Overpersistence Bias in Individual Income Expectations and its Aggregate Implications*

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Abstract

Using micro level data, we document a systematic, income-related component in household income forecast errors. We show that these errors can be formalized by a modest deviation from rational expectations, where agents overestimate the persistence of their income process but otherwise form expectations in a perfectly rational and forward-looking manner. We then investigate the implications of these distortions in expectations on consumption and saving behavior and find two effects. First, low income households with this bias are too pessimistic and hence choose to borrow less than their fully rational counterparts even though their borrowing constraint is not binding. This allows a quantitative model to match the joint distribution of liquid assets and income. Second, the bias alters the distribution of marginal propensities to consume which makes government stimulus policies less effective.

JEL codes: E21, D91, D84, D14, H31
KEYWORDS: household income expectations, savings, durable consumption, MPC

1 Introduction

Fluctuations in income represent one of the most important sources of economic risk for households. Households who have different expectations about their future income realizations will hence make different decisions about consumption and saving today. Unfortunately,

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data on individual income expectations and corresponding realizations are not readily available. Despite the importance of household income expectations, testing their rationality or the identification of systematic biases has therefore been difficult.

In this paper we first use micro data on household income expectations, devise a new way to construct individual level forecasting errors and provide evidence of non-rationality in the form of a systematic bias related to the level of income.[1] Second, we show that these empirical findings are consistent with a process of expectation formation where households are perfectly forward-looking but overestimate the persistence of their individual income process and are too pessimistic about the development of the aggregate economy. This formulation of expectations is an expression of Kahneman and Tversky (1973)'s finding of non-regression to the mean in people's probabilistic judgments. Third, we show how this bias affects consumption and savings behavior in an otherwise standard, fully optimization-based model of durable consumption. Including the bias allows the model to fit the joint distribution of liquid assets and income. In particular, this mechanism can explain why low income households do not borrow more to smooth consumption. Moreover, the bias alters the distribution of marginal propensities to consume which makes government stimulus policies less effective.

The first contribution of the paper is to empirically analyze forecast errors in individual household income expectations. Using data from the Michigan Surveys of Consumers, we show that current income is systematically correlated with the error people make when they forecast their individual future income growth. In particular, people in the upper part of the income distribution overestimate their future income growth while the opposite is true for lower income households: they are too pessimistic and underestimate their future income growth. In terms of magnitudes, on average people in the highest income quintile overestimate their income growth by 2 percentage points while people in the lowest income quintile underestimate it by 7 percentage points. Moreover, we show that people across the whole income distribution are too pessimistic about aggregate variables such as inflation and the unemployment rate.

Analyzing errors in income expectations requires the knowledge of both a household's income expectation and the same household's ex post income realization over the corresponding time period. However, to the best of our knowledge none of the existing panel

[1]Here we contribute to the recent wave of papers which document departures from rational expectations in household data (Malmendier and Nagel, 2015; Das et al., 2017; Kuchler and Zafar, 2018). In contrast to these papers, our variable of interest is the *individual* income rather than *aggregate* variables such as unemployment or inflation. We believe that forecast errors in individual income are particularly interesting, because shocks to the idiosyncratic income component have direct and large effects on a household's income and budget constraint.

surveys satisfies these requirements.[2] We exploit that the Michigan Surveys of Consumers reinterview a subset of households after 6 months and use the provided information to impute the income realization for each household. Using this methodology we are able to overcome the mismatch of time periods between expectations and realizations. We thus obtain expectation errors for each household which allows us to document the systematic patterns in individual income forecast errors. We also ensure that our findings are not an artifact of the imputation procedure by showing qualitatively similar effects using directly reported income realizations for a subset of households.

The second contribution of the paper is to present a rule for expectation formation that can explain the empirical findings. We show that the observed patterns in forecast errors are consistent with a form of expectation formation where people are fully forward looking but overestimate the persistence of their income process. We hence call this bias *overpersistence bias*. It implies that people overreact to shocks to their income and that this overreaction is persistent. The distorted expectations can be expressed as the sum of rational expectations and a function of current income, i.e. a function of all past shocks. Our formulation of expectations is therefore similar to "Diagostic Expectations" proposed by Gennaioli and Shleifer (2010) and Bordalo et al. (2018). The difference is that in their setup the bias term is a function of only the latest news, whereas in our setup it is a function of the full history of shocks.

The distorted expectations can be formulated parsimoniously in the context of a standard income process with persistent and transitory income shocks as in Storesletten et al. (2004): We implement the overpersistence bias by allowing the agents' belief about the autocorrelation parameter to differ from the true underlying parameter. Moreover, we allow households to be too pessimistic about aggregate variables. This parsimonious representation of distorted expectations with only two free parameters is able to match the empirically observed expectation errors across the whole income distribution. The reason is that even though households share the same (distorted) beliefs about the data generating process of income, the overpersistence bias leads to heterogeneous expectation errors depending on the particular income realization of a given household. Households with currently high income expect their future income to remain higher than what their true income process would predict. Ex post they hence turn out to be too optimistic on average. The converse is true for households with currently low income: they underestimate their future income and turn out to be too pessimistic. While the overpersistence bias leads to heterogeneous effects, the ag-

[2]For example, the Italian Survey of Income and Wealth (SHIW) contains questions about income expectations over the next 12 months but due to the biannual interview frequency does not provide any corresponding realizations.

gregate pessimism affects households in the same way across the whole income distribution: People are too pessimistic about the future aggregate economy which biases downward their individual income expectations. We show that the combination of the two effects allows the expectations process to match the empirically observed magnitudes of forecast errors across the income distribution.

How does the overpersistence bias in income expectations affect the consumption-saving behavior of households? And does this bias have consequences for the distribution of assets and effectiveness of policy in the aggregate economy? The answer to these questions is the final contribution of this paper. To do so we insert the fitted representation of expectation bias into an otherwise standard incomplete markets, heterogeneous agent model in the tradition of Bewley (1986) and Deaton (1991). Moreover, marginal propensities to consume (MPCs) have been the focus of much recent literature in the field of economics and household finance. Importantly, Kaplan and Violante (2014) argue that it is crucial to include illiquid assets into the modeling framework to be able to capture the distribution of MPCs across the wealth distribution. In order to analyze how biased income expectations affect the distribution of MPCs in the population we therefore include a durable consumption good in our analysis.

Biased income expectations have differential effects on the behavior of households depending on their relative position in the income distribution. High income households hold similar portfolios under biased and under fully rational expectations. For them the overpersistence bias and aggregate pessimism have opposing effects and cancel each other out. In contrast, low income households choose different portfolios if they have biased income expectations. Low income households with biased expectations are too pessimistic about their future income and hence do not want to borrow to smooth consumption even though they would be able to borrow.

We show that this mechanism allows an otherwise standard, fully optimization-based model to fit the distribution of liquid assets as well as durable holdings across different income groups. In particular, including biased income expectation enables the model to match the distribution of liquid assets for low income households. The model with fully rational income expectations, on the other hand, would predict counterfactually large amounts of borrowing. Including biases in income expectations as seen in the data allows the model to overcome this counterfactual behavior and to fit the distribution of borrowing.

We further investigate how the deviations from rational expectations affect the distribution of MPCs. We show that the overpersistence bias reduces the difference between the MPCs of low and of high income households relative to the fully rational model to a level in line with empirical estimates (Johnson et al., 2006; Parker et al., 2013). Relative MPCs are an important determinant of the government's ability to boost aggregate demand using fiscal transfers (Oh and Reis, 2012). In both recent recessions of 2001 and 2008 the U.S. government employed this policy by handing out one-off cash transfers. However, assuming a balanced budget and a progressive tax system, such programs redistribute wealth from high to low income agents. Hence the higher is the difference between the MPC of low and high income households, the higher is the aggregate consumption response. The results in this paper reveal that low income households with biased expectations have lower MPCs than their rational expectations counterparts. High income households, on the other hand, turn out to have similar levels of MPC in both expectation scenarios. Not taking the bias in income expectations into account hence leads to an overestimation of the effectiveness of government stimulus policies.

Most of the aggregate implications of biased income expectations operate through their impact on how much low income households borrow. Would tightening the borrowing constraint in a fully rational model then have similar implications as allowing for biased beliefs? To answer this question we vary the borrowing constraint in the fully rational model. This has two consequences. First, tightening the borrowing constraint mechanically limits the ability of the model to fit the whole distribution of liquid assets: the high levels of borrowing of a small fraction of the population are excluded by construction. Second, while tightening the borrowing constraint increases the MPCs across the whole income distribution, it disproportionally increases the MPC of low income households. Thus, the tighter the borrowing constraint the more effective stimulus policies are predicted to be. This is the opposite effect compared to allowing for biased beliefs. We hence conclude that allowing for overpersistence bias in income expectations has qualitatively different implications to varying the credit supply in a rational model.

The paper contributes to the literature in three fields. First, it contributes to the growing body of empirical studies analyzing expectations of households, firms and professional forecasters. To evaluate whether agents' expectations are rational one has to compare these expectations with the corresponding realizations. Most of this literature has therefore analyzed expectations about aggregate variables, where the realizations are readily available.[3] In contrast, we focus on *individual* level *income* expectations and realizations. Due to data availability, this area has received much less attention in the literature, Dominitz and Manski (1997), Dominitz (1998), and Das and van Soest (1999) being notable exceptions. Compared to the first two papers, the current paper has the advantage of analyzing a much larger sam-

[3]For example, inflation (see, e.g. Carroll (2003), Andolfatto et al. (2008), Malmendier and Nagel (2015), Coibion et al. (2015) and Vellekoop and Wiederholt (2017)), house prices (see, e.g. Gerardi et al. (2008), Piazzesi and Schneider (2009), Case et al. (2012), and Kuchler and Zafar (2018)), unemployment (Kuchler and Zafar, 2018), excess bond returns (Piazzesi et al., 2015) or credit spreads (Bordalo et al., 2018).

ple of expectations and realizations, both in terms of the number of households and in terms of the time period covered. We are hence able to document systematic biases in household income expectations which are present throughout the past 25 years. Das and van Soest (1999) analyze household income expectations in a panel data set from the Netherlands. The difference to the current paper is that the Dutch data set asks households only about the direction of expected income changes, not about the magnitude of these changes. While the authors also find that income expectations are too pessimistic in general they do not speak to the systematic bias we find with respect to the current level of income. We build on Souleles (2004), who, using the same data set as the present paper, explored forecasting errors in a wide range of variables and noted the presence of systematic biases. We improve on his methodology of constructing the income forecast errors by explicitly taking the timing of survey questions into account. Studying the forecasting errors in a much more detailed way allows us to argue for overpersistence beliefs as the cause for the observed patterns in income expectation errors. The structural model further enables us to study the effects of this bias on savings and on the distribution of MPCs. Our paper is also related to a recent study by Das et al. (2017). They document a relationship between socioeconomic status and expectations about a range of aggregate variables and interpret their results as low status agents being too pessimistic. In contrast, our findings suggest that all agents are too pessimistic towards aggregate outcomes. For individual income expectations, on the other hand, we find a differential effect: The overpersistence bias leads high income households to be too optimistic while low income households turn out to be too pessimistic.

The second strand of literature this paper relates to is the formulation of expectation formation. Some of the recent research has focused on assessing whether predictable forecast errors – which are at odds with standard models of rational expectations – can be generated by rational models of information frictions such as sticky information (Mankiw and Reis, 2002) or noisy information (Woodford, 2003; Sims, 2003; Mackowiak and Wiederholt, 2009). Examples here include Coibion and Gorodnichenko (2012, 2015), Andrade and Le Bihan (2013) and Kohlhas and Walther (2018). On the other hand, an increasing number of studies suggest that decision makers do not form their expectations fully rationally (see, e.g., Cutler et al. (1990), DeLong et al. (1990), Greenwood and Shleifer (2014), Barberis et al. (2015), Gennaioli et al. (2016), Fuhrer (2017), Barberis et al. (2018), Broer and Kohlhas (2018) and Carroll et al. (2018)). The paper that is the closest to the present study in this area is Bordalo et al. (2018). They propose that decision makers form their expectations under a representativeness bias, which effectively leads to overweighthing of the most recent innovation to income when forming expectations. In contrast, in the present setting where households overestimate the persistence of their income process, it is the current *level* of their income[4] (rather than the last shock) that determines the forecasting error, which is supported by the predictive power of the level of income for the expectation errors that households make.

The third strand of literature that this paper directly contributes to is the literature on marginal propensities to consume.[5] The two most relevant studies for this paper in terms of modelling approach are Kaplan and Violante (2014) and Berger and Vavra (2015). Kaplan and Violante (2014) demonstrate that the presence of an asset with adjustment costs can generate realistic marginal propensities to consume out of transfer payments. Berger and Vavra (2015) show in a setting similar to ours that the phase of the business cycle further affects the MPC. We contribute to this literature by analyzing the effects of empirically relevant biases in income expectations on the behavior and MPC of households. We show that biased and fully rational expectations have different implications for the joint distribution of liquid assets and income and for the effectiveness of stimulus policies.

The paper proceeds as follows. Section 2 details how we can use the Michigan Surveys of Consumers to obtain household level errors in individual income expectations and documents the systematic bias in household income expectations. Section 3 proposes a formulation of expectation formation which features overestimation of persistence as the cause for the empirical patterns in expectation errors. It also shows that a parsimonious representation of the bias with only two free parameters is able to replicate the expectation errors across the income distribution. Section 4 analyzes the implications of these distorted expectations by inserting the fitted process of expectation formation into an otherwise standard, optimization-based model of consumption. It shows the effects of biased income expectations on the behavior of households in different income groups and how they affect the distribution of MPCs out of transfer payments. Furthermore, the section discusses the interaction with borrowing constraints. Section 5 concludes. The appendix contains further details about the imputation procedure, proofs of the propositions regarding the process of expectation formation as well as a detailed discussion of alternative mechanisms and why they fail to explain the expectations errors observed in the data.

[4] Under AR(1) this can be written as a discounted sum of all past shocks.

[5] Empirically, examples for recent analyses include studies estimating the MPC out of government transfers (Johnson et al., 2006; Parker et al., 2013; Misra and Surico, 2014), housing wealth (Mian et al., 2013; Kaplan and Violante, 2016), transitory income shocks (Jappelli and Pistaferri, 2014) and lottery winnings (Fagereng et al., 2016b). Recent structural models investigate the relationship between MPCs and wealth (see, e.g., Kaplan and Violante (2014) and Carroll et al. (2017)) and between MPCs and the business cycle (Berger and Vavra, 2015).

2 Household Income Expectations in the Data

In this section, we analyze micro level data on household income expectations and show that low income households underestimate their income growth while high income households overestimate their income growth. To do so, we construct a measure of forecast errors on the level of the individual household. After documenting the systematic forecast errors we argue that they are caused by households overestimating the persistence of their income process. This implies that they fail to sufficiently account for mean reversion of their income relative to the cross-section. We further show that this bias can be parsimoniously parametrized and that this parametric representation is able to match the joint distribution of income and expectation errors. While we cannot prove that overpersistence bias is the only mechanism that can generate the observed expectation errors, we discuss various alternative mechanisms in the appendix and show that they are inconsistent with the empirical findings.[6]

The data we analyze comes from the Michigan Surveys of Consumers. This survey interviews a representative cross-section of 500 households every month, with detailed expectation and income data available since July 1986. The households are asked about a wide range of topics, from expectations about the state of the aggregate economy, unemployment and inflation to purchasing conditions. Most importantly for the present analysis, people are also asked about their individual income expectations. Crucially, around one third of households are re-interviewed once after 6 months and they answer the same set of questions in both interviews. While we have income expectations for all households, for a subset of households we thus also have information about realized income growth.[7]

The survey asks households for their expected percentage growth in both income and prices. Specifically, the following questions are asked:

> *Q1a: During the next 12 months, do you expect your income to be higher or lower than during the past year?*
>
> *Q1b: By about what percent do you expect your income to (increase/decrease) during the next 12 months?*
>
> *Q2a: During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?*
>
> *Q2b: By about what percent do you expect prices to go (up/down) on the average, during the next 12 months?*

[6] In detail, we discuss the following mechanisms: learning, inability to distinguish between persistent and transitory shocks, extrapolation from recent experience, systematically wrong expectations about aggregates and measurement error.

[7] See appendix A.1 for a detailed description of the sample selection and a comparison of the income information with the Panel Study of Income Dynamics (PSID).

2.1 Construction of Expectation Errors

The fact that a subsample of the surveyed households is re-interviewed after 6 months allows us to confront income growth expectations with realized income changes. The basic idea is to compare expected income growth with ex post realized income growth. The challenge is, however, that there is only imperfect overlap between the periods for which households give expectations and for which they report realizations. For our baseline analysis we therefore employ imputation methods to increase this overlap. To ensure that our results are neither driven by the imputation method nor by the imperfect overlap, we also conduct two robustness checks: First, we conduct the analysis on directly reported data for a subsample of households. This analysis is completely unaffected by imputation. Second, we analyze the subsample where after imputation the overlap is perfect.

The exact data structure is as follows. When reporting their income, households are asked to state their total household income in the previous *calendar year*. Expectations, on the other hand, refer to *the following 12 months*. This has two implications. First, households who are interviewed for the first time in the first half of a year (January to June) report their income twice for the same time period since their re-interview falls into the same calendar year as the first interview. Households interviewed for the first time in the second half of a year (July to December), on the other hand, are re-interviewed in the next calendar year and hence report income for two consecutive years. Only for those households do we therefore have a reported income growth realization. Figure 1 illustrates the timing problem, showing as an example the data reported by households interviewed for the first time in January 2002 (panel (a)) and July 2002 (panel (b)), respectively. The second implication of the data structure, however, is that even for households interviewed in the second half of the year, the overlap between the reported income realizations and the time period that refers to the expectations is not perfect. Figure 1(b) shows that the overlap between expected and realized income is only 6 months for a household interviewed for the first time in July. This overlap is further decreasing for August to December households.[8]

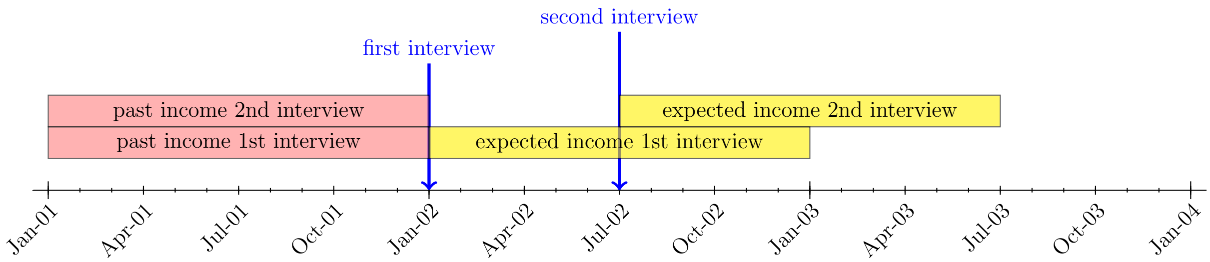
For our baseline analysis we exploit the fact that income growth reported by households interviewed in the second half of a year can be used to infer a relationship between this income growth in a particular year and the level of income as well as household characteristics in the year prior to that. We use this relationship to impute income growth realizations for the households interviewed in the first half of the year (see panel (c) of figure 1).[9] Furthermore,

[8] In contrast to our study, Souleles (2004) does not consider the implications of the timing of interviews or the imperfect overlap of expectations and realizations.

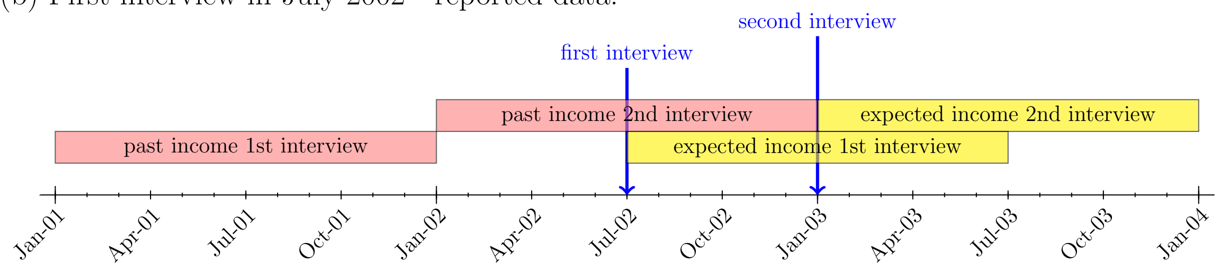
[9] We implement the imputation separately for each year. Our specification is therefore fully flexible regarding the effects of aggregate factors in the economy. A detailed description of the imputation procedure can be found in appendix A.2.

