconfident households will more often be overly optimistic about their future income compared to rational households, consistent with the empirical findings reported in Section 2 (Tables 2 and 3). In the calibration section 3.1 below, we will leverage the empirical findings and target the empirical estimates of the relative shares of optimists among overconfident and rational households, respectively, to calibrate α.

Final goods producers. A representative firm operates an aggregate production function which is linear in labor input N_t

$$Y_t = X_t N_t, \tag{4}$$

where X_t denotes total factor productivity (TFP), assumed to be exogenous, and Y_t denotes total production. Prices are fully flexible such that the real wage per efficient hour equals TFP

$$w_t = X_t. \tag{5}$$

[13] We further restrict α such that all perceived transition probabilities lie between 0 and 1. Given a standard calibration for the income process which are typically estimated to be very persistent, this restriction is not binding.

[14] McClung and Nighswander (2021) introduce belief heterogeneity about employment transition probabilities in a life-cycle model abstracting from nominal rigidities and focus on two employment states only.

Thus, the real wage is exogenous and profits are zero. Since the nominal wage is given by $W_t \equiv w_t P_t = X_t P_t$, we have

$$1 + \pi_t = \frac{1 + \pi_t^w}{1 + a_t^x}, \tag{6}$$

where $\pi_t \equiv \frac{P_t}{P_{t-1}} - 1$ denotes goods price inflation, $\pi_t^w \equiv \frac{W_t}{W_{t-1}} - 1$ wage inflation, and $a_t^x \equiv \frac{X_t}{X_{t-1}} - 1$ TFP growth. If we abstract from changes in TFP, goods inflation and wage inflation coincide.

Unions. We follow the recent HANK literature and assume that hours worked n_t are determined by union labor demand and that wages are sticky whereas prices are flexible (see Erceg et al. (2000), and most closely to our setup, see Auclert et al. (2018)).[15] Each worker provides $n_{k,t}$ hours of work to a continuum of unions indexed by $k \in [0,1]$. Each union aggregates efficient units of work into a union-specific task $N_{k,t} = \int \bar{e}_i e_{i,t} n_{i,k,t} di$, where i here denotes the individual household and thus, indicates both its permanent type as well as its current idiosyncratic state.

A competitive labor packer then packages these tasks into aggregate employment services according to the CES technology

$$N_t = \left(\int_k N_{k,t}^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}} \tag{7}$$

and sells these services to final goods firms at price w_t.

We model wage stickiness by imposing a quadratic utility cost $\frac{\psi}{2} \int_k \left(\frac{W_{k,t}}{W_{k,t-1}} - 1 \right)^2 dk$ that shows up in the households utility function. A union sets a common nominal wage W_{kt} per efficient unit for each of its members.

In doing so, the union trades-off the marginal disutility of working given average hours against the marginal utility of consumption given average consumption. The union then calls upon its members to supply hours according to a specific allocation rule: in stationary equilibrium all households supply the same amount of hours. Outside stationary equilibrium, we assume that each households labor supply is a linear function of changes in aggregate hours according to her productivity (which depends on both, the worker's cognitive skills g and her transitory idiosyncratic state e_t):

$$n_t = \eta(g, e_t)(N_t - \bar{N}) + \bar{N}. \tag{8}$$

Absent aggregate shocks, $N_t = \bar{N}$, and all households work the same amount.

Fiscal policy. We abstract from government spending and assume that the fiscal authority sets total taxes minus transfers, T_t, following a simple debt feedback rule

$$T_t - \bar{T} = \vartheta \frac{B_t - \bar{B}}{\bar{Y}}. \tag{9}$$

Furthermore, the government budget constraint is given by

$$B_t + T_t = R_t B_{t-1}. \tag{10}$$

[15] Auclert et al. (2021) and Broer et al. (2020) argue in favor of using sticky wages rather than sticky prices in HANK models.

When we abstract from aggregate shocks, government debt B is time invariant and given by

$$r\bar{B} = \bar{T}. \tag{11}$$

Monetary policy. The monetary authority sets the nominal interest rate, i_t, following a simple Taylor rule

$$i_t = r + \phi_\pi \pi_t, \tag{12}$$

where r denotes the steady state interest rate, π_t the inflation rate and ϕ_π the response coefficient of nominal interest rates to inflation. Absent aggregate shocks inflation is zero and $i_t = r$ for all t.

Equilibrium. Given permanent heterogeneity in cognitive skills and overconfidence, the general equilibrium absent aggregate shocks, i.e., $X_t = 1$ for all t, is standard and defined as follows.

Definition. Given an initial price level P_{-1}, initial nominal wage W_{-1}, initial government debt level B_{-1}, and an initial distribution of agents $\Psi_{g,0}(b_{-1}, e_0)$ in each fixed group g, a general equilibrium is a path for prices $\{P_t, W_t, \pi_t, \pi_t^w, r_t, i_t\}$, aggregates $\{Y_t, C_t, N_t, B_t, T_t\}$, individual allocation rules $\{c_{g,t}(b_{t-1}, e_t), b_{g,t}(b_{t-1}, e_t)\}$ and joint distributions of agents $\Psi_{g,t}(b_{t-1}, e_t)$ such that households optimize (given their beliefs), all firms optimize, unions optimize, monetary and fiscal policy follow their rules, and the goods and bond markets clear:

$$\sum_{g,e} \mu_g p(e) \int c_t \Psi_{g,t}(b_{t-1}, e_t) = Y_t \tag{13}$$

$$\sum_{g,e} \mu_g p(e) \int b_t \Psi_{g,t}(b_{t-1}, e_t) = B_t. \tag{14}$$

3.1 Calibration

One period in the model corresponds to a quarter. We calibrate the standard parameters to values often used in the literature. To calibrate the idiosyncratic skill process, we follow McKay et al. (2016) and set the autocorrelation of e_t to $\rho_e = 0.966$ and its variance to $\sigma_e^2 = 0.033$ to match the volatility of the distribution of five-year earnings growth rates found in Guvenen et al. (2014). We then discretize this process into an eleven-states Markov chain using the Rouwenhorst (1995) method. We set the tax weights of households such that they equal their idiosyncratic productivities. Together with our union assumptions, this implies the same relative tax payments as a flat labor tax would do. We adjust the discount factor, β, to match a steady state real interest rate of 2%. Risk aversion is set to $\gamma = 2$, the inverse Frisch elasticity to $\varphi = 2$, and the borrowing limit to $\underline{b} = 0$. We set the average wealth to average annual income ratio to 4 as in Kaplan and Violante (2022).

Our key innovation is the permanent heterogeneity in cognitive skills and in overconfidence. We calibrate these new parameters with our empirical findings in Section 2. We calibrate the share of overconfident households to 0.38. Given the extremely strong (negative) correlation between cognitive skills and overconfidence (see Table 1), we assume, for now, that all overconfident households have relatively low cognitive skills and all rational households relatively high cognitive skills. We thus have two permanent-heterogeneity groups, $g \in \{1, 2\}$, where $g = 1$ denotes the low-skilled and overconfident group, and $g = 2$ the high-skilled and rational group. We set the average skill level of the low-skilled households to $\bar{e}_1 = 0.8$, and that of high-skilled households to $\bar{e}_2 = 1$. Table A4 in the Appendix shows that there is indeed a very strong positive correlation between cognitive skills and income in the data. We discuss other cases, including one in which all households are rational and only differ in their average skill levels, later on.

