Microfounding Household Debt Cycles with Extrapolative Expectations

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November 2022

Preliminary and incomplete. Please do not cite.

Abstract

Using transaction-level data uniquely paired with survey-based beliefs elicitation for the same consumers, we show that after unexpected positive income shocks consumers on average form excessively positive expectations about future income and debt capacity relative to ex-post realizations. They also raise debt to finance higher current spending, which increases their likelihood of default in the medium run. These effects are larger for lower-income consumers and consumers who face more volatile income streams. Consistent with a model of diagnostic income expectations featuring time-varying income volatility and with aggregate evidence about household debt cycles, the effects of extrapolative beliefs on spending, debt accumulation, and default are asymmetric following positive vs. negative income shocks—reactions are substantially larger after negative shocks relative to positive shocks of similar size.

Keywords: Extrapolative Beliefs, Income Expectations, Consumption, Debt Cycles, Household Surveys, Expectations Elicitation and Measurement, Income Volatility.

JEL codes: D14, D84, E21, E71, G51.

I Introduction

Since the Global Financial Crisis, there has been a burgeoning of the study about household debt cycle and economic fluctuations. The peaks of household debt predict eruption of economic crises across space and over time in the US (Mian and Sufi, 2014) and across other developed economies (Reuven and Lansing, 2010; Mian et al., 2017). When analyzing the drivers of household credit cycles, existing research supports a potential role for both shocks to the supply of finance to the household sector (Agarwal et al. (2017), Mian et al. (2020), etc.) as well as potential shocks to the demand for credit, which might be driven by ex-post incorrect expectations about aggregate and individual income (Bordalo et al., 2018; Bianchi et al., 2021; Chodorow-Reich et al., 2021).

Dissecting and studying these potential channels in aggregate observational data is empirically challenging. First, disentangling the role of shocks to credit supply and changes in the demand for credit is hard when considering country-level data on household debt and GDP growth. Moreover, testing directly for a potential role of rational or biased income expectations on households' debt accumulation requires observing individual level data that includes, at the same time, information about households' income flows, spending, and debt accumulation as well as direct elicitation of beliefs about future individual outcomes.

In this paper, we propose a unique setting that allows us to overcome these empirical challenges. Our setting builds on transaction-level bank-account information for a large population, which includes households' debt and spending decisions as well as their consumer-credit limits, income inflows, and demographic characteristics. The unique feature of this setting is the direct elicitation of individual income and debt capacity expectations through state-of-the-art surveys that were administered to the consumers across several survey waves for the same individuals. The data therefore provides a panel structure that enables us to study the dynamics of beliefs and debt within individuals. [1]

The setting in this paper allows us to measure a set of dimensions that are important

[1]For a recent review of survey-based research in economics, see Haaland et al. (2021). Examples in macroeconomics include Bachmann et al. (2013), Coibion et al. (2019), and D'Acunto et al. (2021b), among others.

to understand the role of income expectations formation on consumption and debt choices at the individual level. First, in each period we can measure not only consumers' income levels, but also the deviation between realized income levels and previous-period income expectations (contemporaneous unexpected income shocks). Second, we can assess the extent to which income expectations differ from future income realizations—a direct measure of the ex-post accuracy of consumers' income expectations. In this way, we can study how individual income expectations react when consumers face unexpected income shocks, and which consumption and debt decisions individuals make based on such expectations.

We start by showing that the income expectations of the average consumer in our data overreact to unexpected income shocks after both positive and negative shocks. Moreover, our quantitative measures of beliefs allow us to show that the size of this overreaction increases with the size of the part of the income shock that was unexpected. This form of extrapolative income beliefs survives when we control for a large set of individual-level demographics as well as within locations and within occupations, which we proxy with the industries in which individuals work. The size of the systematic expectations mistake is larger for lower-income consumers, for consumers who face more volatile income flows, and for younger consumers. Facing larger income shocks increases also the second moment of consumers' income expectations—an effect that looms larger for negative shocks than for equally sizable positive shocks.

To better understand the economic channels that drive these results and obtain additional predictions to test empirically, we propose a simple theoretical framework of the intertemporal consumption choice problem featuring extrapolative expectations. In the framework, we use the diagnostic-expectations formulation of Bordalo et al. (2018) as a microfoundation of consumer expectation-formation process. This choice is motivated by our results that consumers overreact to the unexpected component of income shocks, which suggests that they put excessive weights on the states of the world that have objectively become more representative of future states based on observed realizations. This finding directly matches the key characteristics of diagnostic expectations nicely.

In this framework, a larger deviation between expected future income and realized future income predicts higher consumption today and, when consumers are allowed to borrow to finance current consumption, higher borrowing and a higher likelihood of subsequent default. We find empirical evidence consistent with these three predictions: the larger is the difference between consumers' expected income and their realized future income, the larger is the present-day increase in spending and consumer debt borrowing and the higher is the likelihood of default in the medium run.

In terms of channels, we document that, after unexpected positive income shocks, consumers form excessive expectations not only about their future income but also about their debt capacity, which we proxy by computing the difference between their quantitative expectations about future credit limits and the actual observed subsequent limits on their consumer debt accounts. Excessive expected debt capacity induced by extrapolative income expectations is therefore likely to contribute to explain consumers' higher debt accumulation after positive unexpected income shocks.

Once augmented with time-varying income volatility, the theoretical framework predicts that the consumption responses to unexpected income shocks should be asymmetric around zero: negative shocks should loom more than same-size positive shocks—a prediction for which we also find evidence in our data. Documenting this fact at the individual level is important to microfound the aggregate dynamics of household debt cycles with inaccurate beliefs, as existing literature shows that the buildup of spending and borrowing in times of positive GDP growth shocks is slower than the sudden drop in spending and borrowing after negative aggregate shocks (Mian, Sufi, and Verner (2017)).

Overall, our results provide direct micro-level evidence of a demand-side channel that might help explain the dynamics of household debt cycles across space and over time: the average consumer forms systematically excessive beliefs about future income when facing unexpected positive income shocks. He/she consequently raises more debt to finance higher current spending and, once subsequent income does not reach the expected levels, he/she is more likely to default.

Given the panel structure of the data, we can isolate the effects of misbelief by exploiting the emergence of idiosyncratic income shocks across consumers who make decisions at the same point in time by using within-individual variation in expectations and outcomes over time. Because we observe elicited expectations and outcomes for the same individual over time, our empirical analysis can also abstract from aggregate shocks that affect all consumers at the same point in time, such as the COVID-19 pandemic, which falls within our sample period. At the same time, the individual-level channel we document can be important to understand aggregate household debt cycle dynamics around economy-wide shocks: in the aggregate, in times of positive GDP growth more and more consumers might face unexpected income shocks and hence, through extrapolative income expectations, a larger fraction of consumers increase consumption and debt accumulation. To the contrary, in times in which GDP growth turns negative, more and more consumers face unexpectedly negative income shocks, drop their consumption and borrowing, and are more likely to default.

Note that our paper does not argue that supply-side channels are irrelevant to explain the dynamics of household debt cycles. To the contrary, credit limits and, more broadly, consumers' debt capacity are determined not only by consumers' income but also by banks' credit decisions. For instance, Aydin (2022) and Yin (2022) study the impact of such decisions on credit uptake and consumer spending in which increases in credit card limits are randomized. Moreover, we use the diagnostic-expectations framework in our setting because such framework is portable to various theoretical and empirical applications in economics, but we do not argue that diagnostic expectations are the only theoretical underpinning of the expectations-formation process that can be consistent with our results. Other forms of extrapolative expectations might also be consistent with some or all our results (for instance, see Barberis et al. (2018) and Barberis (2018)).

This study mainly contributes to three strands of literature. First, it contributes to the study of the drivers of credit cycles. The theoretical explanations usually fall into two categories. On the one hand, works by Kiyotaki and Moore (1997), Gertler and Kiyotaki (2010), He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), He and Krishnamurthy (2019), Li (2019), and Mian et al. (2020) point out the importance of financial frictions in the corporate and household sectors as an amplification mechanism that induces cycles in credit supply. On the other hand, Gorton and Ordoñez (2014) and Dang et al. (2020) posit that beliefs could change when the incentives of producing information over time, thereby inducing swings in asset prices and macroeconomic fluctuations. In addition, Bordalo et al. (2018), Bianchi et al. (2021), and Bianchi et al. (2021) suggest that consumer extrapolative expectation-formation process could generate credit cycles. In addition, Krishnamurthy and Li (2020) calls for the importance of both financial frictions and beliefs in explaining credit fluctuations.

On the empirical side, assessment of credit cycle fluctuations mainly focuses on macro or regional level data to suggests the relationship between credit supply shocks or sentiment and leverage (See Bordo et al. (2001), Borio and Lowe (2002), Claessens et al. (2010), Reinhart and Rogoff (2009), Borio and Lowe (2013), Jordà et al. (2013), Baron and Xiong (2017), Greenwood et al. (2020), Krishnamurthy and Muir (2017), Mian and Sufi (2018), Mian et al. (2020), and Baron et al. (2020) for some examples). In this study, we focus on the household sector, and contribute to this literature by providing the micro-evidences in a panel structure about how unexpected income shocks could induce over-reaction about future income, which leads to over-reactions in total borrowing and default rate. The findings therefore posit the importance of borrower misbelief as an important demand-side driver of credit cycle.

This study also contributes to the rich literature of marginal propensity to consume out of income shocks (Parker et al., 2013; Fuster et al., 2020; Kueng, 2018; Olafsson and Pagel, 2018; Baugh et al., 2021; Fagereng et al., 2021)[2]. While most previous literature directly looks at the relationship between shocks to income and consumption, we contribute the this literature by offering direct evidences on income shocks affecting consumption through a misbelief channel. In addition, by matching with transaction-level data with debt information, we contribute the current literature by also providing evidences on the effects of incomes shocks on borrowing and default decisions.

Lastly, this paper contributes to a growing literature focusing on the role of beliefs in explaining consumer spending-saving decisions (see DellaVigna (2009) and Benjamin (2019) for a review). For example, Ameriks et al. (2016), Ameriks et al. (2020), and Ameriks et al. (2020) have provided recent advances by linking survey evidence to retirement choices. Manski (2004a), Ameriks et al. (2020), and Giglio et al. (2021) study

[2]See Attanasio and Weber (2010) and Jappelli and Pistaferri (2010) for a review before 2010.)

the relationship between investor beliefs and stock investment. Bucks and Pence (2008), Bailey et al. (2019), and Kuchler et al. (2022) analyze how beliefs affect mortgage leverage choices. Our work builds on this literature by exploring a quantitative survey matched to transaction-level data on consumer spending-saving decisions. Our survey, designed to directly elicit income beliefs for the same consumers over several periods, offers direct evidences about the relationship between beliefs and decision-making within individuals.