Figure 1: Timing of Income Realizations versus Expectations

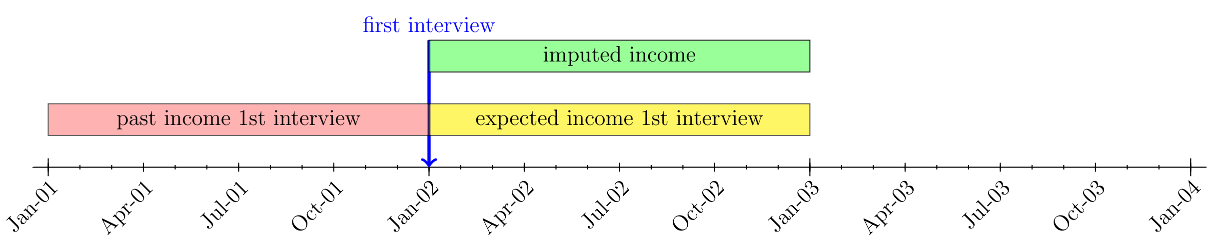
(a) First interview in January 2002 - reported data:



(b) First interview in July 2002 - reported data:



(c) First interview in January 2002 - imputed income:

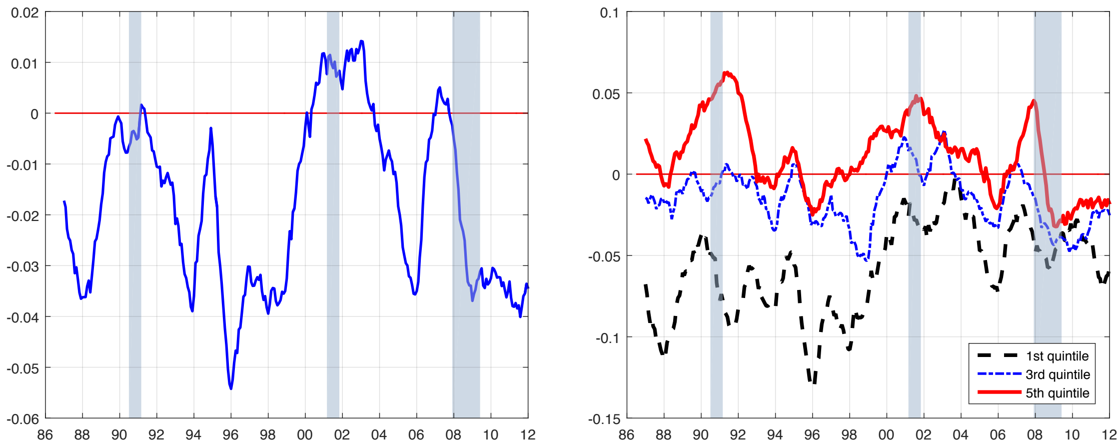


to increase the overlap for households interviewed in the second half of the year, we impute their income growth using growth realizations of households interviewed in the following year. Imputation therefore both increases the number of observations and improves the timing overlap between expectations and realizations.

To ensure that our findings are not an artifact of the imputation method, we conduct the analysis also on non-imputed data for July households as there is the largest overlap for directly reported data. Since we find similar results on this sample as we do on the full sample we can be assured that our results are not driven by the imputation procedure. Moreover, we conduct another robustness check to ensure that the imperfect timing of expectations and

Figure 2: Expectation errors in real income growth

(a) mean (b) mean by income quintile



Note: The figure plots the mean expectation errors in individual real income growth smoothed with 12-month moving average filter. Expectation errors are winsorized at 5% and 95%. Data from the Michigan Surveys of Consumers and own calculations. Grey areas represent NBER recessions. On the y-axis, 0.01 corresponds to 1 percentage point.

realizations does not affect our results. We re-run our analysis on the subsample of January, the month for which the timing overlap is perfect once we have imputed income growth realizations. Since our results also hold on this subsample we are confident the patterns we find are not driven by imperfect overlap of expectations and realizations either.

2.2 Analysis of Expectation Errors

The expectation error of household i is constructed as

$$\psi_{i,t} = \hat{g}_{i,t+1|t} - \tilde{g}_{i,t+1}, \tag{1}$$

i.e. it is equal to the difference between the household's expected growth rate in income $\hat{g}_{i,t+1|t}$ and its realized growth rate $\tilde{g}_{i,t+1}$, where $\tilde{g}_i$ is either the imputed realized growth or the directly reported realized growth rate. Under this definition of the forecast error, a household who was too optimistic about its future income growth has a positive error.

Figure 2 shows the average expectation error in real income growth over the sample period.[10] For the population as a whole, people tend to be too pessimistic about their

[10] In this section we focus our analysis on expectations about *real* income growth. However, the results we find are the same for *nominal* income expectations. Appendix B shows the corresponding time series plots to figure 2 for nominal income expectations. Moreover, when we control for household characteristics we will also show the regression results for errors in nominal income. These results will turn out to be very similar, both quantitatively and qualitatively, to the results for real income expectations.

income growth (the average forecasting error is mostly negative, see panel (a)). However, there is considerable heterogeneity in the forecast error by household income. While the low income group on average underestimates their income growth in all time periods, households in the high income group are in fact too optimistic for prolonged periods of time. Panel (b) shows the average expectation errors for three different income groups over time. Throughout the whole time period, the expectation errors are the lowest for the lowest income group (1st quintile) and highest for the highest income group (5th quintile).[11]

Since households in different income quintiles are likely to also differ along other characteristics, we control for other observables using the following OLS regression:

$$Z_i = \alpha + \beta X_i + \sum_{k=1}^{K} \gamma_k D_{ik} + \varepsilon_i, \tag{2}$$

where Z_i is the outcome variable of interest of household i (in this case the expectation error ψ_i), X_i are household demographics as well as dummies for the month in which this household was interviewed, and D_{ik} are dummy variables which take the value 1 if household i belongs to income group k.[12] Table 1 shows the results of this regression. Even after controlling for other household characteristics, the effect of income in the first interview on expectation errors is highly significant and economically important.[13] Looking at expectation errors in real income (column 1), households in the highest income quintile have on average an expectation error which is 3.5 percentage points more positive compared to households in the middle income group. At the same time, people in the lowest income group underestimate their income growth by 5.2 percentage points more than people in the middle income group.

Columns 2-4 repeat the analysis on different subsamples to ensure that the results are neither driven by imperfect overlap between the period of expectations and realizations nor by the imputation of realized changes. Columns 2 and 3 show the results when the sample is restricted to interviews in January or December only. For these months the overlap is perfect

[11] Households are allocated to income quintiles based on the cross-sectional distribution of per adult income in the year of the first interview.

[12] Appendix C contains robustness checks to this specification. The first robustness check is to include interaction terms of income quintiles with age bins and education dummies. Most of these interaction terms are not significant and the relationship between expectation errors and income quintiles is robust to this change: it remains statistically and economically significant and of very similar magnitude as in the main specification. In a second robustness check we control for cohort effects, in one specification instead of age and in another specification instead of time effects (and include dummies for month of the interview to control for seasonal effects). Our results are virtually unchanged by these alternative controls. The last robustness check is to limit our analysis only to the period 2000 and later. Our results are qualitatively the same as in the main specification. The magnitudes of the effects are smaller but still economically and statistically significant.

[13] Standard errors account for the uncertainty that is induced by the imputation using multiple imputation procedures and standard errors based on Rubin (1987), Barnard and Rubin (1999) and Reiter (2007).

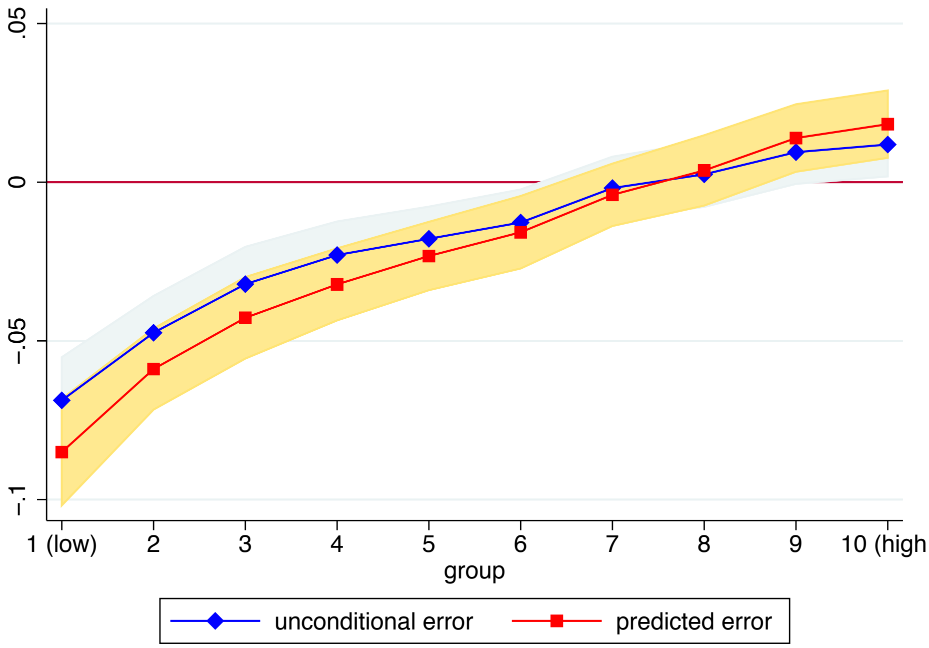
Table 1: OLS of expectation errors on household characteristics

	(1) real	(2) real	(3) real	(4) real	(5) nominal	(6) inflation
Income Quintile						
1 (low)	−0.052***	−0.046**	−0.049*	−0.075***	−0.049***	0.004***
	(0.006)	(0.018)	(0.027)	(0.021)	(0.007)	(0.000)
2	−0.018***	−0.013	−0.025	−0.038*	−0.016***	0.002***
	(0.006)	(0.017)	(0.024)	(0.020)	(0.006)	(0.000)
4	0.019***	0.026*	0.030	0.025	0.018***	−0.002***
	(0.005)	(0.013)	(0.024)	(0.016)	(0.005)	(0.000)
5 (high)	0.035***	0.046***	0.040*	0.067***	0.032***	−0.004***
	(0.006)	(0.015)	(0.022)	(0.017)	(0.006)	(0.000)
Education						
no high school	0.014	0.015	0.015	0.000	0.019	0.002**
	(0.013)	(0.029)	(0.059)	(0.036)	(0.013)	(0.001)
college	−0.014***	−0.024**	−0.007	−0.032**	−0.017***	−0.003***
	(0.004)	(0.012)	(0.016)	(0.013)	(0.004)	(0.000)
Age						
age	−0.004***	−0.003	−0.007	−0.006	−0.004***	0.000***
	(0.001)	(0.003)	(0.006)	(0.004)	(0.002)	(0.000)
age × age	0.000**	0.000	0.000	0.000	0.000*	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Racial background						
black	0.019**	0.025	0.009	0.021	0.024***	0.002***
	(0.008)	(0.018)	(0.032)	(0.022)	(0.008)	(0.000)
hispanic	0.013	0.005	0.018	0.018	0.018*	0.003***
	(0.009)	(0.027)	(0.046)	(0.033)	(0.009)	(0.001)
Number of adults						
1	−0.025***	−0.004	−0.035	0.026	−0.025**	0.001***
	(0.009)	(0.026)	(0.039)	(0.042)	(0.010)	(0.001)
3 or more	0.020***	0.014	0.021	0.021	0.018**	−0.002***
	(0.007)	(0.018)	(0.030)	(0.022)	(0.007)	(0.000)
Other family characteristics						
female	−0.008*	−0.005	−0.007	−0.006	−0.002	0.005***
	(0.004)	(0.010)	(0.016)	(0.012)	(0.004)	(0.000)
not married	0.023**	0.004	0.030	−0.019	0.024**	0.000
	(0.009)	(0.024)	(0.034)	(0.040)	(0.009)	(0.000)
Region						
North Central	−0.022***	−0.023	−0.030	−0.020	−0.022***	−0.000
	(0.006)	(0.015)	(0.024)	(0.017)	(0.006)	(0.000)
Northeast	−0.020***	−0.021	−0.036	−0.005	−0.020***	0.001
	(0.006)	(0.017)	(0.027)	(0.018)	(0.006)	(0.000)
South	−0.018***	−0.014	−0.029	0.013	−0.017***	0.001**
	(0.006)	(0.016)	(0.024)	(0.016)	(0.006)	(0.000)
Constant	0.136**	0.097	0.170	0.132	0.131**	−0.016***
	(0.052)	(0.078)	(0.148)	(0.094)	(0.054)	(0.002)
Sample	MAIN	JAN	DEC	JULY	MAIN	INF
Imputed Data?	yes	yes	yes	no	yes	no
Observations	58369	6973	2723	2805	58369	88017

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: Table shows regressions results from OLS on equation (2), where the dependent variable is the household expectation error in real income (columns 1-4), in nominal income (column 5) and in inflation (columns 6). The regressions included month dummies as additional controls. Standard errors take the uncertainty induced by the imputation procedure into account whenever imputed data is used; without imputed data heteroskedasticity-robust standard errors are computed.

Figure 3: Expectation errors in real income by income group



Note: The figure shows the unconditional mean expectation error (blue line, diamonds) and predicted expectation error (red line, squares) in real income growth by income decile. Predicted expectation errors are based on regression results from table 1 column 1, except that income is split in income deciles instead of quintiles. Predicted values are computed for all other explanatory variables at the weighted sample mean. Bands refer to 95% confidence intervals (standard errors take the uncertainty induced by the imputation procedure into account). On the y-axis, 0.05 corresponds to 5 percentage points.

or almost perfect (11 out of 12 months), repectively. Since the results on these subsamples are very similar to the results on the full sample, we conclude that imperfect overlap does not generate our findings. Column 4 shows that the results also hold when the analysis is done on July interviews only using directly reported income changes instead of imputed ones. The sample in this specification is hence not affected by any imputation. The fact that the results hold confirms that the findings are not driven by the imputation procedure.

While the coefficients in table 1 are informative about the errors in the respective income group relative to the middle income group, they cannot directly tell us whether a particular income group is too optimistic or too pessimistic. Figure 3 thus plots both the unconditional mean expectation error by income decile and the expectation error predicted by the OLS regression when all other regressors are at their sample mean. The figure shows that while low income households underestimate their income growth, high income households are too optimistic and overestimate their income growth. In terms of magnitudes, on average people in the lowest income quintile underestimate their income growth by 7 percentage points and people in the highest income quintile overestimate it by 2 percentage points. The systematic relationship between forecast error and income group is thus robust to controlling for other household characteristics. In fact, as seen in figure 3, controlling for other demographics increases the effect of income on expectation bias.

Are households only systematically biased with respect to their individual income expectations? Or are they also biased in their expectations about aggregate conditions? In addition to the regression results for real income expectations, table 1 also splits the results in expectation errors in nominal income (column 5) and expectation errors in inflation (column 6). While income quintiles also have a significant effect on errors in inflation expectations, column 5 shows that most of the effects on expectation errors in real income are driven by the effects on expectation errors in nominal income. This is also confirmed in figure 4 where unconditional and predicted expectation errors are plotted for expectations in nominal income and inflation. The pattern for nominal income is very similar to that of real income. The reason for this small difference is that errors in inflation expectations are almost an order of magnitude smaller than errors in individual income expectations.[14] Moreover, note that inflation expectations are too high across the whole income distribution. While there is an economically small variation in the size of errors in inflation expectations, this variation is not strong enough to change the sign of the bias as we move along the income distribution.

Another aggregate variable that households in the Michigan Surveys of Consumers are asked about is unemployment.[15] In particular, the question about unemployment expectations is the following:

> *How about people out of work during the coming 12 months – do you think that there will be more unemployment than now, about the same, or less?*

We code an expected increase in unemployment as -1, no change as 0 and and expected decrease as 1. This categorical expectation can be compared to the realized change in the U.S. unemployment rate in the 12 months following the interview.[16] Categorical expectation errors are then defined as "categorical expectation" - "categorical realization". The outcome categories for expectation errors range from "-2: far too pessimistic" to "+2: far too optimistic". We use an ordered logit regression to isolate the effect of individual income on

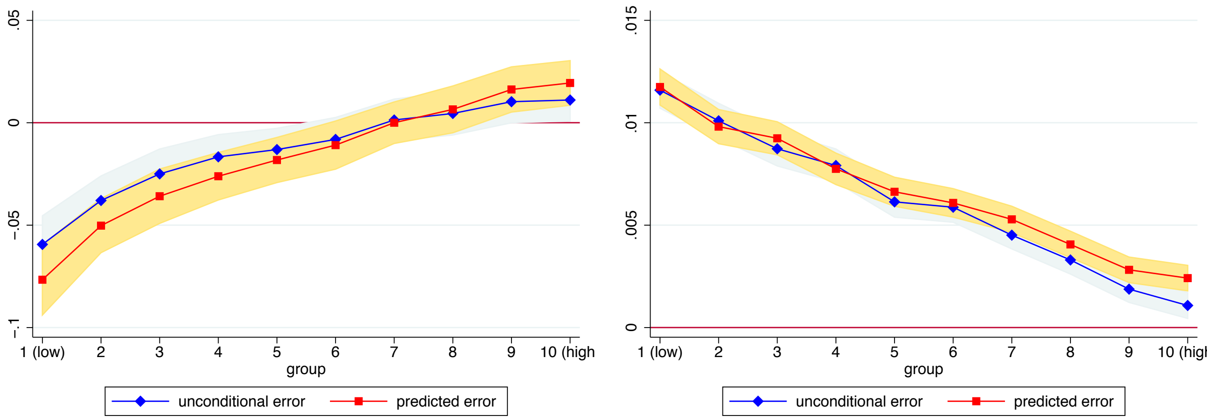
[14] The small impact of inflation expectations relative to income expectations is in line with Bachmann et al. (2015) who find that consumers' spending attitudes are hardly affected by their inflation expectations.

[15] The survey also elicits expectations about the development of interest rates. Unfortunately, the survey doesn't specify which interest rate, only that people should think of "interest rates for borrowing money". It is hence not clear which interest rates people refer to when they answer the question. This implies that is unclear to which realizations the expectations should be compared.

[16] We code a realized change within +/- 0.1% as "0: no change", an increase in more than 0.1% as "-1: increase in unemployment" and a decrease of more than 0.1% as "+1: decrease in unemployment". We computed all the analyses for alternative assumptions about the band for "the same" (+/- 0.05%, +/- 0.20% and +/- 0.25% and the results were robust to these specifications.

Figure 4: Expectation errors by income group

(a) nominal income growth (b) inflation



Note: The figure shows the unconditional mean expectation error (blue line, diamonds) and predicted expectation error (red line, squares) by income decile. Predicted expectation errors are based on regression results from table 1 column 5 and 6, except that income is split in income deciles instead of quintiles. Predicted values computed for all other explanatory variables at the weighted sample mean. Bands refer to 95% confidence intervals (for nominal income growth standard errors take the uncertainty induced by the imputation procedure into account; for inflation heteroskedasticity-robust standard errors are computed). On the y-axis, 0.05 corresponds to 5 percentage points.

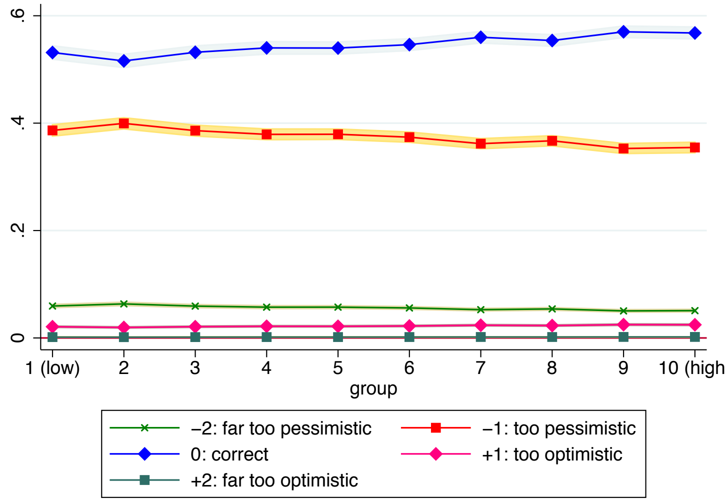
errors in unemployment expectations (we keep the same control variables as in the analysis above).[17] Figure 5 shows the predicted likelihoods of each category for different income deciles, holding all other characteristics constant at their sample mean. The likelihood of a correct prediction is very stable around 55% to 58% for all income groups while the likelihood of being too pessimistic lies between 37% to 40%. At the same time, however, the likelihood of being too optimistic is very low for all income deciles. This indicates that - similarly to inflation expectations - people are too pessimistic across the whole income distribution.[18]

The analyses in this section thus reveal two forms of bias in household expectations. First, errors in individual income expectations vary systematically with income: Low income households underestimate their income growth while high income households overestimate their income growth. Second, households in all income groups are too pessimistic regarding their forecasts of aggregate variables.

[17] See appendix D for the full regression results.

[18] This finding of general pessimism in aggregate variables is in line with the results in Bhandari et al. (2016) who show that unemployment and inflation expectations are on average too pessimistic across various population groups (including income groups) relative to the Survey of Professional Forecasters.

Figure 5: Unemployment Expectations: predicted likelihood of each category by subgroups



Note: The figure shows the predicted likelihoods of each outcome category of unemployment expectations (-2 (far too pessimistic) to +2 (far too optimistic)) by income decile. Predicted likelihoods are based on a ordered logit regression of categorical forecast errors on income deciles and other demographics as in previous regressions.

3 Expectation Formation: Overestimation of Persistence in Income Process

In this section we present a formulation for expectation formation that can generate the observed pattern in expectation errors: We argue that people overestimate the persistence of their income process. This explanation can be seen as an expression of people's failure to properly account for regression to the mean in their probabilistic judgments (Kahneman and Tversky, 1973; Kahneman, 2012). While we cannot claim that this is the only mechanism that can generate the observed patterns, we did consider various alternative explanations and found that none of them was able to account for the observed joint distribution of income and expectation errors. A detailed description of the mechanisms considered and why they are not fully consistent with the observed data can be found in appendix F.