Following equation (3), we capture overconfidence by one parameter, α. As in our empirical strategy (see Section 2, in particular Table 3), we compute the share of households in the stationary equilibrium in the model whose labor income is lower than what that they expected it to be four periods previously (which corresponds to the one-year ahead expectations used in the data). These households classify as being overly optimistic about their labor income. So, also rational households can be classified as being overly optimistic, in case they were hit by relatively bad productivity shocks. We compute these shares of overly optimistic households separately for rational and overconfident households and then set α such that overconfident households are about 1.5 times as likely to be too optimistic (as found empirically, see Table 3). This results in $\alpha = 1.9$. Table 5 summarizes our baseline calibration.

Table 5: Stationary Equilibrium Calibration

Parameter	Description	Value
R	Steady State Real Rate (annualized)	2%
γ	Risk aversion	2
φ	Inverse of Frisch elasticity	2
$\underline{b}$	Borrowing constraint	0
$\frac{\bar{B}}{4\bar{Y}}$	Average wealth to average income	4.0
Idiosyncratic risk		
ρ_e	Persistence of idiosyncratic risk	0.966
σ_e^2	Variance of idiosyncratic risk	0.033
Permanent heterogeneity		
μ_g	Mass of households	$\{0.38, 0.62\}$
$\bar{e}_g$	Cognitive skills	$\{0.8, 1\}$
α	Degree of overconfidence	1.9

Note: This table summarizes our baseline calibration in the one-asset model with two groups of permanent heterogeneity: group one has relatively low average skill levels and households in that group are overconfident, whereas households in group two are relatively high skilled and have rational expectations.

4 Cognitive Skills, Overconfidence and MPCs

We abstract from aggregate shocks and focus on the effects that introducing permanent heterogeneity in cognitive skills and overconfidence in a HANK model has on the stationary distribution and on the marginal propensity to consume of households which is a key statistic in HANK models (see Auclert et al. (2018), Kaplan and Violante (2022)). Table 6 compares the share of households who are hand-to-mouth—i.e., households that are at the borrowing constraint—across four different models: first in our baseline model, a HANK model with permanent heterogeneity in productivity and in which households with lower productivity are overconfident (*"Baseline"*), second, a standard HANK model absent any heterogeneity in permanent productivity levels ($\bar{e}_g = \{1, 1\}$) and in which all households are fully rational ($\alpha = 1$) (*"Standard HANK"*), third, a HANK model with permanent heterogeneity in skill levels in which, however, all households are fully rational ($\alpha = 1$) (*"HANK w\ skills"*), and fourth, a HANK model in which a group of households is permanently overconfident but in which the average productivity of all households is the same ($\bar{e}_g = \{1, 1\}$) (*"HANK w\ OC"*).[16]

Starting with the standard, one-asset HANK model, column (2) in Table 6 shows that this model has a very low average MPC of only 0.031 and only 0.0228% of households are hand-to-mouth (HtM). Both of these findings are not supported by the data. This is a common feature of one-asset HANK models when they are calibrated to match average wealth (Auclert et al. (2018), Kaplan and Violante (2022)). The reason is that rational households have a high incentive to self-insure themselves by accumulating liquid wealth. With a high enough liquidity supply in the economy, almost no households end up being borrowing constrained.

What if we introduce permanent heterogeneity in the sense that a subgroup of households has lower cognitive skills and therefore lower average income as supported by the data? In this case, column (3) shows that the average MPC and the amount of HtM households are practically unchanged. The reason is that still every household has a high incentive to self-insure no matter what their average productivity is as each households is perfectly rational with respect to her own income risk. If anything, households with lower average productivity tend to be even less likely to be HtM and have slightly lower average MPCs. The reason is that relative to their average productivity and thus, their average income, the amount of liquidity they can use to self-insure is even higher. In other words, permanent heterogeneity in average skill levels alone cannot account for the systematic differences in savings behavior and HtM status presented in Section 2 and in Table A5 in the Appendix, but rather, they contradict them.

How does this compare to our baseline HANK model with permanent heterogeneity in average productivity and in which the low-skilled households are overconfident? In this model, the average MPCs are 0.178 and the share of HtM households are 0.25, and thus a magnitude larger than in the

[16]When comparing these four different models, we always recalibrate the discount factor such that all models have the same asset supply and the same steady state real interest rate.

Table 6: MPCs and shares of HtM households across the models.

	Baseline (1)	Standard HANK (2)	HANK w\skills (3)	HANK w\OC (4)
HtM Share	0.2461	0.0228	0.023	0.2489
Avg. MPC	0.178	0.031	0.031	0.1833
HtM rational HHs	0.0121	0.0228	0.0227	0.0108
Avg. MPC rat. HHs	0.021	0.031	0.031	0.01911
HtM OverConfident HHs	-	-	-	0.6374
Avg. MPC OC HHs	-	-	-	0.4512
HtM rat. HHs Low-Skilled	-	-	0.0226	-
Avg. MPC rat. HHs LS	-	-	0.030	-
HtM OC HHs LS	0.6278	-	-	-
Avg. MPC OC HHs LS	0.434	-	-	-

Note: MPCs refer to MPCs out of a $500 dollar stimulus check. "Baseline" is our baseline model, in which we allow for skill heterogeneity and overconfidence, "Standard HANK" denotes a standard one-asset model, in which we abstract from heterogeneity in skills and overconfidence, "HANK w\skills" denotes the same model, but in which we allow for heterogeneity in skills, and "HANK w\OC" denotes a model in which we only allow for overconfidence but not for skill heterogeneity.

models absent overconfidence. Both of these findings are well in line with the data. What explains this result? In line with our empirical findings, a group of households is overconfident which leads them to overestimate their expected income. In other words, they perceive their income risk to be lower than it actually is.[17] Consequently, overconfident households accumulate less precautionary savings than rational households facing the same (actual) income risk would do. Rational households, in contrast, make use of the plenty self-insurance means that are available in the economy. As a result and in line with our empirical findings in Section 2, overconfident households are much more likely to end up being HtM than rational households (63% of overconfident households are HtM, but only 1.2% of rational households in this model are HtM). This also results in a high average MPC in the group of low-skilled, overconfident households (0.434 vs. 0.021 for the rational households) which drives up the average MPCs. Note that the share of HtM households and the average MPCs of rational households is even lower than in a standard HANK model: the reason is that the overconfident household do not demand that much liquidity for self-insurance, so for a given price of liquidity, the available per capita supply for rational households is larger.

