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

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Abstract

Using micro level data on households' cognitive skills and their financial situations, we find that: households with lower cognitive skills (i) are persistently overconfident about their abilities, (ii) are overly optimistic about their future financial situations, and (iii) are substantially more likely to be hand-to-mouth. We introduce permanent heterogeneity in households' cognitive skills and beliefs about their future cognitive skills in an otherwise standard incomplete-markets model and show that our model matches these empirical findings. Differences in cognitive skills alone—i.e., absent belief biases—cannot account for these findings as in that case cognitively less-skilled households are less likely to be hand-to-mouth, inconsistent with what we document empirically. The one-asset version of our model jointly matches the average marginal propensities to consume and the average wealth in the U.S. while the two-asset version is able to match both with a rather small return gap between illiquid and liquid asset. The systematic relationship between cognitive skills, overconfidence and liquid-asset holdings also matters for fiscal policy: providing liquidity by the government is substantially less effective in bringing households away from the borrowing constraint than in the model that abstracts from belief heterogeneity.

1 Introduction

A growing body of work is showing how heterogeneity in household savings behavior and financial situations can have significant implications for macroeconomic fluctuations and policy design.[1] Yet, by assuming ex-ante identical households, this literature typically abstracts

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[1]See, e.g., Werning (2015), Kaplan et al. (2018), Auclert (2019), Bayer et al. (2022), Luetticke (2021), Hagedorn et al. (2019), Patterson (2022), Almgren et al. (2022), Holm et al. (2021) on shock transmission

from more fundamental dimensions of heterogeneity which may shape households' savings behavior and financial situations. But what dimensions of heterogeneity matter?

A natural starting point are differences in cognitive skills as heterogeneity in cognitive skills have been shown to play a crucial role in shaping households' expectation about the macroeconomy, how households respond to changes in these expectations, and heterogeneity in cognitive skills has been empirically linked to people's behavioral biases (e.g., Stango and Zinman (2022b), D'Acunto et al. (2019, 2020), Chapman et al. (2022)).[2]

And indeed, we find that households' cognitive skills are highly related to heterogeneity in households' financial situations and savings behavior. Most strikingly, households with lower cognitive skills are substantially more likely to be *Hand-to-Mouth* (HtM). Yet, as we show formally, adding persistent heterogeneity in cognitive skills to an otherwise standard, general equilibrium heterogeneous-agent New Keynesian (HANK) incomplete-markets model has counterfactual predictions: if, at all, lower-skilled households are less likely to be HtM.

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 a standard HANK model in which households self-insure their idiosyncratic income risk by accumulating wealth by introducing both permanent heterogeneity in cognitive skills (modeled as differences in average idiosyncratic productivity levels) and permanent heterogeneity in perceptions of one's own skills (modeled as differences in forecasts of one's own idionsyncratic productivity). We model lower-skilled consumers as persistently overestimating their future productivity ("overconfident"), and the higher-skilled as well-calibrated ("rational").[3]

Our model predicts that overconfident households tend to be (i) overly optimistic about their future financial situations and (ii) more likely to be HtM.[4] 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 but otherwise identical household would do.

The same mechanism allows us to match the U.S. average marginal propensity to consume (MPC) 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

and policy efficacy, and Dávila and Schaab (2023), McKay and Reis (2021), Bhandari et al. (2021), Bilbiie (2021) on optimal policy design.

[2] Andre et al. (2022), Roth et al. (2023), Weber et al. (2022), Coibion et al. (2022) document vast heterogeneity in households' and firms' subjective beliefs and how these beliefs affect their behavior.

[3] Relatedly, Balleer et al. (2022) and Mueller et al. (2021) study the role of households' (potentially nonrational) beliefs about future income situations, but focus on labor markets, and Rozsypal and Schlafmann (2020) introduce an overpersistence bias in individual income expectations in a partial equilibrium setting.

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

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 (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 close 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.

We discipline our model 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., a population share in the same ballpark as Huffman et al. (2022) share of persistently overconfident managers. We next show, in keeping with prior work (e.g., Chapman et al. (2022)) 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 to hold persistently overly optimistic views about their future financial situation. Additionally, overconfident households are substantially more likely to be persistently financially constrained per eight complementary measures of HtM status.