3.1 Mechanism: Overpersistence Bias

Formally, overestimating the persistence of income can be described as follows.[19] Assume that income (net of age effects and the effects of other demographics) is generated by the

[19]Proofs of all results in this section can be found in appendix G.

process

$$\ln Y_{i,t} = \ln P_{i,t} + \ln T_{i,t}, \tag{3}$$

$$\ln P_{i,t} = \rho \ln P_{i,t-1} + \ln N_{i,t}, \tag{4}$$

where P_{it} is a persistent component and T_{it} is a transitory shock. Persistent income depends on past persistent income and on a shock N_{it}. Both shocks are independently and log-normally distributed with mean 1. Overestimating the persistence implies that the households believe their persistence parameter to be larger than it actually is:

$$1 > \hat{\rho} > \rho \tag{5}$$

Theorem *If the true income process is governed by equations* (3) *and* (4) *and the household overestimates the persistence of the process according to equation* (5)*,*

(a) $\exists! \bar{P}$:

$$\mathsf{E}\left[\hat{\mathsf{E}}_t[\ln(Y_{i,t+1})] - \ln(Y_{i,t+1}) | P_{i,t} > \bar{P}\right] > 0$$

and vice versa for $P_{it} < \bar{P}$*, where* $\hat{\mathsf{E}}_t[\ln(Y_{i,t+1})]$ *is the distorted expectation of* $Y_{i,t+1}$ *given information at time* t*.*

(b) *Let* $\Delta_{i,t} \equiv P_{i,t} - \bar{P}$*, then*

$$\frac{\partial \mathsf{E}\left[\hat{\mathsf{E}}_t[\ln(Y_{i,t+1})] - \ln(Y_{i,t+1}) | \Delta_{i,t}\right]}{\partial \Delta_{i,t}} > 0.$$

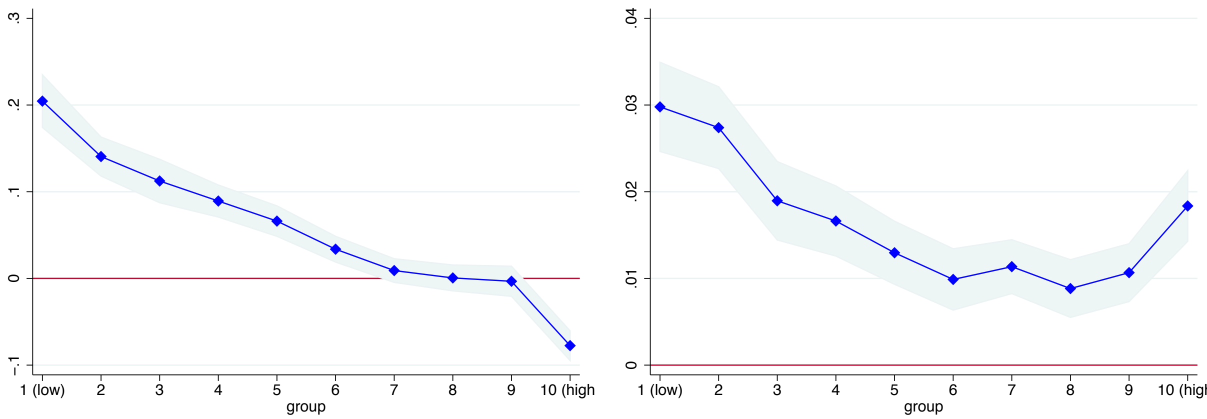
The proposition thus states that overestimating the persistence of the income process generates expectation errors in income growth that are (a) positive if the persistent income component is above a certain threshold (and negative if it is below this threshold) and (b) increasing in the distance from this threshold. Overpersistence can hence generate the pattern of systematic expectation errors observed in figure 3.

Intuitively, overestimating the persistence of the income process has the effect that people do not sufficiently account for mean-reversion of income in the cross-section.[20] This interpretation is supported by figure 6. Panel (a) shows that income is indeed mean-reverting by plotting the realized real income growth rates that are predicted for each income decile

[20]We do not aim to explain the cause of the overpersistence bias. However, in the light of Bidder and Dew-Becker (2016), it could be an outcome of people being ambiguity averse.

Figure 6: Realized growth and growth expectations in real income by income group

(a) realized growth (b) growth expectation



Note: The figure shows the predicted realized growth (panel (a)) and growth expectations (panel (b)) in real income by income decile. Predicted values are based on OLS regression results from regressing individual realized growth rates or expectations on all regressors as in table 1. Sample: for realized growth only directly reported income growth rates are used (first interviews in second half of the year); for growth expectations all observations are used (with or without reinterview and all months). Predicted values computed for all other explanatory variables at the weighted sample mean. Bands refer to 95% confidence intervals (based on heteroskedasticity-robust standard errors). On the y-axis, 0.01 corresponds to 1 percentage point.

if all other household characteristics are at their sample mean.[21] Low income households are predicted to experience a large income growth and the predicted growth is decreasing in income. High income households, in fact, are predicted to have a negative income growth. Panel (b) further plots the growth expectations that are predicted for each income decile, again holding all other characteristics constant at their sample mean. Growth expectations, like realized income growth, decrease with income. However, comparing the magnitudes we see that households fail to anticipate the magnitude of the mean reversion. We interpret this finding as evidence in favor of households overestimating the persistence of their income process.

The expectations under the overpersistence bias can also be expressed as a function of rational expectations and the history of past innovations:

Corollary *If the true income process is governed by equations* (3) *and* (4) *and the household overestimates the persistence of the process according to equation* (5)*, the distorted*

[21] These predicted values have been constructed from estimating equation (2) where the outcome variable Z_i is set to the reported realized income growth g_i of households interviewed for the first time in July to December (only those households who directly report income changes). Detailed estimation results can be found in appendix E.

expectation at time t of income in period $t = t+1$, $\hat{\mathsf{E}}_t[\ln Y_{i,t+1}] = \hat{\rho} \ln P_t$, can be expressed as

$$\hat{\mathsf{E}}_t[\ln Y_{i,t+1}] = \mathsf{E}_t[\ln Y_{i,t+1}] + (\hat{\rho} - \rho) \cdot \sum_{s=0}^{\infty} \rho^{s-1} \big(\mathsf{E}_{t-s}[\ln Y_{i,t-s+1}] - \mathsf{E}_{t-s-1}[\ln Y_{i,t-s+1}] \big) \qquad (6)$$

where $\mathsf{E}_t[\ln Y_{i,t+1}] = \rho \ln P_t$ is the rational expectation of income in period $t+1$ based on information available at time t.

This implies that due to the overpersistence bias the distorted beliefs are equal to the sum of the rational expectation and a weighted sum of all innovations to past rational expectations. People under the overpersistence bias hence overreact to income shocks and the overreaction to a specific shock is persistent but decaying over time. This formulation of expectation formation is related to expectations formed by "Diagnostic Expectations" proposed in Gennaioli and Shleifer (2010) and Bordalo et al. (2018).[22] The difference is that in their setup the distortion would only be a function of the latest shock, $\hat{\mathsf{E}}_t[\ln Y_{i,t+1}] = \mathsf{E}_t[\ln Y_{i,t+1}] + \theta \cdot \big(\mathsf{E}_t[\ln Y_{i,t+1}] - \mathsf{E}_{t-1}[\ln Y_{i,t+1}] \big)$, where the parameter θ governs the magnitude of the bias due to diagnostic expectations. In contrast, with the overpersistence bias distortions accumulate over time. This persistence in distortions explains why empirically the level of income is systematically related to the forecast error households make.

3.2 Modeling and Quantifying Biased Beliefs

From the analyses in the previous sections we conclude that there are two forms of systematic bias in household income expectations: First, low income households are too pessimistic about their income growth while high income households are too optimistic. This pattern is consistent with people overestimating the persistence of their income process. Second, households across the whole income distribution are too pessimistic about aggregate conditions. We will now formulate how to parsimoniously incorporate these distortions in a model framework and quantify their magnitudes by matching the expectation errors in the model with those documented in the data.

[22]Note that mathematically, the overpersistence bias can be expressed in the general framework of Bordalo et al. (2018):

$$h^{\theta}(\ln \hat{P}_{i,t+1}) = h(\ln \hat{P}_{i,t+1} | \ln P_{i,t} = \ln \hat{P}_{i,t}) \cdot \left(\frac{h(\ln \hat{P}_{i,t+1} | \ln P_{i,t} = \ln \hat{P}_{i,t})}{h(\ln \hat{P}_{i,t+1} | \ln P_{i,t} = (\rho - 1) \ln \hat{P}_{i,t})} \right)^{\theta} \frac{1}{Z}$$

where $h^{\theta}(\ln \hat{P}_{i,t+1})$ is the distorted probability distribution, $\theta = \hat{\rho} - \rho$, $h(\ln \hat{P}_{i,t+1} | \ln P_{i,t} = \ln \hat{P}_{i,t})$ is the true probability distribution based on current information and $h(\ln \hat{P}_{i,t+1} | \ln P_{i,t} = (\rho - 1) \ln \hat{P}_{i,t})$ is a specific reference distribution, which in this case is a normal distribution with mean $(\rho - 1) \ln \hat{P}_{i,t}$ and variance $var(\ln N_{i,t})$. This is a different reference distribution compared to the one Bordalo et al. (2018) employ in their paper.

We proceed in three steps. First, we assume a particular type of income process that is typically used in the quantitative literature.[23] Second, we allow households to have wrong beliefs about the persistence of the process as well as to be too pessimistic about aggregate developments. Third, we calibrate these two belief parameters and show that this parsimonious representation is able to replicate the observed expectations errors across the income distribution.

Underlying Income Process The exogenous income of a household is a combination of three mutually independent exogenous components: a persistent aggregate component Z_t, a persistent idiosyncratic component $P_{i,t}$ and a idiosyncratic transitory component $T_{i,t}$:

$$Y_{i,t} = Z_t \cdot P_{i,t} \cdot T_{i,t}. \tag{7}$$

Transitory shocks $T_{i,t}$ are iid lognormally distributed with

$$T_{i,t} \sim \log N\left(-\sigma_T^2/2, \sigma_T^2\right). \tag{8}$$

The idiosyncratic persistent component $P_{i,t}$ follows an AR(1) process in logs such that

$$\ln P_{i,t} = \rho \ln P_{i,t-1} + \epsilon_{i,t}^P, \qquad \epsilon_{i,t}^P \sim N(0, \sigma_P^2) \tag{9}$$

and the aggregate persistent component is a two state Markov process

$$\mathbb{Z} = \begin{bmatrix} Z^h \\ Z^l \end{bmatrix}, \qquad \Pi_Z = \begin{bmatrix} \pi_{11} & 1-\pi_{11} \\ 1-\pi_{22} & \pi_{22} \end{bmatrix}, \tag{10}$$

where the high state refers to boom periods and the low state to recessions.

Incorporating Beliefs Motivated by our findings discussed above, we allow households to have biased beliefs about their income process. The overpersistence bias in expectations is implemented by allowing agents to believe that the persistence of the idiosyncratic component P is different than its true value. Formally, agents believe that their persistent income component evolves according to the following process:

$$\ln P_{i,t} = \hat{\rho} \ln P_{i,t-1} + \epsilon_{i,t}^P, \qquad \epsilon_{i,t}^P \sim N(0, \sigma_P^2), \tag{11}$$

where the persistence belief $\hat{\rho}$ is allowed to differ from the true persistence of the process ρ.

The pessimism in aggregate developments is implemented by allowing agents to believe

[23] For example, see Berger and Vavra (2015).

that the level of the aggregate states will differ from the true levels by a factor μ:

$$\hat{Z}_{t+1} = \mu \mathsf{E} Z_{t+1} = \mu \Pi_Z(Z_t)\mathbb{Z}, \tag{12}$$

where $\Pi_Z(Z_t)$ is the row of Π_Z that corresponds to Z_t. To quantify the biases, we find both bias parameters - the overpersistence belief $\hat{\rho}$ and the pessimism parameter μ - by matching the empirically observed forecasting errors by income quintile with the ones generated in this model.

Matching Expectation Errors Before fitting the bias parameters we need to parametrize the true income process. We follow Storesletten et al. (2004) who estimate an income process with persistent and idiosyncratic shocks. We transform their income process to quarterly frequency and obtain the following parameters: The persistent income component has an autocorrelation parameter of $\rho = 0.9774$ with standard deviation $\sigma_P = 0.0424$. The transitory income shocks have a standard deviation of $\sigma_T = 0.1$. To determine the transition matrix for the aggregate component of income we target the average duration of NBER recessions and booms in the post-war period (1945-2009).[24] On average in this period, booms lasted 58.4 months while recessions lasted 11.1 months. This leads to the probability of entering a recession of 6.85% and of leaving a recession of 36.04%. The levels of the boom and recession states have been chosen to reflect the average positive and the average negative deviation from trend in HP-filtered GDP. The resulting levels of booms and recessions are 1.0040 and 0.9790, respectively.[25]

We choose the overpersistence parameter $\hat{\rho}$ and the aggregate pessimism parameter μ to match the empirically observed expectation errors by income group. The parameters that match the errors are $\hat{\rho} = 0.9831$ (compared to the true persistence of $\rho = 0.9774$) and $\mu = 0.9778$. Table 2 shows that with these two parameters the model is able to match the expectation errors for all five income quintiles perfectly up to the second digit: The

[24]This specification leads to an asymmetric transition matrix. As a robustness check we have run all analyses (both the quantification of the biases as well as the solution of the complete model of consumption in the next section) also with a symmetric specification where we let the aggregate component Z_t follow an AR(1) process, parametrized as in Berger and Vavra (2015). Under this specification, all the results remain qualitatively identical and quantitatively very similar.

[25]The exact formula is

$$\text{avg\_dev} = \frac{1}{T_{pos}} \sum_{t=1}^{T} \hat{y}_t \cdot I(\hat{y}_t > 0) - \frac{1}{T_{neg}} \sum_{t=1}^{T} \hat{y}_t \cdot I(\hat{y}_t < 0) \tag{13}$$

where T_{pos} (T_{neg}) is the number of periods where $\hat{y}$ is *positive* (*negative*) in the sample and $\hat{y}_t$ is HP-filtered log(GDP). This difference between the good and the bad state combined with the fraction of time spent in booms and recessions (which results from the transition matrix) as well as the constraint that the mean of the overall process is 1 gives the levels of the two states.

Table 2: Mean expectation errors

	data	model
income quintile 1	-0.072	-0.068
income quintile 2	-0.037	-0.040
income quintile 3	-0.019	-0.021
income quintile 4	-0.000	-0.004
income quintile 5	0.016	0.020

Note: Data moments are the expectation errors predicted by equation (2) when all control variables apart from income are held constant at their sample mean.

overpersistence belief generates the spread across the income distribution while the aggregate pessimism shifts down the expectations errors for all income groups.

Another benefit of the parsimony of this specification is that it makes the bias simple to implement in various settings. In the remainder of this paper, we focus on consumption-saving implications. However, using this specification it would be straightforward to implement and study the overpersistence bias in other settings, for example in a model of asset pricing.

4 Implications of Biased Income Expectations

In this section we analyze how the distortions that we documented in income expectations affect consumption and saving decisions and investigate their aggregate implications. To do so we insert the representation of beliefs that we fitted in the previous section into a standard incomplete markets, heterogeneous agent model in the tradition of Bewley (1986) and Deaton (1991). To be able to meaningfully analyze the distribution of MPCs we include a durable good into our quantitative analysis.[26] Our model setting is close to the one used by Berger and Vavra (2015). Apart from allowing for biased income expectations the most important difference is in the treatment of the borrowing constraint. Whereas Berger and Vavra (2015) assume that agents can only save (no borrowing), we allow households to borrow up to a limit determined by their income state and durable holdings.[27] This assumption is not only more realistic, but it also has important consequences. First, a significant fraction of US households holds negative liquid assets. In order for the model to fit the data borrowing is

[26] Kaplan and Violante (2014) argue that it is crucial to include an illiquid asset into structural models to be able to match MPCs across the wealth distribution.

[27] Kaplan and Violante (2014) allow for borrowing, but their borrowing limit is independent of the value of the durable good. The main difference between our setting and Kaplan and Violante (2014) is that the latter analyzes a life-cycle model, whereas we have an infinite horizon setup (which we share with Berger and Vavra (2015)).

hence essential. However, fitting the distribution of how much people borrow, as opposed to only the fraction of households that borrow, is challenging for the class of models that we study. We show that including the biases in income expectations as seen in the data allows the model to replicate the empirical distribution of borrowing. Lastly, the ability to borrow, other things equal, reduces the number of constrained agents and consequently affects the marginal propensity to consume.

4.1 Model Setup

We consider the following partial equilibrium framework. Households are infinitely lived and derive utility from two sources: a non-durable consumption good and a flow of services from a durable good.[28] The stock of durable goods depreciates and is subject to non-convex adjustment costs. Households hence optimally adjust their durable holdings only infrequently. In addition to durable goods, households can also invest in a riskless liquid asset which they can also use to borrow. The only source of risk the households face are fluctuations in their exogenous income.

Households maximize their discounted life time utility[29]

$$\max_{\{c_t\}_{t=0}^{\infty},\{d_t\}_{t=0}^{\infty},\{s_t\}_{t=0}^{\infty}} \quad \sum_{t=0}^{\infty} \beta^t \; \mathsf{E}\big[U(c_t, d_t)\big], \tag{14}$$

subject to the following budget constraint

$$c_t + d_t + s_t + A(d_t, d_{t-1}) \leq Y_t + (1-\delta)d_{t-1} + R(s_{t-1}). \tag{15}$$

Households have available resources based on their income Y_t, the value of their depreciated durable stock $(1-\delta)d_{t-1}$, and the current value of the liquid asset holdings they chose in the previous period $R(s_{t-1})$. The current value of their liquid assets is determined as follows:

$$R(s_t) = [1 + r\,(s_t)]s_t \text{ where } r(s_t) = \begin{cases} r^l & \text{if } s_t > 0 \\ r^b & \text{if } -(\kappa_y P_t + \kappa_v d_t) \leq s_t \leq 0 \end{cases} \tag{16}$$

where $r^b > r^l$. Households can either save or borrow in liquid assets but have to pay a higher rate of interest for borrowing than they obtain when they are saving. The borrowing limit $(\kappa_y P_t + \kappa_v d_t)$ depends on their current persistent income (a loan-to-income constraint $\kappa_y P_t$) and the value of their durable stock (a loan-to-value constraint $\kappa_v d_t$).

[28] Appendix H shows the results of a version of the model without durable goods. The results of the full model hold in this restricted setting. As is to be expected, however, this simplified model is not able to accurately capture the cross-sectional distribution of assets.

[29] To simplify notation we have dropped the subscript i which indicates the individual household.

Households spend their available resources on non-durable consumption c_t, liquid assets s_t and the new durable stock d_t subject to adjustment costs $A(d_t, d_{t-1})$:

$$A(d_t, d_{t-1}) = \begin{cases} 0 & \text{if } d_t = (1-\delta)d_{t-1} \\ F^d(1-\delta)d_{t-1} & \text{otherwise.} \end{cases} \quad (17)$$

Equation (17) states that there are no adjustment costs if the household chooses to keep its depreciated durable stock, i.e. $d_t = (1-\delta)d_{t-1}$. On the other hand, if the household adjusts its durable stock, it has to pay adjustment costs equal to fraction F^d of the depreciated stock before the it is free to choose any new level of durable stock d_t.

Finally, the period utility function is

$$U(c,d) = \frac{\left[\left((1-\theta)c^{\frac{\xi-1}{\xi}} + \theta(\bar{d}+d)^{\frac{\xi-1}{\xi}}\right)^{\frac{\xi}{\xi-1}}\right]^{1-\gamma}}{1-\gamma}. \quad (18)$$

Note that every household obtains utility from a small free stock of durable $\bar{d}$. This captures the fact that even a very old car with almost zero resale value can be used as means of transport. This specification of the utility function hence enables the model to match the empirical distribution of durable stocks with its substantial share of low values.

The only source of risk in the model is income risk. We assume that income follows the process as described in the previous section (equations (7)-(10)) and that households have biased beliefs according to equations (11) and (12).

4.2 Matching the Model to the Data

The model is calibrated at quarterly frequency. We proceed in two steps. First, we set the parameters of the environment (interest rates, borrowing constraints, depreciation rate and adjustment costs) exogenously according to either our empirical estimates or results from the literature. Second, we calibrate the remaining preference parameters to match the empirical distributions of liquid assets and durable holdings. Note that the belief parameters are independent of the specification of the consumption model so that we can use the parameters obtained in the previous section. Table 3 reports the complete parametrization.