II Theoretical Framework

Before describing our empirical setting and results, we propose a simple theoretical framework to clarify the assumptions that, in a partial equilibrium intertemporal consumption optimization problem with extrapolative expectations, produces the three predictions we test in the data.

A. Intertemporal Consumption Optimization with Extrapolative Expectations

We consider the standard lifetime consumption optimization problem of a consumer whose preferences display constant absolute risk aversion (CARA) subject to a standard budget constraint. In each period, subjects' wealth depends on the previous period's savings and income:

$$\max_{c_t} E_0 \left[-\frac{1}{\gamma} \sum_{t=0}^{\infty} \beta^t e^{-\gamma c_t} \right].$$

$$s.t. \quad a_{t+1} = R(a_t - c_t + y_t).$$

Moreover, we assume that income evolves as an AR(1) process that follows:

$$y_{t+1} = y_t + \epsilon_{t+1},$$

where ϵ_{t+1} is a normal error that follows $N(0, \sigma^2)$. A neoclassical agent would form rational expectations over this income process. Instead, an agent with extrapolative expectations would overweighs the most recent news about income. In particular, we consider a diagnostic-expectations agent, who would overweigh the most recent news about income because such news provide information about states of the world that have objectively become more likely after such contemporaneous news. This intuition captures the *kernel of truth* feature of the representativeness principle, which microfounds diagnostic expectations in settings such as Bordalo et al. (2018).

To capture this feature of diagnostic expectations in a simple reduced form, we assume that the representative consumer puts a positive weight ($\theta > 0$) on contemporaneous income shocks when forming expectations about future income, which implies the following law of motion of income[3]:

$$y_{\theta,t+1} = y_t + \theta\epsilon_t + \epsilon_{t+1}. \tag{1}$$

The first order conditions with diagnostic expectations imply a closed-form optimal value of current consumption. Relative to the neoclassical version, consumption rule is augmented so that it also depends on current unexpected income shocks (news relative to past expectations, ϵ_t):

$$c_t = \frac{r}{R}a_t + y_t - \frac{\log(\beta R)}{r\gamma} - \frac{\gamma\sigma^2}{2r} + \frac{\theta}{r}\epsilon_t. \tag{2}$$

With the additional term relative to the standard neoclassical first-order condition, current consumption of an agent with diagnostic expectations will be higher than a neoclassical agent's if current unexpected income shocks are positive ($\epsilon_t > 0$) and lower otherwise. We hence have the following proposition:

Prediction 1 (Consumption). *For a diagnostic-expectations agent, current unexpected positive income shocks increase the amount of current consumption relative to a neoclassical agent, whereas current unexpected negative income shocks reduce it. These differences increase with the size of the shock.*

[3]The detailed derivation of the functional form based on diagnostic expectation follows directly from Bordalo et al. (2018).

Because agents can borrow to finance current consumption at the expense of future wealth in this setting, higher consumption after unexpected positive income shocks implies higher borrowing and current debt for borrowers. We thus also assess the probability that a diagnostic-expectations agent default on his/her debt relative to the neoclassical counterpart. Given the standard budget constraint, we can define the probability of default of the representative consumer as the probability that the growth wealth in the next period falls below an exogenous threshold (ψ)[4], which is distributed according to a standard normal distribution function:

$$\begin{aligned} p_{d,t+1} &= Pr\left(a_{t+1} + y_{t+1} < \psi\right) \\ &= \Phi\left(\frac{\psi - R(a_t - c_t + y_t) - y_t}{\sigma}\right). \end{aligned}$$

Because current consumption, c_t, is higher after unexpected positive income shocks than for a neoclassical agent, future wealth is lower and hence the likelihood that the sum of future wealth and future income falls below the default threshold is higher than for a neoclassical agent, ceteris paribus.[5] In particular, the larger the current unexpected positive income shock, the higher is the probability of default in this setting.

Prediction 2 (Debt and Default). *A diagnostic-expectations agents borrows more than a neoclassical agent after unexpected positive income shocks and faces a higher probability of default. These differences increase with the size of the shock.*

B. Introducing Time-Varying Income Volatility

So far, we have compared the consumption and borrowing choices of a diagnostic-expectations consumer relative to a neoclassical consumer in a setting in which income

[4]The simple framework doesn't allow for strategic default. Consumer default choice is assumed to follow a threshold rule over the amount of saving, ceteris paribus. This assumption is motivated by the micro-foundation of previous literature that studies household debt and default behaviors (e.g., Livshits et al. (2007)). When the value of defaulting does not change with the amount of debt, and the value of repaying is decreasing in the debt level, then the default decision follows a simple threshold rule over total wealth.

[5]The opposite is true if the diagnostic-expectations agent faces an unexpected negative income shock.

followed a simple AR(1) process. Because all the differences between these two agents boil down to the assumptions we make about the dynamics of income, and hence income expectations, assessing the role of diagnostic expectations in a setting in which income follows a law of motion that is closer to what earlier research has documented in observational data is important.

One feature earlier research based on micro-level data has documented is the presence of time-varying volatility in individual-level life-cycle income (for instance, see Guvenen and Smith (2014); Fagereng et al. (2018); Chang et al. (2021)). Below, we show that incorporating this feature in our simple setting provides richer predictions on the differences between diagnostic-expectations agents and neoclassical agents' consumption choices. To see this, we assume that income follows the following rule in which volatility increases with the size of current income shocks, which are distributed according to a standard normal distribution:

$$
\begin{aligned}
y_{t+1} &= y_t + \sigma_{t+1}\epsilon_{t+1} \\
\epsilon_{t+1} &\sim N(0,1) \\
\sigma^2_{t+1} &= \alpha_0 + \alpha_1(\sigma_t\epsilon_t)^2.
\end{aligned}
$$

With the restriction that[6]

$$
\omega_t = 1 + \frac{\alpha_1}{\alpha_0}(\sigma_t\epsilon_t)^2 < \left(1 + \frac{1}{\theta}\right)^{\frac{1}{2}}.
$$

Then the expectations of future income of a diagnostic-expectations agent follows

$$
\begin{aligned}
E_t[y_{\theta,t+1}] &= E_t[y_{t+1}] + \tilde{\theta}\left(y_t - E_{t-1}[y_t]\right) \\
\sigma^2_{\theta,t+1} &= \sigma^2_{t+1}\frac{1}{1-\theta(\omega_t^2-1)} \\
\tilde{\theta} &= \theta\frac{\omega_t^2}{1-\theta(\omega_t^2-1)}.
\end{aligned}
$$

[6]This condition ensures that the variance does not increase excessively, and thus diagnostic expectations are normalizable. This condition always holds in the limit of rational expectations. See Bordalo et al. (2018) for more details.

We can thus write the dynamics of income for a diagnostic-expectations agent as follows:

$$y_{\theta,t+1} = y_t + \tilde{\theta}\epsilon_t + \epsilon_{\theta,t+1},$$

and the first order conditions from the Euler equation imply the following closed form expression for optimal current consumption:

$$c_t = \frac{r}{R}a_t + y_t - \frac{\log(\beta R)}{r\gamma} - \frac{\gamma\sigma^2_{\theta,t+1}}{2r} + \frac{\tilde{\theta}}{r}\epsilon_t. \tag{3}$$

We can see that in this case higher current-income volatility, σ^2_t, increases both $\sigma^2_{\theta,t+1}$ and $\tilde{\theta}$ and hence negative realizations of ϵ_t reduce optimal current consumption by more than equally sized positive realizations increase it.

Prediction 3 (Asymmetry). *When facing time-varying income volatility, a diagnostic-expectations agent cuts current consumption after negative unexpected income shocks by more than he/she increases current consumption after equally-sized positive unexpected income shocks.*

III Institutional Setting and Data

We collaborate with a Chinese national-level commercial bank to obtain transaction-level information on a large representative sample of consumers from whom we also elicit a set of individual-level economic expectations through multiple survey waves. The bank operates nationally and is among the top 10 commercial banks in China by total assets. In 2020, the bank's total assets amounted to more than one trillion dollars. Because of the broad customer base such a financial intermediary accesses, the random sample for which we obtain data and elicit expectations is representative of the Chinese banked population.

A. Sample Restrictions

Consumers might have multiple bank accounts. As a result, single-provider transaction-level data sets raise concerns about the completeness of the data in covering the full extent of consumers' spending and cash savings.

To alleviate these concerns, we follow recent works using single-provider transaction-level data (e.g., see Ganong and Noel (2019)) and impose two restrictions on the accounts that enter our empirical analysis to capture consumers who are most likely to use the bank with which we collaborate as their primary banking institutions.

First, we only include in the sample consumers whose bank accounts include at least 15 outflow transactions during the sampling period. An outflow is any debit from a checking, saving, or credit card account, including a cash withdrawal, an electronic payment, or a card transaction. Imposing this criterion reduces the original sample by approximately 35%.

The second restriction we impose is that consumers' income can be identified and calculated directly the bank by observing regular inflows to the checking accounts, which amounts to a drop of the about 10% of the observations.

B. Measuring Income and Spending

The transaction-level data allows direct measurement of consumers' income inflows and spending outflows. In terms of income, we follow the steps the bank with which we cooperate uses, which identify individual income following a classification rule of regular inflows. The bank classifies income into three main categories: salary, business cash flows, and financial investment.

Salary is defined as the regular monthly income flow over the total of annual income flows and bonuses if the customer declares working as an employee. The bank calculates this number in one of two alternatives ways. First, if income is paid as a direct deposit from the consumers' employers to this bank, the number is directly labeled as salary in the bank's system. Otherwise, the bank can identify monthly income if the consumer's social security insurance is paid through this bank, which is a fixed portion of the consumer's income.[7] Removing customers whose income cannot be identified and computed with certainty drops the sample by another 10.3%.

As far as income from financial investment is concerned, the bank computes it as the difference between the total inflow and the total outflow from an investment account with the financial institutions. Instead, income from business operations is the difference between total inflow and total outflow when these transactions are categorizes as business operations.