The joint distribution of cognitive skills, overconfidence, and financial constraints matters greatly for the model's policy implications. Consider a fiscal policy where the government provides more liquidity to 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 extend our analysis to a two-asset HANK model with permanent skill heterogeneity and overconfidence. A standard practice to reconcile the high average MPC and 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. A drawback of these models is that they require an arguably implausibly 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 significantly lower return gap between liquid and illiquid assets.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 than related work to-date. Ilut and Valchev (2023) is perhaps most similar in approach, showing that imperfect knowledge of one's optimal policy function can better fit the data on persistent HtM shares. Our model allows for nominal rigidities and two types of assets; together with our empirically-grounded heterogeneity in cognitive skills and overconfidence thereon, we can also better fit the data on asset holdings and asset return spreads. Broadly, we build on other prior work in behavioral macroeconomics by allowing for heterogeneity in beliefs rather than imposing a representative behavioral decision maker.[5] 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 Aguiar et al. (2021).[6]

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.[7] 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.

[5]For example, Gabaix (2014), Gabaix (2020), Bordalo et al. (2020), Angeletos et al. (2021), Lian (2023) focus on a representative behavioral decision maker.

[6]Aguiar et al. (2021) introduce heterogeneity in preferences and patience to match a number of empirical facts about the behavior of HtM households and acknowledge that behavioral models might provide a potential micro-foundation for their modelling choices.

[7]For HANK models with a homogeneous behavioral or information friction about an aggregate variable, see e.g., Farhi and Werning (2019), Auclert et al. (2020), Angeletos and Huo (2021) or Pfäuti and Seyrich (2022).

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 aggregate dynamics and macroeconomic 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 (2022a,b), 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 (2022b)). 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 (2022b)).[8]

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).[9] 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). 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

[8] Chapman et al. (2022) also finds positive correlations among the three overconfidence varieties, and negative correlations between overconfidence and cognitive skills.

[9] 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?")

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.[10]

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 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.

Financial condition forecasts and forecast errors tilt both optimistic in the aggregate (see Appendix Table A1).[11] 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.[12] 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.[13] Nor is there evidence of substantial overcorrection: Appendix Table A2 shows that optimists are about 0.095/0.003

[10]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 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.

[11]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.

[12]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.

[13]Comparing the first to last forecast-realization pair we observe for those with multiple pairs, A3 shows that the accuracy rate increases from 55 to 62 percent and the optimistic slant decreases from $16/21 = 77$ percent to $13/18 = 72$ percent.

= 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 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.[14] 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 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 saving 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

[14] 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 (2022b)). 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.

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 show in the table (see Stango and Zinman (2022b) 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 (2022b)). 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.

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 $\geq$ 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 (2022b)). 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.

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 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	Mean	Mean
	(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 (2022b)). 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	Mean	Mean
	(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	0.425	0.450
s.e.	0.053	0.085	0.049	0.077	0.018	0.028
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	0.570	0.633
s.e.	0.065	0.078	0.050	0.058	0.021	0.026
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.

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 $t = 1, 2, ...$ We first focus on the case in which households can only save in one asset; a liquid bond provided by the government. In Section 5, we introduce a second asset in the form of illiquid productive capital.

Households. There is a unit mass of households subject to idiosyncratic risk, incomplete markets, and exogenous borrowing constraints. We allow for permanent heterogeneity in households' 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 $\bar{e}_t e_t$. Here, $\bar{e}_t$ 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

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

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

where c_t denotes consumption, n_t hours worked, r_t the net real interest rate, w_t the real wage, $\bar{\tau}$ denotes the tax rate and $\tau_{g,t}(e_t)$ denotes the tax weights of a household of group g and idiosyncratic state e_t.

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 model it as overconfidence about cognitive skills. We assume that households observe their current cognitive skills $\bar{e}_g e_t$ but are overly confident about their future cognitive skills. In other words, households 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.[15] 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. Note, that in contrast to the overpersistence bias in Rozsypal and Schlafmann (2020), 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 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

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

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

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

[15]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.