Exogenous Parameters of the Environment Households can both save and borrow in the liquid asset but earn a rate of return that depends on their balance. The interest rate for saving is set to the mean real interest rate on 3 month treasury bills in the post-war period (1948-2015). On quarterly frequency this value is equal to $r^l = 0.0016$. The interest rate for borrowing is set equal to $r^b = 0.02$ which reflects interest rates on credit cards and on auto

Table 3: Parameter Values

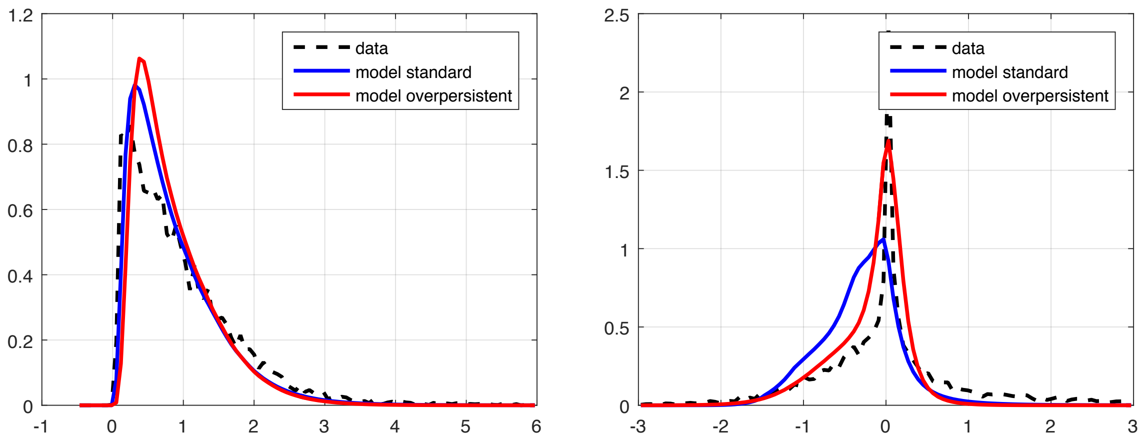
Parameter		Value
technology:		
interest rate (lending)	r^l	0.0016
interest rate (borrowing)	r^b	0.02
loan-to-income constraint	κ_y	0.56
loan-to-value constraint	κ_v	0.8
depreciation rate	δ	0.05
adjustment costs	F^d	0.3
income:		
persistence of idiosyncratic income process	ρ	0.9774
std dev of idiosyncratic persistent shocks	σ_P	0.0424
std dev of idiosyncratic transitory shocks	σ_T	0.1
high aggregate income state	Z^h	1.0040
low aggregate income state	Z^l	0.9790
prob. of entering recession	$1-\pi_{11}$	6.85%
prob. of leaving recession	$1-\pi_{22}$	36.04%
beliefs:		
persistence of income	$\hat{\rho}$	0.9831
aggregate pessimism	μ	0.9778
preferences:		
discount factor	β	0.9825
risk aversion	γ	1.5
weight of durable goods in utility	θ	0.075
elasticity of substitution in utility	ξ	3
free durable services	$\bar{d}$	0.5

loans. Data on credit card rates is available since 1994 ("Commercial Bank Interest Rate on Credit Card Plans, All Accounts") and interest rates on auto loans since 1972 ("Finance Rate on Consumer Installment Loans at Commercial Banks, New Autos 48 Month Loan"). The mean real interest rates on quarterly frequency for these two series are 0.0268 and 0.0127, respectively. Since households in the model borrow at the same rate against their income (which reflects credit card debt) and against durables (which resembles auto loans), we set the borrowing rate to 0.02, a value that is roughly in the middle of the two interest rates. Moreover, this value is well within the range of interest rates on car loans for new and used cars documented by Attanasio et al. (2008) for the Consumer Expenditure Survey.

To set the loan-to-income constraint we turn to data from the Survey of Consumer Finances and compare the credit card limit of an individual household to its quarterly income. On average in the period 1992-2010, households have a borrowing limit that is 56% of their quarterly income. We hence set $\kappa_y = 0.56$. Moreover, we further assume that households

Figure 7: Model fit

(a) distribution of durable goods (b) distribution of liquid assets



Note: The figure depicts the distribution for (a) durable goods and (b) liquid savings. Data distributions (dash-dotted black line) are compared to the distributions implied by model which allows for biased expectation (solid red line) and the model where expectations are assumed to be rational (dashed blue line). The x-axis is normalised by the value of median quarterly income.

can borrow up to 80% against the value of their durable and set $\kappa_v = 0.8$.[30]

To determine the depreciation rate δ and the proportional adjustment costs F^d we proceed as follows. The adjustment costs can be understood as the share of value a car loses just because it is sold to another person, i.e. the fraction of the purchase price which is not recovered if a car was resold immediately after the original purchase. We assume that this fraction is equal to 30% compared to the original value of the car and hence set $F^d = 0.3$. Furthermore, we assume that the resale value of a durable is negligible after 10 years. Given the adjustment costs F^d, this is the case for a quarterly depreciation rate of 5%. We therefore set $\delta = 0.05$.

Preference parameters The remaining five parameters are the preference parameters which affect the trade-off between non-durable consumption and the durable good $(\theta, \xi, \bar{d})$, risk aversion (γ) and the discount factor (β). The values of these parameters are chosen to match the aggregate distribution of liquid assets and the stock of durable goods in the data.

The data distributions we target have been obtained from the Survey of Consumer Finances (SCF), waves 1992-2010. The data counterpart for liquid assets is the sum of checking accounts, savings accounts, stocks, bonds, and mutual funds minus outstanding credit card debt after last payment and outstanding auto loans. Durable goods are defined as the cur-

[30] Attanasio et al. (2008) report that the average finance share for households buying cars is 0.78.

rent value of all vehicles belonging to the household. To eliminate effects of life-cycle savings we focus on the sample of vehicle owners aged 25-55.[31]

The optimal parameter values are found using a grid search procedure. The resulting values are the discount factor $\beta = 0.9825$, risk aversion $\gamma = 1.5$, weight of durable goods $\theta = 0.075$, elasticity of substitution between durables and non-durables $\xi = 3$ and free durable services $\bar{d} = 0.5$.

Figure 7 shows that the model is able to replicate key features of the distributions of both durable goods and liquid assets. The model achieves a very good fit for the distribution of durable goods in the economy. In terms of liquid assets, the model succeeds in replicating the mass of households with zero liquid assets. It is important to stress that each of the two distributions is an infinite dimensional object and the model has only 5 parameters to achieve a good fit. The model struggles to replicate the thick right tails of the liquid assets distribution. In the model agents hold liquid assets for transactionary (due to the adjustment costs in durables) and precautionary reasons. It does not, however, capture life cycle motives for savings, nor does it include heterogeneity in preferences or heterogeneity in returns that households earn on their investments. Life-Cycle savings motives have been shown to help generate wealth inequality (see, e.g., De Nardi and Fella (2017) for a survey). Moreover, recent evidence shows that empirically, heterogeneity in returns is pronounced and can explain the large concentration of wealth at the top (see Fagereng et al. (2016a), Bach et al. (2017)). Hubmer et al. (2017) show that Bewley-type models like the one in this paper are not able to match the asset concentration at the top without adding heterogeneity in both preferences and returns. They also find that even with both of these sources of heterogeneity the models are unable to match the wealth holdings at the very top. Since our focus here is not on the top end of the wealth distribution we choose to abstract from these additional complexities.

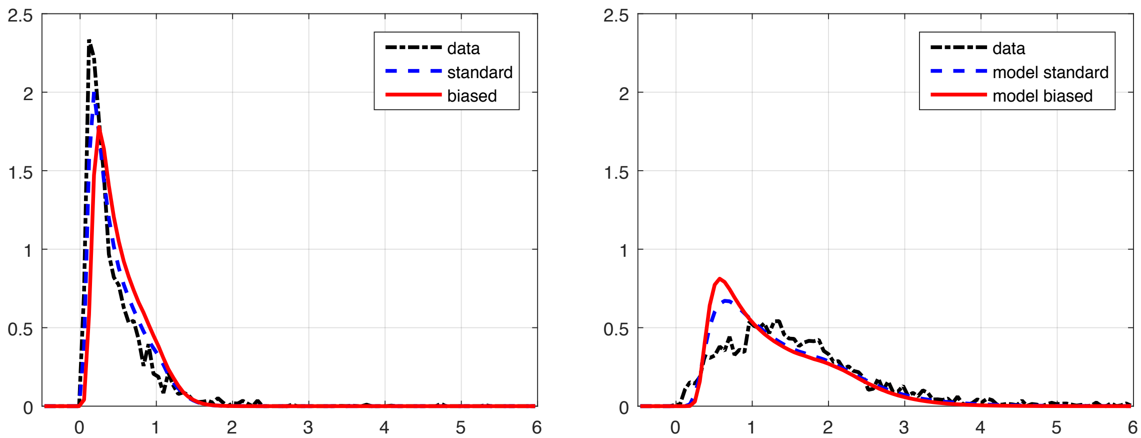
4.3 Effects of Biased Income Expectations

In this section we first show how the beliefs about income expectations affect the behavior of households in different income groups and show that it is in line with the empirical distributions. We demonstrate that under rational expectations the model predicts counterfactually large borrowing for low income households. Allowing for overpersistence belief and aggregate pessimism in income expectations hence reconciles the model predictions with the data. Furthermore, we show how biased income expectations affect the marginal propensity to consume (MPC) out of unanticipated transfer payments. We find that the overpersistence bias differentially affects the MPC in different income quintiles. Low income households turn out

[31] Households without any vehicle constitute 13% of the sample population.

Figure 8: Durable stock by income quintile

(a) lowest quintile (b) highest quintile



Note: The figure depicts the distribution of durable goods in the model versus data for different income quintiles. The panels show the data distribution (dash-dotted black line) against the model distribution when households have non-rational expectations (solid red line). For comparison, the distribution under rational expectations is also plotted (dashed blue line).

to have a lower MPC if they have biased expectations while the MPC of high income households is hardly affected by the beliefs. Overall, the differences in MPC's across the income distribution are hence smaller than what would be predicted under rational expectations.[32]

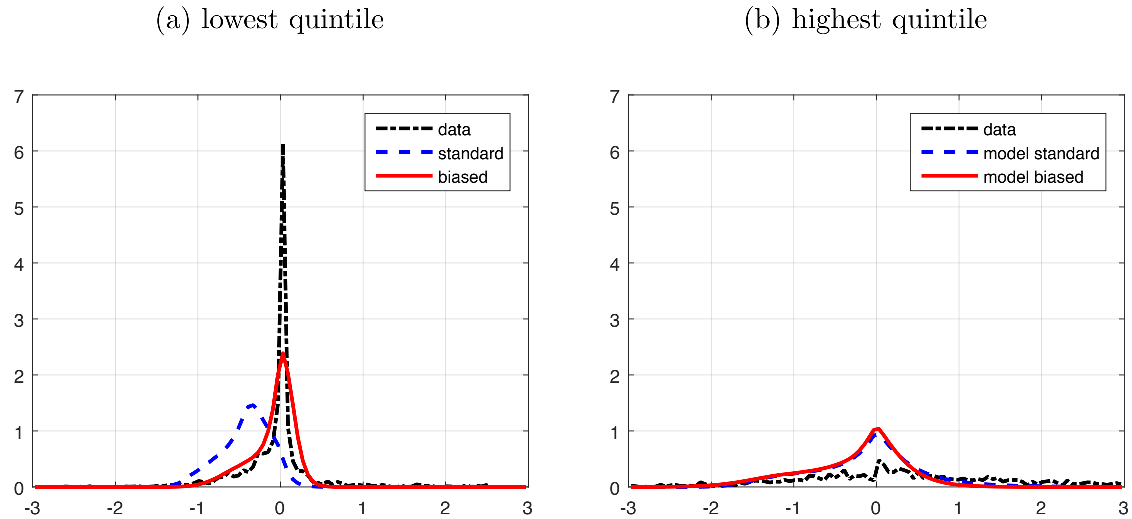
4.3.1 Effects on Behavior Across Different Income Groups

Figure 8 shows the distribution of durable goods for households in the lowest and highest income quintiles. The model is able to match the cross-sectional variation in durable holdings. This is true for both the model that allows for the expectation bias and for the fully rational model. In terms of durable holdings, biased expectations hence do not change the distributions much compared to the distributions implied by rational expectations.

However, this is not true for the distribution of liquid assets. Figure 9 shows the distribution for liquid assets for the two different income quintiles. While the distribution in the highest income group is not much affected by biased income expectations, the behavior of the low income group depends on what households believe about their future income. Low income households with biased beliefs are too pessimistic about their future income. They are therefore less willing to borrow even though their borrowing constraint is not binding.

[32] In this section we compare the implications of a model with biased expectations to the implications of the same model (i.e. same parametrization) under rational expectations. In appendix I we show the corresponding results when we instead calibrate the parameters to maximize the fit of the fully rational model. The qualitative results are the same as what is described in the main text.

Figure 9: Liquid assets by income quintile



Note: The figure depicts the distribution of liquid assets in the model versus data for different income quintiles. The panels show the data distribution (dash-dotted black line) against the model distribution when households have non-rational expectations (solid red line). For comparison, the distribution under rational expectations is also plotted (dashed blue line).

Figure 9(a) shows that this mechanism allows the model with biased income expectations to fit the empirical distribution of liquid assets in the lowest income group very well. It is important to note that with biased beliefs, low income households choose not to borrow more even though they could. If people had rational expectations instead, the model would predict counterfactually large amounts of borrowing (mode of -0.5 versus 0 in the data). We are not claiming that there is no extension of the rational model which would be able to match the distribution of borrowing. However, allowing for the small deviation from rational expectations that we found in the data allows the model to match this empirical fact without introducing any further complexities into the model.

4.3.2 Implications for Marginal Propensity to Consume

Government stimulus policies are a popular instrument during recessions to boost household consumption in order to stabilize the overall economy. In both recent recessions in 2001 and 2008, the U.S. government employed this strategy by giving households one-off cash transfers. However, how effective these stimulus programs are depends on how much households effectively spend out of the transfer. Moreover, stimulus payments have to be financed in some way, which is often done through taxes. Since high income households typically pay higher taxes than low income households, stimulus payments are a form of redistribution. How much aggregate consumption increases due to this transfer therefore depends on the ratio between the MPC of low income households relative to the MPC of high income households. This ratio can be seen as a measure for the first order effect in the transfer multiplier. In this section we show that biased income expectations directly affect this measure. In particular, we find that biased income expectations make stimulus policies less effective.

Figure 10 shows the reaction of household consumption to a one-time, unanticipated transfer payment. Panel (a) shows the fraction of the transfer payment that the population as a whole spends on non-durable consumption (cumulative responses over time). Panels (b) and (c) show the corresponding MPCs of the lowest and highest income quintile, respectively. Since the magnitude of the MPCs was not targeted in the calibration it is instructive to compare it to empirical estimates. Fagereng et al. (2016b) compute MPCs out of lottery winnings using administrative data from Norway. They estimate that people spend on average around 35 percent of their lottery winnings within the year of their win. Taking into account that winning the lottery is an unusual life-event and thus might trigger some unusual expenses, their estimate of the MPC is not too far from the 25 percent that the model predicts at a 4-quarter horizon. Furthermore, there is empirical evidence from the consumption responses after the two recent stimulus payments in the U.S.. For the 2001 stimulus Johnson et al. (2006) obtain a range of estimates for the average MPC on impact of 20-40 percent while Parker et al. (2013) obtain a range of 12-30 percent for the stimulus of 2008.[33] While our predicted value of 9 percent for the average MPC on impact is at the low end of these ranges, due to large standard errors it is well within the 95 percent confidence interval of each of these estimates. We therefore conclude that the MPCs predicted by our model are in line with empirical estimates.

Focusing on the low income households, figure 10 depicts that low income households with biased expectations have an average MPC that is between 5-10 percentage points lower than the MPC of rational households, depending on the horizon. These differences are the result of two effects. First, low income households with biased expectations are too pessimistic about their income going forward. This implies that they are more cautious in spending the transfer payment and more likely to save out of it. Second, income is persistent so that these households have typically already been too pessimistic in the past. They will therefore currently have a different asset position compared to their rational expectations counterparts: They are less likely to be close to the borrowing constraint and hence have a lower MPC than fully rational households with the same history of income realizations. Figure 10 disentangles these two effects by displaying the MPC that biased households would have if they had the same asset position as their rational expectations counterparts. We find

[33] Johnson et al. (2006) analyze the 2001 tax rebate of $300-$600 per adult. Parker et al. (2013) analyze the economic stimulus in 2008 of $300-$600 per adult and $300 per child.

that both forces contribute to the reduction in the MPC of biased households and that the magnitude of the two effects is similar.

High income households, on the other hand, spend about the same fraction of the transfer payment whether they have biased expectations or not. This implies that the ratio between the MPC of low income households relative to that of high income households is smaller once the empirically observed biases in income expectations are taken into account. In detail, the model with biased expectations predicts a MPC ratio of 1.94 on impact whereas the fully rational model predicts a ratio of 2.98. Ignoring the expectation biases thus inflates this measure of transfer effectiveness by around 50 percent. How do these numbers compare to estimates from the data? Johnson et al. (2006) and Parker et al. (2013) obtain point estimates of this MPC ratio of 2.33 and 1.16 for the stimulus payments in the United States in 2001 and 2008, respectively.[34] The predicted ratio from our model with biased expectations is thus well within the range of the empirical estimates.[35]

To summarize, we find that biased income expectations directly affect the MPC of low income households: On average they spend 5-10 percent less of a one-time transfer. This difference implies that transferring resources from high income households to low income households can be expected to lead to a smaller increase in aggregate consumptions than what a fully rational model would predict. We thus argue that it is important to take biases in income expectations into account when assessing the effectiveness of government stimulus policies.

4.3.3 Interaction with Borrowing Constraints

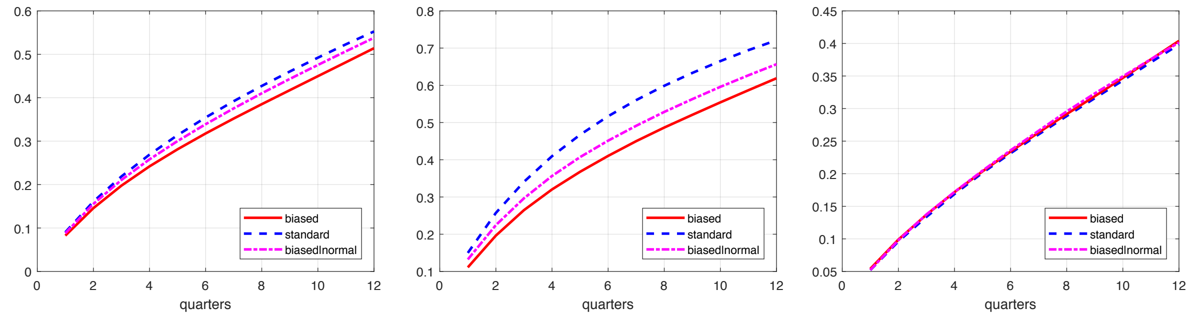
We have shown that the model without biased expectations predicts that low income households borrow too much compared to the empirical distributions. When we incorporate biases in income expectations as seen in the data, however, the model no longer has this problem. The reason is that households with low income choose to borrow less due to their pessimistic income expectations. Could a version of the fully rational model achieve similarly low levels of borrowing? One mechanism used in the literature to prevent people from borrowing too much is to impose exogenous borrowing constraints which turn out to be binding. In this section we argue that allowing for biased income expectations has qualitatively different implications than tightening borrowing constraints in a fully rational model. First, tightening the borrowing limit mechanically limits the ability of the model to fit the whole distribution of liquid assets as the high levels of borrowing of a small fraction of the population are

[34] Johnson et al. (2006) define income groups as: low $<$ \$34K, high $>$ \$69K. Parker et al. (2013) define income groups as: low $<$ \$32K, high $>$ \$75K.

[35] Note, however, that the standard errors in these studies are quite large so that further empirical analyses will be necessary to conclusively determine the difference in MPCs between low and high income households.

Figure 10: Cumulative MPC out of unexpected transfer

(a) aggregate (b) lowest income (c) highest income



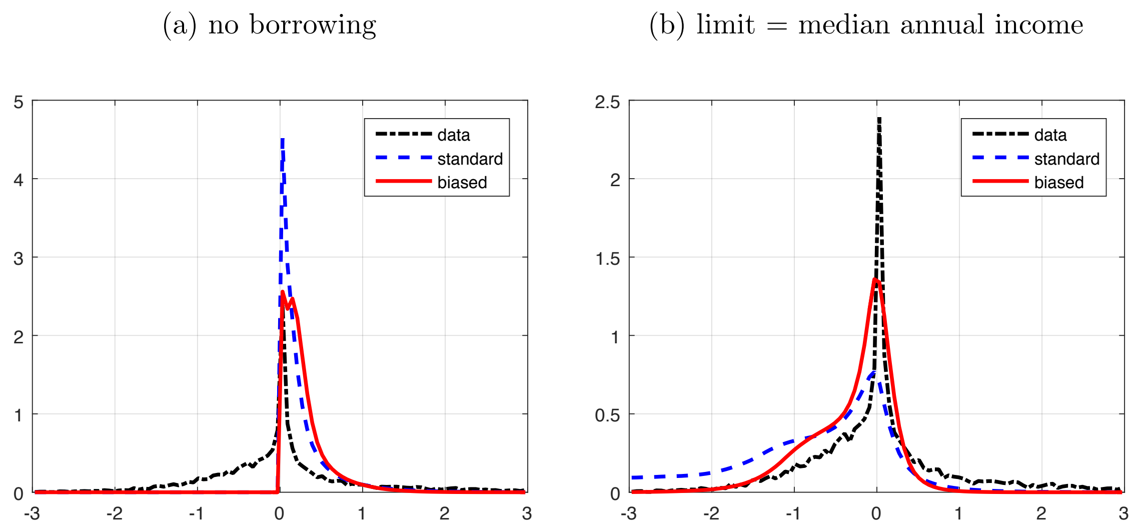
Note: The figure depicts the fraction of an unanticipated one-time transfer payment that is spent on non-durable consumption under different expectation scenarios: the red line depicts the MPC under biased expectations, the dashed blue dashed line depicts the MPC under rational expectations and the magenta dash-dotted line shows what the MPC of the overpersistent population would be if they were given the liquid assets and durable stock of the standard agents. Panel (a) shows the MPC in the aggregate population while panels (b) and (c) show the MPC for the lowest and highest income quintile, respectively. The transfer size is equal to 1% of median quarterly income in the economy.

excluded by construction. Second, while tightening the borrowing constraint increases the MPCs across the whole income distribution, it disproportionally increases the MPC of low income households. Tightening the borrowing constraint thus exacerbates by how much the rational model overestimates the effectiveness of stimulus policies.