When aggregating all incomes in our sample, the split of the three components is 62.33% from salary, 26.11% from business operations, and 11.56% from financial investment. We can directly verify that these figures are not only representative of the Chinese banked population but also accurately computed at the individual level by matching the income computations at the consumer-year level from the bank to individual-level data from the Chinese tax administrative agency. We report the results of this comparison in Panel A of Figure A.1. The figure is a bin scatter plot that compares, for the individuals in our sample, the income computed by the bank based on transaction-level data and under the assumptions discussed above and the income the same individuals report to the Chinese tax authority.

Moving on to the measurement of spending, we calculate consumer monthly total spending as the sum of all nondurable purchasing transactions from consumers' checking account plus the total amount of repayment of linked credit cards' end-of-month balances between the end of the last billing cycle and the current billing cycle. Debt is the outstanding interest-incurring balance on the credit card.

[7] In China, social security payments have six components: five types of insurance and a housing provident fund. The types of insurance are paid with a fixed proportion of workers' monthly income. One such insurance is retirement saving insurance, which is similar to the retirement savings plan in the US. With a monthly income of 5,000 CNY, the monthly contribution is 8%. However, the income base for social security is usually capped at the two tails of the income distribution. The numbers are different by geographic area but are usually at 30% and 300% or 40% and 400% of the previous year's average income in that area. Therefore, for those who earn more than 300% of the last year's average income in the area, the total monthly payment is equal to $8\% \times 300\% \times \bar{Y}$, where $\bar{Y}$ is the previous year's average income in the area. However, the uncapped distribution is wide enough to cover most of the workers in China. In the analysis, we remove the consumers in the capped region from the final sample.

C. Eliciting Expectations

To elicit consumers' expectations, we designed a short survey that the bank administered to the consumers in our sample. We report our English translation of the full survey (originally in mandarin) in Appendix I.

The survey starts with indicating its purpose of study. On top of the survey,consumers are informed that the survey is used for research purposes and to "understand the impact of credit cards on people's lives. [The answers] will not, in any way, change the types of financial products we provide". With this disclosure, the respondents are expected to not have any incentives to give answers that are not based on their true beliefs.

The survey first asks the participants to report their average income over the past six months. We use this survey for a sanity check of the data quality. If the consumers fill random answers, then we would expect that their answers to this question to be quite different from the numbers from the bank. Panel B of Figure A.1 is a binned scatter plot of income from the survey and that from the bank. The plot shows a clear linear relationship. A regression between the two variables yields a very large R^2 of around 72.56%. Therefore, the answers from the survey should have high qualities that reflect the participants' true beliefs.

We then elicit the expectations about individual economic outcomes. The questions are based on Survey questions 3 to 8. Our goal is to elicit numerical expectations about consumers' income as well as expected future credit-card limits, which proxy for expected future debt capacity. The elicitation of the first moment of consumer expectation is based on the following questions:

Q3: What would your total credit card limit most likely be in 6 months?

Q6: What would your average monthly income most likely be in the next 6 months?

Following recent research on subjective expectations, we aim to obtain measures not only of consumers' point estimates for these variables but also the full subjective distribution of beliefs across potential future states of the world (Manski (2004b)). We rely on the following questions:

Q4/5:What's the lowest/highest possible credit card limit you believe you could have in 6 months?

Q7/8: What would be the lowest/highest possible level of average monthly income you believe you would get over the next 6 months?

This elicitation style for the higher-moment belief avoids asking probability-distribution questions, as these types of questions are quite cognitive demanding. In this case, probability-distribution style questions could confound the measurement of actual beliefs with the measurement of cognitive abilities. This might affect outcomes in their own right (D'Acunto et al. (2019, 2021b)) – and are unlikely to be fully understood by the population in our setting.

For these reasons, we rely on the triangular question design recently proposed in economics (for instance, see Guiso et al. (2002); Christelis et al. (2020)). This design consists of asking respondents for a point estimate of the numerical value of the expected minimum of a variable, of the expected maximum, and the mean. This form of elicitation allows computing the second moment of individual-level subjective expectations after imposing the assumption that the distribution of beliefs is symmetric around the midpoint between the minimum and maximum possible expect values.

The survey is filed in two rounds, with each round contains two waves of surveys sent to the same participants. The first two waves of surveys were sent waves in January 2020 and July 2020, and the second two waves were sent waves in January 2021 and July 2021. In this way, the surveys cover consumer expectation over four six-month period. Given that the

We supplement each of the two rounds of surveys with consumer bank-account data over the same periods, and also one period before each of the two rounds of surveys. In the end, we have two three-period data. With data covering the same individuals for each round of data, we have variation in income and debt capacity beliefs within individual over time. This allows us to exploit within-individual variation in beliefs and economic outcomes to absorb systematic time-invariant unobserved characteristics, such as cognitive abilities and financial literacy. Moreover, with multiple years of data, we can assess our baseline predictions within time periods and hence after absorbing the effects of aggregate economic shocks that all consumers faced at the same point in time. This feature is important in our setting given that the early sample spans the times before and after the start of the COVID-19 pandemic as well as periods in which the pandemic had it utmost negative effect on economic outcomes (January to June 2020).

D. Summary Statistics

Table I gives the summary statistics in period 0 (January 2020 to June 2020). Panel A summarizes consumer demographic information, and panel B summarizes consumer expectation information from the surveys. All variables are converted to US dollars and are winsorized at 1% level. The average age of participants is around 38 years old; the average monthly income is around 2,000 dollars, and the average total savings is 18,000 dollars. The average credit limit elicited from survey question 10 is around 13,500 dollars, and the average outstanding interest-incurring debt is around 1,000 dollars and around 2,500 conditional on holding a positive amount of debt before the experiment. A simple calculation indicates that around 42% of the individuals in the sample held positive credit card debt. This proportion is similar to the range of 40% to 60% found in the previous literature using data in the US (Gross and Souleles, 2002; Zinman, 2009; Fulford, 2015).

IV Unexpected Shocks and Expectations

The main empirical challenge the econometrician faces when trying to bring the three predictions we propose to the data is the need of a consumer-level measure of unexpected shocks to income from one period to the other. Such information typically cannot be measured in standard observational data that do not include information on income expectations.

In our setting, we address this issue directly by measuring consumers' quantitative expectations of future income through our survey waves and observing their ex-post income realizations based on transaction-level data. In this way, at each point in time we have continuous measures of three crucial dimensions at the individual consumer level: (i) the realized (and observed by consumers) income changes between the previous period and the current period (ΔY_t); (ii) the unexpected news about current-period income ($Y_t - E[Y_t]$); and (iii) the deviation from current expectations of future income and actual realizations of future income ($E[Y_{t+1}] - Y_{t+1}$).

A. Extrapolative Income Expectations

These three measures allow us to test directly whether unexpected current income shocks determine a higher deviation of future income expectations from actual future income realizations. Hence we can test whether, on average, the income expectations of the consumers in our data are extrapolative like those of diagnostic-expectations agents. Running this test before moving to the predictions about economic decisions (consumption and debt) is important to assess whether our diagnostic-expectations interpretation has any scope in the data. That is, whether features of diagnostic expectations about income we can test in the data are corroborated by the data.

We first illustrate some motivating results about consumer income misbeliefs. Panel A of Figure 1 gives the binned-scatter plot of ex post realized income and ex ante income expectation as elicited from the survey. As shown by the figure, there is a close linear relationship between the realized income and the ex ante forecasts. This indicates that consumers' forecasts are on average very close to the realize values. However, Panel B plots the forecast errors. Despite a linear relationship between forecasted income and realized income, there is a quite wide distribution of the forecast errors. The standard deviation of the forecast errors is around 35% of the standard deviation of the distribution of income.

Figure 2 gives a binned-scatter plot of misbeliefs about next-period income and unexpected income shocks in the current period. Panel A gives the raw measures. In Panel B, we residualize both measures by a set of consumer characteristics. The plots show a clear positive relationship between shocks to current-period income and misbelief about future income. In addition, one pattern to note is that the positive relationship is quite linear and is not driven by any outliers.

We continue to estimate the effects of current-period income shocks on misbeliefs about next-period income. The regressions have the following specification:

$$E[Y_{i,t+1}] - Y_{i,t+1} = \beta(Y_{i,t} - E[Y_{i,t}]) + X'_{i,t}\delta + \eta_{k,j} + \eta_s + \epsilon_{i,t}, \tag{4}$$

where X is a vector of individual-level characteristics that include age and its square, education-level dummies, the number of weekly hours worked in period t, the logarithms of monthly income and credit-card limit levels in period t, which proxies for consumer's debt capacity, consumer expected income changes from period $t-1$ to t, and a full set of industry×round fixed effects ($\eta_{k,j}$) and city of residence (η_s) fixed effects. Our coefficient of interest is β, which measures the marginal relationship between current-period income shock and next-period expectation errors. As predicted by Proposition 1, β should be zero for an agent with rational expectations, but positive for an agent with extrapolative expectations.

Table II reports the results for estimating equation (4). Column (1) only includes the unexpected income changes in period t as the right-hand-side variable; column (2) adds in individual characteristics X as controls; column (3) controls fro the city fixed effects; and column (4) further controls the industry×round fixed effects. Across all columns, β is significantly larger than zero and are quite stable regardless of the controls. With all controls, the estimate of β is 0.308. This is to say, for a one-dollar unexpected income change in the current period, the consumers tend to over-estimate their income in the next period by around 31 cents. Mapped to (1), the estimate implies a θ of 0.31.

The results so far suggest that the average consumer in our data displays income expectations whose overreaction to unexpected income shocks is consistent with the notion of diagnostic expectations. If these patterns were attributable to diagnostic expectations, though, we should also observe substantial heterogeneity in the association between the size of observed income news and of the inaccuracy of expectations about future income across consumers. In particular, consumers who face more volatile incomes should overreact more to unexpected income shocks than others, because they are more likely to observe larger unexpected shocks.

To assess this potential source of heterogeneity in the data, we consider four proxies for consumers' income volatility – the actual implied standard deviation of the logarithm of expected income growth;[8] whether the consumer belongs to the bottom half of the income distribution, which earlier research finds have more volatile income realizations (); consumers' age, because incomes tend to be more volatile among younger individuals; and consumers' education levels, because incomes tend to be more volatile among non-college-educated individuals.