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)).[16] 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

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

[16] 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

We calibrate the typical HANK parameters to standard values 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 (2021) method. We set the tax weights of households such that they equal her 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 $\bar{e}_2 = 1$. 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. In order to calibrate α, we target the fact that overconfident households are about 1.5 times as likely to be too optimistic about their future financial conditions (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
$\tau_t(\bar{e}_g e_t)$	Tax weigths	$\bar{e}_g e_t$
Idiosyncratic risk		
ρ_e	Persistence of idiosyncratic risk	0.966
σ_e^2	Variance of idiosyncratic risk	0.033
α	Degree of overconfidence	1.9
Permanent heterogeneity		
μ_g	Mass of households	$\{0.38, 0.62\}$
$\bar{e}_g$	Cognitive skills	$\{0.8, 1\}$

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

For now, 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 model"*), 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"*).[17]

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 productivity 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, but rather, they contradict them.

[17] 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	-	-	-

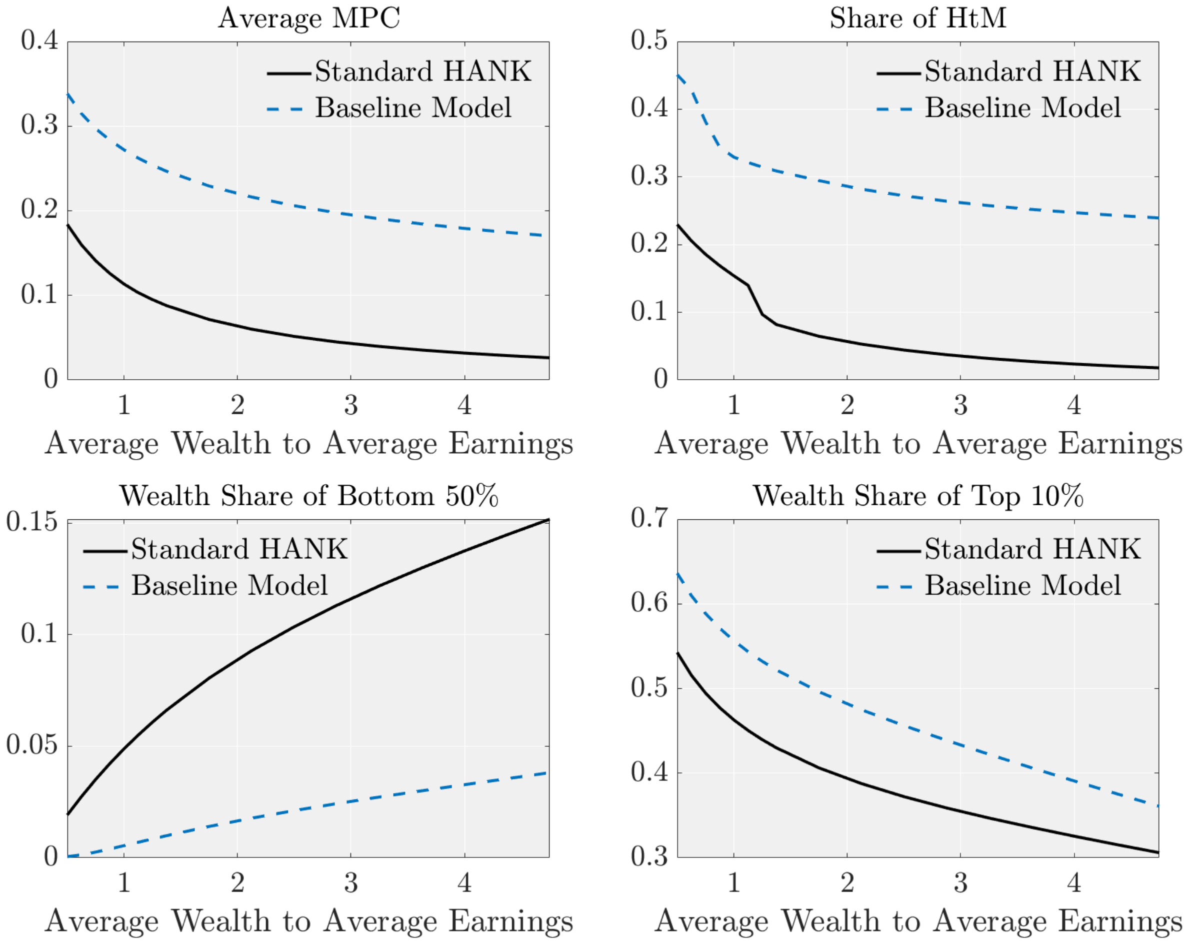
Note: MPCs refer to MPCs out of a $500 dollar stimulus check. "Baseline" is our baseline model, in which we allow for skill heterogeneity and overconfidence, "Standard HANK" denotes a standard one-asset model, in which we abstract from heterogeneity in skills and overconfidence, "HANK w\skills" denotes the same model, 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.

