Subjective Income Expectations and Household Debt Choices

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Abstract

Matched transaction-level, credit-registry, and survey data show that consumers over-extrapolate from unexpected income shocks to their income expectations. Over-optimistic income forecasts raise current spending and lead to greater debt accumulation and higher default when incomes subsequently fall short. A consumption-savings model with defaultable unsecured debt and extrapolative Kalman filtering, in which consumers overreact to income surprises reconciles our empirical findings and shows extrapolative expectations can generate state-dependent household debt cycles.

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

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I Introduction

Understanding the causes and consequences of household debt decisions is crucial, as spikes in household leverage reliably predict economic contractions across space and over time. At the same time, both supply- and demand-side channels have been documented as key factors shaping debt dynamics.[1] Yet, disentangling these channels empirically is challenging: unobserved shocks may affect both credit supply and household borrowing demand, and the two forces often reinforce each other.

This paper develops a micro-to-macro approach to estimate how subjective income expectations shape household debt and to assess their aggregate implications. We combine transaction-level records on income and spending from bank accounts, debt positions and defaults from credit-registry data, and repeated surveys eliciting individuals' income forecasts.[2] From 2020 to 2025, we survey the same individuals about their six-month-ahead income expectations multiple times and link these forecasts to their realized income that we observe in administrative bank data, allowing us to trace the evolution of individuals' forecast errors over time. In addition, the combination of transaction histories, credit-registry data, and survey expectations further enables us to examine how forecast errors for income relate to individuals' consumption, borrowing, and default decisions.

We start by documenting that the average consumer's income expectations overreact to unexpected income shocks after both positive and negative shocks: after an unexpected shock in either direction today, expectations about future income are systematically inaccurate in the direction of the shock relative to subsequent realizations. The size of the forecast error, defined as the difference between subjective income expectations over the next six months and the realized income over the same period, increases proportionally with the size of the income shock. These results hold after keeping constant a rich set of individual-level characteristics. At the same time, the extent of overreaction is heterogeneous across demographic groups. The size of the forecast error is larger for

[1] See, e.g., Reuven and Lansing (2010), Mian and Sufi (2014), Mian et al. (2017), Agarwal et al. (2017), Mian et al. (2020), Bordalo et al. (2018), Bianchi et al. (2021), and Chodorow-Reich et al. (2023).

[2] For recent reviews of survey-based research in economics, see Haaland et al. (2021) and D'Acunto and Weber (2024).

consumers who face more volatile incomes and for younger consumers. These patterns hold when we only exploit variation within individuals over time in specifications with individual fixed effects.

We then examine whether inaccurate income expectations are associated with consumption and borrowing behavior and find they are: the larger the forecast error, the greater the contemporaneous increase in spending. Moreover, consumers with larger forecast errors subsequently borrow more and face a higher likelihood of default.

These patterns are a robust feature of the data. For example, our results are robust to only focusing on data from 2023 onwards, which excludes the COVID-19 period; the results also stay nearly unchanged if we focus on subjects with small survey reporting errors on past income, indicating inattention to current income is unlikely a reason driving our results.

To further strengthen identification, we instrument individual income shocks and forecast errors with the average shock among similar consumers in other locations and its interaction with a high-income-volatility indicator. The estimates are very similar to the baseline results, reinforcing the impacts of forecast errors for income on spending, borrowing, and default.

Overall, the first part of the paper provides direct evidence at the micro level for an expectations-based channel of household debt accumulation. In particular, consumers form systematically more optimistic expectations about future income following unexpected positive shocks. These overoptimistic beliefs result in higher contemporaneous consumption, and when realized income falls short of expectations, consumers borrow more and are more likely to default.

The second part of the paper assesses the aggregate implications of the micro-level evidence. While our empirical analysis mainly exploits variation in income shocks within individuals over time, in the aggregate such shocks are likely correlated across individuals: during periods of strong aggregate growth, many consumers experience positive income shocks, part of which are unanticipated. Given biased income expectations, a larger share of households then increases consumption and accumulates more debt. Conversely, when GDP growth slows or turns negative, more consumers experience unexpected declines in

income and respond by cutting spending and reducing borrowing.

Based on this intuition, we augment a standard consumption model in partial equilibrium with incomplete markets and heterogeneous agents with defaultable debt to assess the dynamics of subjective income expectations for aggregate household debt cycles. In the model, consumers learn about the permanent innovation of their income process from their realized income. Meanwhile, we allow consumers to over-extrapolate income shocks by overreacting to surprising signals. We then compare the implications to a model in which consumers are Bayesian learners. The model matches several empirical moments of the liquidity distribution, such as the fraction of debtors in the economy as well as the average and median wealth to income ratios. The model also matches successfully the relationship between forecast errors and economic choices we observe in the micro data, but only when consumers overreact to the signals.

We use the model to simulate a heterogeneous-agent economy to study the effects of extrapolative income expectations on the dynamics of aggregate consumption, debt, and defaults. Extrapolative expectations amplify the effect of income shocks on income expectations and consumption. For this reason, agents start accumulating more debt after positive income shocks relative to the Bayesian benchmark. Once the economy is hit with a small negative shock, debt and default increase substantially compared with the Bayesian benchmark. These results are consistent with many patterns that have motivated the recent strand of research in macroeconomics on household debt cycles. For instance, the facts that elevated consumer sentiment implies higher subsequent growth in debt (López-Salido et al., 2017) and that the end of a boom usually coincides with times of high financial fragility (Greenwood et al., 2019; Maxted, 2023).

Our evidence of a demand-side channel of household debt cycles does not imply the irrelevance of supply-side channels to explain consumption and household debt choices. For instance, Aydin (2022) and Yin (2025) document the impact of banks' credit choices on consumers' debt and spending using randomized increases in credit card limits. Bornstein and Indarte (2023) find that expanding social insurance via Medicaid eligibility increases households' financial resilience and hence credit supply, which leads to higher household debt accumulation. Finally, Kluender et al. (2024) show both beliefs (demand) and

constraints (supply) drive low-income workers' consumption decisions.

We mainly contribute to three strands of literature. First, we contribute to the rich literature on the consumption response to income changes and especially on the marginal propensity to consume (MPC) out of income shocks (Parker et al., 2013; Kueng, 2018; Olafsson and Pagel, 2018; Fuster et al., 2020; Jappelli and Pistaferri, 2020; Baugh et al., 2021; Fagereng et al., 2021; Colarieti et al., 2024).[3] Our study is closely related to work on the consumption response to total income shock rather than one-time wealth transfers (Ganong et al., 2025; Krueger et al., 2023). We are the first to combine repeated surveys eliciting income expectations within individuals over time with transaction-level bank data and comprehensive credit-registry information, allowing us to directly link belief formation to realized income and financial behavior. This unique design offers micro-level evidence on how forecast errors for income transmit to spending, borrowing, and default decisions through an expectation channel, and informs models of household consumption and saving and the design of social-insurance and redistribution policies.

We also contribute to the literature on credit cycles in the household sector. The literature has proposed two broad mechanisms: financial frictions that amplify shocks and generate cycles in credit supply (e.g., Kiyotaki and Moore, 1997; Gertler and Kiyotaki, 2010; Mian et al., 2020), and shifts in subjective beliefs that drive fluctuations in credit demand (e.g., Bordalo et al., 2018, 2021; L'Huillier et al., 2023). Our paper provides micro-level evidence consistent with the latter mechanism. We show unexpected income shocks lead households to overreact in their income expectations, resulting in excessive borrowing and higher subsequent default. This individual-level evidence complements aggregate studies linking belief dynamics to credit booms and busts (e.g., Kaplan et al., 2020; Mian and Sufi, 2018).

Lastly, we contribute to the literature linking beliefs to intertemporal consumption choices (see DellaVigna (2009); Benjamin (2019)). Existing work relates subjective beliefs to discrete or long-horizon decisions such as retirement, portfolio allocation, and housing (e.g., Ameriks et al., 2020; Giglio et al., 2021; Kuchler et al., 2022; Beutel and Weber, 2025), how extrapolative income expectations affect saving behavior (e.g., Rozsypal and

[3]See Attanasio and Weber (2010) and Jappelli and Pistaferri (2010) for earlier reviews and Kaplan and Violante (2022) for a recent review of MPCs in heterogeneous agent models.

Schlafmann, 2023; Bellifemine et al., 2024), or studies how macroeconomic and personal expectations shape consumption and saving (e.g., Roth and Wohlfart, 2020; Coibion et al., 2022; D'Acunto et al., 2022; Kluender et al., 2024). Relatedly, Exler et al. (2024) examine the welfare implications of over-optimism about income risk in a model with lender screening. Finally, Balleer et al. (2025) study biased beliefs of labor-market transitions and quantify the implications for wealth inequality in a structural life-cycle model.

While recent studies exploit rich survey data on income and labor-market expectations, to the best of our knowledge no prior work exists that jointly observes individual expectations, realized income, and subsequent economic choices within the same administrative panel. We therefore focus on biased income expectations within individuals over time and study their effects on consumption, borrowing, and default. By combining repeated individual-level survey measures with transaction data and comprehensive credit-registry records, we link belief distortions to dynamic financial behavior not jointly observed in prior work.

II Expectation Formation

Before describing our empirical setting and results, we lay out a conventional income process to highlight how forecast errors for income behave when agents' expectation formation deviates from Bayesian learning. This section motivates our subsequent empirical analysis and guides the estimation equations.

Let Y_t denote income and $y_t \equiv \log(Y_t)$ log income. Suppose log income y_t follows

$$\begin{aligned} y_t &= \alpha + z_t + \epsilon_t \\ z_t &= z_{t-1} + \eta_t, \end{aligned} \tag{1}$$

as in a standard buffer-stock model (Carroll, 1997; Blundell and Preston, 1998). Here, z_t is the permanent component in the income process. ϵ_t and η_t are i.i.d. normal shocks with $\mathbb{E}[e^{\epsilon_t}] = 1$ and $\mathbb{E}[e^{\eta_t}] = 1$, and variances σ_ϵ^2 and σ_η^2, respectively. α represents a time-invariant deterministic component of log income, which we assume is common knowledge.

Consumers do not observe the true value of z_t. Instead, each period they observe y_t

and update beliefs about z_t according to:

$$\hat{z}_t = \hat{z}_{t-1} + (1+\theta)\kappa\left[y_t - \alpha - \hat{z}_{t-1}\right], \tag{2}$$

where κ is the steady-state Kalman gain in a standard Kalman filter (Guvenen, 2007). The parameter θ captures deviations from Bayesian learning: when $\theta > 0$, consumers overreact to signal surprises. Overconfidence about signal precision (Daniel et al., 1998; Daniel and Hirshleifer, 2015; Angeletos et al., 2021) can microfound this specification. Throughout, we use $E_t[\cdot]$ to denote expectations under Bayesian learning and $E_t^{\theta}[\cdot]$ for expectations that overreact to the signal.

Define the income shock as $s_t \equiv y_t - E_{t-1}[y_t]$ and the one-period-ahead forecast error under overreaction as $FE_{t+1}^{\theta,y} \equiv E_t^{\theta}[y_{t+1}] - y_{t+1}$. We then have:

Proposition 1: The regression coefficient of $FE_{t+1}^{\theta,y}$ *on* s_t *is* $b_{log} = \kappa\theta$.

The proof is in online appendix Section I.A. Proposition 1 states income shocks positively predict next-period's forecast errors only under overreaction ($\theta > 0$), because when $\theta = 0$, the Kalman orthogonality condition holds, so that income shocks are uncorrelated with future forecast errors, that is, agents fully condition their forecasts on all available information.

Note s_t is not directly observable because beliefs about the latent state are unobserved. However, we can express the log income process as:

$$y_t = y_{t-1} + s_t - (1-\kappa)s_{t-1}. \tag{3}$$

Thus, we can recover s_t by estimating an ARMA(1,1) model for log income.

Later we study the effects of income shocks on consumption and borrowing behavior. Since borrowing often equals zero at the individual level, estimating borrowing elasticities using log values is problematic. We therefore derive level analogues of income shocks and forecast errors to obtain estimates for marginal propensities.

Define level shocks as $s_t^Y \equiv Y_t - E_{t-1}[Y_t]$ and level forecast errors as $FE_{t+1}^{\theta,Y} \equiv E_t^{\theta}[Y_{t+1}] - Y_{t+1}$. We then have:

Proposition 2: The regression coefficient of $FE_{t+1}^{\theta,Y}$ *on* s_t^Y *is* $b_{level} = \kappa\theta\Gamma$, *where* $\Gamma > 0$.

For small shock variances, $\Gamma \approx 1$.

The difference between b_{log} and b_{level} arises from Jensen's inequality when moving from logs to levels. As the variance of income shocks approaches zero, b_{level} converges to b_{log}.

Propositions 1 and 2 characterize the relationship between next-period forecast errors and current income shocks. These shocks are measured relative to rational expectations rather than consumers' own beliefs. Alternatively, we can study the relationship between future forecast errors and current *income surprises*, defined as $s_t^\theta \equiv y_t - E_{t-1}^\theta[y_t]$, which is the difference between realized income and consumers' ex-ante forecasts. Note income surprises equal the negative of current forecast errors. Regressing future forecast errors on current income surprises is therefore equivalent to estimating the negative of the first-order autocorrelation of forecast errors.

Proposition 3: The regression coefficient of $FE_{t+1}^{\theta,y}$ *on* s_t^θ *is* $\kappa\theta\tilde{\Gamma}$*, where* $\tilde{\Gamma} \in (0,1)$.

Using income surprises yields qualitatively similar but attenuated results compared to using income shocks, due to additional noise in subjective expectations induced by overreaction.

III Institutional Setting and Data

We collaborate with a large national commercial bank in China that ranks among the country's top ten banks by total assets. As of 2023, the bank held more than one trillion U.S. dollars in assets and served over 70 million active account holders.

We combine transaction-level data from this bank with multiple waves of a customized survey that elicits consumers' subjective income expectations. The survey covers a population representative of the Chinese banked population, and our main sample period spans January 2020 to June 2025.

In addition, we obtained data from the Credit Reference Center of the People's Bank of China, the country's official credit registry, which aggregates borrowing information from all financial institutions. These data allow us to observe each borrower's total outstanding debt and its composition across lenders.

III.A Identifying Primary Bank Users

The credit registry does not collect spending information. To study consumption choices, we thus need to rely on the transaction-level data from the bank. Consumers might have multiple banking relationships and multiple spending accounts, though. This would be a concern for our analysis if consumers had systematically different spending habits across accounts and these habits were a function of income expectations and past income shocks.

To alleviate this concern, we follow recent research using single-provider transaction-level data (Ganong and Noel, 2019; Boehm et al., 2025) and impose two restrictions on the accounts that enter our empirical analysis to capture consumers who are likely to use the bank as their primary banking institution. First, we only consider consumers who have their regular income directly deposited at our partner bank. Second, we only consider active users that use the accounts at the bank for at least 20 transactions per month. In Section V.E, we verify that using different thresholds has no material impact on our results.

III.B Measuring Income, Spending, and Debt

We retrieve income data based on account-level data. For employees, we calculate income based on a consumer's social insurance contributions, because these payments typically represent a fixed fraction of total income, which includes salary, commissions, and bonuses. For self-employed individuals or employees with business-related income, this part of income is calculated from tax payments and the associated tax rates. This approach provides a reliable estimate of non-financial income.[4] In online appendix Figure A.1, Panel A, we compare the income data used in our analysis with administrative income records from a provincial tax authority, which cover about 13% of our sample, to validate our measure. The plot shows a strong linear relationship with an R^2 of 0.92, indicating that our income measure closely matches the administrative benchmark for the common sample.