Table III reports the results for estimating equation (4) in a form that includes interactions with our four proxies for income volatility. The results show that the extent of overreaction to unexpected news about income appears systematically lower for consumers whose incomes are less volatile: consumers above the median of the income distribution overreact about half less than others; those whose implied expected income growth is higher overreact by more; older consumers and college-educated consumers overreact by less.

We continue to study the asymmetric effects of income shocks on misbeliefs. Especially, the two rounds of surveys provide a great opportunity to study the asymmetric degree of extrapolation across business cycles. The first wave, which happens at the onset of the COVID crisis, is filled with heightened uncertainty and breakdown of multiple types of real activities.[9] While for the second round of surveys, most areas in China have turned to a relatively normal condition. Therefore, we can use results from the two rounds of surveys to respectively assess the extrapolative behaviors during recessions and expansions.

The results are shown in Table IV. In general, we observe over-extrapolation across both rounds of surveys and both for positive and negative shocks. At the same time, there are some notable heterogeneity across the two periods. As shown from columns (1) and (2), the degree of extrapolation is slightly larger for the first round of surveys. This indicates that the degree of extrapolation tends to be larger during economic downturn. While for asymmetric effects. The results are quite striking. From columns (1) and

[8] We follow the literature on the elicitation of the distribution of beliefs using a triangular distribution and survey questions about minimum, maximum, and point estimates about future income growth ().

[9] In China, COVID induced a nation-wide lockdown starting at the end of January. However, most areas turned to relatively normal conditions around late February to early March. Wuhan was the latest for which the lockdown policy was removed, and the date was April 8, 2020.

(2), extrapolation is stronger when the income shocks are negative during contractionary periods (bootstrapped z-statistic of 1.87 with 500 draws). However, the results are to the opposite during expansionary periods. In particular, from columns (3) and (4), the degree of extrapolation is larger when the income shocks are positive (bootstrapped z-statistic of 3.70 with 500 draws). This indicates that the degree of belief over-extrapolation tends to be stronger when in general the direction of individual-level income shocks is the same as the direction of aggregate economy growth.

Overall, the expectations-formation process of the average consumer in our setting, which we can observe directly rather than through revealed choices or by imposing assumptions on the relationship between expectations and choices, appears consistent with the diagnostic-expectation framework.

V Extrapolative Expectations and Consumption, Debt, Defaults

In this section, we move forward to bring the predictions of our theoretical setting regarding the role of unexpected income shocks on consumption and debt choices implied by the diagnostic-expectations framework.

Our first prediction in the theoretical setting relates to current consumption choices: because diagnostic-expectations agents overestimate future income when facing positive unexpected income shocks (and the opposite when facing negative unexpected income shocks), the extent of excess expected income should imply the choice of higher current consumption. Total consumption can be defined as debt-finance spending and non-debt financed spending. That is, for any amount of higher spending, the consumer can pay for it by drawing down saving or accumulate more debt. To study the effects of misbelief on spending and borrowing in more detail, we thus distinguish between debt-finance spending and non-debt financed spending when study the consumption response to misbeliefs. Our estimation specification follows

$$\Delta C_{i,t} = \gamma(E[Y_{i,t+1}] - Y_{i,t+1}) + X'_{i,t}\delta + \eta_{k,j} + \eta_s + \epsilon_{i,t}, \tag{5}$$

where $\Delta C_{i,t}$ is the change in non-debt financed consumption at time t relative to the previous period ($t-1$), and all other variables are defined as in equation (4). We report the results for estimating equation (5) in Table V. Columns (1) considers a baseline univariate specification in which we do not absorb any individual-level observables. In this case, we can see that consumers who have income expectations \$1,000 higher than future actual realizations increase their current consumption spending by about \$154 dollars more than other consumers. The statistical significance and size of this association is similar once, in column (2), we absorb all the observable characteristics we have available. Adding these controls increases the explained variation of the individual current change in spending from an R^2 of 3.66% to about 10.57%, and yet the estimated association between excess income expectations and change in spending barely changes.

Because consumers in our setting can borrow to finance their spending, we also assess whether excessive income expectations predict an increase in borrowing at the current period relative to the previous period. Note that, ex ante, this association could be positive or zero – the latter would be the case if diagnostic-expectations agents were liquidity and financially unconstrained and could finance the increased spending with available cash.[10] For this test, we estimate a version of equation (5) in which the left-hand-side variable is $\Delta B_{i,t}$ – the difference between the average outstanding interest-incurring credit card debt over the six months after the taking the survey and that before taking the survey.

Table V reveals that the larger is the difference between income expectations and actual ex-post income realization, the higher is the increase in the credit-card debt consumers raise, and the estimated magnitude is similar irrespective of whether we consider the univariate association (column (3)) or we include the full set of observables in our analysis (column (4)). The sum of the estimates from column (2) and column (4) gives the effects of misbelief on total consumption. That is, for each dollar higher misbelief in the average monthly income in the next-period, average monthly spending in the current period increases by around 24 cents.

The third outcome we consider is the likelihood that consumers default on their credit-card debt within our sample period. This outcome is important to assess because

[10]Note also that this effect would be zero if consumers had access to other borrowing accounts that we do not observe, and if they used such borrowed funds to finance the spending we observe.

if consumers are merely increasing the amount of their debt but repay such debt fully, then defaults do not increase, and the fact that excessive income expectations produce higher debt accumulation would represent a potential microfoundation for household debt cycles but would not necessarily be worrisome for policy purposes. To assess the relationship between misbelief and default likelihood, we use 60-day delinquency indicator in period $t + q$ as the default events, and re-fit (4) with the default indicator as the left-hand-side variable. Default is multiplied by 100 for easier interpretation. Columns (5) - (6) of Table V document that, indeed, a higher distance between income expectations and ex-post realization is associated with a higher probability of default. From column (6), for each \$1000 higher misbelief about income in $t+1$, default likelihood is around 0.85 percentage point higher. With an average default rate of around 2.5%. This is equivalent to a 34% higher likelihood of default.

VI Asymmetric Effects: Positive and Negative Unexpected Income Shocks

An important feature of household debt cycles as described in aggregate data by earlier research is that these cycles and their correlations with households' spending decisions build up slowly in times of positive income growth (positive domain) but drop quickly in times of negative income growth (negative domain), that is, as soon as a recession hits.

In our theoretical framework, we have shown that diagnostic expectations can rationalize this asymmetric effect of income expectations once we allow for consumers' income volatility to vary over time. The framework suggests that not only should unexpected income shocks have a stronger effect of economic choices when in the negative domain, but that this effect should largely be driven by consumers who expect more volatile income growth going forward.

Before assessing the implications of introducing time-varying income volatility, we test in the data whether unexpected income shocks affect consumers' subjective income volatility. We do so by estimating versions of equation (4) in which the outcome variable is the standard deviation of consumers' expected income growth, which we compute based on our survey question under the assumption that income beliefs follow a triangular distribution. Because we are considering the second moment of the distribution, we take the absolute value of the unexpected income shocks on as the main covariate of interest.

In columns (1) - (2) of Table VI, we find that as the size of the unexpected income shock increases, irrespective of its sign, the standard deviation of expected future income growth increases as well and this association stays similar when we control for observables. Moreover, to assess whether negative and positive unexpected income shocks of the same size relate to expectations differently, in columns (3)-(4) we interact the absolute value of the unexpected income shock with a dummy variable for whether the shock is negative. We find that, indeed, not only the second moment of future income growth is higher after negative income shocks, but the association between the unexpected income shock and income-expectations volatility is higher for negative shocks than for positive shocks of the same size.

We now move on to test whether unexpected income shocks in the negative domain have an effect on consumption and debt choices of larger size relative to income shocks in the positive domain. Columns (1) and (3) of Table VII reveal that, indeed, the consumption and consumer debt accumulation response to unexpected income shocks is stronger for negative shocks relative to positive shocks. Note that, for negative shocks, the control variable is negative and hence the shock is larger the lower, rather than higher, is the variable $Y_0 = E[Y_0]$. For this reason, a positive coefficient means that the higher is the shock, the more negative is the change in current consumption.

VII Income Expectations and Expected Future Debt Capacity

In this part of the analysis, we ask if indeed, at least in part, consumers translate their excessive income expectations following unexpected income shocks into a higher expected debt capacity going forward. At the same time, we ask if extrapolative income expectations can explain household debt cycles because households, by expecting higher income, also expect that they will be able to borrow more than what they actually will be allowed to borrow in future periods.

To assess this channel, in Table VIII we consider a specification similar to equation (4) in which the outcome variable is the difference between consumers' expected credit-card-limit and the actual realization of the credit-card-limit the following period. We uniquely observe consumer expected credit limit in the next period in our survey and serves as a proxy for consumers' overall expected debt capacity.

In columns (1) - (2) of Table VIII, we find that, after an increase in income, consumers indeed form excessive expectations about their credit-card limits going forward. Moreover, based on columns (3) - (5), the unexpected component of the current income shock relative to the previous period does have an effect on excessive credit-card limit beliefs above and beyond the effect of expected income changes. This analysis thus reveals that not only unexpected income shocks make consumers, on average, form excessive future income expectations relative to ex-post realizations, but they also make consumers form excessive expectations of future debt capacity (in the form of future credit-card limits) relative to the actual credit-card limits the same consumers face going forward.

The excessive expected debt capacity consumers form after (unexpected) income shocks might be a by-product of excessive income expectations and hence be unrelated to economic choices above once excessive income expectations are accounted for. Or, to the contrary, excessive debt capacity expectations might affect current economic choices above and beyond the effect of excessive income expectations. We find that the latter possibility is borne out in our data. Table IX reports the results for estimating equation (5) when adding consumers' excess debt-capacity expectations to the right-hand-side of the linear specification.

We find that all three economic choices we consider – current change in spending relative to the previous period, current change in borrowing, and likelihood of future defaults on consumer debt – are positively associated with excess debt-capacity expectations and this association holds above and beyond the effect of excessive income expectations on the same variables we documented above, both economically and statistically. To sum up, a \$1 shock to current income leads consumers to overestimate their next-period income by around \$0.30, and next-period borrowing capacity by \$1.18, the resulted income misbelief then leads to $0.3 \times (0.146 + 0.091) \approx 0.072$ dollars; the resulted borrowing-capacity misbelief leads to $1.18 \times (0.006 + 0.010) \approx 0.019$ dollars. As a results, a \$1 shock to current income leads to a 0.091 higher consumption through extrapolative beliefs. Of the total effects, the weight of income misbelief is around 79%.