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 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 are overconfident which leads them to overestimate their expected income. In other words, they perceive their income risk to be lower than it actually is. 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 into 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 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 more clear in a counterfactual, in which we assume that the high-skilled households are overconfident but that the low-skilled households are rational. 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 low cognitive skills do not adjust their consumption plans in response to changes in their inflation expectations, even when focusing on high-income men. In our model, overconfident households, even those with relatively high permanent incomes, are more likely to be at the borrowing constraint and therefore they would not respond to changes in intertemporal incentives such as changes in inflation expectations.

The effects of liquidity provision. This endogenous distribution of cognitive skills and overconfidence along the asset distribution matters greatly for the model's policy implications. In Figure 1, we show 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 lines 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. We see that when the government provides more liquidity, this policy is highly effective in reducing the share of HtM households and hence, the average MPC in the standard HANK model. 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 baseline model with heterogeneous cognitive abilities and overconfidence, however, a large part 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 decrease in the share of HtM households slows down substantially above 0 and 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. Thus, policies that provide liquidity to the economy can help to reduce the share of people at the borrowing constraint, but less so when accounting for households' overconfidence.

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.

5 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 asset is perfectly liquid the other asset gives a higher return in equilibrium but is illiquid. Hence, illiquid assets are a good saving 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)).

We show in this section how introducing permanent heterogeneity in skills together with overconfidence in a two-asset HANK model, can match the average MPCs and total wealth while it simultaneously predicts a reasonable return differences between liquid and illiquid assets compared to the data.

5.1 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:

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

$$b_t, k_t \geq 0, \tag{16}$$

where k is illiquid asset of the household and r^k is its dividend. Capital depreciates at rate δ and depreciated capital has to be replaced for maintenance, such that the dividend, r_t, 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 dividends and can adjust their bond holdings. We further assume that both holdings of bonds and holdings of capital have to be non-negative.

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

$$Y_t = K_{t-1}^{\alpha} N_t^{1-\alpha}, \tag{17}$$

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:

$$\sum_{g,e} \mu_g p(e) \int k_t \Psi_{g,t}\left(k_{t-1}, e_t\right) = K_t. \tag{18}$$

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.

5.2 Stationary Equilibrium Results

Table 7 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 side, first accumulate a liquid buffer stock to self-insure their income risk, before they start saving in the illiquid asset.

Table 7 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 MPCs 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. When re-calibrating the rational model (*"two-asset recalib."*), it can also match the average MPCs in the data, but in order to do so, it needs a more than three times as large return gap of 4.8% to do so.[18]

[18] In other to achieve this, we need to decrease the discount factor, the depreciation rate as well as the

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.

6 Conclusion

In this paper, we analyze the implications of heterogeneity in cognitive skills on households' perception of their skills and their financial situations. We find in U.S. micro level data 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 intrinsic tensions in HANK models: our one-asset HANK model can match the average MPC estimates in the data while simultaneously matching average wealth in the data which is not possible in standard one-asset HANK models. A two-asset HANK model matches the average MPCs while still predicting a reasonable return gap between liquid and illiquid assets.

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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.