The model in which the low-skilled households have the same average productivity but are overconfident has more or less the same share of HtM households and the same average MPCs as our baseline model. This confirms our intuition that it is the *overconfidence* of low-skilled households' that makes them more likely to be borrowing constrained and not their actual lower skills. This point becomes even clearer in a counterfactual, in which we assume that the high-skilled households are overconfident but that the low-skilled households are rational (not shown in

[17] Caplin et al. (2023) find that subjective earnings risk is substantially lower than actual earnings risk.

the table). In that model, the average MPCs is 0.1879 while the average MPC among the rational low-skilled households is only 0.0174. Thus, the model is able to account for the observation in D'Acunto et al. (2020) who show that men with relatively low IQ do not adjust their consumption plans in response to changes in their inflation expectations, even when focusing on high-income men. Through the lens of our model, when we proxy low IQ with overconfidence, these households are substantially more likely to be borrowing constrained and hence, would not respond to changes in their inflation expectations, even though they have a relatively high permanent income.

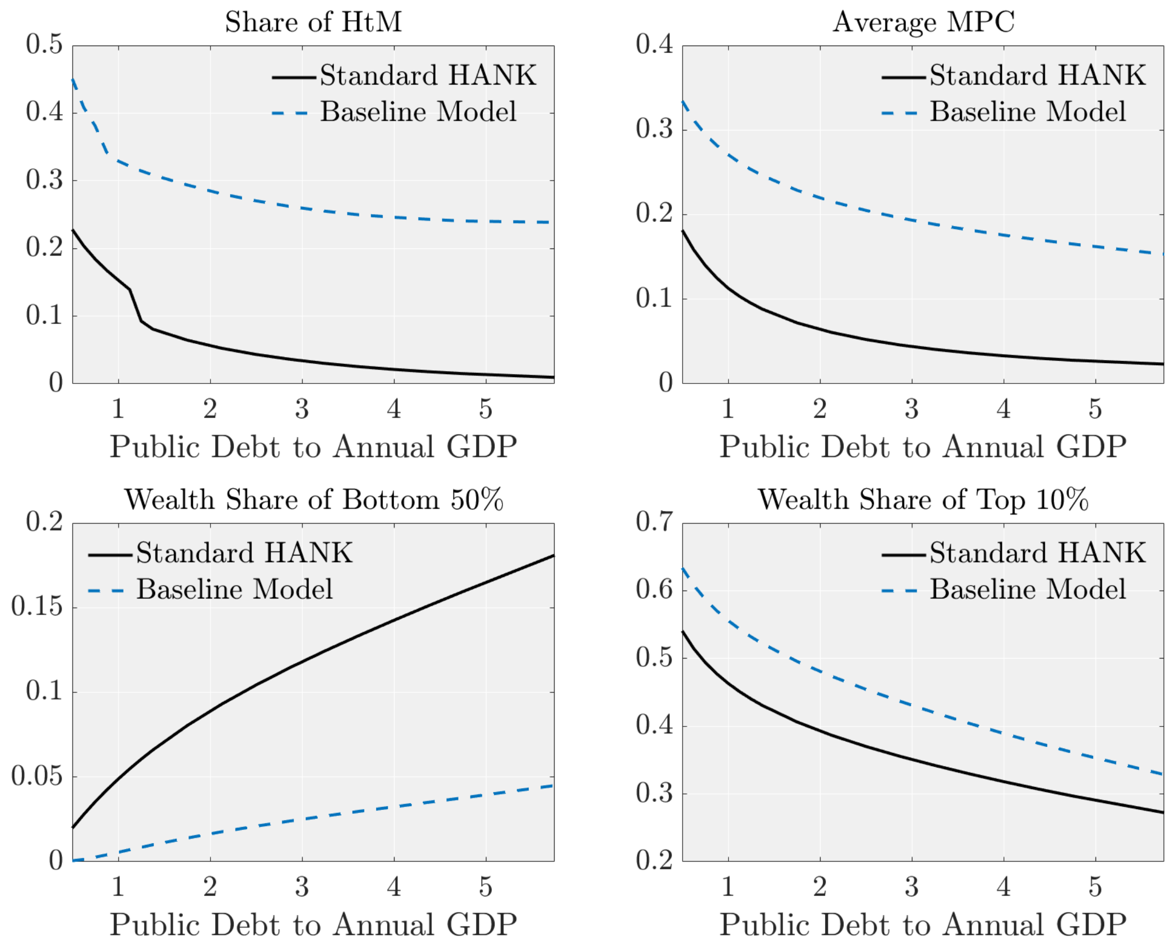
5 Implications for Fiscal Policy

In this section, we show that accounting for persistence heterogeneity in cognitive skills and overconfidence matters greatly for the conduct of fiscal policy. The central feature of heterogeneous-agent, incomplete-markets models is that households can only partly self-insure their idiosyncratic income risk by accumulating liquid bonds. Fiscal policy can manage the supply of liquid bonds by issuing more debt, which makes government debt an effective fiscal policy tool in incomplete markets models. However, we find that when accounting for skill heterogeneity and overconfidence, managing the supply of liquid assets is less effective as in standard models in the sense that more liquidity does not reduce the share of HtM households as much and leads to a substantially smaller decrease in wealth inequality. We then solve for the optimal level of government debt and find that it is much smaller in our model compared to standard models.

5.1 The Effects of Liquidity Provision

Figure 1 shows four important stationary equilibrium statistics as a function of the amount of government debt both for our baseline model (blue-dashed lines) as well as in the standard HANK model without permanent skill heterogeneity and without overconfidence (black-solid lines). To this end, we fix the discount factor of households and let the real interest rate adjust to clear the bond market. The top left panel of Figure 1 shows the share of hand-to-mouth households. It shows a striking difference between the two models: first, for all government debt levels, the share of HtM households is much higher in our baseline model. Secondly, while in the standard model the share of HtM households converges relatively quickly towards zero, it stays substantially above zero even for high government debt levels in our baseline model. Thus, increasing the government debt level is not as effective in bringing households away from the borrowing constraint in the model with overconfidence as it is in standard models. As households at or close to the borrowing constraint have the highest incentives to save in liquid assets, these households eagerly absorb additional liquidity in standard models. In our baseline model with heterogeneous cognitive abilities and overconfidence, however, a large part of the households that are HtM—the overconfident ones—are borrowing constrained because they underestimate their income risk. Thus, even when the government provides more liquidity, these households do not substantially increase their liquid-

Figure 1: The Role of Liquidity



Note: This figure shows the average marginal propensity to consume (upper-left panel), the share of hand-to-mouth households (upper right), the wealth share of the bottom 50% of households (lower left), and the wealth share of the top 10% of households (lower right) for varying degrees of average wealth to average earnings ratios (horizontal axis). The black-solid shows the case for the standard HANK model that abstracts from permanent heterogeneity in cognitive skills and overconfidence, and the blue-dashed line shows the case for our baseline HANK model featuring permanent heterogeneity in cognitive skills and overconfidence.

asset holdings. As a result, also the average MPCs are much higher in our baseline model compared to the standard model (see upper right panel).