We discuss in detail two alternative specifications for the borrowing limit: In the first economy households cannot borrow at all (zero borrowing economy). In the second economy households are allowed to borrow up to the median annual income in the population independent of their own current income (generous limit economy). Formally, we replace the borrowing limit $\kappa_y P_t + \kappa_v d_t$ in equation (16) with a constant $\underline{s}$ and solve the model for values $\underline{s}$ in a range from no borrowing up to a borrowing limit of one median annual income. We discuss the distributions of liquid assets for the two extreme cases in detail and then show the implications for MPCs as a function of $\underline{s}$.

Effects on the distribution of liquid asset Figure 11 shows the distributions of liquid assets in the two extreme economies for households with rational and biased expectations. By construction, imposing a zero borrowing constraint renders the model unable to fit the significant fraction of households that hold negative assets. Instead, a large fraction of households turns out to be bunched at zero liquid assets so that this constraint is binding. This is particularly true for households with rational expectations. In the economy with the generous borrowing limit, households with rational beliefs more often make use of the opportunity to borrow. This leads to a significant mass of households with very large levels

Figure 11: Distribution of liquid assets under different borrowing constraints



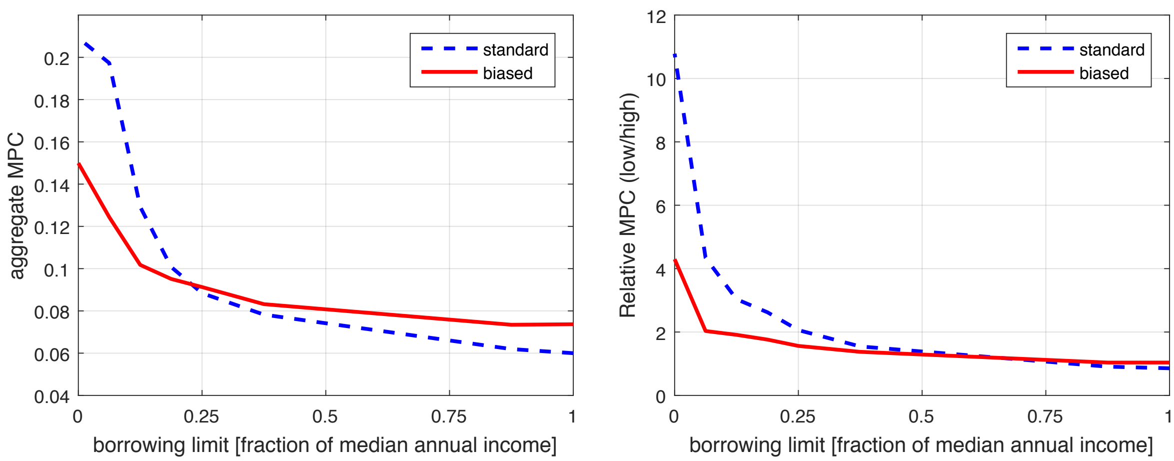
Note: The figure depicts the distribution for liquid assets under two alternative specification for the borrowing constraint: (a) no borrowing at all and (b) unconditional borrowing limit equal to median annual income. Data distributions (dashed black line) are compared to the distributions implied by the model which allows for biased expectation (solid red line) and the model where expectations are assumed to be rational (solid blue line). The x-axis is normalised by the value of median quarterly income.

of negative liquid assets. Households with biased beliefs, on the other hand, borrow much less. In particular, figure 11(b) shows that they do not even get close to the borrowing limit. This shows that fully rational agents are more responsive to changes in the borrowing constraint compared to households with biased income expectations. Moreover, tightening the borrowing constraint can be a means to match specific moments of the liquid asset distribution such as, e.g., the fraction of households with positive assets. By construction, however, it prevents the model from matching the whole distribution of liquid assets.

Implications for consumption The more restrictive the borrowing limit, the more likely it is to be binding. Therefore, changing the borrowing limit also affects the MPC of households. Figure 12 shows the average and the relative MPC out of an unexpected transfer payment as a function of the borrowing limit. Figure 12(a) shows that the model predicted average MPC is sensitive to the borrowing limit, especially for tight borrowing constraints. Making credit less available increases the MPC, in particular when the model does not allow for biased income expectations. The reason for this higher sensitivity in the rational model is that the borrowing behavior is much more responsive to the borrowing constraint than the behavior of biased agents (as seen in the distributions of liquid assets). Figure 12(b) displays the relative MPC of low income households and high income households, our measure of the transfer multiplier for fiscal stimulus programs. The ratio increases as the borrowing

Figure 12: MPC out of unexpected transfer as a function of borrowing limit

(a) average MPC (b) MPC low/high income



Note: The figure depicts the relationship between the MPC and the borrowing limit. The size of the transfer is 1% of median income and the borrowing limit is on a grid from zero to a full median annual income. Subfigure (a) shows the average MPC and subfigure (b) the ratio of the MPC of low income households over the MPC of high income households.

limit is tightened. This implies that the MPC of low income households increases more than the MPC of high income households. Thus, while tightening the borrowing constraint can increase the average MPC, it comes at the cost of worsening the fit of the relative MPCs. The model hence increasingly overpredicts the effectiveness of stimulus payments as the borrowing constrained is tightened. This undesirable effect is particularly strong if the model does not allow for biased income expectations.

Admittedly, the quantitative results in this section are model and parametrization specific. Nevertheless, it shows that allowing for biased income expectations is qualitatively different to tightening the borrowing constraint in a rational model. Moreover, we interpret the results in this section as a sign to be cautious when setting the parameters regarding borrowing constraints. Tightening the borrowing constraint can help to avoid large amounts of borrowing in a model with fully rational agents. At the same time, however, it can have strong effects on the consumption behavior that the model predicts.

5 Conclusion

In this paper we investigate the role of income expectations on consumption behavior of households. We document a systematic bias in income expectation, show how it can be formally incorporated into the process of expectation formation and investigate its implications for consumption-saving decisions in a quantitative model.

Using household level data from the Michigan Surveys of Consumers, we find that households with high income today tend to overestimate their future income and those with low income underestimate their future income. We argue that this feature of expectation bias can be explained by households overestimating the persistence of their income process. This overpersistence belief is consistent with the observation that people fail to sufficiently appreciate regression to mean. This observation is not new to behavioral economics and psychology (see Kahneman and Tversky (1973) and Kahneman (2012, chapter 17)). However, to the best of our knowledge this paper is the first to quantify the extent of the bias in income expectations and investigate its implications for consumption decisions using a quantitative model.

We find that income expectation biases of the magnitude seen in the data significantly affect the distribution of liquid assets in the cross section. While households with high income turn out to have similar portfolios of durable goods and liquid savings whether they have biased income expectations or not, this is not true for low income households. Low income households with biased beliefs are too pessimistic about their future income and are hence unwilling to borrow to smooth consumption. This prediction of the model with biased beliefs is in line with the distribution of liquid assets in the data. If we instead assumed households to have rational expectations the model would predict counterfactually large amounts of borrowing for low income households and for the population as a whole.

The paper further shows that accounting for income expectations is crucial when analyzing the effectiveness of stimulus payments. In the model with rational expectations, the MPC of low income households is too high relative to the MPC of high income households to be consistent with empirical estimates. On the other hand, allowing for biases in income expectations of the magnitude seen in the data leads to a model prediction of this ratio that is well within the range of values estimated for the stimulus payments in the U.S. in 2001 and 2008. If stimulus payments are financed through taxes (which are predominantly paid by high income households), stimulus payments are a form of redistribution. In this light the ratio between the MPC of low income households and high income households can be regarded as a measure of the first order effect in the transfer multiplier. Based on the present analysis we hence conclude that taking biases in income expectations into account is crucial when considering the use of stimulus payments.

We believe that our empirical finding opens an avenue for further research in two main areas. First, while the available data from the Michigan Surveys of Consumers allows us to document patterns in income expectation biases, the data set has an important limitation: it has only a very short panel dimension. This limitation makes it impossible to follow the same households and their expectations over time. Using the Michigan Surveys of Consumers we are therefore unable to investigate in detail the process of expectation formation and expectation updating. Other existing panel surveys do not include enough information to analyze expectation biases in individual income expectations.[36] To learn more about how income expectations are formed it thus seems very important to collect new data both on income expectations and on the corresponding realizations in a panel survey.

Second, our analysis shows that there are substantial movements in income expectation errors at the business cycle frequency. This suggests a role for income expectation errors for macroeconomic business cycle analysis. In the present paper we have focused on the cross-sectional patterns of expectation errors. In future work it would be interesting to study these business cycle movements in expectation errors and analyze the effects that household income expectations have for the amplification of other types of macroeconomic shocks.

[36]For example, the Italian Survey of Income and Wealth (SHIW) does not contain any overlap between the time period of the expectations and that of the realizations due to its biannual interview frequency. The Survey of Consumer Expectations of the Federal Reserve Bank of New York only collects income realizations in the form of income bins and the short tenure of each household in a rotating monthly panel precludes the analysis of expectation formation in individual income over time.

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A Further Details about Empirical Analyses

A.1 Sample Selection

The Michigan Surveys of Consumers interview around 500 households per month of which around one third are re-interviewed after 6 months. The time period that includes precise income information (previously income was only surveyed as bins) is July 1986 - December 2013. Overall, there are observations on 153,241 households (with or without re-interviews). We restrict the sample in the following way: (a) We only select households where the respondent is at most 65 years of age (excludes 30,701 observations). (b) We exclude observations with missing information on demographics (7,605 observations). (c) We exclude observations where the income is lower than the average unemployment benefits in that year (15,525 observations). (d) For households with re-interview we exclude households where the respondent changes between interviews (as identified by the demographics such as gender, age, education, marriage status and racial background, excludes 2,901 observations). Moreover, we exclude households where the number of adults changes between interviews (excludes 3,182 observations). This restriction is made since we are analyzing per adult income in the household, so that changes in the number of adults in the household will reflect changes in this measure of income that might not be anticipated by respondents when they are asked about their income growth expectations.

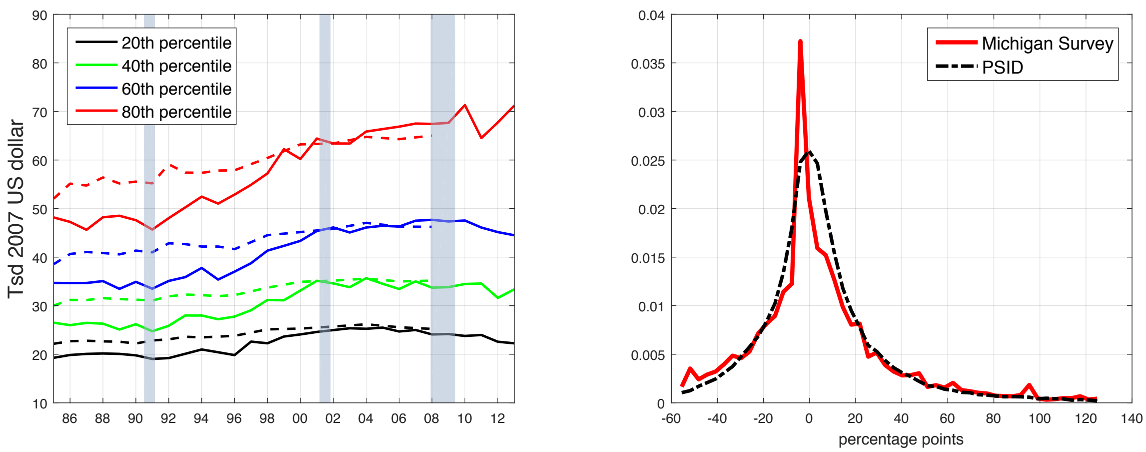
Overall, this leaves a sample of 88,017 households for which we have full information on demographics as well as inflation expectations (sample INF). 17,500 of these households are both first interviewed in the second half of a year and have a re-interview (sample H2RE). This is the sample for which we have information on realized income growth. Out of sample INF, 41,742 households also provide income expectations and are first interviewed in the first half a year (sample H1), 44,010 provide income expectations and are first interviewed in the second half a year (sample H2).

Figure 13 shows how the income information in our sample compares to the income information in the Panel Study of Income Dynamics (PSID). The PSID is a panel survey that has been running since 1968 which has been widely used to analyze income dynamics. Plot (a) shows that in the first part of the sample real per capita income in the Michigan Surveys is slightly lower than in the PSID. Since the late 1990s, however, the levels of income in both surveys are very similar. Note that we are not using the levels of income in our analysis. Instead, individual income growth rates are the center of our investigation. Plot (b) displays the distribution of these growth rates in the Michigan Surveys and in the PSID. The distribution of income growth is very similar in both surveys. The only difference is that in the Michigan Surveys more households report zero change in nominal income (around

15% of weighted observations, compared 2% in the PSID). To ensure that our results are not driven by these observations, we conduct a robustness check of our main analysis where we exclude all households that report zero income change (see appendix C.4). Our results hold and in fact become stronger once these observations are excluded.

Figure 13: Comparison with Income Panel Study of Income Dynamics

(a) percentiles (b) distribution of income growth



Note: The figure plots a comparison of reported income in the Michigan Surveys and in the Panel Study of Income Dynamics (PSID). Plot (a) shows the percentiles of per capita real income over time: solid lines refer to the Michigan Surveys distribution of income, dashed lines to the corresponding percentiles in the PSID. Plot (b) shows the distribution of real income growth rates in the Michigan Surveys and in the PSID. Since the PSID changed to biannual surveys in 1997, the income growth rates have been constructed from PSID data 1986-1996 only.

A.2 Details about the Imputation Procedure

To increase the overlap of expectations and realizations we impute income growth realizations using the information of households with similar household characteristics who report their income growth for the relevant period. In the example of figure 1, households interviewed for the first time between July 2002 and December 2002 report both their income in 2001 as well as their income in 2002. We can hence use their income in 2001 as well as all available household characteristics to predict their income growth 2001-2002. We then use this relationship to impute income growth 2001-2002 for all households interviewed for the first time in January 2002 to June 2002. The equation that we use to impute income growth realizations is the following:

$$g_{i,t+1} = \alpha + \beta X_{i,t} + \varepsilon_{i,t} \tag{19}$$

where $g_{i,t+1}$ is the growth rate in income of individual i from year t to year $t+1$ and $X_{i,t}$ includes a quadratic term in $\log(income_{i,t})$, a quadratic term in age, as well as indicators for education, gender, ethnic background, marriage status, number of adults, region, income growth expectations, inflation expectations and household weight in the survey. The imputation procedure is implemented as a multiple imputations algorithm using the predictive mean matching method with 5 nearest neighbors and 25 imputations. The imputation procedure is done separately for each survey year, using the observations from sample H2RE which report income changes for the respective year.

Figure 1(c) shows that for January households the overlap between expectation and imputed realization is now perfect. For February to June this overlap decreases but is still larger than the maximum overlap we obtain for July to December households on directly reported data. Moreover, for January to June households we do not need any re-interview so that we can use all observations in the data, not only the ones with re-interview. This greatly increases the sample size: We are able to obtain income growth realizations (and thus forecast errors) for the whole sample H1.

Furthermore, we can also increase the overlap for July to December households by imputing income changes for the following year. In the example of figure 1 we use the information provided by households interviewed for the first time in July to December 2003 to impute income growth 2002-2003 for the households first interviewed in July to December 2002. This increases the overlap between their expectations and imputed realizations. The largest overlap is 11 months for December households, which is close to perfect. Note that for this step we base the imputation on the income that households reported in their second interview. Unlike in the case of the sample H1, we are hence only able to impute income changes for households who have a re-interview. Combined with the imputed sample H1 this generates the main sample of forecast errors of 58,369 observations (sample MAIN). Table 4 shows the distribution of imputed individual income growth rates in this sample compared to the directly reported income growth rates in sample H2RE. The distribution in the imputed data is very close to the distribution of the original data.

Table 4: Distribution of real reported income changes and imputed values

	mean	p5	p25	p50	p75	p95
directly reported	0.034	-0.378	-0.097	-0.015	0.133	0.572
imputed	0.032	-0.365	-0.103	-0.016	0.130	0.577

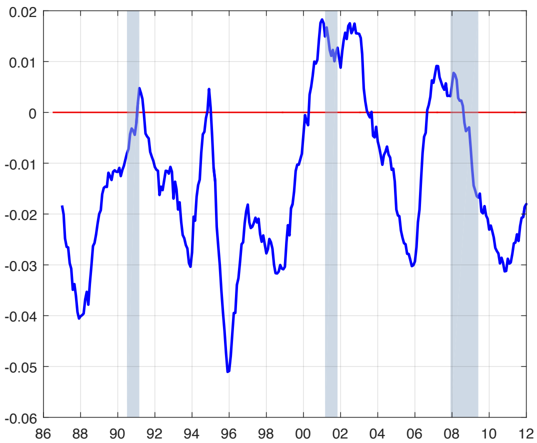
Note: The table compares the distribution of imputed individual growth rates in real income in sample MAIN with the growth rates in directly reported income in sample H2RE.

The main analyses reported in this paper are conducted on the sample MAIN where realized income growth has been imputed to maximize both the timing overlap and the number of observations. However, we have conducted robustness checks on the following subsamples: JAN (households with interview in January, income growth imputed, overlap perfect: 6,973 observations); DEC (households with first interview in December, income growth imputed, overlap close to perfect: 2,723 observations); JULY (households with interview in July, directly reported income growth, maximum overlap for directly reported data: 2,805 observations). Whenever imputed income growth is used, standard errors account for the additional uncertainty using multiple imputation procedures and standard errors based on Rubin (1987), Barnard and Rubin (1999) and Reiter (2007).

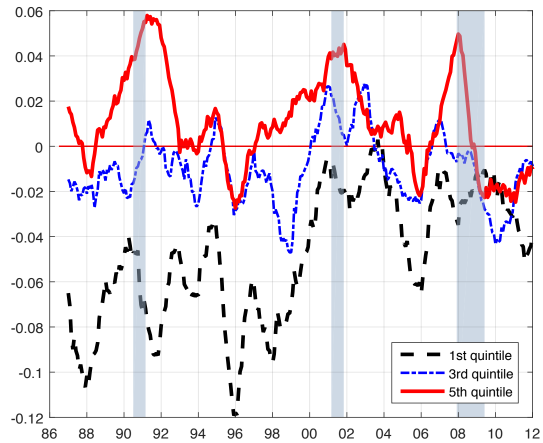
B Time Series Plots of Errors in Nominal Income

Figure 14: Expectation errors in nominal income growth

(a) mean



(b) mean by income quintile



Note: The figure plots the 12-month moving average of mean expectation errors in individual nominal income growth. Expectation errors are winsorized at 5% and 95%. Data from the Michigan Surveys of Consumers and own calculations. Grey areas represent NBER recessions. On the y-axis, 0.01 corresponds to 1 percentage point.