Overall, our results suggest that unexpected income shocks make consumer form beliefs about future income and future debt capacity that are systematically biased upwards relative to the actual realizations of these variables in subsequent periods, and both these excessive expectations help explain consumers' decisions about current spending increases, current debt accumulation, as well as the future likelihood of defaulting on consumer debt.

VIII Robustness Check

The previous results show that consumers over-extrapolate beliefs about future income following unexpected income shocks in the current period. The resulting misbeliefs have strong effects on their spending and borrowing. Analyses based on differences in expectations and consumption rule out potential unobserved heterogeneity that could simultaneously affect the level of consumption and expectation. However, one possible source of confounding variables could be individual-level unobserved heterogeneity that induces consumers that are on a rising consumption path to have long-lasting over- or under-optimism about earning ability. We solve such possibilities in two ways. First, of the 4,456 individuals in our sample, 1,276 participants have completed both rounds of surveys. In this case, we can focus on these consumers and control for individual fixed effects. In this way, we are directly studying the effects of shocks to income on expectations and changes in consumption within individuals.

Table A.1 and A.2 in the Online Appendix report the results. In all columns, we add individual fixed effects as well as year and industry fixed effects[11]. Over all columns, despite a much smaller sample size, the relationship between income shocks and misbeliefs, and that between misbeliefs and spending and default behaviors, are very similar to the

[11] The inclusion of individual fixed effects and industry fixed effects is because of participants changing their jobs.

estimates without individual fixed effects.

As a second way, we assume, when forming expectations about future income, consumers perform the forecasting task by assuming that income follows an AR(1) process. The specification follows

$$Y_{i,t+1} = \rho_{j,k,a} Y_{i,t} + \Gamma X_{i,t} + \epsilon_{i,t+1}, \tag{6}$$

where $\rho_{j,k,a}$ is the industry-city-age quintile level growth rate, and $X_{i,j,t}$ is a collection of consumer characteristics including age, age-squared, degree, gender, log saving, log credit limit, city fixed effects, and industry fixed effects. We then use the difference between the realized income and the income as predicted by (6) as the misbeliefs. We fit (6) using a random 5% of the data in the bank's data based, and out-of sample forecast the participants' income during the sampling periods. The effects of misbeliefs measured with (6) on spending, borrowing, and default are in Table A.3 in the Online Appendix. We focus on the same participants as using the surveys. The odd columns focuses on the same sampling periods, for the even columns, we extend our sample to include the earlier years for which we could observe the participants' bank-account information. The effects are very much similar to previous results, even for the extended samples that cover multiple years before 2019. Therefore, our results are likely to hold over a longer sample, while exploiting only within-individual variations.

IX Conclusions

When agents' belief-formation process about their income follows diagnostic-expectation, they would have upward biased income expectations after unexpected positive income shocks and hence spend more (and borrow more to finance higher current spending) than what a neoclassical life-cycle consumption optimizer would do, and vice versa after unexpected negative income shocks. Moreover, if income volatility is time-varying, the effect would be stronger for negative shocks than for same-size positive shocks. These predictions correspond with aggregate features of household debt cycles documented in the literature.

Combining survey-based elicitation with transaction-level bank-account data, we bring these predictions to the field in a unique setting in which we observe, for the same consumers and at the same time, income and debt-capacity expectations as well as actual past, current, and future spending and borrowing choices. We find evidence consistent with these predictions.

Our results suggest that extrapolative expectations could act as a microfoundation for aggregate household debt cycles, because the micro-level evidence pairs with aggregate evidence on household debt cycles: in good times, a larger fraction of consumers is likely to face unexpected positive income shocks, whereas in bad times a larger fraction of consumers is likely to face unexpected negative income shocks, relative to normal times. We propose a framework based on diagnostic expectations but do not argue that this specific formulation is the *only* form of extrapolative expectations that could rationalize our results. We use diagnostic expectations as a beliefs-formation structure that economic research has found portable theoretically and empirically to other features of micro- and macroeconomic outcomes, rather than assessing ad-hoc explanations for the facts we want to interpret. We encourage future research on non-standard belief-formation mechanisms that could at the same time explain household debt cycles as well as other economic choices by consumers in the laboratory and in the field.

Our research also beget follow-up work on the aggregate effects of household debt cycles both theoretically and empirically. Theoretically, it sheds light on the general-equilibrium macroeconomic models featuring diagnostic expectations to explain the mechanisms behind aggregate economic dynamics. On the empirical side, this study suggests the importance of structural and calibration analysis to characterize the functional forms and parameter sizes that would make diagnostic expectations best fit the wealth of micro and macro data available to researchers.

Moreover, our reduced form analysis considers the prediction of a simple representative-agent theoretical framework in which all agents are endowed with diagnostic income expectations, which pairs with the empirical analysis based on average expectations and choices in the field. The extent to which consumers' expectations-formation process deviates from the full-information rational-expectations paradigm might vary in the cross section of consumers, potentially based on dimensions that would shape the cross-sectional variation in the accuracy of macroeconomic expectations, such as cognition (e.g., see D'Acunto et al. (2019, 2021b,a)), socioeconomic status (Kuhnen and Miu (2017); Das et al. (2020)), or lifetime experiences (Malmendier and Nagel (2016); Kuchler and Zafar (2019)). Advancing heterogeneous macroeconomic models in the direction of heterogeneous belief-formation processes as well as studying empirically the individual-level characteristics that help explain why different consumers form expectations differently are all exciting avenues for future research.

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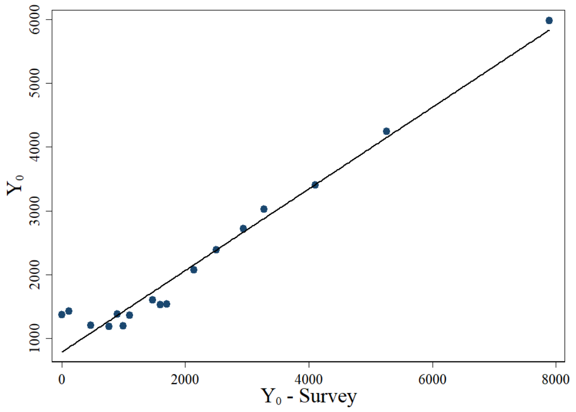
A. Figures

Figure 1. Beliefs in Future Income

Panel A is a binned scatter plot of consumer ex ante income expectation and ex post income realization. Panel B plots the histograms of misbeliefs in future income. $E[Y_1]$ is the expected level of income (\$) in period $t+1$ based on survey question 8. Y_1 is consumer realized income (\$) in period $t+1$. All variables are winsorized at 1% level by each wave.

Panel A: Expectations vs Realizations



Panel B: Misbeliefs in Future Income

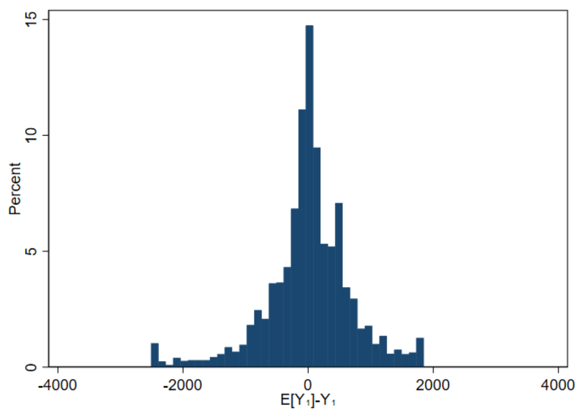
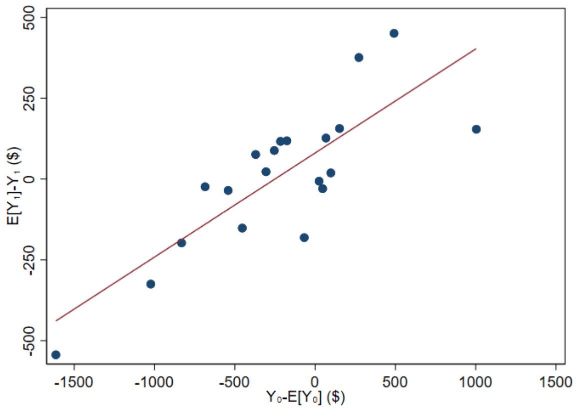


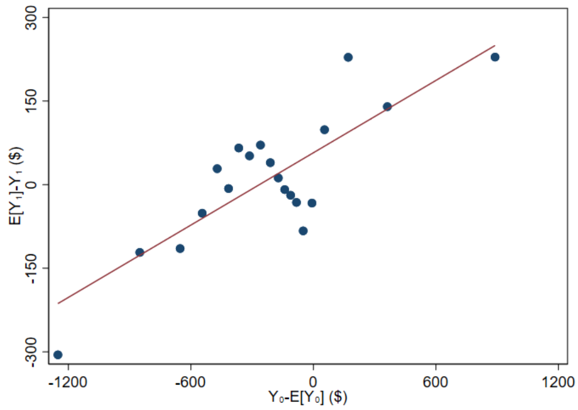
Figure 2. Income Shocks and Misbeliefs in Future Income

This figure presents the binned scatter plots of past income shocks and misbeliefs in future income. $E[Y_0]$ ($E[Y_1]$) is the expected level of income (\$) in period 0 (1) based on survey question 8 sent in period -1 (0). Y_0 (Y_1) is consumer realized income (\$) in period 0 (1). In Panel B, variables are residualized by income changes in period 0, age age-squared, degree, expected log standard deviation of expected income growth in period 1, number of hours worked every week, log income in period 0, industry fixed effects, city fixed effects, and wave fixed effects. All variables are winsorized at 1% level by each wave.

Panel A: Income Shocks and Misbeliefs in Future Income



Panel B: Income Shocks and Misbeliefs in Future Income – Residualized



B. Tables

TABLE I. Summary Statistics

Spending is the average monthly spending from the consumers' bank account plus that from the credit card account. Income is the average monthly income. Saving is the average saving. Limit the credit card limit based on survey question 10. Debt is the average interest-incurring credit card debt. Debt|Debt> 0 is the average interest-incurring credit card debt for those that have positive debt. E[Income], E[min. Income], E[max. Income], E[Limit], E[min. Limit], and E[max. Limit] are respectively based on the answers from survey Q8, Q6, Q7, Q5, Q3, and Q4. All level variables are in dollars and are winsorized at 1% level by each wave.