[4]In China, social security consists of five types of insurance and a housing fund. Each insurance is usually paid as a fixed share of monthly income; the retirement insurance, similar to U.S. retirement plans, mostly requires an 8% contribution. The income base is typically capped at both tails, with regional caps set at about 30%-300% or 40%-400% of the previous year's local average income. Since these caps affect only around 10% of workers, we exclude them from the final sample.

We compute monthly total spending as the sum of all purchase transactions excluding installment payments on mortgages and vehicles plus the total repayments of linked credit cards' end-of-month balances between the end of the last billing cycle and the current billing cycle.[5]

Debt data come from the Credit Reference Center (CRS) of the People's Bank of China, the official credit registry, based on credit reports retrieved by the bank. CRS aggregates personal credit information from all financial institutions, including detailed monthly information on credit accounts (term loans, credit cards, and other personal credit lines), bank names, outstanding balances and limits, recent credit utilization, repayment history, end-of-billing cycle total amount payable and unpaid balances for each account, housing fund and social security contributions, etc. Given its comprehensive coverage, this dataset provides a complete view of consumers' borrowing behavior. We then define debt as the unpaid balance at the end of the interest-free billing cycle.[6]

The credit reports contain information which banks consumers borrowed from. When survey participants only have debt from our partner bank, we can check if the debt amounts reported on credit reports correspond to the numbers we observe in bank data. In online appendix Figure A.2, we compare unsecured debt as computed from the bank and unsecured debt from the credit reports for borrowers who hold debt exclusively with the partner bank. We observe an almost perfect linear relationship, verifying the quality of the credit registry data.

III.C Survey Design and Answers' Reliability

To elicit consumers' expectations, we designed a customized survey administered by the partner bank. Figure 1 shows the survey timeline. The bank conducted two waves per year, each at the beginning of January and July, from 2020 to 2025, excluding 2022. Each wave elicited expectations for the subsequent six months.[7]

[5]During our sample period, most Chinese residents made payments through Alipay or WeChat Pay. These platforms can be used either by linking debit or credit cards or by storing small balances in their built-in "change" wallets. Our data capture the card-linked transactions, which account for the vast majority of payments. A supplementary bank survey indicates that only 5.46% of transactions are made using wallet balances.

[6]Section IV in the online appendix provides an example of a credit report translated to English.

[7]The bank requested six-month lags, which align with their business auditing frequency.

To limit survey fatigue, the bank imposed a limit of 12 questions.[8] We report the English version of the survey (which was administered in Mandarin) in Appendix III. On average, survey participants spent about 4 minutes answering the survey. The average compensation was 10 CNY, which is above the 95th percentile of the hourly wage rate in China and allowed us to achieve a high response rate (68%).

The survey starts by describing its purpose. Besides ensuring informed participation, this step aims to eliminate any potential strategic motives in answers: without explanations, respondents might incorrectly infer that their answers are used to shape the types and quantities of financial services the bank would offer them going forward. To avoid this interpretation, the survey started with the following paragraph:

> *The data will be analyzed by third-party research scholars for scientific research purposes and will not be evaluated by this bank. We will not disclose participants' identifiable information in any respect. We will not, to any extent, change the types of financial products we provide, including credit scores, credit limits, deposit rates, etc., based on participants' answers. Therefore, please answer based on your actual opinion.*

Respondents then report their total income over the previous 12 months. We can assess the accuracy of survey responses by comparing the answers to this question and income based on transaction histories. If respondents answered carelessly or intentionally misreported their income, reported income should deviate from observed inflows. Panel B of Figure A.1 compares reported income with inflows from account-level data, showing a strong linear relationship. The corresponding regression yields an R^2 of 0.74, supporting the reliability of our survey measures.[9]

For individuals' income beliefs, we follow standard elicitation methods to measure both the first and second moments (Manski, 2004). First moments are based on

What will your total income be most likely over the next 6 months?

[8]The overall sample receives nine questions. 29% of participants with transactions in investment accounts over the six months before fielding the surveys receive three additional questions about financial market returns.

[9]Table A.1 in the online appendix shows that forecast errors are not correlated with likely credit constraints, suggesting misreporting to obtain more credit is unlikely.

To ensure participants have the same definition of income in mind when answering, which corresponds to the one we use to calculate total income in the account-level data, we add:

> *Note: income includes wages, salaries, bonuses, commission, etc., excluding earnings from financial investments.*

In addition, unemployed consumers might be unsure about whether to report a zero income value or the expected income from a possible future job. To avoid these issues, our analysis focuses on employed consumers and we add the following clarification:

> *For the following three questions, we would like to ask you about your income expectations over the next six months. Please assume that you will not change your current job.*

A potential concern is that respondents anticipating a job change within six months may report their current income but spend according to the income expected from their new job. In our data, only about 4% of respondents switched jobs during each forecasting period, and results are virtually unchanged when we include or exclude them. To err on the side of caution, we exclude job switchers from the main analysis.

To elicit the second moment of income expectations, we use a minimum-maximum elicitation, in which respondents report the lowest and highest possible realizations of their future income (e.g., Guiso et al., 2002; Christelis et al., 2020). We then get income uncertainty as the standard deviation from assuming subjective income growth follows a triangular distribution.[10] This simple format keeps the response burden low and facilitates consistency across survey waves especially when participants face cognitive constraints (D'Acunto et al., 2019, 2023).[11]

Specifically, we ask the following two questions:

[10] Denote $a = \log(E_t^\theta[\min Y_{t+1}]/Y_t)$, $b = \log(E_t^\theta[Y_{t+1}]/Y_t)$, and $c = \log(E_t^\theta[\max Y_{t+1}]/Y_t)$, then the squared income uncertainty is $(a^2 + b^2 + c^2 - ab - ac - bc)/18$.

[11] This coarse measure may induce measurement errors. However, we use subjective income uncertainty only as a sorting variable to study heterogeneity in overreaction. As long as the reported spread is positively correlated with true subjective uncertainty, such noise should be largely immaterial for our analysis.

What would be the lowest possible level of total income you believe you could make over the next 6 months?

What would be the highest possible level of total income you believe you could make over the next 6 months?

These two estimates allow us to compute the second moment of subjective expectations.[12]

We restrict the sample to individuals who completed at least two survey waves. This panel structure allows us to exploit within-person variation in forecast errors for income, income shocks, and economic choices over time. By controlling for individual fixed effects, we absorb time-invariant unobserved traits, such as cognitive ability and financial literacy, that could confound the relationship between expectations, consumption, and debt. In addition, observing multiple cross-sections over time enables us to estimate results within each period, netting out common aggregate shocks. This feature is particularly important because our sample begins at the onset of the COVID-19 pandemic.

III.D Summary Statistics

Table I reports summary statistics for our working sample. All currency values are in thousand CNY, and all continuous variables are winsorized at the 1st and 99th percentiles to limit the influence of outliers.

The final sample includes 6,285 unique individuals and 26,449 total observations. On average, each person completed 4.2 of the nine possible survey waves.[13] Demographically, the sample is balanced and representative of the working-age population. The age distribution is centered around 40 years, with an interquartile range between 34 and 46. Women account for 52% of the sample and men for 48%, alleviating concerns that transaction data from banks with strong online operations overrepresent men or younger users. Representativeness matters for external validity because prior work shows that men and women differ systematically in their expectations and in how they respond to economic news (e.g., D'Acunto et al., 2021; Coibion et al., 2022).

Turning to the transaction data, the average monthly income is 13.0 thousand CNY and average monthly spending is 7.1 thousand CNY. Both distributions are right-skewed:

[12]We do not additionally elicit the subjective probability that income exceeds the mode or midpoint, as both versions yield nearly identical first and second moments (Weber et al., 2022; Coibion et al., 2024).

[13]See Figure A.3 for the histogram of the number of completed waves.

the medians are 8.3 and 5.1 thousand, respectively. Respondents spend on average 2.8 thousand CNY per month on installment payments for mortgages or vehicle loans. The average stock of interest-bearing unsecured debt is 5.0 thousand CNY, though the median consumer has zero debt. Conditional on having any debt, the average balance is 12.5 thousand CNY. About 40% of respondents carry positive credit card debt, broadly in line with estimates from the U.S. (40-60%) (Gross and Souleles, 2002; Zinman, 2009; Fulford, 2015).

Average total credit limits across all banks are about 81.3 thousand CNY, suggesting that most consumers have substantial unused borrowing capacity.[14] Liquidity is defined as checking plus savings account balances minus unsecured debt, divided by annual income. On average, participants hold liquid wealth equal to 1.13 times annual income, though roughly 30% are net debtors with negative liquidity. 17% of respondents simultaneously hold positive liquid assets and credit card debt (co-holders), consistent with the well-known co-holding puzzle (Gross and Souleles, 2002; Telyukova, 2013; Gorbachev and Luengo-Prado, 2019; Gathergood and Olafsson, 2024). Defining hand-to-mouth households as those with liquid assets below two months of income, 31% of the sample falls into this category.

Finally, income expectations are on average close to realizations: the mean forecast error is 270 CNY, and the median is zero. However, variation is sizable, with an interquartile range from negative 1,500 CNY to 2,500 CNY. In addition, we verify the surveyed consumers are broadly comparable to the bank's overall customer base (see Table A.2), with the exception of slightly lower income and spending.

IV Income Shocks and Subjective Income Expectations

Matched transaction-level data and survey-based beliefs allow us to relate income shocks to income forecast errors at the individual level. To identify income shocks, we estimate equation (3) using the following ARMA specification for log income:

$$y_{i,t} = \rho_{j,k,a} y_{i,t-1} + \Gamma X_{i,t-1} + s_{i,t} + \omega s_{i,t-1}. \tag{4}$$

[14]The ratio of average credit limit to average personal income, which is around 52% in our sample, is slightly larger but close to the roughly 43% in the U.S. in 2023.

This approach is similar to the estimation of expected and unexpected tax refunds in Baugh et al. (2021), but it is specifically tied to our income process. The vector $X_{i,t}$ includes age, age squared, education, gender, the log of savings and credit limits in the previous period, city fixed effects, and industry-by-period fixed effects. The period is defined as half a year to align with the survey frequency. The persistence parameter $\rho_{j,k,a}$ is estimated at the industry-city-age-quintile level. Equation (4) is estimated on a random 10% sample of all customers in the bank's database between January 2020 and June 2025.

We construct log income shocks as $\hat{s}^y_{i,t} = y_{i,t} - E_{i,t-1}[y_{i,t}]$, where $E_{i,t-1}$ is the predicted income from equation (4). We define level income shocks analogously as $\hat{s}^Y_{i,t} = Y_{i,t} - E_{i,t-1}[Y_{i,t}]$, where $E_{i,t-1}[Y_{i,t}] = \exp\{y_{i,t} - \hat{s}_{i,t} + \hat{\sigma}^2_s/2\}$ is the expected value of $Y_{i,t}$ implied by equation (4), and $\hat{\sigma}^2_s$ is the estimated variance of $s_{i,t}$ at the industry-city-age-quintile level.[15]

Finally, we use the negative of forecast errors in period t as income surprises. Panels A and C of Figure 2 show binned scatter plots of income shocks and income surprises in logs and levels, respectively; Panels B and D control for individual fixed effects. The shaded regions correspond to 95% confidence intervals for the fitted lines. Without residualization, the R^2 is around 0.1, indicating a positive but imperfect correlation between the two measures. Including individual fixed effects reduces measurement noise and modestly increases the R^2, but the two measures remain distinct. Overall, consumers' income surprises are positively related to realized income shocks, yet the correlation is far from one, leaving room for systematic errors in subjective expectations.

Serially correlated income shocks are a potential concern, which would bias the estimated effects of these shocks on subsequent outcomes. To assess this concern, we examine the autocorrelation of $\hat{s}_{i,t}$ in Figure A.4 and find no evidence of serial dependence. This validation supports our focus on income shocks rather than income surprises in the main analysis. When individuals overreact to past information, income surprises, defined as the negative of forecast errors, exhibits negative autocorrelation, which would mechanically attenuate estimates of behavioral responses. Using income shocks avoids

[15]Results are unaffected if we assume a common $\hat{\sigma}^2_s$ across individuals. This normalization only rescales the predicted level income by a constant factor and therefore does not affect the time-series variation in income shocks that identifies our estimates.

this issue.

IV.A Extrapolative Subjective Income Expectations

We now study how income shocks shape forecast errors.

IV.A.1 Income shocks, income surprises, and forecast errors

The measures of realized income, subjective income expectations, and income shocks allow us to assess how unexpected income changes relate to the ex-post accuracy of consumers' expectations.

We begin by documenting systematic departures of income forecasts from subsequent realizations. Panel A (B) of Figure 3 shows a binned scatter plot of ex-post realized income changes (growth) against ex-ante expected income changes (growth). The shaded regions give the 95% confidence intervals for the fitted lines. In both cases, the correlation is positive: consumers' forecasts tend to move in the same direction as realized changes (Caplin et al., 2023, see also). At the same time, the cross-sectional dispersion in forecast errors is substantial. Panel C of Figure 3 displays the distribution of forecast errors, which is wide, centered at 0 and tends to be symmetric. Panel D shows this dispersion remains even after taking out individual fixed effects. The large heterogeneity in forecast errors motivates our subsequent analysis of how forecast errors shape economic behavior.

We next examine the relationship between current-period income shocks and subsequent forecast errors by estimating

$$FE^{\theta}_{i,t+1} = b_0 s_{i,t} + X'_{i,t}\delta + \nu^{FE}_{i,t+1}, \tag{5}$$

where $FE^{\theta}_{i,t+1} \in \{FE^{\theta,y}_{i,t+1}, FE^{\theta,Y}_{i,t+1}\}$ are forecast errors in logs and levels, respectively. $FE^{\theta}_{i,t+1}$ is defined as the difference between forecasted and realized income in period $t+1$, with forecasts made at the beginning of that period. For instance, if $t+1$ corresponds to the first half of 2024, $FE^{\theta,y}_{i,t+1}$ equals the log of forecast of income from January to June 2024, made in early January, minus the log realized income over the same period. $s_{i,t} \in \{\hat{s}^{y}_{i,t}, \hat{s}^{Y}_{i,t}, \hat{s}^{\theta,y}_{i,t}, \hat{s}^{\theta,Y}_{i,t}\}$ denotes income shocks and income surprises in logs and levels, respectively.

$X_{i,t}$ includes individual characteristics such as credit limit, income growth, and liquidity to control for borrowing constraints and the demand for debt. The specification

controls for individual fixed effects, which absorb time-invariant traits, such as persistent optimism or financial sophistication, and for industry×wave fixed effects, which capture aggregate shocks common to all individuals within an industry, particularly relevant during the COVID-19 period. Standard errors are clustered at the industry×wave level.

We first present plots that describe relationships in the raw data. Panels A and B of Figure 4 plot next-period forecast errors against current income shocks in levels and logs, respectively, whereas Panel C and Panel D use current-period income surprises as the sorting variable. All plots control for individual fixed effects. Across specifications, both income shocks and income surprises positively predict next-period forecast errors, both in levels and in logs.[16]

Table II reports the results from estimating equation (5). All columns include individual fixed effects. In the even-numbered columns, we additionally control for demographics and industry×wave fixed effects. Across all columns, the estimated coefficients $\hat{b}$ are positive and statistically significant. A positive $\hat{b}$ indicates that consumers' income expectations tend to move excessively in the direction of recent shocks. Focusing on column (2), the inclusion of industry×wave fixed effects absorbs local shocks that may shift the income processes of all consumers in a given location, whereas individual fixed effects account for time-invariant personal traits that could jointly affect forecast errors and income shocks. This specification therefore identifies how the size of income shocks relates to the accuracy of the same individual's expectations over time. The estimate $\hat{b} = 0.431$ implies that, on average, a one-CNY unexpected income in the current period leads the average consumer to overpredict next-period income by about 0.43 CNY.