C Robustness Checks: Expectation Errors

C.1 Interaction with Age and Education

Table 5: OLS of forecast error on observables, interaction with education and age

	real	real	nominal	nominal
1st	-0.051^{***}	-0.057^{***}	-0.047^{***}	-0.054^{***}
	(0.007)	(0.010)	(0.007)	(0.010)
2nd	-0.017^{***}	-0.021^{**}	-0.016^{***}	-0.018^{*}
	(0.006)	(0.010)	(0.006)	(0.010)
4th	0.019^{***}	0.027^{***}	0.017^{***}	0.025^{***}
	(0.005)	(0.009)	(0.005)	(0.009)
5th	0.035^{***}	0.047^{***}	0.032^{***}	0.043^{***}
	(0.006)	(0.010)	(0.006)	(0.011)
no high school	0.013	0.023	0.019	0.030
	(0.014)	(0.027)	(0.014)	(0.028)
college	-0.014^{***}	-0.008	-0.017^{***}	-0.010
	(0.004)	(0.008)	(0.004)	(0.008)
age < 35	0.026^{***}	0.021^{**}	0.026^{***}	0.021^{**}
	(0.005)	(0.010)	(0.005)	(0.010)
$50 \leq$ age < 65	-0.013^{***}	-0.015	-0.014^{***}	-0.015
	(0.004)	(0.009)	(0.004)	(0.009)
1st $\times$ no high school		-0.019		-0.021
		(0.030)		(0.030)
2nd $\times$ no high school		-0.008		-0.011
		(0.034)		(0.035)
4th $\times$ no high school		0.015		0.013
		(0.037)		(0.038)
5th $\times$ no high school		0.020		0.021
		(0.045)		(0.046)
1st $\times$ college		0.005		0.003
		(0.013)		(0.013)
2nd $\times$ college		0.001		-0.000
		(0.012)		(0.013)
4th $\times$ college		-0.013		-0.011
		(0.011)		(0.011)
5th $\times$ college		-0.021^{*}		-0.021^{*}
		(0.012)		(0.012)
1st $\times$ age < 35		0.012		0.014
		(0.015)		(0.015)
2nd $\times$ age < 35		0.007		0.007
		(0.014)		(0.014)
4th $\times$ age < 35		-0.004		-0.005
		(0.012)		(0.012)
5th $\times$ age < 35		0.007		0.008
		(0.013)		(0.014)
1st $\times$ $50 \leq$ age < 65		0.010		0.010
		(0.015)		(0.015)
2nd $\times$ $50 \leq$ age < 65		0.005		0.003
		(0.014)		(0.014)
4th $\times$ $50 \leq$ age < 65		-0.003		-0.004
		(0.012)		(0.012)
5th $\times$ $50 \leq$ age < 65		-0.001		-0.001
		(0.012)		(0.012)
Month dummies	57498	57498	57498	57498

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The table shows the results from the multiple imputations OLS regression of equation (2) (dependent variable is error in either real or nominal income growth on the household level) with additional interaction terms of income quintiles with education and age groups. Additional regressors (coefficients not shown) are a constant, racial background, number of adults in the household, gender, marriage status as well as region and month dummies. Standard errors take the uncertainty induced by the imputation procedure into account.

C.2 Controlling for Cohort Effects

Table 6: OLS of expectation errors on household characteristics, controlling for cohort and time effects

	(1) real	(2) real	(3) real	(4) real	(5) nominal	(6) inflation
Income Quintile						
1 (low)	−0.051***	−0.046**	−0.047*	−0.077***	−0.048***	0.004***
	(0.006)	(0.018)	(0.027)	(0.021)	(0.007)	(0.000)
2	−0.017***	−0.013	−0.024	−0.039**	−0.016***	0.002***
	(0.006)	(0.017)	(0.024)	(0.020)	(0.006)	(0.000)
4	0.019***	0.026*	0.028	0.021	0.017***	−0.002***
	(0.005)	(0.013)	(0.024)	(0.016)	(0.005)	(0.000)
5 (high)	0.034***	0.045***	0.039*	0.064***	0.031***	−0.004***
	(0.006)	(0.015)	(0.022)	(0.017)	(0.006)	(0.000)
Education						
no high school	0.013	0.013	0.018	−0.002	0.019	0.002***
	(0.013)	(0.029)	(0.060)	(0.036)	(0.014)	(0.001)
college	−0.014***	−0.024**	−0.007	−0.036***	−0.017***	−0.002***
	(0.004)	(0.012)	(0.016)	(0.013)	(0.004)	(0.000)
Racial background						
black	0.019**	0.024	0.007	0.021	0.023***	0.002***
	(0.008)	(0.018)	(0.033)	(0.022)	(0.008)	(0.000)
hispanic	0.012	0.005	0.017	0.017	0.017*	0.003***
	(0.009)	(0.027)	(0.046)	(0.033)	(0.009)	(0.001)
Number of adults						
1	−0.025**	−0.003	−0.036	0.019	−0.025**	0.001**
	(0.009)	(0.026)	(0.039)	(0.042)	(0.010)	(0.001)
3 or more	0.018***	0.012	0.017	0.021	0.016**	−0.002***
	(0.007)	(0.018)	(0.029)	(0.022)	(0.007)	(0.000)
Other family characteristics						
female	−0.008*	−0.005	−0.007	−0.008	−0.002	0.005***
	(0.004)	(0.010)	(0.016)	(0.012)	(0.004)	(0.000)
not married	0.023**	0.003	0.033	−0.011	0.024**	0.000
	(0.009)	(0.024)	(0.035)	(0.041)	(0.009)	(0.000)
Region						
North Central	−0.022***	−0.023	−0.031	−0.021	−0.023***	−0.000
	(0.006)	(0.016)	(0.024)	(0.017)	(0.006)	(0.000)
Northeast	−0.020***	−0.021	−0.037	−0.005	−0.020***	0.001
	(0.006)	(0.017)	(0.027)	(0.018)	(0.006)	(0.000)
South	−0.018***	−0.014	−0.029	0.013	−0.017***	0.001**
	(0.006)	(0.016)	(0.024)	(0.016)	(0.006)	(0.000)
Constant	0.010	0.013	−0.051	0.114	0.000	−0.017***
	(0.052)	(0.084)	(0.111)	(0.093)	(0.054)	(0.002)
Sample	MAIN	JAN	DEC	JULY	MAIN	INF
Observations	58369	6973	2723	2805	58369	88017

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The table shows results from the multiple imputations OLS regression of equation (2), where the dependent variable is the household expectation error in real income (columns 1-4), in nominal income (column 5) and in inflation (columns 6). The regressions include cohort dummies and month dummies as additional control. Standard errors take the uncertainty induced by the imputation procedure into account whenever imputed data is used; without imputed data heteroskedasticity-robust standard errors are computed.

Table 7: OLS of expectation errors on household characteristics, controlling for age and cohort effects

	(1) real	(2) real	(3) real	(4) real	(5) nominal	(6) inflation
Income Quintile						
1 (low)	−0.052***	−0.047**	−0.049*	−0.078***	−0.048***	0.004***
	(0.006)	(0.018)	(0.027)	(0.021)	(0.007)	(0.000)
2	−0.017***	−0.011	−0.024	−0.038*	−0.015**	0.002***
	(0.006)	(0.017)	(0.024)	(0.020)	(0.006)	(0.000)
4	0.019***	0.026*	0.029	0.022	0.018***	−0.002***
	(0.005)	(0.013)	(0.024)	(0.016)	(0.005)	(0.000)
5 (high)	0.035***	0.045***	0.041*	0.065***	0.032***	−0.004***
	(0.006)	(0.015)	(0.022)	(0.017)	(0.006)	(0.000)
Education						
no high school	0.014	0.013	0.021	0.008	0.020	0.002***
	(0.013)	(0.029)	(0.059)	(0.036)	(0.014)	(0.001)
college	−0.014***	−0.024**	−0.007	−0.033**	−0.017***	−0.002***
	(0.004)	(0.012)	(0.016)	(0.013)	(0.004)	(0.000)
Age						
age	−0.003*	−0.000	−0.006	−0.006	−0.003	0.001***
	(0.002)	(0.004)	(0.007)	(0.005)	(0.002)	(0.000)
age × age	0.000	0.000	0.000	0.000*	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Racial background						
black	0.019**	0.024	0.008	0.019	0.023***	0.003***
	(0.008)	(0.018)	(0.033)	(0.022)	(0.008)	(0.001)
hispanic	0.013	0.006	0.017	0.014	0.018*	0.003***
	(0.009)	(0.027)	(0.046)	(0.034)	(0.009)	(0.001)
Number of adults						
1	−0.025**	−0.002	−0.037	0.024	−0.024**	0.002***
	(0.009)	(0.026)	(0.040)	(0.043)	(0.010)	(0.001)
3 or more	0.019***	0.012	0.018	0.027	0.017**	−0.002***
	(0.007)	(0.018)	(0.030)	(0.022)	(0.007)	(0.000)
Other family characteristics						
female	−0.008*	−0.006	−0.006	−0.010	−0.003	0.005***
	(0.004)	(0.010)	(0.016)	(0.012)	(0.004)	(0.000)
not married	0.023**	0.002	0.032	−0.017	0.023**	−0.000
	(0.009)	(0.024)	(0.036)	(0.042)	(0.009)	(0.001)
Region						
North Central	−0.022***	−0.023	−0.032	−0.023	−0.023***	−0.000
	(0.006)	(0.016)	(0.024)	(0.018)	(0.006)	(0.000)
Northeast	−0.020***	−0.021	−0.037	−0.007	−0.021***	0.001*
	(0.006)	(0.017)	(0.026)	(0.018)	(0.006)	(0.000)
South	−0.018***	−0.014	−0.029	0.012	−0.017***	0.001*
	(0.006)	(0.016)	(0.023)	(0.016)	(0.006)	(0.000)
Constant	0.085**	0.020	0.078	0.080	0.039	−0.062***
	(0.038)	(0.108)	(0.185)	(0.125)	(0.040)	(0.002)
Sample	MAIN	JAN	DEC	JULY	MAIN	INF
Observations	58369	6973	2723	2805	58369	88017

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The table shows results from the multiple imputations OLS regression of equation (2), where the dependent variable is the household expectation error in real income (columns 1-4), in nominal income (column 5) and in inflation (columns 6). The regressions include cohort dummies and indicators for the month of year of the interview as additional controls. Standard errors take the uncertainty induced by the imputation procedure into account whenever imputed data is used; without imputed data heteroskedasticity-robust standard errors are computed.

C.3 Subsample year 2000 and later

Table 8: OLS of expectation errors on household characteristics, sample year 2000 and later

	(1) real	(2) real	(3) real	(4) real	(5) nominal	(6) inflation
Income Quintile						
1 (low)	−0.031***	−0.026	−0.028	−0.013	−0.026***	0.005***
	(0.008)	(0.022)	(0.036)	(0.029)	(0.009)	(0.001)
2	−0.010	−0.007	−0.024	−0.010	−0.007	0.002***
	(0.007)	(0.022)	(0.033)	(0.026)	(0.008)	(0.001)
4	0.014**	0.017	0.017	0.038	0.013*	−0.002***
	(0.006)	(0.018)	(0.034)	(0.025)	(0.007)	(0.001)
5 (high)	0.025***	0.029	0.027	0.072***	0.020**	−0.005***
	(0.008)	(0.024)	(0.033)	(0.025)	(0.008)	(0.001)
Education						
no high school	−0.002	−0.023	0.032	0.015	0.000	0.000
	(0.021)	(0.051)	(0.094)	(0.038)	(0.021)	(0.001)
college	−0.011*	−0.021	−0.008	−0.016	−0.014**	−0.003***
	(0.006)	(0.015)	(0.021)	(0.019)	(0.006)	(0.000)
Age						
age	−0.004*	−0.003	−0.007	0.003	−0.004*	0.000***
	(0.002)	(0.004)	(0.009)	(0.007)	(0.002)	(0.000)
age × age	0.000	0.000	0.000	−0.000	0.000	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Racial background						
black	0.025**	0.045	0.002	0.028	0.026**	0.000
	(0.011)	(0.027)	(0.047)	(0.032)	(0.011)	(0.001)
hispanic	0.030***	0.021	0.024	−0.016	0.030***	0.000
	(0.011)	(0.035)	(0.061)	(0.046)	(0.012)	(0.001)
Number of adults						
1	−0.005	0.019	−0.038	−0.009	−0.004	0.001
	(0.012)	(0.034)	(0.049)	(0.057)	(0.012)	(0.001)
3 or more	0.017**	0.002	0.030	−0.010	0.015*	−0.002***
	(0.008)	(0.025)	(0.041)	(0.028)	(0.008)	(0.001)
Other family characteristics						
female	−0.009*	−0.004	−0.009	−0.002	−0.005	0.005***
	(0.005)	(0.013)	(0.020)	(0.016)	(0.005)	(0.000)
not married	0.008	−0.015	0.040	0.015	0.009	0.001*
	(0.011)	(0.031)	(0.043)	(0.054)	(0.012)	(0.001)
Region						
North Central	−0.019**	−0.018	−0.034	−0.003	−0.018**	0.000
	(0.009)	(0.021)	(0.030)	(0.024)	(0.009)	(0.000)
Northeast	−0.011	−0.014	−0.019	0.007	−0.011	0.001**
	(0.008)	(0.023)	(0.033)	(0.025)	(0.008)	(0.001)
South	−0.012	−0.013	−0.016	0.013	−0.010	0.002***
	(0.008)	(0.021)	(0.031)	(0.022)	(0.008)	(0.000)
Constant	0.120**	0.095	0.240	−0.064	0.107**	−0.018***
	(0.051)	(0.100)	(0.199)	(0.148)	(0.053)	(0.003)
Sample	MAIN	JAN	DEC	JULY	MAIN	INF
Observations	27279	3315	1252	1262	27279	40434

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The table shows results of the multiple imputations OLS regression of equation (2), where the dependent variable is the household expectation error in real income (columns 1-4), in nominal income (column 5) and in inflation (columns 6). The regressions include month dummies as additional controls and use only observations for sample of year 2000 and later. Standard errors take the uncertainty induced by the imputation procedure into account whenever imputed data is used; without imputed data heteroskedasticity-robust standard errors are computed.

C.4 Exclude observations with zero reported income change

Table 9: OLS of expectation errors on household characteristics, July only, observations with zero reported income change excluded

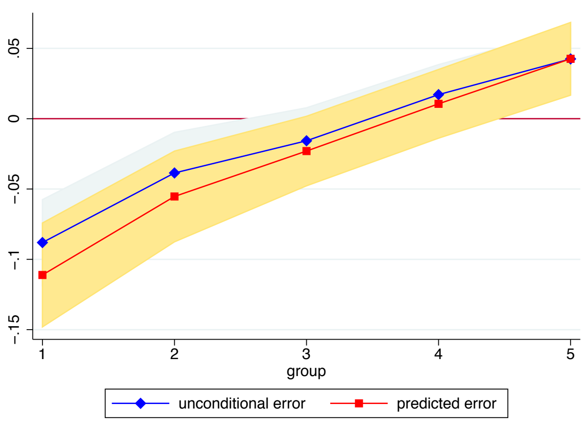
	(1) real	(2) real
Income Quintile		
1 (low)	−0.075***	−0.091***
	(0.021)	(0.025)
2	−0.038*	−0.040*
	(0.020)	(0.024)
4	0.025	0.032
	(0.016)	(0.020)
5 (high)	0.067***	0.083***
	(0.017)	(0.021)
Education		
educ=1	0.000	0.012
	(0.036)	(0.044)
educ=3	−0.032**	−0.047***
	(0.013)	(0.016)
Age		
age	−0.006	−0.008
	(0.004)	(0.005)
age × age	0.000	0.000*
	(0.000)	(0.000)
Racial background		
black	0.021	0.023
	(0.022)	(0.025)
hispanic	0.018	0.022
	(0.033)	(0.038)
Number of adults		
1	0.026	0.031
	(0.042)	(0.047)
3 or more	0.021	0.028
	(0.022)	(0.027)
Other family characteristics		
female	−0.006	0.004
	(0.012)	(0.014)
not married	−0.019	−0.028
	(0.040)	(0.045)
Region		
North Central	−0.020	−0.021
	(0.017)	(0.021)
Northeast	−0.005	−0.006
	(0.018)	(0.022)
South	0.013	0.017
	(0.016)	(0.020)
Constant	0.132	0.163
	(0.094)	(0.110)
Sample	JULY	JULY
Observations	2805	2244

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

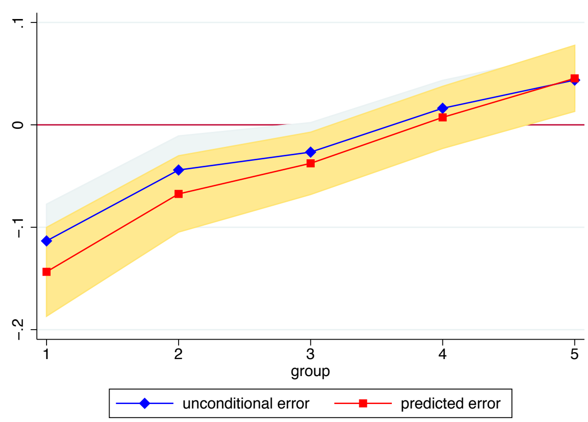
Note: The table shows results of the OLS regression of equation (2), where the dependent variable is the household expectation error in real income growth. Column 1 repeats the estimation on the full JULY sample (from table 1), column 2 excludes observations which report no change in nominal income. The regressions include month dummies as additional controls. Standard errors are heteroskedasticity-robust.

Figure 15: Expectation errors in real income by income quintile, JULY sample, with and without observations that report zero income change

(a) all households



(b) exclude no change



Note: The figure shows the unconditional mean expectation error (blue line, diamonds) and predicted expectation error (red line, squares) by income quintile. Predicted expectation errors are based on regression results from table 9. Predicted values computed for all other explanatory variables at the weighted sample mean. Bands refer to 95% confidence intervals (based on heteroskedasticity-robust standard errors). On the y-axis, 0.01 corresponds to 1 percentage point.

D Regression tables for error in aggregate unemployment expectation

Table 10: Ordered Logit / Ordered Probit of Unemployment Expectations

	(1) ologit	(2) oprobit
Income Quintile		
1st	−0.086***	−0.046***
	(0.023)	(0.013)
2nd	−0.032	−0.018
	(0.022)	(0.012)
4th	0.064***	0.036***
	(0.021)	(0.012)
5th	0.119***	0.069***
	(0.022)	(0.012)
Education		
no high school	−0.042	−0.017
	(0.039)	(0.022)
college	0.084***	0.048***
	(0.015)	(0.008)
Age		
age	−0.054***	−0.031***
	(0.005)	(0.003)
age × age	0.001***	0.000***
	(0.000)	(0.000)
Racial background		
black	−0.160***	−0.074***
	(0.029)	(0.016)
hispanic	0.078**	0.051***
	(0.035)	(0.020)
Number of adults		
1	−0.050	−0.025
	(0.030)	(0.017)
3 or more	0.083***	0.048***
	(0.024)	(0.014)
Other family characteristics		
female	−0.133***	−0.084***
	(0.014)	(0.008)
not married	−0.038	−0.024
	(0.028)	(0.016)
Region		
North Central	0.002	−0.002
	(0.020)	(0.011)
Northeast	−0.074***	−0.041***
	(0.022)	(0.012)
South	0.042**	0.023**
	(0.019)	(0.011)
Month dummies	yes	yes
Observations	96332	96332

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The table shows the results from the ordered logit and ordered probit regression of categorical errors in individual expectations about aggregate unemployment development. The ordered categories are as follows: -2: far too pessimistic, -1: too pessimistic, 0: correct expectation, +1: too optimistic, +2: far too optimistic. Standard errors are heteroskedasticity-robust.

E Regression tables for actual and expected income growth

Table 11: OLS of growth expectations on observables

	(1) actual growth (real)	(2) actual growth (nominal)	(3) expected growth (real)	(4) expected growth (nominal)
Income Quintile				
1st	0.124***	0.128***	0.017***	0.022***
	(0.011)	(0.011)	(0.002)	(0.002)
2nd	0.052***	0.054***	0.006***	0.009***
	(0.009)	(0.010)	(0.002)	(0.002)
4th	−0.044***	−0.045***	−0.001	−0.003**
	(0.007)	(0.008)	(0.002)	(0.002)
5th	−0.086***	−0.089***	0.003	−0.001
	(0.009)	(0.009)	(0.002)	(0.002)
Education				
no high school	−0.065***	−0.067***	−0.023***	−0.019***
	(0.017)	(0.017)	(0.003)	(0.003)
college	0.074***	0.076***	0.022***	0.019***
	(0.007)	(0.007)	(0.001)	(0.001)
Age				
age	0.007***	0.007***	−0.003***	−0.003***
	(0.002)	(0.002)	(0.000)	(0.000)
age × age	−0.000***	−0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Racial background				
black	−0.052***	−0.054***	0.011***	0.016***
	(0.011)	(0.011)	(0.002)	(0.002)
hispanic	−0.034***	−0.035***	−0.005	0.002
	(0.013)	(0.013)	(0.003)	(0.003)
Number of adults				
1	0.077***	0.078***	0.001	0.003
	(0.020)	(0.021)	(0.003)	(0.003)
3 or more	−0.050***	−0.052***	0.003	0.001
	(0.010)	(0.011)	(0.002)	(0.002)
Other family characteristics				
female	−0.024***	−0.025***	−0.020***	−0.013***
	(0.006)	(0.006)	(0.001)	(0.001)
not married	−0.066***	−0.067***	0.010***	0.009***
	(0.018)	(0.019)	(0.003)	(0.003)
Region				
North Central	0.001	0.001	−0.018***	−0.018***
	(0.009)	(0.009)	(0.002)	(0.002)
Northeast	0.013	0.014	−0.011***	−0.011***
	(0.010)	(0.010)	(0.002)	(0.002)
South	0.005	0.006	−0.009***	−0.008***
	(0.009)	(0.009)	(0.002)	(0.002)
Constant	−0.082*	−0.065	0.125***	0.160***
	(0.045)	(0.047)	(0.013)	(0.013)
Observations	18181	18181	89079	93764
R^2	0.039	0.040	0.046	0.047

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The table shows the results from the OLS regression of equation (2) where the dependent variable is either actual income growth (columns 1 & 2) or expected growth (columns 3 & 4) in real or nominal income on the household level. Estimation for actual income growth performed on all households with re-interview; the regression includes year dummies as additional controls. Estimation for expected growth performed on full sample of households (with or without re-interview (first interview if there are two interviews), all interview months); the regression includes month dummies as additional controls. Standard errors are heteroskedasticity-robust.