The lower panel focuses on the effects of government debt on two inequality measures, the wealth share of the bottom 50% and the wealth share of the top 10%. One thing that stands out is that at all liquidity levels, the wealth share of the bottom 50% in our baseline model lies substantially below the one in the standard HANK model, whereas the wealth share of the top 10% lies above it. Thus, our model generates more wealth inequality through the introduction of permanent heterogeneity in skills and overconfidence.

The reason is again that in standard models households at or close to the borrowing constraint have the highest incentives to save in liquid assets which pushes up the wealth share of the bottom 50% substantially as more liquidity is provided. In our baseline model, in contrast, a large share of the households are overconfident households who only slightly increase their wealth when the supply of wealth increases. This slows down the increase in the wealth share of the bottom 50%.

The wealth share of the top 10%, on the other hand, decreases in a similar fashion in both models, as in both models the asset-rich households are (mostly) rational households and thus, behave similarly across models. Thus, policies that provide liquidity to the economy can help to reduce the share of people at the borrowing constraint, but significantly less so when accounting for households' overconfidence and trigger a smaller decrease in wealth inequality. We next turn to a normative analysis of liquidity provision through increasing the government debt level.

5.2 The Optimal Amount of Government Debt

In the face of incomplete markets, there is a clear trade-off for fiscal policy when it comes to the amount of government debt: on the one side, through issuing more debt and therefore providing more liquid assets, fiscal policy can increase the insurance possibilities of households which, eventually, helps them to better smooth consumption. On the other side, higher government debt requires higher distortionary tax rates to finance the interest payments of households. A natural question is therefore: what is the optimal level of government debt?

In this section, we show that this answer drastically depends on whether one accounts for households' overconfidence or not. To this end, we compute the average welfare defined as the average value function of households as a function of the amount of government debt. Figure 2 shows average welfare for our baseline model (blue-dashed line) and compares it to a standard rational HANK model without skill and belief heterogeneity (black-solid line). The most important take-away is that average welfare peaks much earlier in our baseline model than in the standard model: the optimum amount of government debt is about 113% of annual GDP instead of 325% of annual GDP as in the standard model.[18]

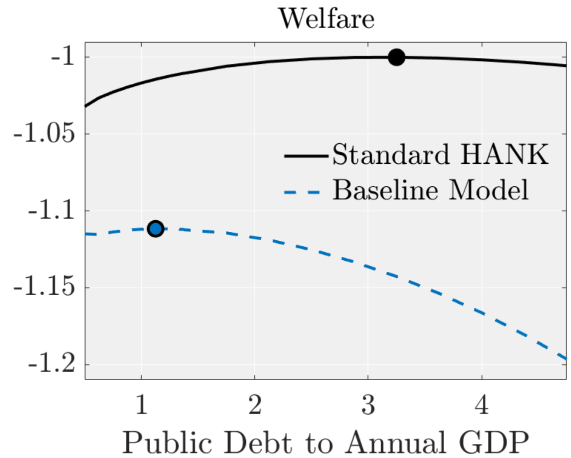
Why is the optimum amount of public debt so much lower in our model compared to the standard model? The benefit of higher government debt is that households can better self-insure their idiosyncratic risk. Yet, households that are over-confident underestimate their income risk. As a result, even with higher government debt, these households are ex-post not as well insured as an identical rational household would be. This diminishes the average benefits of higher government debt compared to the standard model. The fact that more households are ex-post badly insured compared to the standard model also shows in the much larger share of HtM households presented in Figure 1.

Figure 3 shows that at the same time, the interest rate is higher for any given amount of government debt since the average asset demand of households is lower when some households are

[18]Large optimal government debt levels are a typical feature of rational, one-asset, incomplete markets models. Note however that we abstract from capital (as for example in Aiyagari and McGrattan (1998) or in Bayer et al. (2022)) or from default risk both of which would decrease the optimal level of government debt in both models. The same is true if we allowed for a lower borrowing limit. See, e.g., Angeletos et al. (2022), Woodford (1990) for further analyses of optimal public liquidity provision.

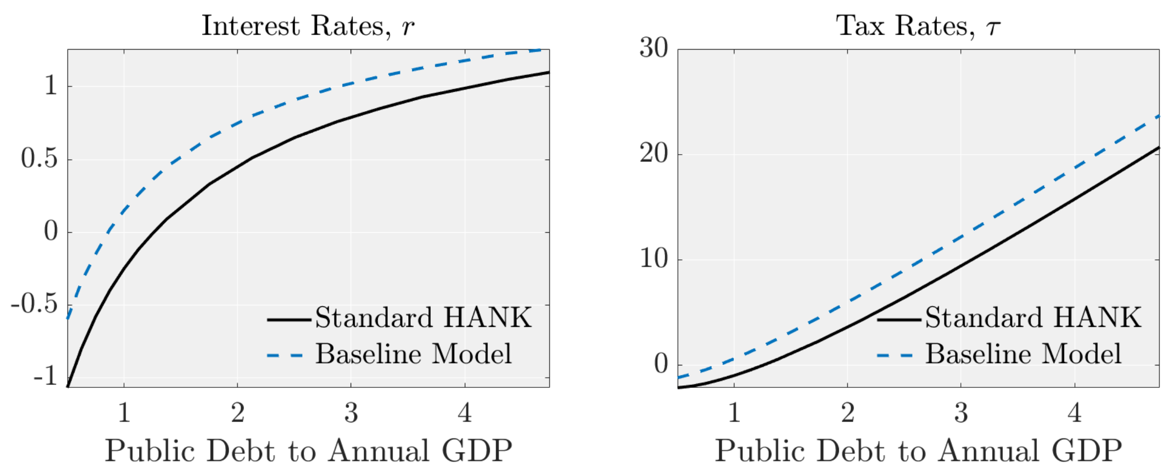
overconfident. The higher interest rates, in turn, push up the costs of higher government debt, as they imply higher interest rate payments for the government and, thus, higher distortionary taxes. With benefits being lower and costs being higher, the optimal amount of government debt is lower than in the standard model.

Figure 2: Welfare



Note: This figure shows the average welfare defined as average value function as a function of government debt and the dots show the welfare-maximizing amount of government debt for our baseline model (blue-dashed lines) and the rational counterpart (black-solid line). Y-axis shows (normalized) average expected lifetime utility, x-axis shows public debt to annual GDP, $\frac{B}{4Y}$.

Figure 3: Interest Rates, Taxes and Government Debt



Note: This figure shows the interest rate (left panel) and the tax rate (right panel) as a function of higher public debt levels in our baseline model (blue-dashed lines) and the rational counterpart (black-solid lines).

6 A Two-asset HANK model with skill heterogeneity and overconfidence

The literature (Kaplan et al. (2018), Kaplan and Violante (2022), Auclert et al. (2018)) has shown that by introducing a second asset in the form of an illiquid asset, HANK models can match the average MPCs while simultaneously matching total wealth in the economy. The idea is that while one of the assets is perfectly liquid the other asset yields a higher return in equilibrium but is illiquid. Hence, illiquid assets are a good savings vehicle for long-run savings but are not well-suited for self-insurance purposes. Yet, in order to match high average MPCs, two-asset HANK models typically require a high return difference between liquid and illiquid assets which is at odds with the data (Kaplan and Violante (2022)).