Because the estimates are similar across specifications, we use income shocks in levels as our preferred measure of income innovations for two reasons. First, many individuals don't borrow, that is, borrowing frequently equals zero at the individual level, making log transformations for estimating elasticities problematic. We therefore use level measures of income shocks and forecast errors to obtain interpretable marginal-propensity estimates. Second, since income surprises are the negative of forecast errors, the positive predictability of future forecast errors implies negative serial correlation. Using surprises

[16]Bellifemine et al. (2024) document a similar pattern using Italian survey data.

would thus bias estimates of behavioral responses, whereas level income shocks avoid this issue.[17]

IV.A.2 Heterogeneous responses by individual characteristics

We next examine heterogeneity in the relationship between income shocks and forecast errors. Recent research finds individuals tend to overreact more when forming beliefs under noisier or more volatile signals (Ba et al., 2022; Augenblick et al., 2024). We therefore test whether consumers facing more volatile incomes overreact more strongly to unexpected income shocks. We use three proxies for income volatility: (i) age, since younger individuals typically experience more volatile earnings; (ii) the standard deviation of expected income growth; and (iii) a government-sector dummy, as government employees generally face stable incomes.

Columns (1)-(3) of Table III report the results. Overreaction is systematically stronger among consumers with more volatile incomes: income shocks predict forecast errors more strongly for younger individuals and those with greater volatility in expected income growth. In contrast, no economically significant relationship between income shocks and forecast errors exists for government employees, that is, the interaction term and the baseline estimate are similar in magnitudes but of opposite signs. Overall, these findings show the degree of overreaction is larger when income uncertainty is higher.[18]

Recent studies document substantial within-job earnings volatility, largely driven by commissions, bonuses, and other irregular income components (Andresen et al., 2025; Ganong et al., 2025).[19] Because salaried income is more predictable and varies less from one period to the next, individuals who receive a larger share of their income from salaries should extrapolate less from income shocks. We test this intuition by defining salaried workers as those in the top quartile of the regular-income share and examining whether

[17] In addition, Liao (2024) highlights that regressing forecast errors on forecast revisions can introduce a mechanical bias. Our approach avoids this concern by using realized income shocks from the previous period as the regressor, which has no mechanical overlap with the dependent variable.

[18] In online appendix Section I.B, we show that stronger overreaction among individuals with more volatile income is consistent with greater cognitive uncertainty about the informativeness of current income.

[19] Using administrative data from the U.S., Ganong et al. (2025) document substantial monthly variation in total earnings. In online appendix Figure A.5, we plot the histogram of the standard deviation of log income growth at the individual level for the participants in our sample and also document large variations.

survey participants in this group form expectations differently than others.[20] Column (4) of Table III indeed shows that salaried workers exhibit significantly weaker overreaction to income shocks.

A potential concern is that COVID systematically introduced negative income shocks. If this period also coincided with widespread over-pessimism, our estimates might capture unobserved heterogeneity rather than true overreaction. The inclusion of industry×wave fixed effects already partially alleviates this concern by absorbing time-specific shocks common to workers in the same industry. We further interact income shocks with a post-2023 dummy to test whether the pattern persists after the pandemic, where post-2023 dummy is one if individuals participate in the survey in waves from 2023 to 2025. Column (5) shows the degree of extrapolation is slightly smaller after 2023 but the difference is not statistically significant.

Finally, column (6) of Table III tests whether extrapolation differs by the sign of the shock. We cannot reject equality: the degree of overreaction is similar following positive and negative income shocks, both economically and statistically.

V Income Expectations, Spending, Debt, and Defaults

To assess whether forecast errors for income also shape actual economic decision making, we examine whether individuals adjust current consumption in line with their expectations. In particular, overly optimistic (pessimistic) expectations should raise (lower) current spending. Using transaction-level data on actual expenditure allows us to test this prediction directly.

V.A Spending Responses

We estimate variations of the specification

$$\Delta C_{i,t} = b_1 \hat{s}^Y_{i,t} + b_2 FE^{\theta,Y}_{i,t+1} + X'_{i,t}\delta_c + \nu^C_{i,t}, \tag{6}$$

where $\Delta C_{i,t}$ is the change in consumption from period $t-1$ to period t. The coefficient b_2 captures the effect of forecast errors about next period's income on current consumption,

[20] We classify income as regular if an individual receives at least four payments labelled as salary payments within the last 12 months with identical amounts and transactions, capturing stable salary income and excludes irregular components such as bonuses, commissions, and other variable transfers. Then regular income share is the share between total regular income and total income.

controlling for current-period income shocks $\hat{s}^Y_{i,t}$. All other variables are defined as in equation (5).[21]

Table IV reports the results. All columns include industry×year and individual fixed effects, which absorb time-varying local shocks common within industries and time-invariant individual heterogeneity (e.g., persistent optimism) that could otherwise induce spurious trends in consumption. Column (1) relates consumption to income shocks only, yielding an estimate of the MPC: each one-CNY income shock raises contemporaneous consumption by about 0.254 CNY.[22] In column (2), forecast errors are also positively correlated with current spending: each one-CNY forecast error raises contemporaneous consumption by about 0.207 CNY.

Column (3) includes both current income shocks and forecast errors about next period's income. The MPC out of income shocks declines by 35% (from 0.254 to 0.166). At the same time, a one-CNY higher forecasted than realized income is associated with about 0.196 CNY higher current consumption.

The estimates in Tables II and IV decompose the marginal propensity to consume (MPC) out of income shocks into a *belief channel* and a *residual (liquidity) channel*. The overall MPC is defined as

$$\frac{dC_{i,t}}{d\hat{s}_{i,t}} = \frac{\partial C_{i,t}}{\partial \hat{s}_{i,t}} + \frac{\partial C_{i,t}}{\partial FE^{\theta}_{i,t+1}} \times \frac{\partial FE^{\theta}_{i,t+1}}{\partial \hat{s}_{i,t}},$$

where the first term captures the direct liquidity-driven response and the second term captures the indirect response through changes in expectations. From Table II column (2), we estimate $\partial FE^{\theta}_{i,t+1}/\partial \hat{s}_{i,t} = 0.431$; from Table IV column (3), $\partial C_{i,t}/\partial \hat{s}_{i,t} = 0.166$ and $\partial C_{i,t}/\partial FE^{\theta}_{i,t+1} = 0.196$. Combining these yields a back-of-the-envelope MPC of $dC_{i,t}/d\hat{s}_{i,t} = 0.250$, which closely matches the total effect of 0.254 reported in Table IV column (1). Meanwhile, controlling for forecast errors, $\hat{b}_1$ reflects the conventional MPC to income shocks, a key measure of consumption insurance (Blundell et al., 2008).

[21]Note that this specification estimates the total effects of the forecast errors on current consumption. Presumably, we are not controlling for expectation changes further in the future. This specification is only valid under the (conventional) assumption that the state of income follows an AR(1) process and consumption is chosen according to the standard first-order Markov property with frequency of half a year, so that expectations of next-period income suffice to summarize the continuation value.

[22]Estimates are consistent with recent evidence; online appendix Table A.3 reports elasticities similar to those in U.S. data (e.g., Ganong et al. (2025)).

Columns (4)-(7) examine heterogeneity by liquidity constraints. We proxy constraints by using (i) the average credit line utilization rate and (ii) the ratio of liquid savings to income, both measured over the six months prior to period t. High Util_t equals one for utilization above the sample median at t, and High Liq_t equals one for liquid savings-to-income above the median at t. The effects of income shocks and forecast errors on consumption are larger for consumers with tighter constraints (high utilization or low liquidity), consistent with higher marginal propensities to consume among more constrained households.

V.B Debt and Default

Because forecast errors raise current consumption while future realized income increases by less than expected, positive forecast errors cause consumption to deviate from its optimal path. The combination of higher current spending and lower than expected subsequent income implies that debt should rise on average when expectations are overly optimistic. We therefore test whether extrapolative income expectations predict higher subsequent borrowing.

To do so, we estimate a version of equation (6) in which the dependent variable is the change in total unsecured debt, $\Delta B_{i,t+1}$. For example, if $t+1$ corresponds to the first half of 2024, $\Delta B_{i,t+1}$ is the difference between consumer i's total outstanding interest-bearing unsecured debt at the end of June 2024 and that at the end of December 2023.

Column (1) in Table V shows that time-t income shocks weakly but insignificantly predict next-period debt. Columns (2) and (3) instead show the larger the difference between expected and realized income, the greater the increase in unsecured borrowing in the future. In column (3), which includes the full set of controls and fixed effects, each additional CNY of forecast error in average monthly income is associated with about a 6.2-cent increase in unsecured debt. This magnitude is economically meaningful, given that unconstrained consumers do not need to borrow to finance additional spending and therefore exhibit little response.

A remaining concern is that forecast errors could be negatively correlated with current income shocks, which would mechanically reduce net assets. To isolate the effect of forecast errors, we include income shocks in the same period as forecast errors as an

additional control in column (4). In this specification, we estimate the impact of forecast errors on debt accumulation conditional on contemporaneous income shocks. We find a one-CNY positive income shock lowers debt by about 0.030 CNY, while each one-CNY forecast error still raises debt by roughly 0.065 CNY.

The results on consumption and debt indicate that positive income shocks lead to an MPC smaller than one. And yet, debt on average does not decline after these shocks. While this pattern may seem puzzling at first, it arises because debt is bounded below by zero; consumers with high saving rates often have little or no debt to reduce. In contrast, increased spending driven by forecast errors typically results in higher debt among consumers with limited savings, as the expected additional income ultimately does not materialize.

The third outcome we examine is default. When realized incomes are lower than expected, consumers who cannot draw on savings may fail to repay their debt in full. We estimate equation (5) using a dummy variable that equals one if a consumer defaults over the next period as the dependent variable.[23] By construction, we observe outcomes only up to period $t + 1$, while some defaults may occur later. Our estimates therefore likely represent a lower bound of the true relationship between forecast errors for income and default risk. For ease of interpretation, we multiply the default indicator by 100 and standardize income shocks and forecast errors.

Columns (5)-(8) of Table V show income shocks do not significantly predict future default. Meanwhile, larger gaps between forecasted and realized income are associated with a higher probability of default. A one-standard-deviation increase in forecast errors for income raises the default rate by about 0.85 percentage points (column (7)). This effect is economically significant: given an average default rate of around 3.6%, a one-standard-deviation higher forecast error for income implies roughly a 24% increase in the likelihood of default. These results align with aggregate evidence linking optimistic credit-market sentiment to financial fragility (López-Salido et al., 2017). Similar to the debt results, column (8) shows controlling for contemporaneous income shocks barely

[23]For example, the default indicator in the first half of 2020 reflects 90-day delinquencies recorded between October 2020 and March 2021.

affects the estimated relationship between forecast errors and default.[24]

V.C Addressing Endogeneity: 2SLS Estimation

Spending and borrowing responses to forecast errors may be endogenous if unobserved traits or common shocks jointly affect income expectations and behavior. We mitigate this concern by including individual fixed effects, which absorb time-invariant heterogeneity, and industry×wave fixed effects, which capture aggregate shocks common to the same industry. To further improve identification, we employ an instrumental-variables (IV) approach that helps to focus on the exogenous variation in income shocks and forecast errors on behaviors.

Our IV design uses two instruments and is closely related to a location-by-treatment interaction strategy commonly used to isolate indirect treatment channel when shocks affect outcomes through multiple channels (e.g., Kling et al. (2007); Abdulkadiroğlu et al. (2014); Kline and Walters (2016)).

First, to proxy for exogenous income shocks, we divide the 10% bank panel for which we estimate equation (4) into 37 consumer types and compute the mean income shock within each type-period cell, excluding (i) all individuals in our sample and (ii) all individuals in the same city as the survey participant.[25] This type-level average shock, similar in spirit to co-worker income shocks (Ganong et al., 2025), captures common innovations faced by similar consumers while minimizing local spillovers. In addition, we expect this instrument to only capture within-type systematic innovations to income, and therefore it should be uncorrelated with individual private information. As a result, the 2SLS design also alleviates the concern that part of the income shocks we extract captures participants' private information.

Second, following Yin (2025), we interact the type-level income shock with an indicator for provinces with above-median average income volatility. The validity of the location-by-treatment strategy requires that the degree of expectation updating varies systematically across locations with different levels of income uncertainty, and this

[24]Similar to spending, Table A.4 in the online appendix shows debt and default also react stronger for those with higher utilization rates.

[25]We do so based on K-means clustering over age, gender, education, industry, location, income, spending, debt, and credit scores, with the number of clusters chosen by ten-fold cross-validation.

variation is different from that of the type-specific income shocks. This assumption is plausible because the interaction exploits the findings that consumers facing higher income uncertainty update their beliefs more strongly in response to a given income shock. As a result, the interaction term provides additional, plausibly exogenous variation in belief updating, strengthening the first-stage relationship between income shocks and forecast errors.

Table VI reports the results. The first-stage estimates in columns (1) and (2) confirm the relevance of the instruments. The within-type average income shocks are strongly positively correlated with individual income shocks. At the same time, the instrument is negatively correlated with forecast errors in low-volatility environments. A potential explanation is that when income risk is limited, consumers devote less attention to systematic income innovations and thus react less, consistent with rational inattention. In contrast, the positive interaction term in high-volatility cases indicates stronger belief updating, as consumers react more to the same income news when uncertainty is higher.

The second-stage estimates produce magnitudes and signs similar to the baseline OLS results. Columns (3)-(5) show that each one-CNY higher income shock raises current spending by 0.126 CNY but has no significant effect on subsequent debt accumulation or default. Controlling for income shocks, a one-CNY higher forecast error in period $t+1$ increases spending in t by 0.216 CNY. As a result, debt increases by 0.088 CNY more in $t+1$, and default rises by 1.276 percentage points for each one-standard-deviation higher forecast error. Overall, these results reinforce the robustness of our conclusions.

V.D Dynamic Effects

Our analysis so far focuses on six-month horizons. In the longer run, consumers observe income realizations and observe their expectations did not materialize. Over time, we might expect spending and borrowing to revert as biased expectations are corrected. To examine whether and how quickly consumption adjusts to income forecast errors, we estimate the relationship between cumulative consumption and income forecast errors over different horizons:

$$C_{i,\tau+k} - C_{i,\tau-1} = b^{(k)} FE^{\theta,Y}_{i,t+1} + X'_{i,t}\delta^{(k)} + \nu^{C}_{i,\tau+k}. \tag{7}$$

The specification combines two time frequencies: income forecast errors are observed at a half-year frequency, indexed by t, while for better inspection of adjustment dynamics, we use quarterly consumption, indexed by τ. Let τ denote the first quarter of half-year t, so that period t corresponds to quarters τ and $\tau+1$, and period $t+1$ to quarters $\tau+2$ and $\tau+3$, etc. The forecast error $FE^{\theta,Y}_{i,t+1}$ therefore refers to income realizations in quarters $\tau+2$ and $\tau+3$.