	(1) Mean	(2) SD	(3) p25	(4) Median	(5) p75	(6) N
Spending	1390.96	2010.90	193.13	560.29	1536.17	5,732
Income	2000.61	1957.65	590.51	1141.15	2923.08	5,732
Saving	18504.28	31176.05	1647.19	4425.99	19965.42	5,732
Limit	13614.77	12158.86	4375.00	10029.92	20105.58	5,732
Debt	1081.73	1899.69	0	0	1553.91	5,732
Debt|Debt> 0	2582.61	2233.41	965.83	1969.91	3555.08	2,417
Age	38.51	8.17	32	38	42	5,732
Female	0.51	0.5	0	1	1	5,732
E[Income]	2057.87	1762.34	700.68	1461.54	2923.08	5,732
E[min. Income]	1543.25	1659.50	350.00	923.08	2153.85	5,732
E[max. Income]	3286.54	3156.59	1093.75	2000.00	4461.54	5,732
E[Limit]	14901.25	12987.80	4523.99	11053.89	21875.00	5,732
E[min. Income]	10577.64	10601.03	2905.65	7036.35	14615.39	5,732
E[max. Income]	17463.61	15504.60	5468.75	12475.96	24609.38	5,732
E[Δ Limit]	1239.65	5379.57	-1195.91	769.23	2734.37	5,732

TABLE II. Income Shocks and Excessive Income Expectations

$E[Y_{t+1}]$ is the expected level of income ($ thousands) in period $t+1$ based on survey question 8 sent in period t. $E[\Delta Y_t]$ is the expected changes ($ thousands) in income between period $t-1$ and period t. $SD(E[\Delta \log Y_{t+1}])$ is the log standard deviation of expected income growth in period $t+1$ based on survey questions 6, 7, and 8 assuming income growth follows a Triangular distribution. *Degree* is the consumers' highest degree earned. *Hours* is the number of hours the customers usually work every week in period t. $\log Y_t$ and $\log L_t$ are respectively log monthly income and log credit card limit in period t. All variables are winsorized at 1% level by each wave.

	(1) $E[Y_{t+1}]-Y_{t+1}$	(2) $E[Y_{t+1}]-Y_{t+1}$	(3) $E[Y_{t+1}]-Y_{t+1}$	(4) $E[Y_{t+1}]-Y_{t+1}$
$Y_t - E[Y_t]$	0.322***	0.343***	0.324***	0.308***
	(0.027)	(0.061)	(0.059)	(0.055)
$E[\Delta Y_t]$		0.122***	0.123***	0.096**
		(0.045)	(0.045)	(0.041)
Age		0.021**	0.019**	0.013
		(0.009)	(0.009)	(0.009)
Age^2		-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)
$Degree$		0.021***	0.020***	0.017**
		(0.008)	(0.008)	(0.007)
$SD(E[\Delta \log Y_{t+1}])$		-0.044**	-0.044**	-0.057***
		(0.017)	(0.017)	(0.016)
$Hours$		0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)
$\log Y_t$		-0.233***	-0.222***	-0.228***
		(0.028)	(0.029)	(0.024)
$\log L_t$		0.022***	0.023***	0.011
		(0.006)	(0.006)	(0.007)
N	5,732	5,732	5,732	5,732
Industry FE × Round FE	No	No	No	Yes
City FE	No	No	Yes	Yes
R^2	7.10%	19.11%	22.06%	31.82%

Standard Errors Clustered at City Level in Parentheses
* p<0.10 ** p<0.05 *** p<0.01

TABLE III. Income Shocks and Excessive Income Expectations—Heterogeneity Analysis

$E[Y_{t+1}]$ is the expected level of income ($ thousands) in period $t+1$. $E[\Delta Y_t]$ is the expected changes ($ thousands) in income between period $t-1$ and period t. Y_H is a dummy variable that's equal to one if the consumers' incomes in period t are in the upper half of the distribution. SD is the log standard deviation of expected income growth in period $t+1$ based on survey questions 6, 7, and 8 assuming income growth follows a Triangular distribution. $Degree$ is the consumers' highest degree earned. SD_H, Age_H, and $Degree_H$ are respectively equal to one if the consumers are in the upper half distribution based on their SD, Age, or $Degree$. Control variables include expected changes in income from period $t-1$ to t, age, age-squared, expected income growth volatility, hours working, log income in period t, and log credit limit in period t. All variables are winsorized at 1% level by each wave.

	(1) $E[Y_{t+1}] - Y_{t+1}$	(2) $E[Y_{t+1}] - Y_{t+1}$	(3) $E[Y_{t+1}] - Y_{t+1}$	(4) $E[Y_{t+1}] - Y_{t+1}$
$Y_t - E[Y_t]$	0.437***	0.141***	0.346***	0.350***
	(0.053)	(0.053)	(0.056)	(0.065)
$Y_H \times (Y_t - E[Y_t])$	-0.227***			
	(0.048)			
$SD_H \times (Y_t - E[Y_t])$		0.331***		
		(0.053)		
$Age_H \times (Y_t - E[Y_t])$			-0.078**	
			(0.037)	
$Degree_H \times (Y_t - E[Y_t])$				-0.092*
				(0.046)
Y_H	-0.362***			
	(0.041)			
SD_H		0.048**		
		(0.023)		
Age_H			0.033**	
			(0.014)	
$Degree_H$				0.028
				(0.019)
N	5,732	5,732	5,732	5,732
Control	Yes	Yes	Yes	Yes
Industry FE × Round FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
R^2	29.08%	33.15%	31.85%	31.96%

Standard Errors Clustered at City Level in Parentheses

* $p<0.10$ ** $p<0.05$ *** $p<0.01$

TABLE IV. Income Shocks and Excessive Income Expectations—Asymmetry

$E[Y_{t+1}]$ is the expected level of income ($ thousands) in period $t+1$ based on survey question 8 sent in period t. $E[\Delta Y_t]$ is the expected changes ($ thousands) in income between period $t-1$ and period t. Y_H is a dummy variable that's equal to one if the consumers' incomes are in the upper half of the distribution. $SD(E[\Delta \log Y_{t+1}])$ is the log standard deviation of expected income growth in period $t+1$ based on survey questions 6, 7, and 8 assuming income growth follows a Triangular distribution. $Degree$ is the consumers' highest degree earned. $Hours$ is the number of hours the customers usually work every week in period t. $\log Y_t$ and $\log L_t$ are respectively log monthly income and log credit card limit in period t. All variables are winsorized at 1% level by each wave.

	(1) *wave 1* $Y_t - E[Y_t] < 0$ $E[Y_{t+1}] - Y_{t+1}$	(2) *wave 1* $Y_t - E[Y_t] \geq 0$ $E[Y_{t+1}] - Y_{t+1}$	(3) *wave 2* $Y_t - E[Y_t] < 0$ $E[Y_{t+1}] - Y_{t+1}$	(4) *wave 2* $Y_t - E[Y_t] \geq 0$ $E[Y_{t+1}] - Y_{t+1}$
$Y_t - E[Y_t]$	0.533***	0.369**	0.124	0.483***
	(0.111)	(0.145)	(0.132)	(0.098)
$E[\Delta Y_t]$	0.052	0.041	0.080	0.064
	(0.070)	(0.047)	(0.087)	(0.114)
Age	0.014*	0.003	0.021	0.009
	(0.008)	(0.010)	(0.020)	(0.026)
Age^2	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Degree$	0.031***	0.024***	0.006	-0.011
	(0.007)	(0.005)	(0.016)	(0.017)
$SD(E[\Delta \log Y_{t+1}])$	-0.127***	-0.053***	-0.127**	0.224***
	(0.015)	(0.015)	(0.049)	(0.046)
$Hours$	0.002*	0.001	0.002	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)
$\log Y_t$	-0.182***	-0.117***	-0.370***	-0.485***
	(0.017)	(0.016)	(0.041)	(0.056)
$\log L_t$	0.020**	-0.002	0.024	-0.016
	(0.009)	(0.006)	(0.022)	(0.019)
N	1,960	1,438	1,312	992
Industry FE × Round FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
R^2	42.15%	42.10%	36.35%	43.20%

Standard Errors Clustered at City Level in Parentheses
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

TABLE V. Excessive Income Expectations and Choices: Consumption, Debt, and Defaults

ΔC_t is the differences ($ thousands) in the monthly average consumption in between t and $t-1$. ΔB_t is the differences ($ thousands) in the end-of-period interest-incurring debt between t and $t-1$. $default_{t+1}$ is a dummy variable that is equal to $t+1$ for 60-day delinquency in t_{t+1}. $E[Y_{t+1}]$ is the expected level of income ($ thousand) in period $t+1$ based on survey question 8 sent in period t. $E[\Delta Y_t]$ is the expected changes ($ thousands) in income between period $t-1$ and period t. $SD(E[\Delta \log Y_{t+1}])$ is the log standard deviation of expected income growth in period 1 based on survey questions 6, 7, and 8 assuming income growth follows a Triangular distribution. $Degree$ is the consumers' highest degree earned. $Hours$ is the number of hours the customers usually work every week in period 0. $\log Y_t$ and $\log L_t$ are respectively log monthly income and log credit card limit in period t. All variables are winsorized at 1% level by each wave.