As shown in the previous section, we can jointly account for the average wealth and average MPC in the economy, even without relying on an illiquid asset. In this section, we now show how introducing permanent heterogeneity in skills together with overconfidence in a two-asset HANK model, can still match the average MPCs and total wealth while it additionally predicts a substantially lower return difference between liquid and illiquid assets.

6.1 Model

The model is the same as our baseline model but for two extensions: first, households' savings decision is now split between a liquid but low-return and an illiquid but high-return asset and, second, the production function now includes capital since we model the illiquid asset as capital.

Households. The households budget constraint now reads:

$$c_t + \frac{b_t}{1+r_t} + k_t = b_{t-1} + (1+r_t^k)k_{t-1} + (1-\tau_t)w_t\bar{e}_g e_t n_t \tag{15}$$

where k denotes the illiquid asset of the household and r^k is its return. Capital depreciates at rate δ and depreciated capital has to be replaced for maintenance, such that r_t^k is the net return on the illiquid asset. Furthermore, we follow Bayer et al. (2023) and assume that households make their savings choices and their portfolio choice between liquid bonds and illiquid capital in light of a capital market friction that renders capital illiquid: participation in the capital market is random and i.i.d. in the sense that only a fraction λ of households are selected to be able to adjust their capital holdings in a given period. All households that do not participate in the capital market ($k_t = k_{t-1}$) still obtain the return on their assets and can adjust their bond holdings. We further assume that both holdings of bonds and holdings of capital have to be non-negative:

$$b_t, k_t \geq 0.$$

Production function. A representative firm operates a Cobb-Douglas production function using capital, K, and labor, N, as input factors:

$$Y_t = K_{t-1}^{\alpha} N_t^{1-\alpha}, \tag{16}$$

where α denotes the capital share in production.

Equilibrium. In addition to the equilibrium conditions in Section 3, now also the capital market needs to clear:

$$\sum_{g,e} \mu_g p(e) \int k_t \Psi_{g,t}\left(k_{t-1}, e_t\right) = K_t. \tag{17}$$

Calibration. All the parameters of the two-asset model that already exist in our baseline model are the same. Table 7 shows the calibration of the additional parameters. We set the capital share $\alpha = 0.314$ and the depreciation rate $\delta = 0.02$ which are standard values in the literature. We then use the probability to participate in the capital market to target a quarterly average MPCs of 0.16 as in Kaplan and Violante (2022). This results in $\lambda = 0.02$.

Table 7: Stationary Equilibrium Calibration

Parameter	Description	Value
α	Capital share	0.314
δ	Depreciation rate	0.02
λ	Capital market participation rate	0.02

Note: This table summarizes the new parameters of the two-asset model. All other parameters stay the same as in our baseline model.

6.2 Stationary Equilibrium Results

Table 8 shows the main result of our two-asset model (*"baseline two-asset"*): it can simultaneously match the average MPCs of 0.16 as well as an annual return gap between the liquid and illiquid asset of 1.62%. 27% of all households are hand-to-mouth which is defined as households who do not hold liquid assets. Again in line with our empirical findings in Section 2, overconfident households are much more likely to be HtM (60% vs. 6.6%). Given their underestimation of their own income risk, they do not merit accumulating a liquid buffer stock but, if they save, they rather save in the illiquid asset which gives a higher return. Rational households on the other hand, first accumulate a liquid buffer stock to self-insure their income risk, before they start saving in the illiquid asset.

Table 8: MPCs and liquidity spread across two-asset models.

	baseline two-asset	rational two-asset	two-asset recalib.
HtM	0.27	0.06	0.23
Avg. MPC	0.16	0.058	0.16
return gap	1.6%	1.5%	4.8%
HtM rat. HHs	0.0658	0.06	0.23
Avg. MPC rat. HHs	0.060	0.058	0.16
HtM OC HHs ls	0.600	-	-
Avg. MPC OC HHs ls	0.323	-	-

Note: MPCs refer to MPCs out of a stimulus check of $500. "baseline two-asset" denotes our two-asset HANK model with heterogeneity in skills and with overconfidence, "rational two-asset" is the same two-asset HANK model minus heterogeneity in skills and minus overconfidence, and "two-asset recalib." is the latter model recalibrated such that it has an average MPC of 0.16.

Table 8 shows that, in contrast, in the standard two-asset model without overconfidence (*"rational two-asset"*), in which all households are fully rational ($\alpha = 1$), the average MPC is only 0.06 and, thus, too low compared to empirical findings. Given the low return gap between illiquid and liquid asset, most households first build a buffer stock of liquid assets before investing in the illiquid asset. We then re-calibrate the rational model (*"two-asset recalib."*) to match the average MPCs in the data. But in order to do so the model generates a return gap of 4.8%, which is more than three times as large compared to our baseline model.[19]

7 Conclusion

We analyze the implications of household heterogeneity in cognitive skills and perceptions thereof for household financial situations and their savings behavior. Using U.S. micro level data, we find that lower-skilled households systematically over-estimate their skills and are persistently overly optimistic about their future financial situations. Additionally, overconfident households are substantially more likely to be hand-to-mouth.

Introducing permanent skill heterogeneity and overconfidence into a HANK model, we can match these empirical patterns. What is more, our model can resolve heretofore seemingly intrinsic tensions in HANK models. Unlike other models, our one-asset HANK model can simultaneously match consensus estimates of both the average MPC and the average wealth level. Our two-asset HANK model matches the data with a lower, and perhaps more empirically realistic, illiquidity premium than required in other models. We further show that our model has novel positive and normative implications for fiscal policy. Positively, issuing more debt and thereby increasing the

[19]When re-calibrating the model, we need to decrease the discount factor, the depreciation rate as well as the probability to be able to adjust the illiquid asset.

supply of the liquid asset is less effective in bringing households away from the borrowing constraint and in reducing wealth inequality than in standard one-asset HANK models. Normatively, we show that the optimal amount of government debt is much smaller than in the standard model.

References

Aguiar, M. A., M. Bils, and C. Boar (2021): "Who are the Hand-to-Mouth?" .

Aiyagari, S. R. (1994): "Uninsured idiosyncratic risk and aggregate saving," *The Quarterly Journal of Economics*, 109, 659–684.

Aiyagari, S. R. and E. R. McGrattan (1998): "The optimum quantity of debt," *Journal of Monetary Economics*, 42, 447–469.

Almgren, M., J.-E. Gallegos, J. Kramer, and R. Lima (2022): "Monetary policy and liquidity constraints: Evidence from the euro area," *American Economic Journal: Macroeconomics*, 14, 309–340.

Andre, P., C. Pizzinelli, C. Roth, and J. Wohlfart (2022): "Subjective models of the macroeconomy: Evidence from experts and representative samples," *The Review of Economic Studies*, 89, 2958–2991.

Angeletos, G.-M., F. Collard, and H. Dellas (2022): "Public debt as private liquidity: Optimal policy," Tech. rep., National Bureau of Economic Research.