The left-hand side measures cumulative consumption from the quarter preceding the first survey ($\tau-1$) up to quarter $\tau+k$. We express both consumption and forecast errors as average monthly level to keep units comparable. We estimate equation (7) for horizons $k=-4,...,8$, excluding $k=-1$, which serves as the benchmark. The resulting coefficients $b^{(k)}$ measure the cumulative changes of consumption from quarter $\tau-1$ to quarter $\tau+k$ in response to each CNY higher forecast errors in period $t+1$.

Panel A of Figure 5 plots the results. The red solid line represents positive forecast errors and the blue dashed line negative errors, with shaded areas denoting two standard-error bands. Consistent with overreaction, consumers increase spending in the two quarters preceding and during the period when forecast errors are measured (quarters 2-3), followed by a gradual reversion that nearly eliminates the excess consumption within five quarters.

Panel B shows similar results for cumulative borrowing. The dynamic pattern mirrors that of consumption: borrowing initially rises with optimistic expectations and later reverts as realized income corrects beliefs. Overall, these findings are consistent with consumers' overreaction to income news followed by subsequent belief adjustment.[26]

V.E Robustness Checks

In this section, we conduct several robustness tests. We first verify that results are qualitatively similar without controls or with different set of fixed effects in Table A.5 in the online appendix, and that the heterogeneity analysis results are similar when using income surprises in Table A.6. Meanwhile, because many participants have a small number of observations, clustering at the individual level may be unreliable due to limited within-

[26]While this pattern aligns with the overreaction mechanism in our model, it is descriptive and does not by itself rule out complementary forces, such as liquidity constraints or transitory adjustment frictions, that may also contribute to the observed dynamics.

cluster variation. So our main analysis clusters at industry × wave level. Nevertheless, Panel A of Table A.7 in the online appendix shows that clustering at the individual level yields similar inference.

A concern is that our sample spans the COVID-19 period, which may feature unusually large forecast errors and income shocks. In the main analysis, we include industry×wave fixed effects to absorb aggregate shocks affecting consumers within the same industry and period. To further verify the pandemic does not drive our results, we exclude data from 2020-2022 and re-estimate income shocks using a 10% bank sample from January 2023 to June 2025. Panel B of online appendix Table A.7 shows the results are nearly identical when restricting the sample to the post-COVID period.

A second concern is that some forecast errors may reflect inattention or reporting mistakes when respondents report current or past income. To assess this concern, we re-estimate the main regressions keeping only individuals whose reporting errors for past income are below the median within each survey wave. Panel C of online appendix Table A.7 shows that the results remain unchanged.

A third concern is that income shocks estimated from equation (4) might capture innovations to the econometrician's information set rather than true surprises to the individual. Part of the residual could thus reflect private information known to respondents. As a robustness check, we re-estimate equation (4) including the respondent's forecasted lowest, highest, and most likely income for the next period. The results, shown in Panel D of online appendix Table A.7 are again very close to the baseline, suggesting that private information is not an important confounding factor.

As a fourth robustness check, we change the criteria for main bank users. Our running sample only includes individuals with at least 20 transactions per month during the sample period. This filter aims to limit the sample to active account users but raises the concern that our sample is tilted towards those with larger spending habits. Panel E of Table A.7 in the online appendix shows that our results are nearly identical when we change the filter to at least 10 transactions per month. In addition, in Panel F, we focus on participants who indicate that they only use one bank for daily transactions. Again, the results remain virtually unchanged.

Note that we estimate equation (4) on a separate sample that excludes survey participants to avoid mechanical endogeneity in shock construction: using the same individuals to estimate (4) would yield in-sample residuals that absorb individual-specific income dynamics and correlate with subsequent forecast errors or spending. Because individual fixed effects cannot be included in this out-of-sample estimation, we incorporate a rich set of demographic controls to capture cross-sectional heterogeneity. As a robustness check, we re-estimate equation (4) in-sample using the same set of controls, and Panel G of Table A.7 shows that the results remain virtually unchanged.

Another concern is that spending decisions could be made at the household level, so our results might be contaminated by intra-household transfers. At the same time, while the survey questions focus on individual income, economic decisions might be made at the household level. Panel H of Table A.7 focuses on single participants, which accounts for 31% of our sample, and finds similar results.

Our spending data is based on the accounts at the bank with which we cooperate. To assess concerns of systematic mismeasurement above and beyond the screening filters to select primary account users, we study the relationship between forecast errors and the changes in net transfers between our bank and external bank accounts (see online appendix Table A.8). We find no relationship between forecast errors and cash withdrawals or net transfers to external accounts, which dismisses the concern that our bank-level data miss relevant transfers to potentially unobserved external accounts. Meanwhile, as a placebo test, Table A.8 shows installment payments on mortgages and vehicle loans, which are more rigid in the short run, do not respond significantly to forecast errors.

Finally, our survey-based panel has a relatively short time dimension. Although results are similar when exploiting either within- or across-consumer variation, income innovations may not fully average out within individuals in short panels (Chamberlain, 1982; Souleles, 2004). To address this concern, we leverage the longer transaction-level panel available from the bank, which spans on average 7.9 years per consumer and includes at least ten periods per individual. Online appendix Table A.9 compares estimates from the extended panel (even columns) to those from the baseline survey sample (odd columns). The conditional relationships between income shocks and spending, borrowing,

and default remain virtually unchanged.

V.F Transitory vs Permanent Shocks

As a final exercise, we decompose the income shocks consumers face into permanent and transitory components and test whether consumers update their subjective expectations based only on persistent shocks or on both types of shocks. The decomposition procedure follows Pistaferri (2001) and we describe in detail how we adapt it to non-rational expectations in online appendix Section V. Table A.10 shows that transitory shocks account for roughly two-thirds of the variation in unexpected income growth in our data.

Building on this decomposition, we regress forecast errors for income on both current transitory and permanent shocks to evaluate their respective contributions. The results, reported in online appendix Table A.11, indicate that despite transitory shocks explaining the majority of income variation, both types of shocks significantly predict forecast errors. Overall, the findings are consistent with the framework in Section II, suggesting that consumers have limited ability to distinguish between transitory and persistent income shocks and therefore react to both.

In sum, the empirical analysis shows consumers excessively extrapolate income shocks, both transitory and persistent, into their expectations. Following positive income shocks, they form subjective expectations of future income that are excessively optimistic relative to ex-post realizations. This tendency is stronger among younger consumers, those facing higher income volatility, and for those not working for the government. Moreover, forecast errors for income, defined as the gap between ex-ante subjective expectations and ex-post realizations, significantly increase current spending, leading to higher subsequent debt and default.

VI Structural Estimation With Overreaction

Our reduced-form results show consumers form extrapolative income expectations after income shocks and that such beliefs predict higher consumption, larger debt accumulation, and elevated subsequent default. We now turn to a quantitative framework to assess how this micro-level, belief-driven demand channel can help explain the aggregate patterns of household debt observed in the data.

To do so, we embed extrapolative income expectations and defaultable debt into a standard partial-equilibrium consumption model with incomplete markets. The model allows us to quantify how unexpected income shocks, forecast errors, and economic choices behave in the presence of extrapolative expectations.

The model has discrete time and infinite horizon. A unit mass of consumers are subject to idiosyncratic income risk. The income process follows the one in Section II. Given an infinite horizon, we follow the common assumption that a sufficient number of periods have passed such that consumers are in a learning steady state, that is, consumers' Kalman gain is constant each period, in which case,

$$\kappa = \frac{\sigma_z^2 + \sigma_\eta^2}{\sigma_z^2 + \sigma_\eta^2 + \sigma_\epsilon^2}, \qquad \sigma_z^2 = \frac{(1-\kappa)\sigma_\eta^2}{\kappa}. \tag{8}$$

VI.A Preferences and Optimality Conditions

In this subsection, we introduce consumer preferences and discuss the optimality conditions.

VI.A.1 Preferences

Household preferences follow the standard framework used in models of consumer credit and default (e.g., Chatterjee et al., 2007; Livshits et al., 2007). Consumers maximize expected lifetime utility with per-period utility given by

$$\frac{c^{1-\gamma} - 1}{1-\gamma} - \chi d,$$

and discount factor β. Here, γ denotes the coefficient of relative risk aversion, and $d = 1$ if the consumer defaults at the end of period t.

Default entails a fixed non-pecuniary utility cost ("stigma") $\chi > 0$. In addition, consumers receive i.i.d. additive utility shocks $\{\xi^D, \xi^N\}$ attached to the default and repayment options, respectively. These shocks are drawn from a Type-I extreme value distribution with scale parameter λ and capture unobserved events, such as marital disruptions or medical expenses, that can trigger default. The inclusion of these shocks ensures a positive probability of default across the entire borrowing range. As noted by Dempsey and Ionescu (2023), smoothing the default decision facilitates model computation.

The budget constraint in period t is

$$a' = \begin{cases} (1+r)(a-c)+y' & \text{if } d=0 \\ (1-\nu)y' & \text{if } d=1 \end{cases} \tag{9}$$
$$a \geq -l,$$

where a is the total amount of available resources. l is the credit limit, and $\nu \in [0,1]$ is the marginal rate of garnishment. Equation (9) states that when consumers do not default, their wealth in the next period is the sum of their income and gross savings. When consumers default, their savings become zero; at the same time, they need to pay a garnishment cost equal to ν times their income in the following period. For simplicity, we assume consumers' borrowing capacity does not change upon default, which allows us to discard one additional state variable.[27] The interest rates differ for saving and borrowing and take the values

$$r = \begin{cases} r_b & \text{if } a < 0 \\ r_s & \text{if } a \geq 0. \end{cases}$$

VI.A.2 Optimality Conditions

Consumers' problem is characterized by a set of two state variables $\Theta = (a, \hat{z})$. Given the state Θ, the consumer's value function is

$$V(\Theta) = \max\left\{V_D(\Theta), V_N(\Theta)\right\}. \tag{10}$$

The continuation value from defaulting and not defaulting are, respectively,

$$V_D(\Theta) = \max_c \frac{c^{1-\gamma}-1}{1-\gamma} - \chi + \beta\, \mathbb{E}_\theta[V(\Theta')] + \xi^D. \tag{11}$$

$$V_N(\Theta) = \max_c \frac{c^{1-\gamma}-1}{1-\gamma} + \beta\, \mathbb{E}_\theta[V(\Theta')] + \xi^N. \tag{12}$$

The subscript θ indicates that expectations are taken under the agents' perceived law of motion, which is parameterized by the extrapolation parameter θ. Given that the utility shocks follow a type I extreme value distribution, the probability of default is

$$pd(\Theta) = \left[1 + \exp\{[V_N(\Theta) - V_D(\Theta)]/\lambda\}\right]^{-1}. \tag{13}$$

[27] Some studies assume defaults go hand in hand with a temporary inability to borrow, that is, $l = 0$ (Chatterjee et al., 2007; Livshits et al., 2007; Dempsey and Ionescu, 2023), but Livshits et al. (2007) show the costs of default from changing borrowing capacities are quantitatively small.

VI.B Reproducing the Empirical Results

We next evaluate the model fit on targeted and untargeted moments and how well it replicates the empirical results.

VI.B.1 Goodness of Fit

We estimate the parameters in two steps.[28] The first step does not rely on solving the model. In this step, we pin down the income and belief formation process and set interest rates using transaction data and survey expectations. We also fix the preference parameters β and γ to conventional values. In the second step, we calibrate the two default-related parameters, χ and λ, using simulated method-of-moments (SMM).

We discipline the degree of overreaction in beliefs, θ, by matching the regression coefficient of forecast errors for income at $t+1$ on income shocks at t. Specifically, we simulate 100,000 periods from equation (1), form expectations using equation (2), and drop the first 100 periods as burn-in. This procedure yields $\theta = 2.54$ (Table VII, Panel A), implying that the subjective Kalman gain is 2.54 times larger than the Bayesian counterpart.[29]

Table VII shows the model closely matches both targeted and non-targeted moments. Conditional on the belief and income process parameters, we match the average wealth-to-half-year consumption ratio and the default rate to characterize default behavior. Panels B and C indicate a good fit of these targeted moments: the average wealth-to-half-year consumption ratio is 0.957 and the default rate is 3.60%, implying $\chi = 2.30$ and $\lambda = 0.25$.

Panel D compares a set of non-targeted moments and shows a similarly good fit. The average (median) wealth-to-six-month income ratio is 1.211 (0.912) in the data and 1.131 (1.000) in the model. Because liquidity shapes MPCs empirically, the stationary savings distribution must align with its empirical counterpart. The model also reproduces key features of the wealth distribution: in the data, 28.97% of total liquid assets are held by the top 5% of savers versus 26.71% in the model, and 19.33% (16.10% in the model) of

[28] Online appendix Section VI details the solution, estimation, and simulation procedures.

[29] Our estimate of θ lies at the upper tail of the range 0.8–2.75 reported in the previous literature in related settings (Bordalo et al., 2019; Chodorow-Reich et al., 2023). However, magnitudes depend on sample frequency and the equilibrium signal-to-noise ratio and are therefore not directly comparable across studies.

consumers have negative net liquid wealth. In the end, the average debt-income ratio is 0.230 in the data and 0.235 in the model. Overall, the model matches several distributional features of the empirical data beyond the first moment.

VI.B.2 Extrapolation of Income Shocks

We use the model to examine how extrapolative income expectations influence economic choices. We first compare the relationship between income shocks and forecast errors under extrapolative and Bayesian learning.

Column (1) of Table VIII reports the results. Panel B reports results for a model in which agents have extrapolative expectations (overreaction) and Panel C represents the Bayesian benchmark, with Panel A showing the empirical counterpart. By construction, the parameter θ is calibrated to match the empirical relationship between forecast errors and income shocks: when $\theta = 2.54$, each one-CNY income shock leads to a 0.431-CNY forecast error, perfectly replicating the data. In contrast, when $\theta = 0$ (Bayesian learning), the relationship is small and negative. Each one-CNY income shock produces a -0.038-CNY forecast error, confirming that a positive θ is necessary to capture the empirical degree of overreaction.[30]

VI.B.3 Consumption, Borrowing, and Defaults

We next assess whether the model can reproduce the empirical relationship between forecast errors and economic choices. We simulate 20,000 individuals for 1,000 periods after 100 periods of burn-in for the model to reach a stationary distribution. We then drop simulated observations with savings-to-income ratios above 10, which is the maximum we observe in the sample.

Using the simulated data, we regress changes in total consumption at t, total debt at the beginning of $t+1$, and default at the end of $t+1$ on forecast errors for income for period $t+1$. Debt at the beginning of $t+1$ is defined as $-a_t$ when $a_t < 0$.

Columns (2)-(4) of Table VIII report the results, with 2SLS counterparts in Panel A. The model with extrapolative expectations (Panel B) replicates the empirical relationships

[30]In Section VII in the online appendix, we replicate the core forecast-error regression assuming expectation formation follows 1. diagnostic Kalman filter, 2. full-information rational expectation, 3. over-persistence bias, and 4. learning about long-run growth. We find that overreaction has the best matches of our empirical relationship.

closely. A one-CNY higher forecast error for income at $t+1$ increases current consumption by 0.174 CNY in the model (0.216 CNY in the data) and debt by 0.068 CNY (0.088 CNY in the data). A one-standard-deviation higher forecast error raises the default rate by 1.32 percentage points in the model versus 1.28 percentage points in the data.