	(1) ΔC_t	(2) ΔC_t	(3) ΔB_t	(4) ΔB_t	(5) $Default_{t+1}$	(6) $Default_{t+1}$
$E[Y_{t+1}] - Y_{t+1}$	0.154***	0.146***	0.076***	0.091***	1.002***	0.849***
	(0.028)	(0.030)	(0.009)	(0.012)	(0.246)	(0.302)
$E[\Delta Y_t]$		0.057***		-0.009		-0.256
		(0.019)		(0.013)		(0.301)
Age		0.020***		0.002		-0.265***
		(0.008)		(0.003)		(0.084)
Age^2		-0.000**		-0.000		0.002*
		(0.000)		(0.000)		(0.001)
$Degree$		0.007		-0.005		-0.674***
		(0.005)		(0.004)		(0.236)
$SD(E[\Delta \log Y_{t+1}])$		0.002		-0.000		0.104
		(0.009)		(0.005)		(0.106)
$Hours$		-0.000		-0.001**		-0.081***
		(0.001)		(0.000)		(0.016)
$\log Y_t$		0.039***		0.002		-0.449**
		(0.008)		(0.007)		(0.208)
$\log L_t$		-0.027***		0.016***		0.663***
		(0.006)		(0.004)		(0.136)
N	5,732	5,732	5,732	5,732	5,732	5,732
Industry FE × Round FE	No	Yes	No	Yes	No	Yes
City FE	No	Yes	No	Yes	No	Yes
R^2	3.66%	10.57%	2.33%	10.13%	0.36%	3.94%

Standard Errors Clustered at City Level in Parentheses

* p <0.10 ** p <0.05 *** p <0.01

TABLE VI. Income Shocks and Subjective Income Uncertainty

$E[Y_{t+1}]$ is the expected level of income ($ thousands) in period $t+1$ based on survey question 8 sent in period t. $E[\Delta Y_t]$ is the expected changes ($ thousands) in income between period $t-1$ and period t. $abs(Y_t - E[Y_t])$ is the absolute value of income surprises at period t. $1_{\{Y_t - E[Y_t]<0\}}$ is an indicator function that's equal to one if the income surprises at period t are negative. $SD(E[\Delta \log Y_{t+1}])$ is the log standard deviation of the income growth in period $t+1$ based on survey questions 6, 7, and 8 assuming income growth follows a Triangular distribution. $Degree$ is the consumers' highest degree earned. $Hours$ is the number of hours the customers usually work every week in period t. $\log Y_t$ and $\log L_t$ are respectively log monthly income and log credit card limit in period t. All variables are winsorized at 1% level by each wave.

	(1) $\Delta SD(E[\Delta \log Y_{t+1}])$	(2) $\Delta SD(E[\Delta \log Y_{t+1}])$	(3) $\Delta SD(E[\Delta \log Y_{t+1}])$	(4) $\Delta SD(E[\Delta \log Y_{t+1}])$
$abs(Y_t - E[Y_t])$	0.337***	0.445***	0.128***	0.195***
	(0.041)	(0.052)	(0.048)	(0.067)
$abs(Y_t - E[Y_t]) \times 1_{\{Y_t - E[Y_t]<0\}}$			0.249***	0.430***
			(0.063)	(0.095)
$1_{\{Y_t - E[Y_t]<0\}}$			0.011	0.032
			(0.052)	(0.045)
$E[\Delta Y_t]$		0.059**		-0.090**
		(0.027)		(0.042)
Age		0.029**		0.027**
		(0.012)		(0.012)
Age^2		-0.000***		-0.000***
		(0.000)		(0.000)
$Degree$		-0.046***		-0.047***
		(0.009)		(0.009)
$Hours$		0.002*		0.002*
		(0.001)		(0.001)
$\log Y_t$		0.027		0.022
		(0.017)		(0.018)
$\log L_t$		0.100***		0.102***
		(0.008)		(0.008)
N	5,732	5,732	5,732	5,732
Industry FE × Round FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
R^2	2.50%	11.72%	3.02%	12.21%

Standard Errors Clustered at City Level in Parentheses
* $p<0.10$ ** $p<0.05$ *** $p<0.01$

TABLE VII. Asymmetric Effects of Excessive Income Expectations

ΔC_t is the differences ($ thousands) in the monthly average consumption in between t_t and t_{-1}. ΔB_t is the differences ($ thousands) in the end-of-period interest-incurring debt between t_t and t_{-1}. $E[\Delta Y_t]$ is the expected changes ($ thousands) in income between period $t-1$ and t. $1_{\{Y_t - E[Y_t]<0\}}$ is an indicator function that's equal to one if the income surprises at time 0 are negative. $SD(E[\Delta \log Y_{t+1}])$ is the log standard deviation of expected income growth in period $t+1$ based on survey questions 6, 7, and 8 assuming income growth follows a Triangular distribution. *Degree* is the consumers' highest degree earned. *Hours* is the number of hours the customers usually work every week in period t. $\log Y_t$ and $\log L_t$ are respectively log monthly income and log credit card limit in period t. All variables are winsorized at 1% level by each wave.

	(1) ΔC_t	(2) ΔC_t	(3) ΔB_t	(4) ΔB_t
$Y_t - E[Y_t]$	0.059***	0.161***	0.129***	0.218***
	(0.018)	(0.047)	(0.016)	(0.026)
$(Y_t - E[Y_t]) \times 1_{\{Y_t - E[Y_t]<0\}}$		0.122**		0.093**
		-0.075***		-0.056***
$1_{\{Y_t - E[Y_t]<0\}}$		(0.021)		(0.018)
		(0.060)		(0.039)
$E[\Delta Y_t]$		0.230***		0.185***
		(0.038)		(0.020)
Age		0.023***		0.004
		(0.007)		(0.003)
Age^2		-0.000***		-0.000
		(0.000)		(0.000)
Degree		0.011*		-0.003
		(0.005)		(0.004)
$SD(E[\Delta \log Y_{t+1}])$		-0.005		-0.005
		(0.009)		(0.005)
Hours		0.000		-0.001*
		(0.001)		(0.000)
$\log Y_t$		0.022**		-0.004
		(0.010)		(0.009)
$\log L_t$		-0.026***		0.016***
		(0.006)		(0.004)
N	5,732	5,732	5,732	5,732
Industry FE × Round FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
R^2	12.30%	13.05%	10.06%	10.86%

Standard Errors Clustered at City Level in Parentheses
* p <0.10 ** p <0.05 *** p <0.01

TABLE VIII. Income Shocks and Excessive Debt Capacity Expectations

$E[L_{t+1}]$ is the expected level of credit limit ($ thousands) in period $t+1$ based on survey question 5 sent in period t. $E[\Delta Y_t]$ is the expected changes ($ thousands) in income between period $t-1$ and period t. $SD(E[\Delta \log Y_{t+1}])$ is the log standard deviation of expected income growth in period $t+1$ based on survey questions 6, 7, and 8 assuming income growth follows a Triangular distribution. *Degree* is the consumers' highest degree earned. *Hours* is the number of hours the customers usually work every week in period t. $\log Y_t$ and $\log L_t$ are respectively log monthly income and log credit card limit in period t. All variables are winsorized at 1% level by each wave.

	(1) $E[L_{t+1}] - L_{t+1}$	(2) $E[L_{t+1}] - L_{t+1}$	(3) $E[L_{t+1}] - L_{t+1}$	(4) $E[L_{t+1}] - L_{t+1}$
$Y_t - E[Y_t]$	0.808***	0.816***	1.165***	1.180***
	(0.159)	(0.301)	(0.293)	(0.296)
$E[\Delta Y_t]$		-0.296	-0.116	-0.105
		(0.281)	(0.305)	(0.304)
Age		0.376***	0.369***	0.358***
		(0.057)	(0.057)	(0.057)
Age^2		-0.005***	-0.004***	-0.004***
		(0.001)	(0.001)	(0.001)
$Degree$		0.023	0.035	0.040
		(0.048)	(0.049)	(0.052)
$SD(E[\Delta \log Y_{t+1}])$		0.694***	0.673***	0.691***
		(0.083)	(0.086)	(0.087)
$Hours$		-0.009	-0.009	-0.009
		(0.007)	(0.007)	(0.007)
$\log Y_t$		0.697***	0.652***	0.671***
		(0.089)	(0.119)	(0.117)
$\log L_t$		-0.502***	-0.508***	-0.514***
		(0.039)	(0.037)	(0.038)
N	5,732	5,732	5,732	5,732
Industry FE × Round FE	No	No	No	Yes
City FE	No	No	No	Yes
R^2	0.74%	4.11%	5.84%	6.39%

Standard Errors Clustered at City Level in Parentheses
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

TABLE IX. Excessive Credit Limit Expectations and Choices: Consumption, Debt, and Defaults

$E[Y_{t+1}]$ is the expected level of income ($ thousands) in period $t+1$ based on survey question 8 sent in period t. $E[\Delta Y_t]$ is the expected changes ($ thousands) in income between period -1 and period 0. $SD(E[\Delta \log Y_{t+1}])$ is the log standard deviation of expected income growth in period $t+1$ based on survey questions 6, 7, and 8 assuming income growth follows a Triangular distribution. *Degree* is the consumers' highest degree earned. *Hours* is the number of hours the customers usually work every week in period t. $\log Y_t$ and $\log L_t$ are respectively log monthly income and log credit card limit in period 0. All variables are winsorized at 1% level by each wave.

	(1) ΔC_t	(2) ΔC_t	(3) ΔB_t	(4) ΔB_t	(5) $Default_{t+1}$	(6) $Default_{t+1}$
$E[L_{t+1}] - L_{t+1}$	0.006***	0.006***	0.009***	0.010***	0.111***	0.132***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.038)	(0.042)
$E[Y_{t+1}] - Y_{t+1}$		0.146***		0.091***		0.861***
		(0.030)		(0.012)		(0.299)
$E[\Delta Y_t]$		0.062***		-0.001		-0.141
		(0.018)		(0.012)		(0.296)
Age		0.018**		-0.002		-0.311***
		(0.008)		(0.003)		(0.087)
Age^2		-0.000**		0.000		0.002**
		(0.000)		(0.000)		(0.001)
$Degree$		0.007		-0.005		-0.679***
		(0.005)		(0.004)		(0.236)
$SD(E[\Delta \log Y_{t+1}])$		-0.002		-0.007		0.012
		(0.009)		(0.004)		(0.109)
$Hours$		-0.000		-0.001**		-0.080***
		(0.001)		(0.000)		(0.016)
$\log Y_t$		0.035***		-0.004		-0.531**
		(0.008)		(0.007)		(0.220)
$\log L_t$		-0.024***		0.021***		0.730***
		(0.006)		(0.004)		(0.145)
N	5,732	5,732	5,732	5,732	5,732	5,732
Industry FE × Round FE	No	Yes	No	Yes	No	Yes
City FE	No	Yes	No	Yes	No	Yes
R^2	0.29%	10.87%	1.86%	12.34%	2.07%	4.29%

Standard Errors Clustered at City Level in Parentheses
* p <0.10 ** p <0.05 *** p <0.01

Online Appendix:

Microfounding Household Debt Cycles with Extrapolative Expectations

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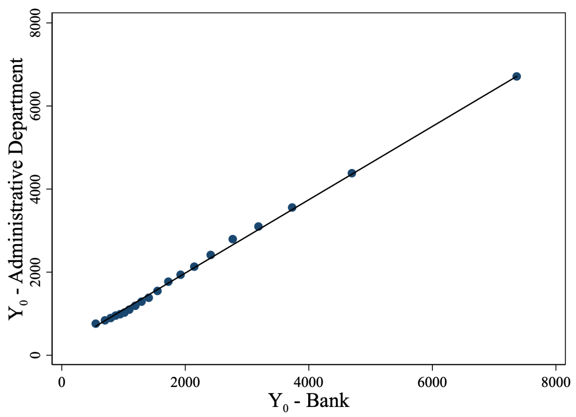
Not for Publication

Figure A.1. Comparing Computed Individual-level Income and Registry-based Income

Panel A in this figure is a binned scatter plot that compares the income values computed by the bank based on the transaction-level data the bank accesses and following the steps described in section *B.* of the paper and the registry income values reported by the same consumers in our sample to the Chinese tax authority, which can be accessed through one-to-one matching of individual tax identifiers. Panel B compares consumer answers from survey question 1 and the income from the bank at the same period. R^2 of regressing the two measures in Panel A is 78.26% ; R^2 of regressing the two measures in Panel B is 72.56%.