Angeletos, G.-M. and Z. Huo (2021): "Myopia and anchoring," *American Economic Review*, 111, 1166–1200.

Auclert, A. (2019): "Monetary policy and the redistribution channel," *American Economic Review*, 109, 2333–67.

Auclert, A., B. Bardóczy, and M. Rognlie (2021): "MPCs, MPEs, and multipliers: A trilemma for New Keynesian models," *The Review of Economics and Statistics*, 1–41.

Auclert, A., M. Rognlie, and L. Straub (2018): "The intertemporal keynesian cross," .

——— (2020): "Micro jumps, macro humps: Monetary policy and business cycles in an estimated HANK model." .

Balleer, A., G. Duernecker, S. Forstner, and J. Goensch (2022): "The Effects of Biased Labor Market Expectations on Consumption, Wealth Inequality, and Welfare," .

Banks, J. and Z. Oldfield (2007): "Understanding pensions: Cognitive function, numerical ability and retirement saving," *Fiscal studies*, 28, 143–170.

Bayer, C., B. Born, and R. Luetticke (2022): "The liquidity channel of fiscal policy," *Journal of Monetary Economics*.

——— (2023): "Shocks, frictions, and inequality in US business cycles," .

Bayer, C., R. Lütticke, L. Pham-Dao, and V. Tjaden (2019): "Precautionary savings, illiquid assets, and the aggregate consequences of shocks to household income risk," *Econometrica*, 87, 255–290.

Bewley, T. (1986): "Stationary monetary equilibrium with a continuum of independently fluctuating consumers," *Contributions to mathematical economics in honor of Gérard Debreu*, 79.

Bhandari, A., D. Evans, M. Golosov, and T. J. Sargent (2021): "Inequality, Business Cycles, and Monetary-Fiscal Policy," *Econometrica*, 89, 2559–2599.

Bianchi, F., C. Ilut, and H. Saijo (2022): "Diagnostic Business Cycles," *Review of Economic Studies (forthcoming).*

Bilbiie, F. O. (2021): "Monetary policy and heterogeneity: An analytical framework," .

Bordalo, P., N. Gennaioli, Y. Ma, and A. Shleifer (2020): "Overreaction in macroeconomic expectations," *American Economic Review*, 110, 2748–82.

Bordalo, P., N. Gennaioli, and A. Shleifer (2022): "Overreaction and Diagnostic Expectations in Macroeconomics," *Journal of Economic Perspectives*, 36, 223–44.

Broer, T., N.-J. Harbo Hansen, P. Krusell, and E. Öberg (2020): "The New Keynesian transmission mechanism: A heterogeneous-agent perspective," *The Review of Economic Studies*, 87, 77–101.

Caballero, R. J. and A. Simsek (2020): "Prudential monetary policy," .

Camerer, C. (2008): "The case for mindful economics," *The foundations of positive and normative economics: A handbook*, 43–69.

Caplin, A., V. Gregory, E. Lee, S. Leth-Petersen, and J. Sæverud (2023): "Subjective Earnings Risk," .

Chapman, J., M. Dean, P. Ortoleva, E. Snowberg, and C. Camerer (forthcoming): "Econographics," *Journal of Political Economy: Micro*.

Coibion, O., Y. Gorodnichenko, and M. Weber (2022): "Monetary policy communications and their effects on household inflation expectations," *Journal of Political Economy*, 130, 1537–1584.

Dávila, E. and A. Schaab (2023): "Optimal monetary policy with heterogeneous agents: A timeless ramsey approach," .

D'Acunto, F., D. Hoang, M. Paloviita, and M. Weber (2019): "Cognitive abilities and inflation expectations," in *AEA Papers and Proceedings*, vol. 109, 562–66.

——— (2020): "IQ, expectations, and choice," *Review of Economic Studies (forthcoming).*

Erceg, C. J., D. W. Henderson, and A. T. Levin (2000): "Optimal monetary policy with staggered wage and price contracts," *Journal of monetary Economics*, 46, 281–313.

Fagereng, A., M. B. Holm, and G. J. Natvik (2021): "MPC heterogeneity and household balance sheets," *American Economic Journal: Macroeconomics*, 13, 1–54.

Farhi, E. and I. Werning (2019): "Monetary policy, bounded rationality, and incomplete markets," *American Economic Review*, 109, 3887–3928.

Gabaix, X. (2014): "A sparsity-based model of bounded rationality," *The Quarterly Journal of Economics*, 129, 1661–1710.

——— (2020): "A behavioral New Keynesian model," *American Economic Review*, 110, 2271–2327.

Gillen, B., E. Snowberg, and L. Yariv (2019): "Experimenting with measurement error: Techniques with applications to the caltech cohort study," *Journal of Political Economy*, 127, 1826–1863.

Guvenen, F., S. Ozkan, and J. Song (2014): "The nature of countercyclical income risk," *Journal of Political Economy*, 122, 621–660.

Hagedorn, M., J. Luo, I. Manovskii, and K. Mitman (2019): "Forward guidance," *Journal of Monetary Economics*, 102, 1–23.

Hanushek, E. A. and L. Woessmann (2008): "The role of cognitive skills in economic development," *Journal of economic literature*, 46, 607–668.

Heidhues, P., B. Kőszegi, and P. Strack (2018): "Unrealistic expectations and misguided learning," *Econometrica*, 86, 1159–1214.

Holm, M. B., P. Paul, and A. Tischbirek (2021): "The transmission of monetary policy under the microscope," *Journal of Political Economy*, 129, 2861–2904.

Huffman, D., C. Raymond, and J. Shvets (2022): "Persistent overconfidence and biased memory: Evidence from managers," *American Economic Review*, 112, 3141–75.

Huggett, M. (1993): "The risk-free rate in heterogeneous-agent incomplete-insurance economies," *Journal of economic Dynamics and Control*, 17, 953–969.

Hyytinen, A. and H. Putkuri (2018): "Household optimism and overborrowing," *Journal of Money, Credit and Banking*, 50, 55–76.

Ilut, C. and R. Valchev (2023): "Economic agents as imperfect problem solvers," *The Quarterly Journal of Economics*, 138, 313–362.

Jappelli, T. and L. Pistaferri (2014): "Fiscal policy and MPC heterogeneity," *American Economic Journal: Macroeconomics*, 6, 107–136.

Johnson, D. S., J. A. Parker, and N. S. Souleles (2006): "Household expenditure and the income tax rebates of 2001," *American Economic Review*, 96, 1589–1610.

Kaplan, G., B. Moll, and G. L. Violante (2018): "Monetary Policy According to HANK," *American Economic Review*, 108, 697–743.

Kaplan, G. and G. L. Violante (2014): "A model of the consumption response to fiscal stimulus payments," *Econometrica*, 82, 1199–1239.

——— (2022): "The marginal propensity to consume in heterogeneous agent models," *Annual Review of Economics*, 14, 747–775.

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

Laibson, D., P. Maxted, and B. Moll (2021): "Present bias amplifies the household balance-sheet channels of macroeconomic policy," .