By contrast, without extrapolative expectations (i.e., $\theta = 0$), the corresponding coefficients shrink substantially: forecast errors do not significantly affect current consumption and next-period debt, and increase next-period default by 53 basis points, which is around 60% smaller than the counterparts under extrapolation.

Overall, incorporating extrapolative expectations can replicate the empirical relationships between forecast errors for income and consumption, debt, and default, whereas the model with Bayesian learning cannot.

VI.C Aggregate Household Debt Cycles

A recent literature shows financial crises often arise after sequences of favorable news that fuel optimistic beliefs, credit expansion, and leverage accumulation, so that subsequent negative shocks are endogenously amplified rather than absorbed smoothly (Baron and Xiong, 2017; Bordalo et al., 2018; Gennaioli and Shleifer, 2018; Mian et al., 2020). In this view, adverse shocks matter not primarily because they are large, but because they arrive when expectations and balance sheets have already been shaped by preceding good times.

Motivated by this literature, we study boom-bust dynamics using a controlled simulation experiment. Starting from the stochastic steady state, we simulate 20,000 consumers under extrapolative expectations ($\theta = 2.54$) for 1,000 half-year periods. We then compare this baseline to an otherwise identical simulation in which consumers experience three consecutive positive transitory income shocks totaling 1.5 standard deviations (periods 901-903), followed by a 0.5 standard-deviation negative transitory income shock. The reported dynamics are computed as differences relative to average income in the no-shock baseline except for income expectation and default, which are percentage difference from the no-shock baseline level. We repeat the same experiment under Bayesian learning ($\theta = 0$) to isolate the role of extrapolative expectations in shaping the economy's response to the shock dynamics.

Figure 6 plots the results. The top panels display the transitory income shocks and the percentage deviations of average income expectations. The bottom panels display changes in consumption-to-income ratio and debt-to-income ratio, and percent change of default. Red solid lines denote the model in which consumers have extrapolative expectations ($\theta = 2.54$) and blue dashed lines represent the Bayesian learning benchmark ($\theta = 0$).[31]

The figure reveals a strong amplification effect of extrapolative expectations on income beliefs. Panel B shows that, following positive shocks, consumers with overreaction (O) raise their expected income more than twice as much as Bayesian learners (B). Higher expected income translates into larger consumption responses. In Panels B and C, O's realized income rises about 20% and consumption about 15% relative to income. Because the model only has one asset, an MPC below one implies an initial decline in debt, consistent with Agarwal et al. (2007) and Coibion et al. (2020). In Panel E, with a lower debt level, both O and B see lower default rate.

As positive shocks persist, both income expectations and consumption of B rise smoothly, and deleveraging continues. In contrast, with extrapolative expectations, income expectations are overly optimistic ex ante and only partially realized ex post. As a result, asset accumulation is weaker for some households, and those with limited savings begin to accumulate debt. Because households with zero debt cannot deleverage further while optimistic households borrow more, average debt gradually increases. Consequently, unlike for B, default rates for O do not continue to decline.

When the sequence of positive shocks ends with a negative shock (period 0), income expectations drop for both types of agents. For O, income expectations drop much more due to (1) the same income shock implies a larger disappointment due to ex-ante elevated prior expectations, and (2) they also react more strongly to the same-sized negative shock due to a larger Kalman gain. As a result, consumption falls more, and debt spikes as O attempt to smooth spending given lower expected income. The combination of lower current assets and lower future income expectations leads to a pronounced surge in default among extrapolative consumers. As expectations converge back to steady state, both debt

[31] In Figure A.6 in the online appendix, we show that the results are nearly identical if we re-calibrate the model while setting $\theta = 0$ before simulating the Bayesian case.

and default rates for O gradually return to those of B.

These dynamics align with recent macro-finance evidence. López-Salido et al. (2017) show that elevated credit-market sentiment predicts higher subsequent credit growth, mirrored in Panel E, where debt growth turns positive for O after the initial good news, but remains negative for B. Likewise, the post-expansion rise in default in Panel E echoes findings by Greenwood et al. (2019) and Maxted (2023) that financial fragility peaks at the end of economic booms.

VI.D Unsecured Debt around the Global Financial Crisis

Economists' renewed interest in the drivers of household debt cycles has been shaped by the experience of the Global Financial Crisis (GFC). Our final exercise therefore assesses whether the model can reproduce the patterns of unsecured borrowing and default risk observed in the United States during the GFC. Since the parameters are estimated using Chinese data, this exercise is mainly illustrative.

Figure 7 presents the results.[32] In each panel, the red solid and blue dotted lines denote simulations with $\theta = 2.54$ and $\theta = 0$, respectively, while black dashed lines represent the data. The model frequency is semiannual. In the left panel, $\overline{B}/\overline{Y}$ denotes the ratio of consumer, credit card, and revolving debt to income; the right panel reports default probabilities measured as delinquency rates on consumer loans.[33]

Two findings stand out. First, aggregate debt in equilibrium (pre-2005) is higher under extrapolative expectations, because overreaction widens the cross-sectional dispersion of income expectations: more consumers become optimistic and borrow more, while pessimists cannot deleverage beyond zero debt. As a result, forecast errors do not offset in the aggregate, producing higher debt in steady-state.

Second, with extrapolative expectations, the model generates a pronounced boom-

[32]The corresponding income shocks, reverse-engineered to match the observed debt dynamics, are shown in Figure A.7 of the online appendix. While it is difficult to find the exact series of shocks that can generate Figure 7, Figure A.7 shows that the picked shocks are highly correlated with the unexpected nonfarm payroll employment growth.

[33]Because we are studying average debt to personal income in the model, we multiply GDP by the labor share to get total income. The resulting series trends down after 2000, so we detrend it over our sample period. For the delinquency rate, the model-implied default probability is based on all consumers, but the delinquency rate from the data is conditional on debt-holders. To make the series comparable, we adjust the delinquency rate by dividing it by the proportion of debtors in the U.S.. Hence, we get a debt delinquency rate for all consumers rather than only for debtor.

bust cycle in the unsecured-debt-to-income ratio that closely tracks the U.S. credit card debt-to-GDP pattern. Without extrapolation, these cycles largely disappear. That is, the 2009 peak never rises significantly above its 2004 level.

The right panel shows the same income shocks can also reproduce the surge in default rates at the end of the expansion, followed by a gradual decline. In contrast, under Bayesian learning ($\theta = 0$), default rates remain nearly flat from 2004 to 2012.

Overall, the model produces an aggregate boom-bust debt cycle akin to the one observed during the Global Financial Crisis only when income expectations are extrapolative, but not when they follow rational learning.

VII Conclusions

We combine repeated survey measures of subjective income expectations within individuals with transaction-level and credit-registry data to study the joint dynamics of forecast errors for income, spending, borrowing, and default. Consumers form extrapolative income expectations by overreacting to income shocks, and this overreaction explains their subsequent consumption and debt choices. Embedding such belief dynamics into a standard consumption-saving model reproduces the patterns in the data when consumers form extrapolative expectations. The model can generate Minsky-Kindleberger-style credit cycles such that a series of positive shocks can build up financial fragility and then a negative shock results in a bust. It can also generate the unsecured-debt and default dynamics observed in the United States during the Global Financial Crisis—patterns that a model with Bayesian learning cannot replicate.

Future research should further explore both the reduced-form and structural implications of these findings. On the reduced-form side, understanding the heterogeneity of income extrapolation across different countries and over different periods, and distinguishing the specific expectation-formation process that induces overreaction is important. Structurally, while agents in our model share a common degree of extrapolation, this parameter is likely heterogeneous across different types of agents.[34] Extending the analysis to macroeconomic models that allow for heterogeneous extrapolation and assessing its

[34]For subjective macroeconomic expectations, heterogeneity has been linked to cognitive ability (D'Acunto et al., 2019, 2021), socioeconomic status (Kuhnen and Miu, 2017), and local experiences (Kuchler and Zafar, 2019), among others.

aggregate consequences represent promising directions for future research. In addition, our specification adopts a parsimonious learning framework that is consistent with our empirical findings and is standard in consumption-saving models. Future work, including laboratory or field experiments, could shed further light on the underlying mechanisms of expectation formation.

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Figure 1. Survey Design

This figure describes the timeline of the survey waves run in each year.

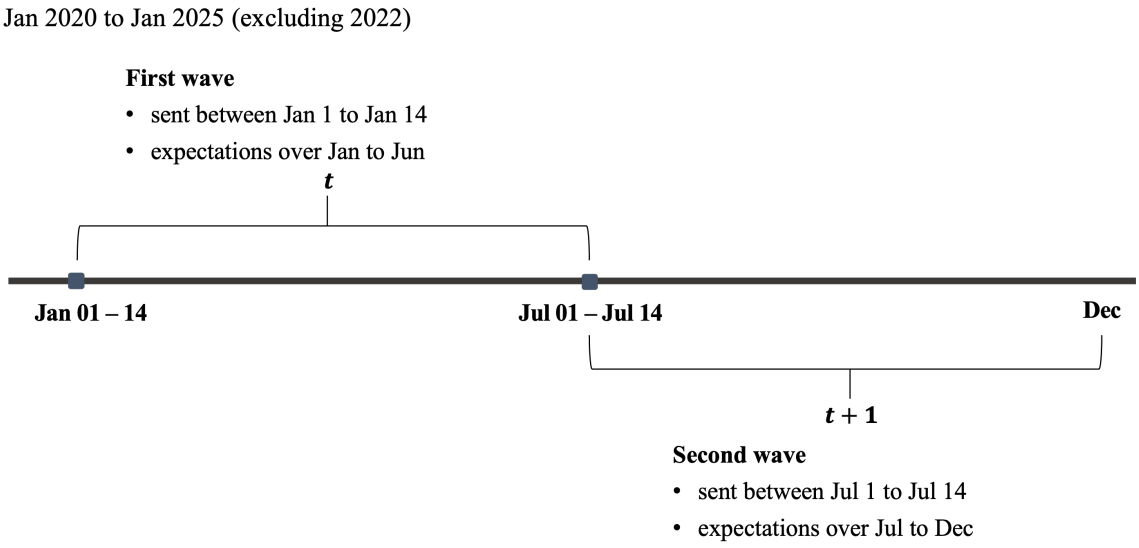
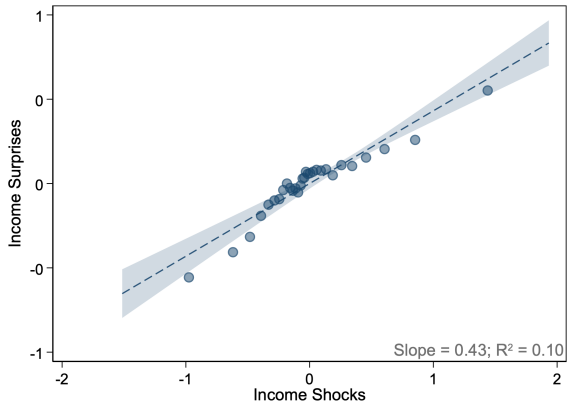


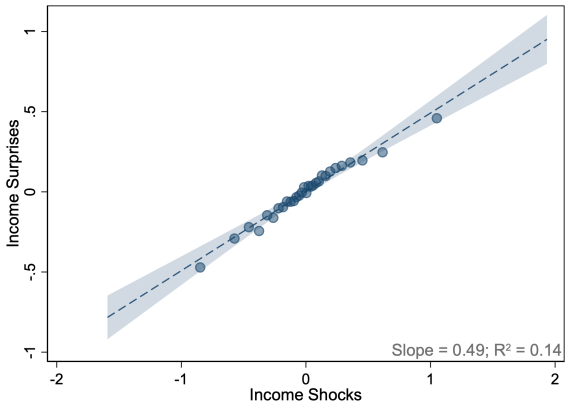
Figure 2. Income Shocks and Income Surprises

This figure plots income surprises vs income shocks. Income surprises - log are defined as the difference between log realized income and log subjective income expectations. Income shocks - log are defined as the unexpected income innovation from estimating (4). Income Surprises - Level and Income Shocks - Level are defined analogously in thousand CNY. Panels A and C plot the raw values, panels B and D control for individual fixed effects. The shaded regions give the 95% confidence intervals for the fitted lines. All variables are winsorized at 1% level within each wave.

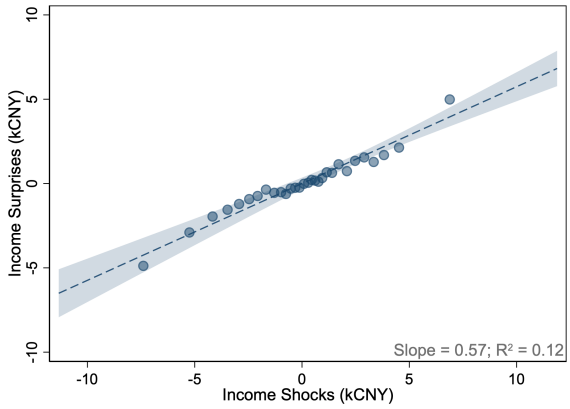
Panel A: Unresidualized - log



Panel B: Residualized - log



Panel C: Unresidualized - Level



Panel D: Residualized - Level

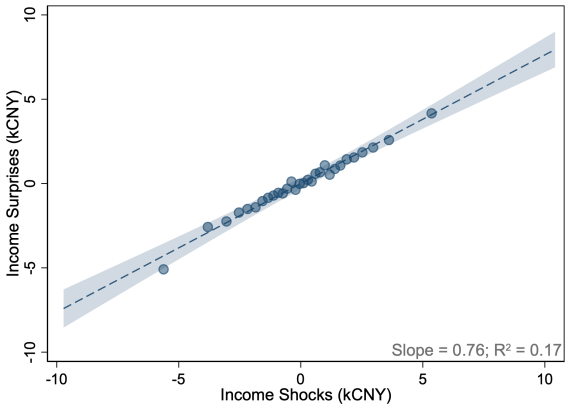
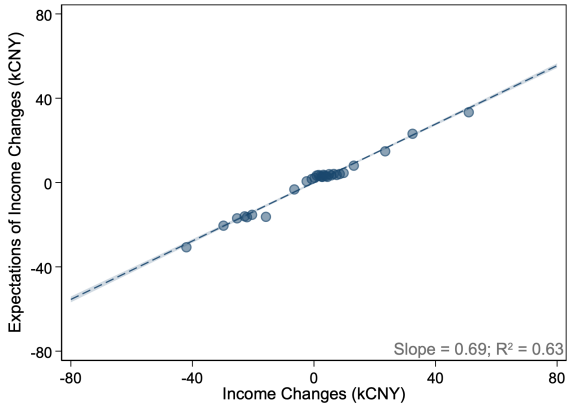


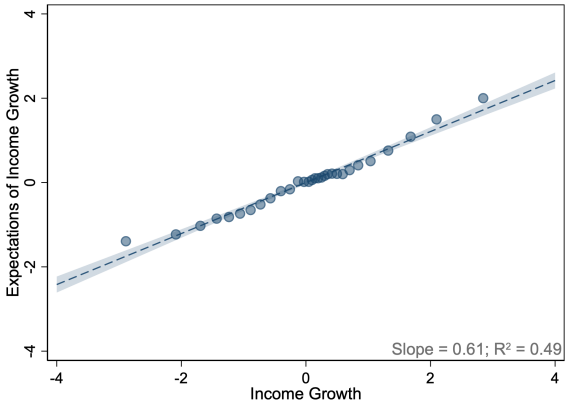
Figure 3. Errors in Subjective Income Expectations

Panels A and B are binned scatter plots of the ex-post realized income changes and income growth against ex-ante subjective expectations. Panels C and D are histograms of the individual-level income forecast errors. Panel D residualizes the forecast errors by individual fixed effects. The units in panels A, C, and D are thousand CNY. The shaded regions give the 95% confidence intervals for the fitted lines, where standard errors are clustered at the industry × wave level. All variables are winsorized at the 1% level within each wave.