F Alternative Mechanisms

In this section we go through alternative mechanisms that could potentially generate the same pattern of expectation errors. We argue that none of them is consistent with the empirical results.

Learning One potential explanation could be that people need to learn about their income potential over time, so that young households could be expected to make larger errors than older households. While in the regressions in the main text we already control for age effects, it might still be the case that expectation errors vary systematically with age. Figure 16 shows the unconditional as well as the predicted expectation errors for different age groups (holding all other characteristics, including income, at their sample mean). Panel (a) shows that the unconditional mean error is hump-shaped in age. However, once all other characteristics are controlled for, expectation errors are in fact decreasing with age, indicating that people become more and more pessimistic with age. It is not the case that expectations would improve as households age. Moreover, panel (b) shows that there is no clear pattern in inflation expectations with regards to age. Based on this result we conclude that people do not seem to learn about their income potential over time.

Inability to distinguish between persistent and transitory shocks In the income process typically considered in the literature there are two types of idiosyncratic shocks which differ in their persistence. The first type of shock is persistent. The other type is completely transitory. Could an inability to distinguish between the two shocks generate the pattern of expectation errors that we observe in the data? If households cannot tell the shocks apart and observe only overall income, they have to rely on some form of filtering to form beliefs about the current state. From linear projection theory we know that Kalman filtering is (conditionally) unbiased and optimal for linear systems and normal shocks. Hence there cannot be a systematic error conditional on past income developments if people form their beliefs optimally.

A sketch of a formal proof is the following. Consider a simple state space model

$$x_t = \rho x_{t-1} + \eta_t \tag{20}$$

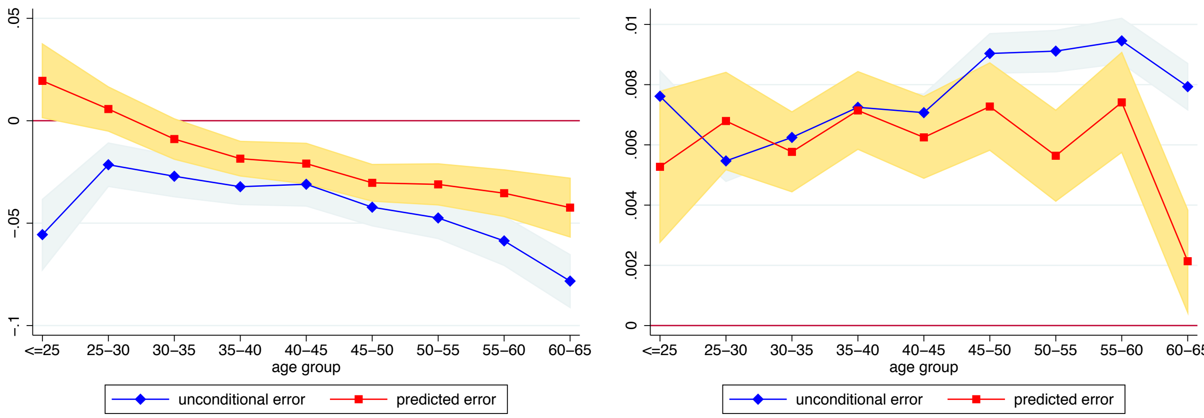
$$y_t = x_t + \mu_t \tag{21}$$

where η and μ are iid zero mean normal shocks with known finite variances. The forecasting error conditional on being in a particular quantile Q is $\mathsf{E}\big[y_{t+1} - y_{t+1|t} | y_t \in Q\big]$.

Suppose that t periods ago, the true state x_0 was known. It is then possible to write y_{t+1}

Figure 16: Expectation errors in real income by age group

(a) real income growth　　　　(b) inflation



Note: The figure shows the unconditional mean expectation error (blue line, diamonds) and predicted expectation error (red line, squares) by income decile. Predicted expectation errors are based on regression results from table 1 column 1 and 6, except that age is split into 5-year age groups instead of the quadratic term in age. Predicted values computed for all other explanatory variables at the weighted sample mean. Bands refer to 95% confidence intervals (for real income growth standard errors take the uncertainty induced by the imputation procedure into account; for inflation heteroskedasticity-robust standard errors are computed). On the y-axis, 0.01 corresponds to 1 percentage point.

as a function of starting state x_0, all previous η's and μ_{t+1}:

$$y_{t+1} = \eta_{t+1} + \mu_{t+1} + \rho\eta_t + \ldots + \rho^{t-1}\eta_1 + \rho^t x_0 \tag{22}$$

Similarly, $y_{t+1|t}$ can be written as a similar sum. However, now the noise terms μ also play a role because of imperfect information. It can be shown that

$$y_{t+1} - y_{t+1|t} = \eta_{t+1} + \mu_{t+1} + \rho\left[(1-K)\eta_t + K\mu_t\right] \tag{23}$$

where we assumed that the kalman gain K does not change over time.[37] The conditional forecasting error behaves similar to

$$\mathsf{E}\left[y_{t+1} - y_{t+1|t}|y_t\right] \approx \mathsf{E}\left[\eta_t - \mu_t \middle| \eta_t + \mu_t + \sum_{\tau=1}^{t-1}\rho^{t+1-\tau}\eta_\tau\right] \tag{24}$$

However, $\eta_t - \mu_t$ is independent of $\eta_t + \mu_t$ and because the shocks are not serially correlated, $\sum_{\tau=1}^{t-1}\rho^{t+1-\tau}\eta_\tau$ does not overturn the fact that the term in the expectations is independent of the condition. Hence the conditional forecasting error is equal to the unconditional, which is equal to zero.

[37] This approximation is better the bigger t is at exponential rate.

Table 12: Effect of Recent Experience on Growth Expectations

	(1) real	(2) real	(3) nominal	(4) nominal
past expectation	0.372***	0.374***	0.373***	0.374***
	(0.016)	(0.016)	(0.016)	(0.016)
past realized growth		−0.021***		−0.022***
		(0.004)		(0.004)
Income Quintile				
1st	0.004	0.007	0.007	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
2nd	0.002	0.003	0.004	0.005
	(0.004)	(0.004)	(0.004)	(0.004)
4th	−0.005	−0.006*	−0.005	−0.006*
	(0.004)	(0.004)	(0.003)	(0.003)
5th	−0.008**	−0.010**	−0.008**	−0.010**
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.061***	0.059***	0.070***	0.068***
	(0.022)	(0.022)	(0.022)	(0.021)
Observations	15931	15931	17210	17210
R^2	0.185	0.187	0.182	0.184

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: OLS estimation of individual growth expectations in 2nd interview as a function of past expectations and recent experience; estimation on sample 2HP (households with first interview in 2nd half of year and reinterview). Additional (unreported) control variables the same as in previous regressions: education, age, age^2, racial background, number of adults, gender, marriage status, region and time dummies. Standard errors are heteroskedasticity-robust.

Extrapolation from recent experience One explanation why current income can predict expectations about future income growth could be that people overweigh their recent experience. This would imply that households with a recent increase in income - which is correlated with being in a higher income group, all else equal - would expect another increase in the future.[38] We test for this explanation by regressing the growth expectations in the second interview on past expectations and recent experience (as well as on the other control variables we included in previous regressions). Table 12 shows that past expectations explain a large portion of current expectations, which means there is persistence in expectations on the individual level. The coefficient on recent experience, on the other hand, turns out to be significantly negative. This shows that households do not extrapolate from their recent experience. In fact, they seem to anticipate that there is mean reversion in their income process. Note, however, that the magnitude of this anticipated reversion is economically

[38]The relationship between expected income change and realized income change has been found to play a role in the analysis of Das and van Soest (1999).

small. We can hence exclude extrapolation from recent experience as an explanation of the systematic expectation errors by income groups.

Systematically wrong expectations about aggregates Another explanation for the observed pattern in expectation errors could be that households have biased expectations about aggregate conditions that vary systematically with their relative position in the income distribution. However, as seen in the analyses in the main text, household expectations about aggregate variables - such as inflation and the unemployment rate - are too pessimistic across the whole income distribution. Moreover, the magnitude of this bias doesn't vary much with income groups. Expectation errors in aggregate variables thus cannot explain the shift from overpessimism to overoptimism we observe as we move along the income distribution.

Measurement Error Since the empirical results are based on survey data we want to ensure that measurement error in reported variables is not the cause for the observed patterns. To do this we simulate an income process with persistent and transitory shocks as in the main text[39] and allow for four types of measurement error: errors in either the reported level income or the reported expectation in income growth, and each of these errors can either be an additive error or a multiplicative error. In detail, the information that is reported in the survey is assumed to have the following form:

$$\check{Y}_{it} = Y_{it} \cdot \xi^y_{it} + \varepsilon^y_{it} \tag{25}$$

$$\check{E}[g_{it}] = \frac{E[Y_{it+1}]}{Y_{it}} \cdot \xi^g_{it} + \varepsilon^g_{it} \tag{26}$$

$$\check{g}_{it} = \frac{\check{Y}_{it+1}}{\check{Y}_{it}} \tag{27}$$

where $\check{Y}_{it}$ and $\check{E}[g_{it}]$ are the reported income and reported growth expectations, respectively. $\check{g}_{it}$ is the realized income growth obtained from the reported level income. The additive measurement errors are normally distributed, the multiplicative errors log-normally:

$$\varepsilon^y_{it} \sim N(0, \sigma^y_\varepsilon) \tag{28}$$

$$\varepsilon^g_{it} \sim N(0, \sigma^g_\varepsilon) \tag{29}$$

$$\xi^y_{it} \sim \log N(-0.5(\sigma^y_\xi)^2, \sigma^y_\xi) \tag{30}$$

$$\xi^g_{it} \sim \log N(-0.5(\sigma^g_\xi)^2, \sigma^g_\xi) \tag{31}$$

[39]The income process is the same as employed in the main text. The difference is that we abstract from aggregate shocks and simulate the process directly on annual frequency.

We proceed by computing the observed forecast errors:

$$\check{\psi}_{it} = \check{E}[g]_{it} - \check{g}_{it} \tag{32}$$

We regress these errors by OLS on indicators for income quintiles, which are in turn determined based on reported income:

$$\check{\psi}_{it} = \alpha + \beta_1 \check{D}^1_{it} + \beta_2 \check{D}^2_{it} + \beta_4 \check{D}^4_{it} + \check{D}^5_{it} + \epsilon_{it} \tag{33}$$

Tables 13-16 show the resulting predicted forecast errors for increasing magnitudes of measurement errors in each of the four cases. The tables also show the distribution of measurement errors by income quintile and compare the magnitudes to the average income or growth rate in the respective income quintile.

Table 13 and table 14 show the results for measurement errors in reported level income. The considered magnitudes of these errors range from a standard deviation of 5% to 30% compared to the standard deviation of persistent income shocks. This translates into substantial measurement errors which are up to about 40% and 26% of mean income in the lowest income quintile for additive and multiplicative errors, respectively. Regarding the forecast errors that the OLS regression would predict, the tables show that the signs of these errors are broadly in line with the empirical findings. Quantitatively, however, even for large variances of measurement errors, the forecast errors are an order of magnitude smaller than what is found in the survey data. Table 15 and table 16 show that even for large measurement errors in reported expectations, there is no systematic effect on forecast errors.

We hence conclude that measurement errors in reported level income might contribute to the observed pattern, but they can at most explain a small fraction of the effects. Measurement errors in reported growth expectations do not contribute to predicted forecast errors.

Other mechanism Brunnermeier and Parker (2005) describe a setting where agents find it optimal to have too optimistic expectations. Alternatively, it might be possible that in order to attempt high risk-high reward projects, one needs to underestimate the chances of failure. The overoptimism for high income households could then arise as a result of survival bias. However, neither of these mechanism can explain why low income households are on average too pessimistic in their expectations. Regarding the low income agents, if there is ambiguity about the true income process, they might find it optimal to form expectations under a worst-case belief (Gilboa and Schmeidler, 1989; Epstein and Schneider, 2003). However, this mechanism cannot explain the overoptimism of high income households.

Table 13: Effects of Additive Measurement Errors in Reported Income Levels

$\sigma_{\varepsilon^y}/\sigma_P$	Predicted Forecast Errors Income Quintile			Distribution of Measurement Errors 1st Income Quintile					3rd Income Quintile					5th Income Quintile				
	1st	3rd	5th	mean(Y)	min	5%	95%	max	mean(Y)	min	5%	95%	max	mean(Y)	min	5%	95%	max
0.05	-0.000	0.000	0.000	0.50	-0.03	-0.01	0.01	0.03	0.97	-0.04	-0.01	0.01	0.03	2.00	-0.03	-0.01	0.01	0.03
0.10	-0.002	0.000	0.000	0.50	-0.06	-0.02	0.02	0.06	0.97	-0.07	-0.02	0.02	0.06	2.00	-0.06	-0.02	0.02	0.07
0.15	-0.005	0.001	0.000	0.50	-0.10	-0.03	0.03	0.09	0.97	-0.11	-0.03	0.03	0.10	2.00	-0.09	-0.03	0.03	0.10
0.20	-0.009	0.001	0.001	0.50	-0.13	-0.04	0.04	0.12	0.97	-0.14	-0.04	0.04	0.13	2.00	-0.12	-0.04	0.04	0.13
0.25	-0.013	0.001	0.001	0.50	-0.17	-0.05	0.05	0.16	0.97	-0.18	-0.05	0.05	0.17	2.00	-0.15	-0.05	0.05	0.16
0.30	-0.019	0.002	0.001	0.50	-0.20	-0.06	0.05	0.18	0.97	-0.21	-0.06	0.06	0.20	2.00	-0.18	-0.06	0.06	0.20

Note: The table shows the effects of additive measurement errors in reported income levels. Column 1 shows the variation of the measurement error relative to the variation in persistent income shocks. Columns 2-4 show the the predicted forecast errors that result from running the main regression on simulated data. The remaining columns show the distribution of measurement errors for the different income quintiles and compare them to the mean income in the respective income quintile.

Table 14: Effects of Multiplicative Measurement Errors in Reported Income Levels

σ_{ξ^y}/σ_P	Predicted Forecast Errors Income Quintile			Distribution of Measurement Errors 1st Income Quintile					3rd Income Quintile					5th Income Quintile				
	1st	3rd	5th	mean(Y)	min	5%	95%	max	mean(Y)	min	5%	95%	max	mean(Y)	min	5%	95%	max
0.05	-0.000	0.000	0.000	0.50	-0.02	-0.01	0.00	0.02	0.97	-0.03	-0.01	0.01	0.04	2.00	-0.17	-0.02	0.02	0.19
0.10	-0.001	-0.000	0.000	0.50	-0.04	-0.01	0.01	0.04	0.97	-0.06	-0.02	0.02	0.06	2.00	-0.34	-0.04	0.04	0.38
0.15	-0.001	-0.000	0.001	0.50	-0.06	-0.02	0.01	0.05	0.97	-0.10	-0.03	0.03	0.09	2.00	-0.50	-0.06	0.06	0.58
0.20	-0.003	-0.000	0.001	0.50	-0.08	-0.02	0.02	0.07	0.97	-0.14	-0.04	0.04	0.12	2.00	-0.66	-0.08	0.08	0.78
0.25	-0.004	-0.001	0.002	0.50	-0.11	-0.03	0.02	0.09	0.97	-0.17	-0.05	0.05	0.15	2.00	-0.82	-0.10	0.10	0.97
0.30	-0.006	-0.001	0.002	0.50	-0.13	-0.03	0.03	0.10	0.97	-0.22	-0.06	0.06	0.18	2.00	-0.98	-0.11	0.12	1.18

Note: The table shows the effects of multiplicative measurement errors in reported income levels. Column 1 shows the variation of the measurement error relative to the variation in persistent income shocks. Columns 2-4 show the the predicted forecast errors that result from running the main regression on simulated data. The remaining columns show the distribution of measurement errors for the different income quintiles and compare them to the mean income in the respective income quintile.

Table 15: Effects of Additive Measurement Errors in Reported Growth Rate Expectations

$\frac{\sigma^2_{\varepsilon g}}{var(g)}$	Predicted Forecast Errors			Distribution of Measurement Errors														
	Income Quintile			1st Income Quintile					3rd Income Quintile					5th Income Quintile				
	1st	3rd	5th	mean(g)	min	5%	95%	max	mean(g)	min	5%	95%	max	mean(g)	min	5%	95%	max
0.01	0.000	0.000	0.000	1.30	-0.26	-0.07	0.07	0.22	1.06	-0.22	-0.07	0.07	0.22	0.87	-0.22	-0.07	0.07	0.23
0.02	0.000	0.000	0.000	1.30	-0.36	-0.10	0.10	0.31	1.06	-0.31	-0.10	0.10	0.31	0.87	-0.32	-0.10	0.10	0.33
0.03	0.000	0.000	0.000	1.30	-0.44	-0.12	0.12	0.37	1.06	-0.38	-0.12	0.12	0.38	0.87	-0.39	-0.12	0.12	0.40
0.04	0.000	0.000	0.000	1.30	-0.51	-0.14	0.14	0.43	1.06	-0.44	-0.14	0.14	0.43	0.87	-0.45	-0.14	0.14	0.46
0.05	0.000	0.000	0.000	1.30	-0.57	-0.15	0.15	0.48	1.06	-0.50	-0.15	0.15	0.49	0.87	-0.50	-0.15	0.15	0.52

Note: The table shows the effects of additive measurement errors in expected income growth. Column 1 shows the variation of the measurement error relative to the variation in income growth. Columns 2-4 show the the predicted forecast errors that result from running the main regression on simulated data. The remaining columns show the distribution of measurement errors for the different income quintiles and compare them to the mean growth rate in the respective income quintile.

Table 16: Effects of Multiplicative Measurement Errors in Reported Growth Rate Expectations

$\frac{var(\xi^g)}{var(g)}$	Predicted Forecast Errors			Distribution of Measurement Errors														
	Income Quintile			1st Income Quintile					3rd Income Quintile					5th Income Quintile				
	1st	3rd	5th	mean(g)	min	5%	95%	max	mean(g)	min	5%	95%	max	mean(g)	min	5%	95%	max
0.01	0.000	0.000	0.000	1.30	-0.43	-0.09	0.09	0.55	1.06	-0.33	-0.07	0.08	0.42	0.87	-0.35	-0.06	0.06	0.34
0.02	0.000	0.000	0.000	1.30	-0.59	-0.12	0.13	0.80	1.06	-0.44	-0.10	0.11	0.62	0.87	-0.48	-0.08	0.09	0.49
0.03	0.000	0.000	0.000	1.30	-0.71	-0.15	0.16	1.00	1.06	-0.53	-0.12	0.13	0.78	0.87	-0.58	-0.10	0.11	0.62
0.04	0.000	0.000	0.000	1.30	-0.81	-0.17	0.19	1.18	1.06	-0.60	-0.14	0.15	0.93	0.87	-0.65	-0.12	0.13	0.73
0.05	0.000	0.000	0.000	1.30	-0.90	-0.19	0.21	1.34	1.06	-0.65	-0.16	0.17	1.06	0.87	-0.72	-0.13	0.14	0.83

Note: The table shows the effects of multiplicative measurement errors in expected income growth. Column 1 shows the variation of the measurement error relative to the variation in income growth. Columns 2-4 show the the predicted forecast errors that result from running the main regression on simulated data. The remaining columns show the distribution of measurement errors for the different income quintiles and compare them to the mean growth rate in the respective income quintile.

G Proof of Results in Section 3.1

G.1 Theorem

Income (net of age effects and the effects of other demographics) follows the process

$$Y_{it} = P_{it} \cdot T_{it} \tag{34}$$

$$P_{it} = P_{it-1}^{\rho} \cdot N_{it} \tag{35}$$

where P_{it} is a persistent component and T_{it} a transitory shock. Persistent income depends on past persistent income and a persistent shock N_{it}. Both shocks are independently and log-normally distributed with mean 1.

We assume that $1 > \hat{\rho} = \rho + \varepsilon > \rho$, so that all relevant moments exist and are finite. Expected income next period in this case is equal to $\mathsf{E}[Y_{it+1}] = \mathsf{E}[P_{it+1} \cdot T_{it+1}] = \mathsf{E}[P_{it}^{\hat{\rho}} \cdot N_{it+1} \cdot T_{it+1}] = P_{it}^{\hat{\rho}}$. Therefore the expected growth rate in income is $\mathsf{E}\left[\frac{\Delta Y_{it+1}}{Y_{it}}\right] = \frac{P_{it}^{\hat{\rho}} - Y_{it}}{Y_{it}}$ and the actual growth rate is equal to $\frac{\Delta Y_{it+1}}{Y_{it}} = \frac{P_{it}^{\rho} \cdot N_{it+1} \cdot T_{it+1} - Y_{it}}{Y_{it}}$ The expectation error can hence be calculated as:

$$\begin{aligned}
\psi_{it} &= E\left[\frac{\Delta Y_{it+1}}{Y_{it}}\right] - \frac{\Delta Y_{it+1}}{Y_{it}} \\
&= \frac{P_{it}^{\hat{\rho}} - Y_{it}}{Y_{it}} - \frac{P_{it}^{\rho} \cdot N_{it+1} \cdot T_{it+1} - Y_{it}}{Y_{it}} = \frac{P_{it}^{\hat{\rho}} - P_{it}^{\rho} \cdot N_{it+1} \cdot T_{it+1}}{Y_{it}} \\
&= \frac{P_{it}^{\rho+\varepsilon} - P_{it}^{\rho} \cdot N_{it+1} \cdot T_{it+1}}{Y_{it}} = \frac{P_{it}^{\rho}}{Y_{it}} \left(P_{it}^{\varepsilon} - N_{it+1} T_{it+1}\right) \\
&= \frac{P_{it}^{\rho-1}}{T_{it}} \left(P_{it}^{\varepsilon} - N_{it+1} T_{it+1}\right)
\end{aligned} \tag{36}$$

The *average* expectation error is then equal to $\mathsf{E}[\psi_{it}] = \frac{P_{it}^{\rho-1}}{T_{it}} \left[P_{it}^{\varepsilon} - 1\right]$. P_{it} can be re-written as a combination of its mean of $\mathsf{E}P = 1 + \bar{P}$ and the deviation from the mean p_{it}: $P_{it} = 1 + \bar{P} + p_{it}$. The term $\bar{P}$ is the lognormal mean correction term.