Panel A: Comparisions of Income Measures



Panel B: Survey Answers and Bank Measures

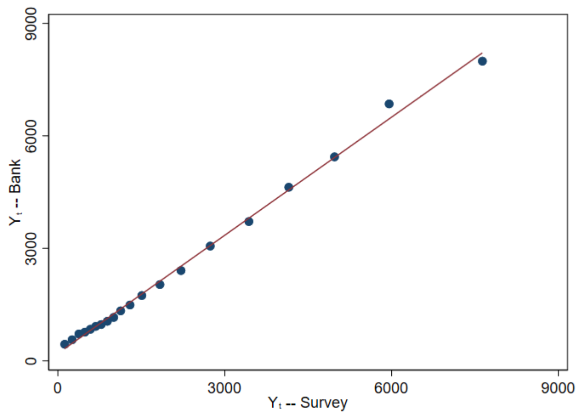


TABLE A.1. Income Shocks and Excessive Income Expectations – Panel Analysis

$E[Y_{t+1}]$ is the expected level of income (\$ thousands) in period $t+1$ based on survey question 8 sent in period t. $E[\Delta Y_t]$ is the expected changes (\$ thousands) in income between period $t-1$ and period t. $SD(E[\Delta \log Y_{t+1}])$ is the log standard deviation of expected income growth in period $t+1$ based on survey questions 6, 7, and 8 assuming income growth follows a Triangular distribution. *Degree* is the consumers' highest degree earned. *Hours* is the number of hours the customers usually work every week in period t. $\log Y_t$ and $\log L_t$ are respectively log monthly income and log credit card limit in period t. All variables are winsorized at 1% level by each wave.

	(1) $E[Y_{t+1}] - Y_{t+1}$	(2) $E[Y_{t+1}] - Y_{t+1}$	(3) $E[L_{t+1}] - L_{t+1}$	(4) $E[L_{t+1}] - L_{t+1}$
$Y_t - E[Y_t]$	0.259***	0.288***	0.768***	0.852***
	(0.071)	(0.069)	(0.262)	(0.234)
$E[\Delta Y_t]$		0.188**		-0.182***
		(0.087)		(0.054)
Age		0.185**		-0.088
		(0.081)		(0.076)
Age^2		-0.001		-0.000
		(0.001)		(0.001)
$Degree$		-0.083*		0.093
		(0.048)		(0.068)
$SD(E[\Delta \log Y_{t+1}])$		0.077**		0.000
		(0.030)		(0.030)
$Hours$		-0.003		-0.004
		(0.005)		(0.007)
$\log Y_t$		-0.729***		0.183**
		(0.207)		(0.084)
$\log L_t$		0.024		-0.031
		(0.015)		(0.022)
N	2,552	2,552	2,552	2,552
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
R^2	79.87%	80.82%	80.90%	81.15%

Standard Errors Clustered at City Level in Parentheses
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

TABLE A.2. Misbeliefs and Economic Behaviors – Panel Analysis

Δc_t is the log differences in the monthly average consumption in between t_t and t_{-1}. Δb_t is the log differences in the one plus end-of-period interest-incurring debt between t and $t-1$. $default_{t+1}$ is an indicator for 30-day delinquency in $t+1$. $E[Y_{t+1}]$ is the expected level of income ($ thousand) in period $t+1$ based on survey question 8 sent in period t. $E[\Delta Y_t]$ is the expected changes ($ thousands) in income between period $t-1$ and period t. $SD(E[\Delta \log Y_{t+1}])$ is the log standard deviation of expected income growth in period $t+1$ based on survey questions 6, 7, and 8 assuming income growth follows a Triangular distribution. $Degree$ is the consumers' highest degree earned. $Hours$ is the number of hours the customers usually work every week in period t. $\log Y_t$ and $\log L_t$ are respectively log monthly income and log credit card limit in period t. All variables are winsorized at 1% level by each wave.

	(1) ΔC_t	(2) ΔC_t	(3) ΔB_t	(4) ΔB_t	(5) $default_{t+1}$	(6) $default_{t+1}$
$E[Y_{t+1}] - Y_{t+1}$	0.096***	0.162***	0.078***	0.089***	0.819***	0.724**
	(0.021)	(0.034)	(0.009)	(0.016)	(0.129)	(0.141)
$E[L_{t+1}] - L_{t+1}$	0.021**	0.013***	0.016***	0.022*	0.129**	0.107**
	(0.005)	(0.013)	(0.004)	(0.011)	(0.052)	(0.047)
$E[\Delta Y_t]$		0.030		-0.018		-0.015*
		(0.057)		(0.052)		(0.008)
Age		-0.038		0.042		0.005
		(0.045)		(0.046)		(0.007)
Age^2		0.001		-0.001**		-0.000
		(0.001)		(0.001)		(0.000)
$Degree$		-0.001		-0.037		-0.010
		(0.026)		(0.027)		(0.007)
$SD(E[\Delta \log Y_{t+1}])$		-0.000		0.018**		0.003
		(0.013)		(0.009)		(0.004)
$Hours$		0.000		-0.001		0.001
		(0.003)		(0.002)		(0.001)
$\log Y_t$		0.111**		-0.069		-0.017
		(0.044)		(0.080)		(0.021)
$\log L_t$		0.029**		0.012		0.007**
		(0.015)		(0.013)		(0.004)
N	2,552	2,552	2,552	2,552	2,552	2,552
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	1.80%	24.60%	0.86%	23.94%	6.53%	36.48%

Standard Errors Clustered at City Level in Parentheses

* p <0.10 ** p <0.05 *** p <0.01

TABLE A.3. Misbelief and Economic Behaviors – Alternative Specification

ΔC_t is the differences ($ thousands) in the monthly average consumption in between t and $t-1$. ΔB_t is the differences ($ thousands) in the end-of-period interest-incurring debt between t and $t-1$. $default_{t+1}$ is an indicator for 30-day delinquency in $t+1$. $E[Y_{t+1}]$ is estimated based on

$$Y_{i,t+1} = \rho_{j,k,a} Y_{i,t} + \Gamma X_{i,t} + \epsilon_{i,t+1},$$

where $\rho_{j,k,a}$ is the industry-city-age quintile level growth rate, and $X_{i,j,t}$ is a collection of consumer characteristics including age, age-squared, degree, gender, log saving, log credit limit, city fixed effects, and industry fixed effects. ΔY_t is the changes ($ thousands) in income between period $t-1$ and period t. Columns (1), (3), and (5) use a longer sample that includes all the data available for the same survey participants. Columns (2), (4), and (6) focuses on the same sample period as that in the main analysis. All variables are winsorized at 1% level by each wave.

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔC_t	ΔC_t	ΔB_t	ΔB_t	$Default_{t+1}$	$Default_{t+1}$
$E[Y_{t+1}] - Y_{t+1}$	0.096***	0.139***	0.084***	0.098***	1.123**	0.975***
	(0.035)	(0.021)	(0.020)	(0.023)	(0.006)	(0.007)
$E[\Delta Y_t]$	0.065*	0.021	0.005	0.049*	-0.134**	-0.297***
	(0.038)	(0.024)	(0.024)	(0.024)	(0.061)	(0.051)
Age	0.017**	0.010**	0.005	0.009*	-0.775***	-0.826***
	(0.007)	(0.005)	(0.003)	(0.005)	(0.135)	(0.229)
Age^2	-0.000**	-0.000*	-0.000	-0.000*	0.003***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
$\log Y_t$	0.026***	0.041***	-0.013**	-0.023**	-0.217***	-0.262***
	(0.008)	(0.014)	(0.006)	(0.010)	(0.043)	(0.051)
N	5,309	21,397	5,309	21,397	5,309	21,397
Individual FE	No	Yes	No	Yes	No	No
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	No	Yes	No	Yes	Yes
Longer Sample	No	Yes	No	Yes	No	Yes
R^2	22.38%	61.76%	5.34%	21.87%	4.76%	3.89%

Standard Errors Clustered at City Level in Parentheses

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

I Household Consumption and Preferences Survey

Credit cards are an important method for daily consumption. To better understand the impact of credit cards on people's lives, we randomly selected a certain number of active credit card users from our bank to participate in a survey. We hope to use this survey to study the consumption behaviors and preferences of the residents generally. Therefore, we will focus only on highly summarized information for scientific research purposes, such as average values. We will not disclose the personal information of the participants in any respect. We will not, in any way, change the types of financial products we provide, including those regarding credit scores, credit limits, deposit rates, etc., based on the participants' personal answers.

1. What was your average monthly income over the past year? ______

2. How many of your credit cards do you usually use as a form of payments?
   (a) 0
   (b) 1
   (c) 2
   (d) 3 or more

3. What's the lowest possible credit card limit you believe you could have in 6 months? ______

4. What's the highest possible credit card limit you believe you could have in 6 months? ______

5. What would your total credit card limit most likely be in 6 months? ______

6. What would be the lowest possible level of average monthly income you believe you would get over the next 6 months? ______

7. What would be the highest possible level of average monthly income you believe you would get over the next 6 months? ______

8. What would your average monthly income most likely be in the next 6 months? ______

9. How many hours do you usually work per week? ______

10. What's the total amount of credit limit you have?