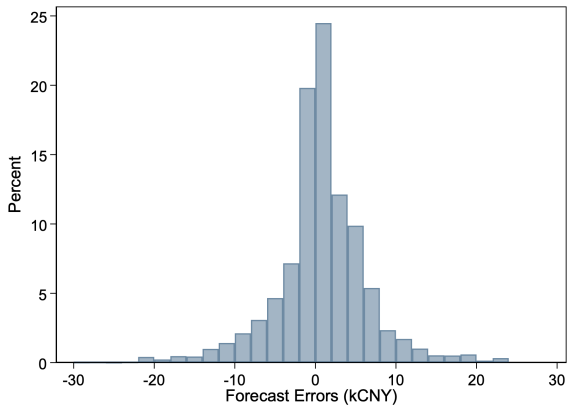
Panel A: Expectations vs Realizations – Changes



Panel B: Expectations vs Realizations – Growth



Panel C: Forecast Errors



Panel D: Forecast Errors – Residualized

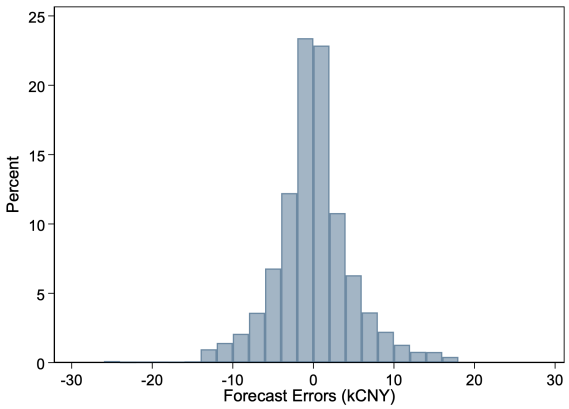
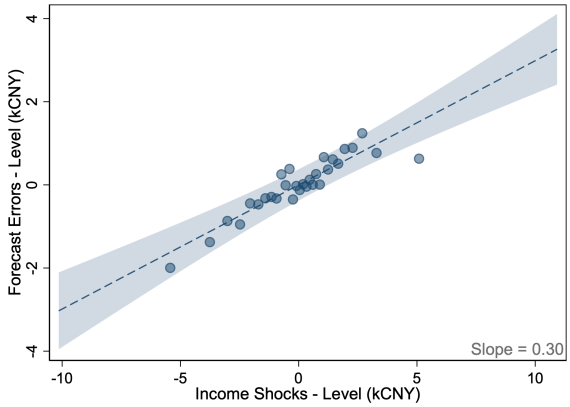


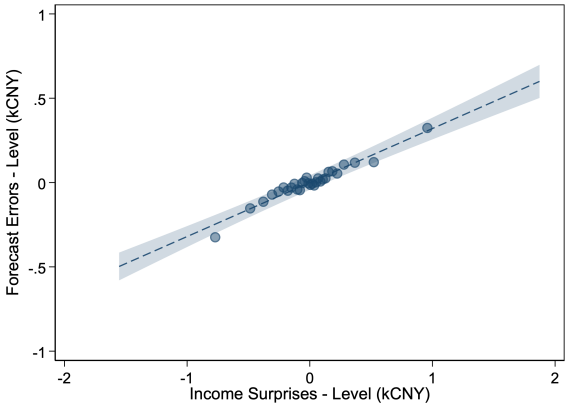
Figure 4. Income Shocks, Income Surprises, and Forecast Errors

This figure plots binned scatter of future income forecast errors against current income shocks in panels A and B, and against current income surprises in panels C and D. The units in panels A and C are thousand CNY. The shaded regions give the 95% confidence intervals for the fitted lines, where standard errors are clustered at the industry × wave level. All plots control for individual fixed effects. All variables are winsorized at the 1% level within each wave.

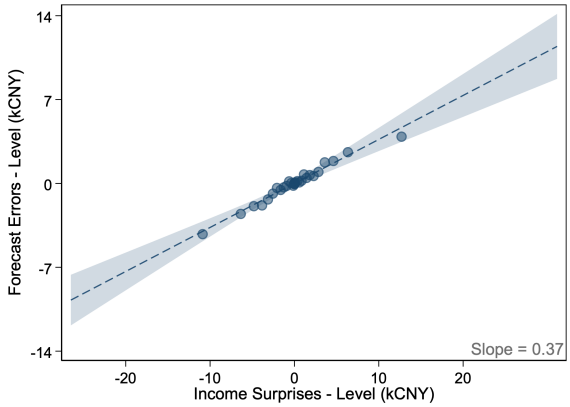
Panel A: Level



Panel B: log



Panel C: Level



Panel D: log

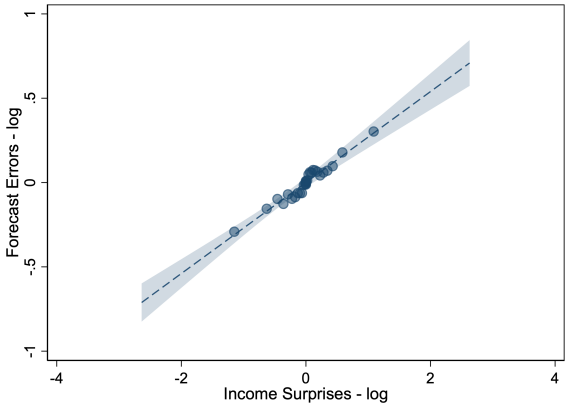
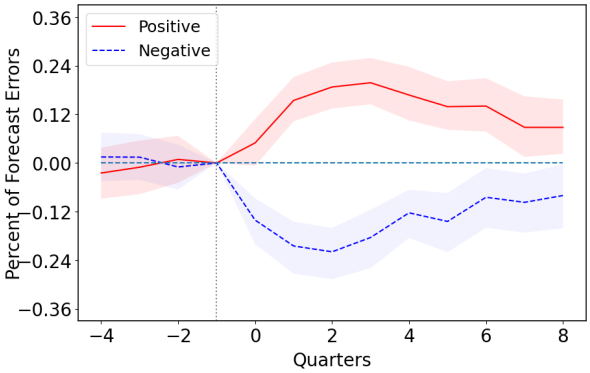


Figure 5. Dynamics of Consumption and Debt Accumulation around Income Forecast Errors

This figure reports the coefficient estimates of cumulative spending and debt on forecast errors. Estimation is based on the specification in equation (7). In Panel A, the outcome variable is total spending. In Panel B, it is the stock of unsecured debt. The red solid lines report the estimates for consumers with positive forecast errors and the blue dashed lines for consumers with negative forecast errors. The width of the shaded regions is twice the size of estimated standard errors.

Panel A: Total Consumption



Panel B: Unsecured Debt

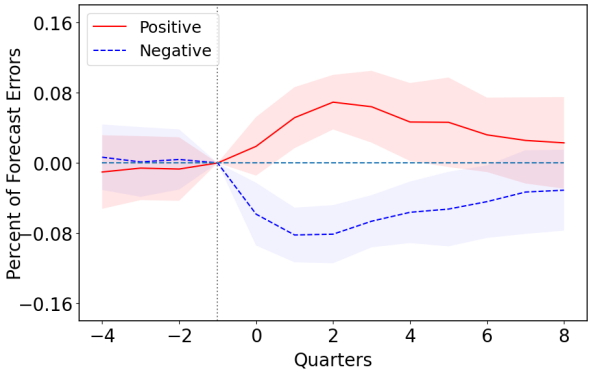


Figure 6. Structural Model - Boom-Bust Household Cycles

This figure shows simulated paths from the structural model following a sequence of transitory income shocks. Red solid lines correspond to overreaction ($\theta = 2.54$) and blue dashed lines to Bayesian learning ($\theta = 0$). The top panels display the income shocks and expected income, and the bottom panels report changes in consumption and debt relative to no-shock average income, and percentage deviations of default relative to the no-shock baseline.

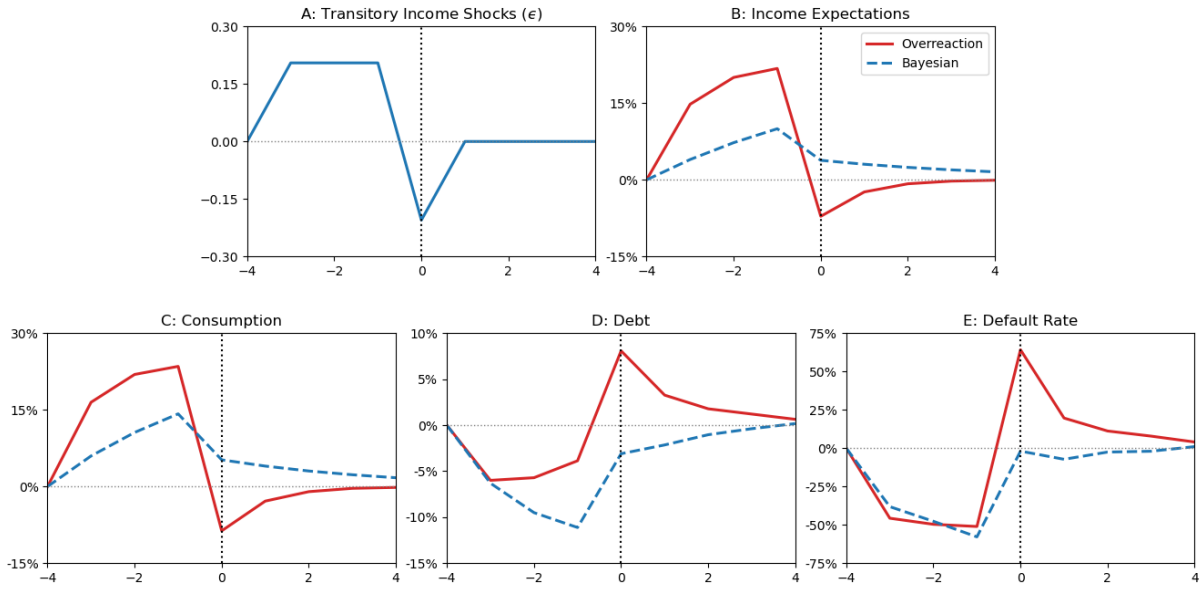


Figure 7. Simulating the Global Financial Crisis in the US

This figure simulates the 2008-2009 Global Financial Crisis using a sequence of transitory income shocks at the semiannual frequency. Red solid lines correspond to overreaction ($\theta = 2.54$), blue dotted lines to Bayesian learning ($\theta = 0$), and black dashed lines to the data. The left panel shows the detrended unsecured-debt-to-income ratio, and the right panel shows the aggregate default rate, defined as the delinquency rate multiplied by the share of debt holders.

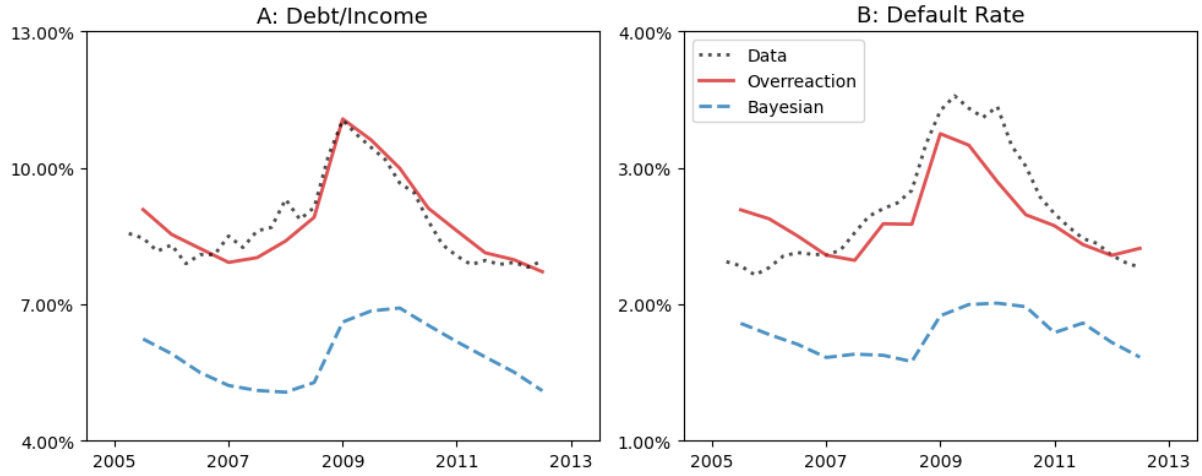


TABLE I. Summary Statistics

Income and Spending are respectively the average monthly income and spending. Credit Limit is the total credit limit across all financial institutions. Debt is the interest-incurring credit card debt for each consumer across all financial institutions. Debt|Debt>0 is the interest-incurring credit card debt for those who hold positive debt. Liquidity is the ratio of liquid wealth to six-month income. Income Growth is the annual log income growth. Income Shock - log is the ϵ_t retrieved from fitting equation (4). Income Shock - Level is $Y_t - E_{t-1}[Y_t]$ implied by equation (4), where Y_t is the level of income. E^{θ}[Income] is the subjective expectations of average monthly income over the next six months. All level variables are measured in thousand CNY and winsorized at the 1% - 99% level within each wave.

	Mean	SD	25-Pctl	Median	75-Pctl	N
Age	39.58	9.24	33.00	39.00	46.00	26,449
Female	0.52	0.50	0.00	1.00	1.00	26,449
College	0.53	0.50	0.00	1.00	1.00	26,449
Income	13.03	13.26	4.20	8.27	16.66	26,449
Spending	7.08	6.53	2.66	5.08	9.27	26,449
Installment	2.82	13.32	0.00	1.55	18.21	26,449
Debt	5.01	11.06	0.00	0.00	4.65	26,449
Debt|Debt>0	12.46	14.53	2.63	7.37	16.83	10,650
Liquidity	1.19	1.54	0.01	0.91	2.54	26,449
Credit Limit	81.33	117.12	15.00	30.00	100.00	26,449
Income Growth	0.04	0.38	-0.00	0.00	0.06	26,449
Income Shocks - log	-0.05	0.39	-0.22	-0.08	0.05	26,449
Income Shocks - Level	-0.92	2.56	-2.13	-0.40	0.07	26,449
E^{θ}[Income]-Income	0.27	5.45	-1.51	0.00	2.49	26,449

TABLE II. Income Shocks, Income Surprises, and Forecast Errors

Forecast Errors$_{t+1}$ - Level is the difference between the subjective expectation of income and realized income in $t+1$. Forecast Errors$_{t+1}$ - log is the difference between the log of subjective income expectations and realized log income in $t+1$. Shocks$_t$ - log is the ϵ_t retrieved from fitting (4). Shocks$_t$ - Level is $Y_t - E_{t-1}[Y_t]$ implied by (4), where Y_t is the level of income in t. Surprises$_t$ - Level and Surprises$_t$ - log are respectively the negative of Forecast Errors$_t$ - Level and Forecast Errors$_t$ - log. Credit Limit$_t$ is the total credit limit across all financial institutions. Liquidity$_t$ is the ratio of liquid wealth to six-month income. Income Growth$_t$ is the annual log income growth. All variables are measured in thousand CNY and winsorized at the 1% - 99% level within each wave.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Forecast Errors$_{t+1}$ - Level				Forecast Errors$_{t+1}$ - log			
Shocks$_t$ - Level	0.351***	0.431***						
	(0.042)	(0.053)						
Surprises$_t$ - Level			0.393***	0.493***				
			(0.057)	(0.040)				
Shocks$_t$ - log					0.320***	0.389***		
					(0.027)	(0.030)		
Surprises$_t$ - log							0.264***	0.352***
							(0.029)	(0.028)
Credit Limit$_t$		0.000		-0.001		0.000		-0.000
		(0.000)		(0.001)		(0.000)		(0.000)
Liquidity$_t$		0.033		-0.331**		0.014*		0.043***
		(0.077)		(0.150)		(0.008)		(0.016)
Income Growth$_t$		0.141		-1.248***		-0.060*		-0.110***
		(0.401)		(0.232)		(0.033)		(0.030)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Wave FE	No	Yes	No	Yes	No	Yes	No	Yes
N Obs	26,449	26,449	15,644	15,644	25,407	25,407	14,354	14,354

Standard errors clustered at industry × wave in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE III. Income Shocks and Forecast Errors – Heterogeneity

Forecast Errors$_{t+1}$ is the difference between the subjective expectation of income and realized income in $t+1$. Shocks$_t$ is $Y_t - E_{t-1}[Y_t]$ implied by (4), where Y_t is the level of income. Young is defined as age smaller than 39. More volatile is one if average subjective income volatility is above the median, and zero otherwise. Government is one if the participants work in the government industry. Salary Worker is one if the individual's regular income payment as a fraction of total income is in the upper quartile. Controls include Liquidity, Credit Limit, and Income Growth in time t. All variables are measured in thousand CNY and winsorized at the 1% - 99% level within each wave.