Using this notation, the expected error becomes

$$\mathsf{E}[\psi_{it}] = \frac{\left(1 + \bar{P} + p_{it}\right)^{\rho-1}}{T_{it}} \left[\left(1 + \bar{P} + p_{it}\right)^{\varepsilon} - 1\right] \tag{37}$$

For big enough current P_{it} (namely $p_{it} > -\bar{P}$), the term in the brackets is positive. This means that agents with income above this threshold on average overpredict their future income growth.

How does the expected error change with current P_{it}? $\frac{\partial \mathsf{E}\psi_{it}}{\partial P_{it}}$ has the same sign as $\frac{\partial F(z)}{\partial z}$

where $F(z) = z^{\rho+\varepsilon-1} - z^{\rho-1}$. We have

$$\begin{aligned} F(z)' &= z^{\rho-1}[(\rho+\varepsilon-1)z^{\varepsilon} - (\rho-1)] \\ &\approx (\rho+\varepsilon-1)\left[z^{\varepsilon} - \frac{\rho-1}{\rho-1+\varepsilon}\right] \\ &= -(1-\rho-\varepsilon)\left[z^{\varepsilon} - \frac{1-\rho}{1-\rho-\varepsilon}\right] \end{aligned} \tag{38}$$

This expression is *positive* as long as $z^{\varepsilon} < \frac{1-\rho}{1-\rho-\varepsilon}$, that is as long as $z < \left(\frac{1-\rho}{1-\rho-\varepsilon}\right)^{1/\varepsilon}$. Because $\rho \gg \varepsilon$ and ε is close to zero, the expectation error is increasing in P_{it} until very very large values of current P_{it}. In the model calibration, we have $\rho = 0.9774$, $\varepsilon = 0.0057$, which translates into a threshold of $z \approx 1.4e22$.

G.2 Corollary

If the true income process is governed by equations (3) and (4) and the household overestimates the persistence of the process according to equation (5), the distorted expectation of next period's income is

$$\begin{aligned} E_t^{\theta}[\ln Y_{i,t+1}] &= \hat{\rho}\ln P_{i,t} \\ &= (\rho+\theta)\ln P_{i,t} \\ &= E_t[\ln Y_{i,t+1}] + \theta\cdot\sum_{s=0}^{\infty}\rho^s \ln N_{i,t-s} \\ &= E_t[\ln Y_{i,t+1}] + \theta\cdot\sum_{s=0}^{\infty}\rho^s\big(\ln P_{i,t-s} - E_{t-s-1}[\ln P_{i,t-s}]\big) \\ &= E_t[\ln Y_{i,t+1}] + \theta\cdot\sum_{s=0}^{\infty}\rho^{s-1}\big(\rho\ln P_{i,t-s} - \rho E_{t-s-1}[\ln P_{i,t-s}]\big) \\ &= E_t[\ln P_{i,t+1}] + \theta\cdot\sum_{s=0}^{\infty}\rho^{s-1}\big(E_{t-s}[\ln P_{i,t-s+1}] - E_{t-s-1}[\ln P_{i,t-s+1}]\big) \\ &= E_t[\ln Y_{i,t+1}] + \theta\cdot\sum_{s=0}^{\infty}\rho^{s-1}\big(E_{t-s}[\ln Y_{i,t-s+1}] - E_{t-s-1}[\ln Y_{i,t-s+1}]\big) \end{aligned}$$

H Simplified Setting: Model without Durables

The results from the main model also hold in a setting without durable goods. In this case the household optimization problem can be summarized as follows:

$$\max_{\{c_t\}_{t=0}^{\infty},\{s_t\}_{t=0}^{\infty}} \quad \sum_{t=0}^{\infty} \beta^t \, \mathsf{E}\big[U(c_t)\big] \tag{39}$$

$$\text{s.t.} \qquad c_t + s_t \leq R(s_{t-1}) + Y_t \tag{40}$$

$$R(s_t) = [1 + r\,(s_t)]s_t \tag{41}$$

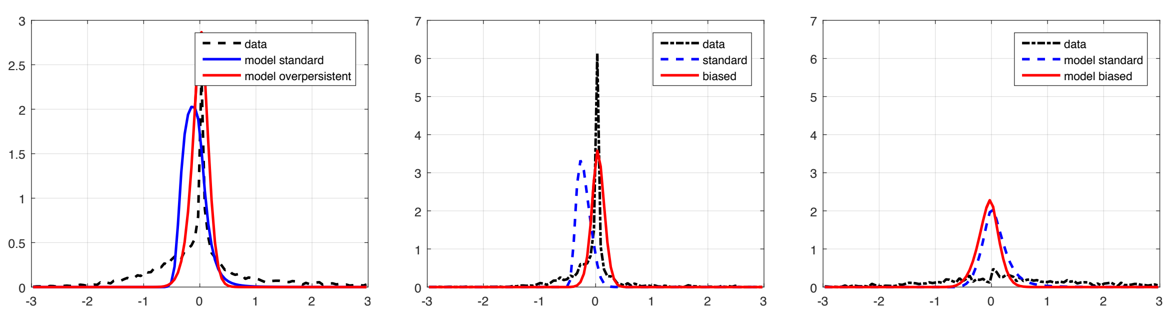
$$r(s_t) = \begin{cases} r^l & \text{if } \; s_t > 0 \\ r^b & \text{if } \; -\kappa_y P_t \leq s_t \leq 0 \end{cases} \tag{42}$$

$$U(c) = \frac{c^{1-\gamma}}{1-\gamma}. \tag{43}$$

Income Y_t has the same functional form as in the main setting (equations (7) - (10)). Moreover, expectation biases are also modeled in the same way as in the full model (equations (11) and (12)). We keep the same parameter values as in the main setting.

Figure 17: Distribution of liquid assets in model without durables

(a) aggregate (b) lowest income (c) highest income

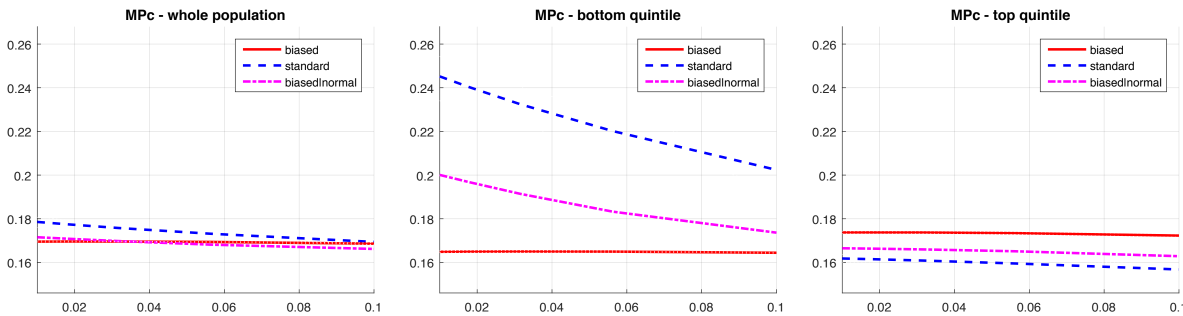


Note: The figure depicts the distribution of liquid assets in the simplified model versus data for the population as a whole and for different income quintiles. The panels show the data distribution (dashed black line) against the model distribution when households have non-rational expectations (solid red line). For comparison, the distribution under rational expectations is also plotted (solid blue line).

The first main implication of biased expectations in the main setting is that they reduce the borrowing of low income households. Figure 17 shows that this result holds in the restricted setting without durable goods. Households with biased beliefs are less willing to borrow than their rational expectations counterparts even though they face the same borrowing constraint. However, without the incentive to purchase durable goods households neither accumulate as much savings nor do they borrow as much as in the data. This simplified model hence retains the main result but has a worse model fit.

Figure 18: MPC out of unexpected transfer in recessions in model without durables

(a) aggregate (b) lowest income (c) highest income



Note: The figure depicts the fraction of an unanticipated one-time transfer payment of varying sizes that is spent on non-durable consumption under different expectation scenarios: the red line depicts the MPC under biased expectations, the dashed blue line depicts the MPC under rational expectations. Panel (a) shows the MPC in the aggregate population while panels (b) and (c) show the MPC for the lowest and highest income quintile. Transfer sizes are expressed as fractions of average quarterly income in the economy.

The second main implication of biased income expectations is that they alter the marginal propensities to consume. Under rational expectations, low income households have a MPC which is much larger than the MPC of high income households. In contrast, this ratio is smaller if people have biased income expectations. Figure 18 shows that this result also holds in the restricted setting without durables.

I Model Calibrated under Fully Rational Expectations

In this section, we choose the parameters to maximize the fit of the model with rational expectations and show that the results described in the main text still hold.

The only parameters which are free to be chosen differently compared to the benchmark model are the five parameters affecting the household preferences. The parameters describing the environment remain the same and the belief parameters are by assumption equal to the true process parameters.

Table 17: Parameter Values

Parameter		Value
preferences:		
discount factor	β	0.9875
risk aversion	γ	2
weight of durable goods in utility	θ	0.075
elasticity of substitution in utility	ξ	2.5
free durable services	$\bar{d}$	0.5

The resulting parameters are captured in table 17. Compared to the parametrization of the benchmark model with biased expectations, three parameters turn out to be different: the agents are more patient and more risk averse and there is less elasticity of substitution between durables and non-durable consumption. Figure 19 shows how well the fully rational model (and the corresponding version with biased expectations) fits the data. Table 18 summarizes the fit at selective quantiles.

Table 18: Model fit, standard model

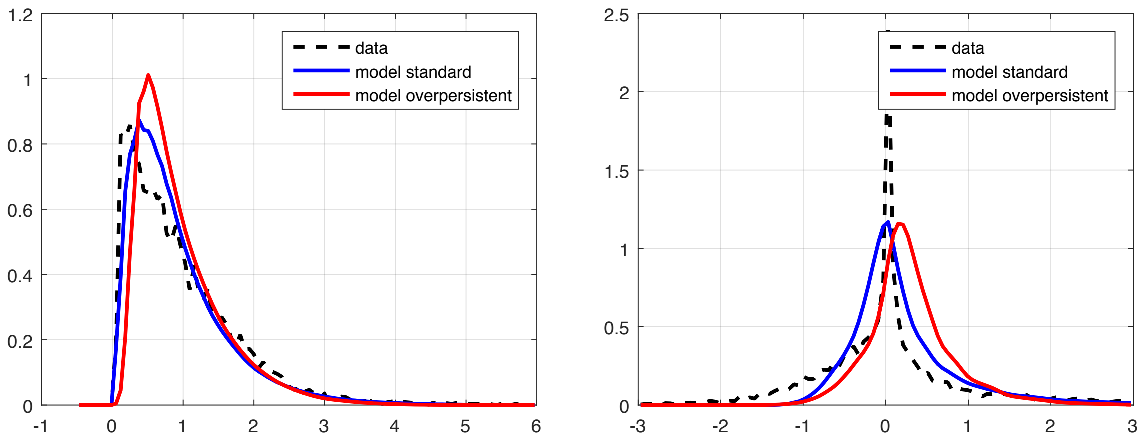
		quantile							mode
		0.05	0.10	0.25	0.50	0.75	0.80	0.90	
liquid assets	data	-1.29	-0.88	-0.30	0.03	0.76	1.36	5.46	-0.02
	model	-0.61	-0.45	-0.18	0.06	0.42	0.55	1.06	0.18
durables	data	0.13	0.20	0.39	0.79	1.43	1.62	2.21	0.23
	model	0.17	0.25	0.42	0.74	1.21	1.36	1.82	0.47

Note: Selected moments generated by the standard model compared to SCF.

Higher risk aversion combined with more patience makes the agents in the aggregate save more compared to the benchmark model. While the fit for the population as a whole is good, this specification remains to have counterfactual implications for liquid assets of low income households. Figure 20 shows that the model without rational expectations still generates too

Figure 19: Model fit, standard model parametrisation

(a) distribution of durable goods (b) distribution of liquid assets

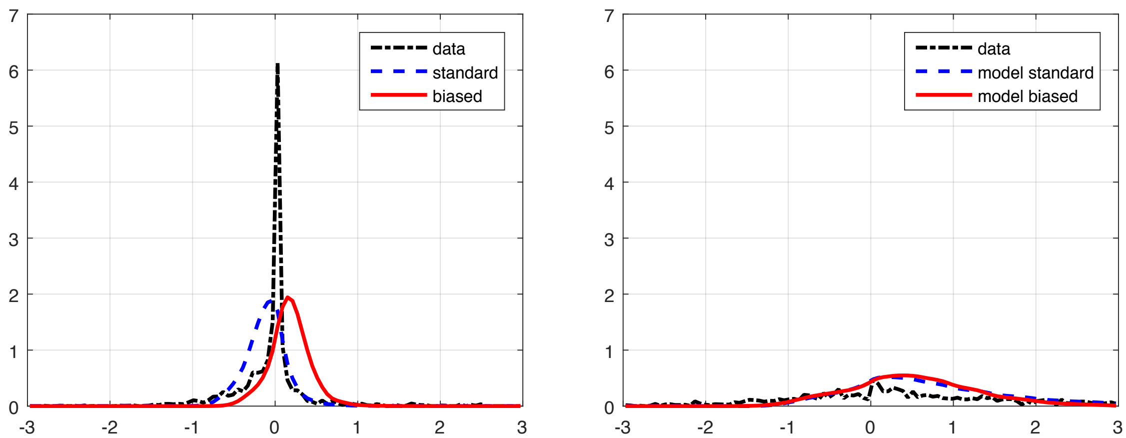


Note: The figure depicts the distribution for (a) durable goods and (b) liquid savings when the parameters are chosen to maximize the fit of the *standard* model. Data distributions (dashed black line) are compared to the distributions implied by model which allows for biased expectation (solid red line) and the model where expectations are assumed to be rational (solid blue line). The x-axis is normalized by the value of median quarterly income.

much borrowing for low income households, even though the preferences now lead to higher savings in the aggregate. Furthermore, the observation that the standard model generates much higher dispersion between the MPC of low and high income households also holds (see figure 21). The results described in the main text are hence robust to allowing the calibration to best fit the fully rational model to the data.

Figure 20: Liquid assets by income quintile (s), standard model parametrisation

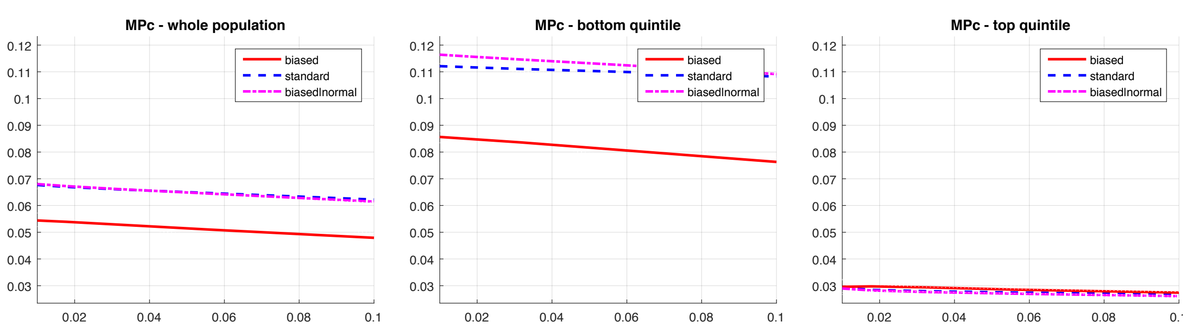
(a) 1st, rational versus both bias (b) 5th, rational versus both bias



Note: The figure depicts the distribution of liquid assets in the model versus data for different income quintiles when the parameters are chosen to maximize the fit of the *standard* model. The panels show the data distribution (dash-dotted black line) against the model distribution when households have non-rational expectations (solid red line). For comparison, the distribution under rational expectations is also plotted (dashed blue line).

Figure 21: MPC out of unexpected transfer in recessions, standard model parametrisation

(a) aggregate (b) lowest income (c) highest income



Note: The figure depicts the fraction of an unanticipated one-time transfer payment of varying sizes that is spent on non-durable consumption under different expectation scenarios: the red line depicts the MPC under biased beliefs, the dashed blue line depicts the MPC under rational expectations. Panel (a) shows the MPC in the aggregate population while panels (b) and (c) show the MPC for the lowest and highest income quintile. Transfer sizes are expressed as fractions of average quarterly income in the economy.

J Numerical implementation

J.1 Solution Algorithm

The model is solved using a value function iteration algorithm with Howard's Improvement. The solution of the rational agent's problem is standard. The policy functions of the agent with biased bieliefs are obtained in two steps. First, the problem is solved using the grid and transition matrices as if the biased beliefs were correct. After the solution converges, we do one more iteration of the value function iteration algorithm, now using the grid corresponding to the true data generating process, keeping the transition matrices and the continuation values $\mathsf{E}V'$ from the biased agent solution.

Including the discretization of the aggregate and idiosyncratic income components, we solve the model using the following grids:

- 120 grid points for liquid assets, unevenly spaced (step size smaller around zero)
- 90 grid points for durable assets, unevenly spaced (step size increasing with the level of durable asset)
- 15 states for the persistent idiosyncratic component P, levels and transition matrices generated using Rouwenhorst method
- 7 states for the idiosyncratic transitory component T, levels and probabilities generated using Gauss-Hermite Quadrature
- 2 states for the aggregate component Z, calibrated so the model delivers the same time spent in booms and recessions as the US economy.

Presence of the durable adjustment costs implies that the household has to decide whether to incur these costs and choose the optimal level of durable asset or let the durable good depreciate. In theory, in each step of the value function iteration, the values for both action and inaction have to be updated. Solving for the optimal action given adjustment is particularly costly, because it involves two-dimensional optimization. However, in practice it is not necessary to update both value functions at all grid points. If one keeps track of the boundary of the inaction region, both values only need to be updated in the neighborhood of the boundary. This step can lower the solution time considerably for well chosen grids, as the inaction region will occupy a large fraction of the state space.

J.2 Simulation

We obtain the distributions by simulating a panel of 125000 households for 1500 periods and discarding the first 500 observations. Using these 1000 periods, which include both booms and recessions as captured by the income component Z, we pool all the agents over all periods to construct the ergodic distributions.

To compute the marginal propensity to consume, we take all periods where the economy was in a recession, discard half and run the transfer experiment. We focus on the mean, because due to the non-linearity of the model, the actual consumption response is highly depending on other variables, both idiosyncratic (like the time since last durable purchase) and aggregate (the length of the recession) and hence vary for each individual in each recession.

J.3 Obtaining expectation errors in income growth

For all starting income levels $\{P, T\}_1$, we construct *all*[40] possible income path realizations and corresponding probabilities for 5 periods $\{P, T\}_1^5$. We then use this data in two ways. First, we use the first 4 periods of the income paths to construct income quintiles for the first year (the *annual* income in the first year Y^1 for a given realization is simply the sum of income in each quarter $Y^1 \equiv \sum_{t=1}^{4} P_t T_t$). This step also gives the probability distribution of $\{P, T\}_4$ conditional on being in a particular quintile of Y^1.

In the second step, we construct a second variable: annual income *conditional on the income state in the last quarter of the previous year*, Y^2. We do this by summing the income in periods two to five $Y^2 \equiv \sum_{t=2}^{5} P_t T_t$, remembering the corresponding probability and the starting state $\{P, T\}_1$. Again, we compute all possible values of Y^2 and the corresponding probabilities.

Finally, we combine the two pieces of information. We construct the growth rate as Y^2/Y^1, requiring that the last quarter of Y^1 is the same as $\{P, T\}_1$ used to compute Y^2. The expected growth rate conditional on being in a particular quintile is then computed by weighting all Y^2/Y^1 by the corresponding probabilities.

In order to find the belief parameters $\hat{\rho}$ and μ we proceed as follows: First we compute the expected growth rates for the true income process. Second, we iterate over guesses for $\hat{\rho}$ and μ until the implied expectation errors in growth rates correspond to the errors documented in the data.

[40] We discard any path with likelihood lower than $1e^{-9}$. The error in expectations introduced by this simplification is smaller than $1e^{-7}$.