Larrick, R. P., K. A. Burson, and J. B. Soll (2007): "Social comparison and confidence: When thinking you're better than average predicts overconfidence (and when it does not)," *Organizational Behavior and Human Decision Processes*, 102, 76–94.

L'Huillier, J.-P., S. R. Singh, and D. Yoo (2022): "Incorporating diagnostic expectations into the New Keynesian framework," .

Lian, C. (2023): "Mistakes in future consumption, high MPCs now," .

Luetticke, R. (2021): "Transmission of monetary policy with heterogeneity in household portfolios," *American Economic Journal: Macroeconomics*, 13, 1–25.

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

MacLeod, C. M. (1991): "Half a century of research on the Stroop effect: an integrative review." *Psychological bulletin*, 109, 163.

McArdle, J. J., G. G. Fisher, and K. M. Kadlec (2007): "Latent variable analyses of age trends of cognition in the Health and Retirement Study, 1992-2004." *Psychology and aging*, 22, 525.

McClung, N. and T. Nighswander (2021): "Belief Heterogeneity and the Income-Wealth Relationship," .

McKay, A., E. Nakamura, and J. Steinsson (2016): "The power of forward guidance revisited," *The American Economic Review*, 106, 3133–3158.

McKay, A. and C. Wolf (2022): "Optimal policy rules in hank," Tech. rep., Working Paper, FRB Minneapolis.

Miyake, A. and N. P. Friedman (2012): "The nature and organization of individual differences in executive functions: Four general conclusions," *Current directions in psychological science*, 21, 8–14.

Moore, D. A. and P. J. Healy (2008): "The trouble with overconfidence." *Psychological review*, 115, 502.

Moschini, E., G. Raveendranathan, and M. Xu (2023): "Over-optimism About Graduation and College Financial Aid," .

Mueller, A. I., J. Spinnewijn, and G. Topa (2021): "Job seekers' perceptions and employment prospects: Heterogeneity, duration dependence, and bias," *American Economic Review*, 111, 324–363.

Parker, J. A. (2017): "Why don't households smooth consumption? Evidence from a $25 million experiment," *American Economic Journal: Macroeconomics*, 9, 153–183.

Patterson, C. (forthcoming): "The matching multiplier and the amplification of recessions," *American Economic Rewview.*

Pfäuti, O. and F. Seyrich (2022): "A behavioral heterogeneous agent new keynesian model," .

Roth, C., M. Wiederholt, and J. Wohlfart (2023): "The Effects of Forward Guidance: Theory with Measured Expectations," .

Rouwenhorst, K. G. (1995): "10 Asset Pricing Implications of Equilibrium Business Cycle Models," in *Frontiers of business cycle research*, Princeton University Press, 294–330.

Rozsypal, F. and K. Schlafmann (forthcoming): "Overpersistence bias in individual income expectations and its aggregate implications," *American Economic Journal: Macroeconomics.*

Sergeyev, D., C. Lian, and Y. Gorodnichenko (2022): "The Economics of Financial Stress,"

.

Solon, G., S. J. Haider, and J. M. Wooldridge (2015): "What are we weighting for?" *Journal of Human resources*, 50, 301–316.

Souleles, N. S. (2004): "Expectations, heterogeneous forecast errors, and consumption: Micro evidence from the Michigan consumer sentiment surveys," *Journal of Money, Credit and Banking*, 39–72.

Stango, V. and J. Zinman (2022): "Behavioral biases are temporally stable," .

——— (forthcoming): "We are all behavioral, more or less: A taxonomy of consumer decision making," *Review of Economic Studies*.

Wang, T. (2023): "Perceived versus calibrated income risks in heterogeneous-agent consumption models," .

Weber, M., F. D'Acunto, Y. Gorodnichenko, and O. Coibion (2022): "The subjective inflation expectations of households and firms: Measurement, determinants, and implications," *Journal of Economic Perspectives*, 36, 157–184.

Werning, I. (2015): "Incomplete markets and aggregate demand," .

Woodford, M. (1990): "Public debt as private liquidity," *The American Economic Review*, 80, 382–388.

——— (2013): "Macroeconomic analysis without the rational expectations hypothesis," *Annu. Rev. Econ.*, 5, 303–346.

——— (2019): "Monetary policy analysis when planning horizons are finite," *NBER Macroeconomics Annual*, 33, 1–50.

Zimmermann, F. (2020): "The dynamics of motivated beliefs," *American Economic Review*, 110, 337–363.

A Additional Tables and Results

Table A1: Household financial condition forecasts and forecast errors tilt optimistic

Panel A. All forecasts, unweighted	Realization this year			
Forecast last year	Better	Same	Worse	Total
Better	0.09	0.13	0.04	0.27
Same	0.06	0.44	0.10	0.61
Worse	0.01	0.05	0.07	0.12
Total	0.16	0.63	0.21	1
Panel B. July 2009 & 2010, unweighted	Realization this year			
Forecast last year	Better	Same	Worse	Total
Better	0.06	0.16	0.05	0.28
Same	0.05	0.40	0.15	0.60
Worse	0.01	0.05	0.07	0.12
Total	0.12	0.61	0.27	1
Panel C. July 2009 & 2010, weighted	Realization this year			
Forecast last year	Better	Same	Worse	Total
Better	0.07	0.18	0.05	0.30
Same	0.04	0.38	0.14	0.56
Worse	0.01	0.07	0.06	0.14
Total	0.12	0.63	0.25	1
Panel D. January 2015 & 2016, unweighted	Realization this year			
Forecast last year	Better	Same	Worse	Total
Better	0.10	0.14	0.04	0.28
Same	0.06	0.47	0.08	0.61
Worse	0.01	0.05	0.06	0.12
Total	0.17	0.66	0.18	1
Panel E. January 2015 & 2016, weighted	Realization this year			
Forecast last year	Better	Same	Worse	Total
Better	0.11	0.13	0.03	0.27
Same	0.05	0.50	0.08	0.63
Worse	0.01	0.04	0.05	0.10
Total	0.17	0.67	0.16	1

Note: Cells report sample proportions. Forecasts: "Now looking ahead - do you think that a year from now you will be better off financially, or worse off, or just about the same as now?" Response options: Will be better off/About the same/Will be worse off. Realizations: "We are interested in how people are getting along financially these days. Would you say that you are better off or worse off financially than you were a year ago?" Response options: Better off/About the same/Worse off. Weighted estimates use sampling probabilities from the realization survey(s), which are correlated 0.90 and 0.93 with the weight from the paired forecast survey. Sample size is 17,266 in Panel A, 1,679 in Panels B and C, and 1,882 in Panels D and E.

Table A2: Household financial condition forecast errors are persistent

	Forecast error this survey			
FCE previous survey	Optimist	Realist	Pessimist	Total
Optimist	0.08	0.10	0.00	0.18
Realist	0.07	0.65	0.03	0.75
Pessimist	0.01	0.04	0.02	0.06
Total	0.16	0.79	0.05	1

Note: Sample is 6,590 forecast error pairs from 2,964 panelists. Sample is smaller here than in Appendix Table A1 because here we require >=2 forecast-realization pairs per panelist and only include realizations of "about the same", to allow for capturing forecast errors in either direction.