	(1)	(2)	(3)	(4)	(5)	(6)
	Forecast Errors$_{t+1}$					
Shocks$_t$	0.370***	0.240***	0.465***	0.501***	0.397***	0.401***
	(0.060)	(0.049)	(0.053)	(0.053)	(0.091)	(0.085)
Shocks$_t$ × Young	0.137***					
	(0.041)					
Shocks$_t$ × More Volatile		0.359***				
		(0.044)				
Shocks$_t$ × Government			-0.469***			
			(0.060)			
Shocks$_t$ × Salary Worker				-0.210***		
				(0.048)		
Shocks$_t$ ×(Year $\geq$ 2023)					-0.070	
					(0.079)	
Shocks$_t$ ×(Shocks$_t$ $<$ 0)						0.098
						(0.088)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N Obs	26,449	25,551	26,449	26,449	26,449	26,449

Standard errors clustered at industry × wave in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE IV. Income Forecast Errors, Liquidity Constraints, and Spending

ΔC_t is the changes in total spending from $t-1$ to t. Shocks$_t$ is $Y_t - E_{t-1}[Y_t]$ implied by (4), where Y_t is the level of income. Forecast Errors$_{t+1}$ is the difference between the subjective income expectation and realized income in $t+1$. High Util$_t$ is one if utilization rate is above the median in t, and zero otherwise. High Liq$_t$ is one if Liquidity is above the median in t, and zero otherwise. Controls include Liquidity, Credit Limit, and Income Growth in time t. All variables are measured in thousand CNY and winsorized at the 1% - 99% level within each wave.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				ΔC_t			
Shocks$_t$	0.254***		0.166***	0.195***	0.317***	0.115**	0.221***
	(0.032)		(0.032)	(0.049)	(0.036)	(0.050)	(0.038)
Forecast Errors$_{t+1}$		0.207***	0.196***			0.171***	0.219***
		(0.020)	(0.022)			(0.029)	(0.022)
High Util$_t$				0.161		0.156	
				(0.187)		(0.185)	
Shocks$_t$ × High Util$_t$				0.118**		0.104*	
				(0.054)		(0.056)	
High Liq$_t$					-0.065		-0.067
					(0.251)		(0.250)
Shocks$_t$ × High Liq$_t$					-0.124**		-0.106**
					(0.048)		(0.049)
Forecast Errors$_{t+1}$ × High Util$_t$						0.049*	
						(0.027)	
Forecast Errors$_{t+1}$ × High Liq$_t$							-0.046*
							(0.025)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N Obs	26,449	26,449	26,449	26,449	26,449	26,449	26,449

Standard errors clustered at industry × wave in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE V. Forecast Errors and Debt/Default Decisions

ΔDebt_{t+1} is the changes in total unsecured borrowing in time $t+1$. Default_{t+1} is one if there is a 90-day delinquency on the unsecured borrowing in $t+1$, and zero otherwise. Shocks_t is $Y_t - E_{t-1}[Y_t]$ implied by (4), where Y_t is the level of income. Forecast Errors is the difference between the subjective expectation of income and realized income. Controls include Liquidity, Credit Limit, and Income Growth in time t. In columns (5) - (8), Shocks_t and $\text{Forecast Errors}_{t+1}$ are standardized. All other level variables are measured in thousand CNY and winsorized at the 1% - 99% level within each wave.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ΔDebt_{t+1}				Default_{t+1}			
Shocks_t	0.024	-0.003	-0.014	-0.015	0.155	0.004	0.002	0.003
	(0.020)	(0.020)	(0.019)	(0.019)	(0.122)	(0.117)	(0.116)	(0.115)
$\text{Forecast Errors}_{t+1}$		0.061***	0.062***	0.065***		0.846***	0.846***	0.842***
		(0.009)	(0.008)	(0.009)		(0.147)	(0.147)	(0.150)
Shocks_{t+1}				-0.030**				0.022
				(0.015)				(0.113)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	No	No	Yes	Yes
N Obs	26,449	26,449	26,449	26,449	26,449	26,449	26,449	26,449

Standard errors clustered at industry × wave in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE VI. Income Shocks, Forecast Errors, and Decisions - 2SLS

Shocks_t is $Y_t - E_{t-1}[Y_t]$ implied by (4), where Y_t is the level of income. Forecast Errors is the difference between the subjective expectation of income and realized income. ΔC_t is the changes in total spending. ΔDebt_{t+1} is the changes in total unsecured borrowing in time $t+1$. Default_{t+1} is one if there is a 90-day delinquency on the unsecured borrowing in $t+1$, and zero otherwise. Shocks Same Type_t is the average of Shocks_t for individuals in the same type excluding the survey sample. High Vol_t is one if the participant is in a type with high income volatility, and zero otherwise. Controls include Liquidity, Credit Limit, and Income Growth in time t. In column (5), Shocks_t and Forecast Errors_{t+1} are standardized. All other level variables are measured in thousand CNY and winsorized at the 1% - 99% level within each wave.

	(1) Shocks_t	(2) Forecast Errors_{t+1}	(3) ΔC_t	(4) ΔDebt_{t+1}	(5) Default_{t+1}
	First Stage		Second Stage		
Shocks Same Type_t	0.059***	0.453***			
	(0.011)	(0.032)			
Shocks Same $\text{Type}_t \times$ High Vol_t	0.185***	-0.221***			
	(0.010)	(0.020)			
Shocks_t			0.126**	-0.022	-0.034
			(0.064)	(0.039)	(0.240)
Forecast Errors_{t+1}			0.216***	0.088**	1.276**
			(0.063)	(0.043)	(0.567)
Individual FE	Yes	Yes	Yes	Yes	Yes
Industry × Wave FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
First-Stage F				104.47	
N Obs	26,449	26,449	26,449	26,449	26,449

Standard errors clustered at industry × wave in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE VII. Structural Model: Estimation

This table reports the estimated parameters of the structural model. Panel A presents the parameters estimated in the first stage and Panel B those estimated in the second stage based on SMM. Panel C reports the matched moments and Panel D the moments not targeted directly. w/c is the average wealth-consumption ratio. p(default) is the proportion of defaults. w/y is the average wealth-income ratio. median(w/y) is the median of the wealth-income ratio. top 5% liq share is the fraction of savings held by the top 5% individuals in the model. debtor% is the fraction of consumers with positive debt. b/y is the average debt-to-income ratio. Estimation of moments in the model is based on a simulation of 20,000 individuals with 1,000 periods, after a burn-in period of 100 periods for the distribution to reach the steady state. Estimation of moments in the data is based on a random 5% of active customers in the bank's database. Model moments are trimmed at savings to average income ratio larger than 20.

Panel A
First-Stage Parameters

	Estimate
	(1)
γ	2.000
β	0.975
r_b	0.045
r_s	0.015
ν	0.050
α	0.000
σ_η	0.089
σ_ϵ	0.410
θ	2.540

Panel B
Second-Stage Parameters

	Estimate	S.E.
	(2)	(3)
χ	2.300	(0.107)
λ	0.250	(0.039)

Panel C
Targeted Moments

	Data	Model
	(4)	(5)
w/c	0.957	0.957
p(default)	3.60%	3.60%

Panel D
Not Targeted Moments

	Data	Model
	(6)	(7)
w/y	1.211	1.131
median(w/y)	0.912	1.000
top 5% liq share	28.97%	26.71%
debtor%	19.33%	16.10%
b/y	0.230	0.235

TABLE VIII. Linking Shocks, Forecast Errors, and Outcomes

ΔDebt_{t+1} is the changes in total unsecured borrowing in time $t+1$. Default_{t+1} is one if there is a 90-day delinquency on the unsecured borrowing in $t+1$, and zero otherwise. Shocks_t is $Y_t - E_{t-1}[Y_t]$ implied by (4), where Y_t is the level of income. Forecast Errors is the difference between the subjective expectation of income and realized income. Controls include Liquidity, Credit Limit, and Income Growth in time t. All level variables are measured in thousand CNY and winsorized at the 1% - 99% level within each wave.

	(1) $\text{Forecast Errors}_{t+1}$	(2) ΔC_t	(3) ΔDebt_{t+1}	(4) Default_{t+1}
		Panel A: Data		
Shocks_t	0.431			
	(0.053)			
$\text{Forecast Errors}_{t+1}$		0.216	0.088	1.276
		(0.063)	(0.045)	(0.567)
N Obs	26,449	26,449	26,449	26,449
		Panel B: $\theta = 2.540$		
Shocks_t	0.431			
	(0.001)			
$\text{Forecast Errors}_{t+1}$		0.174	0.068	1.319
		(0.003)	(0.000)	(0.005)
N Obs	100,000	9,920,072	9,920,072	9,920,072
		Panel C: $\theta = 0$		
Shocks_t	-0.026			
	(0.003)			
$\text{Forecast Errors}_{t+1}$		0.036	0.009	0.532
		(0.000)	(0.000)	(0.003)
N Obs	100,000	9,920,072	9,920,072	9,920,072

Online Appendix:

Subjective Income Expectations and Household Debt Choices

Francesco D'Acunto, Michael Weber, Xiao Yin

I Additional Theoretical Results

I.A Proofs and Derivations

This section provides the detailed proofs for the propositions stated in Section 2 of the main text, which characterize the properties of forecast errors under a deviation from rational updating.

I.A.1 Proof of Proposition 1

We begin by restating the income process and the agent's updating rule. Log income y_t follows:

$$y_t = \alpha + z_t + \epsilon_t,$$

$$z_t = z_{t-1} + \eta_t,$$

where $\epsilon_t \sim N(0, \sigma_\epsilon^2)$ and $\eta_t \sim N(0, \sigma_\eta^2)$ are i.i.d. shocks.

Under rational expectations (RE), the Kalman filter updating is:

$$\begin{aligned} s_t &= y_t - E_{t-1}[y_t] = y_t - \alpha - \hat{z}^{RE}_{t|t-1}, \\ \hat{z}^{RE}_{t|t-1} &= \hat{z}^{RE}_{t-1|t-1}, \\ \hat{z}^{RE}_{t|t} &= \hat{z}^{RE}_{t|t-1} + \kappa s_t, \end{aligned}$$

where κ is the steady-state Kalman gain. The innovation s_t is orthogonal to the information set at $t-1$.

We introduce a deviation from rationality by allowing the agent to over- or under-react to the signal surprise:

$$\hat{z}^{\theta}_{t|t} = \hat{z}^{\theta}_{t-1|t-1} + \tilde{\kappa}(y_t - \alpha - \hat{z}^{\theta}_{t-1|t-1}),$$

where $\tilde{\kappa} = (1+\theta)\kappa$. The case $\theta > 0$ corresponds to overreaction.

The one-period-ahead forecast error for log income under this subjective belief is

$$\begin{aligned} FE^{\theta,y}_{t+1} &= E^{\theta}_t[y_{t+1}] - y_{t+1} \\ &= (\alpha + \hat{z}^{\theta}_{t|t}) - (\alpha + z_{t+1} + \epsilon_{t+1}) \\ &= \hat{z}^{\theta}_{t|t} - z_t - \eta_{t+1} - \epsilon_{t+1}. \end{aligned}$$

Define $e^{RE}_t \equiv z_t - \hat{z}^{RE}_{t|t}$ and $\Delta_t \equiv \hat{z}^{\theta}_{t|t} - \hat{z}^{RE}_{t|t}$. Then

$$FE^{\theta,y}_{t+1} = -e^{RE}_t + \Delta_t - \eta_{t+1} - \epsilon_{t+1}.$$

Derive the law of motion for Δ_t:

$$\hat{z}^{\theta}_{t|t} = \hat{z}^{\theta}_{t-1|t-1} + \tilde{\kappa}(s_t + (\hat{z}^{RE}_{t-1|t-1} - \hat{z}^{\theta}_{t-1|t-1})).$$

Using the rational update and simplifying,

$$\Delta_t = \kappa\theta s_t + (1 - \tilde{\kappa})\Delta_{t-1}.$$

Hence

$$\Delta_t = \kappa\theta s_t + a\Delta_{t-1}, \qquad a \equiv (1 - (1+\theta)\kappa).$$

Consider

$$FE^{\theta,y}_{t+1} = \beta_{0,s} + b_{log} s_t + u_{s,t+1}.$$

Since e^{RE}_t and future shocks are orthogonal to s_t,

$$\mathrm{Cov}(FE^{\theta,y}_{t+1}, s_t) = \mathrm{Cov}(\Delta_t, s_t).$$

Because s_t is i.i.d. and independent of Δ_{t-1},

$$\mathrm{Cov}(\Delta_t, s_t) = \kappa\theta \,\mathrm{Var}(s_t),$$

so $b_{log} = \kappa\theta$. ■

I.A.2 Proof of Proposition 2

Define $Y_t = \exp(y_t)$, $\varepsilon^Y_t = Y_t - E_{t-1}[Y_t]$, and $FE^{\theta,Y}_{t+1} = E^{\theta}_t[Y_{t+1}] - Y_{t+1}$. Let $B_t = \exp(\alpha + \hat{z}^{RE}_{t|t-1})$, $\widetilde{M}_t = \exp(\alpha + \hat{z}^{RE}_{t|t-1})$, and $c = \kappa$.

$$\varepsilon^Y_t = B_t(e^{s_t} - e^{\sigma_s^2/2}), \qquad \sigma_s^2 = \mathrm{Var}(s_t).$$

$$E^{\theta}_t[Y_{t+1}] = \exp(\alpha + \hat{z}^{\theta}_{t|t} + \sigma_s^2/2) = M_t e^{\sigma_s^2/2 + \Delta_t}, \quad M_t = \widetilde{M}_t e^{cs_t}.$$

$$Y_{t+1} = M_t e^{s_{t+1}}, \qquad FE^{\theta,Y}_{t+1} = M_t(e^{\sigma_s^2/2+\Delta_t} - e^{s_{t+1}}).$$