Table A3: Household financial condition forecast learning?

Panel A. First forecast - realization pair	Realization this year			
Forecast last year	Better	Same	Worse	Total
Better	0.09	0.16	0.06	0.31
Same	0.05	0.40	0.12	0.58
Worse	0.01	0.05	0.06	0.12
Total	0.15	0.61	0.23	1
Panel B. Last forecast - realization pair	Realization this year			
Forecast last year	Better	Same	Worse	Total
Better	0.10	0.13	0.04	0.27
Same	0.06	0.46	0.09	0.61
Worse	0.01	0.05	0.06	0.12
Total	0.17	0.64	0.19	1

Note: Sample only considers forecast - realization pairs with multiple pairs, resulting in 2,964 panelists.

Table A4: Weighted pairwise corrs between cognitive skills and income

	Cognitive skills undimensional summstats		
	1st cf score (1)	1st principal component (2)	rowvar mean
Household income	0.522	0.562	56351
s.e. or s.d.	0.053	0.055	43618
N	766	662	1580
ln(Household income)	0.555	0.568	10.548
s.e. or s.d.	0.062	0.068	1.502
N	803	697	1637
Household income category	0.526	0.540	10.839
s.e. or s.d.	0.044	0.051	4.317
N	842	732	1686

Note: Weighted ORIV correlations. Column variables are cross-sectional percentiles. Level income drops obs. in top 5 percentiles. Categorical income based on ALP's standard income elicitation, in which respondents choose among 17 bins.

Table A5: Pairwise correlations between cognitive skills and measures of HtM

	Cognitive Skills	
	Unidim. summstats	
	1st cf score	1st principal component
	(1)	(2)
1=(severe financial distress)	-0.365	-0.407
s.e.	0.040	0.045
N	841	841
1=(HtM basend on nw/inc)	-0.440	-0.450
s.e.	0.041	0.046
N	788	686
1 = nw < 0 & revolving on credit card	-0.172	-0.191
s.e.	0.044	0.050
N	812	709
1 = has prec. savings	0.279	0.285
s.e.	0.068	0.076
N	272	232
1= can cover $2k unexpected expense	0.428	0.485
s.e.	0.078	0.91
N	261	224
Prop. of surveys where has precaut. savings	0.251	0.255
s.e.	0.060	0.061
N	301	256
Prop. of surveys where can cover $2k expense	0.398	0.430
s.e.	0.041	0.043
N	499	434

Note: First five rows use ORIV for the rowvar. Columns (1) and (2) use ORIV for the column var. Non-ORIV correlations estimated using Pearson or tetrachoric. Financial distress is any of 4 severe events (forced move, late payments, hunger, foregone medical care) in past 12 months. '1=HtM' is a standard definition of a Hand-to-Mouth consumer: net work<1/2(total monthly income). Credit card revolver=1 if report revolving typically or in last cycle. Has precautionary savings= has emerg/rainy day funds set side to cover 3-months' expenses. 1=Can cover $2k unexpected expense = expressing the highest confidence or certainty that they could cover.

B Data Appendix

The following descriptions are taken from the working paper version of Stango and Zinman (forthcoming) (pp. 90ff.) and are replicated here for completeness.

B.1 Measuring Cognitive Skills

Fluid intelligence is measured using a 15-question, non-adaptive number series (McArdle et al. (2007)). Number series scores correlate strongly with those from other fluid intelligence tests like IQ and Raven's.

We measure numeracy using: "If 5 people split lottery winnings of two million dollars ($2,000,000) into 5 equal shares, how much will each of them get?" and "If the chance of getting a disease is 10 percent, how many people out of 1,000 would be expected to get the disease?" (Banks and Oldfield (2007)). Response options are open-ended. These questions have been used in economics as numeracy and/or financial literacy measures since their deployment in the 2002 English Longitudinal Study of Ageing, with subsequent deployment in the Health and Retirement Study and other national surveys.

We measure financial literacy using Lusardi and Mitchell (2014) "Big Three": "Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?"; "Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?"; and "Please tell me whether this statement is true or false: "Buying a single company's stock usually provides a safer return than a stock mutual fund." Response options are categorical.

We measure executive function using a two-minute Stroop task (MacLeod (1991)). Our version displays the name of a color on the screen (red, blue, green, or yellow) and asks the subject to click on the button corresponding to the color the word is printed in (red, blue, green, or yellow; not necessarily corresponding to the color name). Answering correctly tends to require using conscious effort to override the tendency (automatic response) to select the name rather than the color. The Stroop task is sufficiently classic that the generic failure to overcome automated behavior (in the game "Simon Says," when an American crosses the street in England, etc.) is sometimes referred to as a "Stroop Mistake" (Camerer (2008)). Before starting the task, the computer shows demonstrations of two choices (movie-style)—one with a correct response, and one with an incorrect response—and then gives the subject the opportunity to practice two choices on her own. After practice ends, the task lasts for two minutes.

B.2 Measuring Overconfidence

We elicit three distinct measures of overconfidence, following e.g., Moore and Healy (2008). The first measures it in level/absolute terms, by following the three Banks and Oldfield numeracy questions, in our second Round 1 module, with the question: "How many of the last 3 questions (the ones on the disease, the lottery and the savings account) do you think you got correct?" We then subtract the respondent's assessment from her actual score. 39% of 1,366 subjects are overconfident ("overestimation" per Moore and Healy) by this measure (with 32% overestimating by one question), while only 11% are underconfident (with 10% underestimating by one question). Larrick et al. (2007), Moore and Healy (2008) and other studies use this method for measuring overestimation, but we are not aware of any that report individual-level prevalence estimates (they instead focus on task-level data, sample-level summary statistics, and/or correlates of cross-sectional heterogeneity in estimation patterns). The second measures overconfidence in precision, as indicated by responding "100%" on two sets of questions about the likelihoods (of different possible Banks and Oldfield quiz scores or of future income increases). This is a coarse adaptation of the usual approaches of eliciting several confidence intervals or subjective probability distributions (Moore and Healy (2008)). In our data 34% of 1,345 responding to both sets respond 100% on ≥ 1 set, and 10% on both. The third measures confidence in placement (relative performance), using a self-ranking elicited before taking our number series test: "We would like to know what you think about your intelligence as it would be measured by a standard test. How do you think your performance would rank, relative to all of the other ALP members who have taken the test?" We find a better- than-average effect in the sample as a whole (70% report a percentile > median) that disappears when we ask the same question immediately post-test, still not having revealed any scores (50% report a percentile > median). We also construct an individual-level measure of confidence in placement by subtracting the subject's actual ranking from his pre-test self-ranking (N=1,395). This measure is useful for capturing individual-level heterogeneity ordinally, but not for measuring prevalence because the actual ranking is based on a 15-question test and hence its percentiles are much coarser than the self-ranking.