We compute

$$b_{level} = \frac{\mathrm{Cov}(FE^{\theta,Y}_{t+1}, \varepsilon^Y_t)}{\mathrm{Var}(\varepsilon^Y_t)}.$$

Using linearization $e^{\Delta_t} \approx 1 + \Delta_t$ and $\Delta_t \approx \kappa\theta s_t$,

$$\mathbb{E}[FE^{\theta,Y}_{t+1}\varepsilon^Y_t] \approx e^{\sigma_s^2/2}\kappa\theta\,\mathbb{E}[M_t\varepsilon^Y_t s_t].$$

With $M_t = \widetilde{M}_t e^{cs_t}$ and $\varepsilon^Y_t = B_t(e^{s_t} - e^{\sigma_s^2/2})$,

$$\mathbb{E}[M_t\varepsilon^Y_t s_t] = \mathbb{E}[\widetilde{M}_t B_t]\,\mathbb{E}[e^{cs_t}(e^{s_t} - e^{\sigma_s^2/2})s_t].$$

For $s_t \sim N(0, \sigma_s^2)$,

$$\mathbb{E}[e^{cs_t}(e^{s_t} - e^{\sigma_s^2/2})s_t] = \sigma_s^2 e^{(c^2+1)\sigma_s^2/2}[(c+1)e^{c\sigma_s^2} - c].$$

Hence

$$\mathbb{E}[FE^{\theta,Y}_{t+1}\varepsilon^Y_t] \approx e^{\sigma_s^2/2}\kappa\theta\,\mathbb{E}[\widetilde{M}_t B_t]\,\sigma_s^2 e^{(c^2+1)\sigma_s^2/2}[(c+1)e^{c\sigma_s^2} - c].$$

and

$$\mathrm{Var}(\varepsilon^Y_t) = \mathbb{E}[B_t^2](e^{2\sigma_s^2} - e^{\sigma_s^2}).$$

Therefore

$$b_{level} = \kappa\theta\frac{\mathbb{E}[\widetilde{M}_t B_t]}{\mathbb{E}[B_t^2]}\frac{\sigma_s^2 e^{(c^2+2)\sigma_s^2/2}[(c+1)e^{c\sigma_s^2} - c]}{e^{2\sigma_s^2} - e^{\sigma_s^2}}.$$

Define

$$\Gamma \equiv \frac{\mathbb{E}[\widetilde{M}_t B_t]}{\mathbb{E}[B_t^2]}\frac{\sigma_s^2 e^{(c^2+2)\sigma_s^2/2}[(c+1)e^{c\sigma_s^2} - c]}{e^{2\sigma_s^2} - e^{\sigma_s^2}},$$

so $b_{level} = \kappa\theta\Gamma$. For small S, $\Gamma \to 1$; thus $\beta^L_{1,\varepsilon} \approx \kappa\theta$. ■

I.A.3 Proof of Proposition 3

Note that income surprise s^θ_t is just the negative of $FE^{\theta,y}_t$, so we estimate the first-order autoregression coefficient $FE^{\theta,y}_t$ to prove Proposition 3.

The posterior gap follows

$$\Delta_t = \kappa\theta s_t + a\Delta_{t-1}, \qquad a = (1 - (1+\theta)\kappa).$$

Forecast errors:

$$FE^{\theta,y}_t = \Delta_{t-1} - s_t,$$

$$FE^{\theta,y}_{t+1} = \kappa\theta s_t + a\Delta_{t-1} - s_{t+1}.$$

Autocovariance:

$$\mathrm{Cov}(FE^{\theta,y}_{t+1}, FE^{\theta,y}_t) = -\kappa\theta S + a\,\mathrm{Var}(\Delta_{t-1}),$$

with

$$\mathrm{Var}(\Delta) = \frac{(\kappa\theta)^2 S}{1-a^2}, \qquad \mathrm{Var}(FE_t^{\theta,y}) = S\left(1 + \frac{(\kappa\theta)^2}{1-a^2}\right).$$

Thus, the first-order autoregression coefficient is

$$b_\theta = \frac{-\kappa\theta + a\frac{(\kappa\theta)^2}{1-a^2}}{1 + \frac{(\kappa\theta)^2}{1-a^2}}.$$

Let $x = \kappa\theta$, $b = 1 - (1+\theta)\kappa$, $a = b$; then

$$b_\theta = \frac{-x(1-b^2) + bx^2}{1 - b^2 + x^2} = -\kappa\theta \frac{1 - (1-\kappa)^2 + \kappa(1-\kappa)\theta}{1 - (1-\kappa)^2 + 2\kappa(1-\kappa)\theta}.$$

Hence

$$\frac{|b_\theta|}{\kappa\theta} = \frac{1 - (1-\kappa)^2 + \kappa(1-\kappa)\theta}{1 - (1-\kappa)^2 + 2\kappa(1-\kappa)\theta} \in (1/2, 1),$$

showing the magnitude is $-\kappa\theta$ attenuated by a factor between $1/2$ and 1. ■

I.B Heterogeneity and Uncertainty

To allow for cross-sectional differences in updating behavior by income uncertainty, we now consider cognitive uncertainty about signal strength as a possible heterogeneity that affects the updating coefficient $(1+\theta)\kappa$.

Cognitive uncertainty can also generate systematic over- and underreaction to income news, depending on signal strength. Following the framework of Augenblick et al. (2024), agents understand the direction of the signal but form imperfect estimates of its strength. As a result, they behave as if the perceived signal strength $\hat{S}_t$ is a power transformation of the true signal strength S_t:

$$\mathbb{E}[\hat{S}_t \mid S_t] = k\, S_t^\beta, \qquad 0 < \beta < 1,$$

where $k > 0$ scales the average perception of strength. Because the perceived strength is a concave function of the true strength, people overinfer from weak signals and underinfer from strong signals, with a unique switching point $S^* = k^{1/(1-\beta)}$.

Let the one-step innovation be $u_t = y_t - \alpha - \hat{z}_{t-1}$, and let its conditional standard deviation in steady state be σ_u. Define the true standardized signal strength

$$S_t \equiv \frac{|u_t|}{\sigma_u}.$$

Equivalently, $u_t = \sigma_u \cdot \mathrm{sgn}(u_t) \cdot S_t$.

In steady state, the Bayesian update is

$$\hat{z}_t = \hat{z}_{t-1} + \kappa u_t.$$

Using the decomposition of u_t,

$$\hat{z}_t = \hat{z}_{t-1} + \kappa\sigma_u \cdot \text{sgn}(u_t) \cdot S_t.$$

Under cognitive uncertainty (ALT), agents know the direction but misperceive the magnitude of strength. They form $\hat{S}_t$ and keep $\text{sgn}(u_t)$ unchanged. So they behave as if the innovation magnitude were $\sigma_u \hat{S}_t$ rather than $\sigma_u S_t$:

$$\hat{z}_t = \hat{z}_{t-1} + \kappa\sigma_u \cdot \text{sgn}(u_t) \cdot \hat{S}_t.$$

Factor out the true innovation u_t:

$$\hat{z}_t = \hat{z}_{t-1} + \kappa\Big(\frac{\hat{S}_t}{S_t}\Big)u_t.$$

Thus the effective weight on the raw innovation is

$$(1+\theta_t)\kappa \equiv \kappa\hat{w}(S_t) \qquad \text{with} \qquad \hat{w}(S_t) \equiv \frac{\hat{S}_t}{S_t}.$$

ALT's strength-perception law is

$$\mathbb{E}[\hat{S}_t \mid S_t] = kS_t^{\beta}, \qquad 0 < \beta < 1,\ k > 0.$$

Taking expectations of the weight conditional on S_t,

$$\mathbb{E}\big[\hat{w}(S_t) \mid S_t\big] = \frac{\mathbb{E}[\hat{S}_t \mid S_t]}{S_t} = \frac{kS_t^{\beta}}{S_t} = kS_t^{\beta-1} = kS_t^{-(1-\beta)}.$$

So the expected effective weight is

$$(1+\theta_t)\kappa = \kappa\hat{w}(S_t) = \kappa\mathbb{E}\big[\hat{w}(S_t) \mid S_t\big] = kS_t^{-(1-\beta)}\kappa,$$

which gives$\theta_t = kS_t^{-(1-\beta)} - 1$.

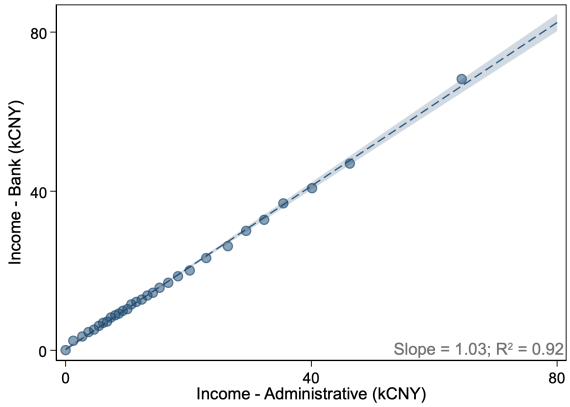
When $\beta < 1$, $\partial\theta_t/\partial S_t < 0$: agents place more weight on weak signals and less on strong ones. Because κ is fixed in the learning steady state (equation (8)), higher cognitive uncertainty, captured by a smaller β, steepens this inverse-S relationship, increasing $\kappa\theta_t$ for weak signals and reducing it for strong signals. In the overreaction region, where $\theta_t > 0$ (i.e., when signals are weak), smaller S_t further raises θ_t, amplifying overreaction to weak income news.

II Additional Results

Figure A.1. Sanity Checks of Income

Panel A in this figure is a binned scatter plot that compares the income computed based on the transaction-level data and the registry income values reported by the same consumers in our sample to the Chinese tax authority. Panel B compares consumer reported past income and the income from the bank at the same period. The shaded regions give the 95% confidence intervals for the fitted lines, where standard errors are clustered at the industry × wave level.

Panel A: Comparisions of Income Measures



Panel B: Survey Answers and Bank Measures

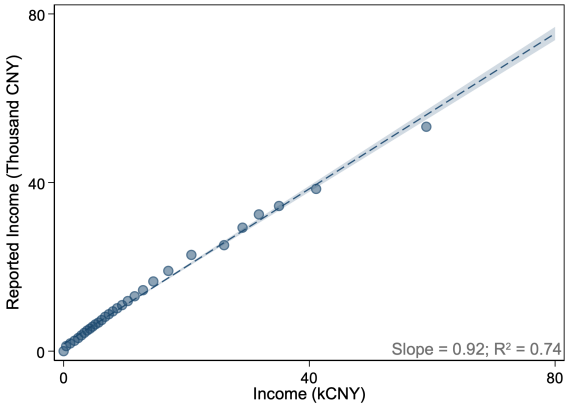


Figure A.2. Comparing Debt from the Bank and from Credit Report

This figure compares debt record from the bank and total debt from shown from the credit reports for those who only have unsecured debt with the bank. Debt includes unpaid balance from all credit cards and personal unsecured debt from the bank.

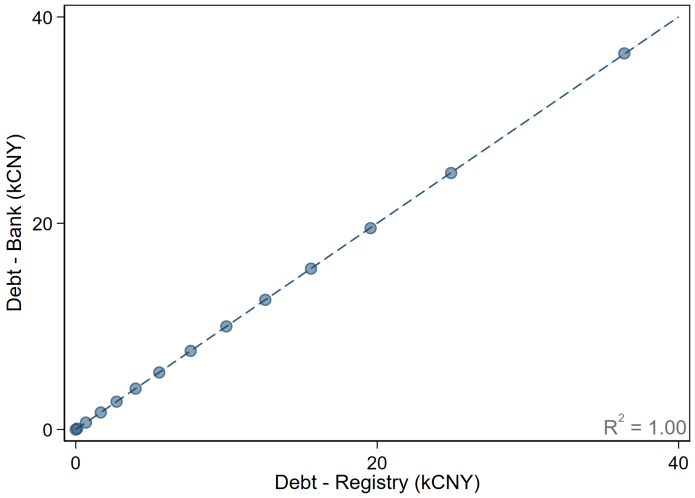


Figure A.3. Number of Waves Completed

This figure plots the histogram of the number of waves the participants have completed.

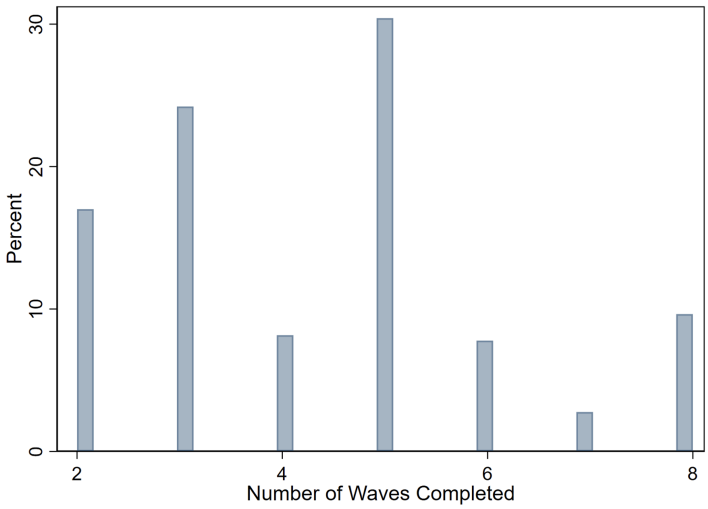
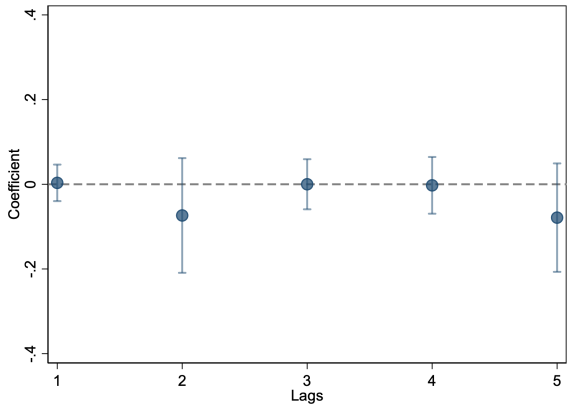


Figure A.4. Autoregressive Coefficients of Income Shocks

This figure gives the coefficients of regressing income shocks on their lags. The left panel focuses on the level shocks and the right panel focuses on the log shocks. The segments give the 95 percent confident intervals, with standard errors clustered at individual level. All regressions control for individual fixed effects.

Panel A: Level



Panel B: log

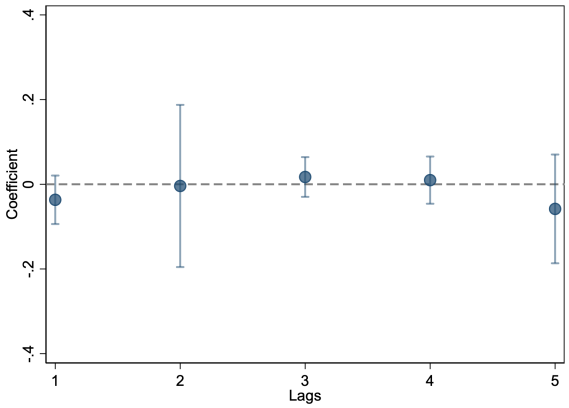


Figure A.5. Distribution of Monthly Income Volatility

This figure is a histogram of the individual standard deviation of monthly log income growth for the participants in our sample from 2020 to 2025. Income growth volatility is trimmed at 1%-99%.

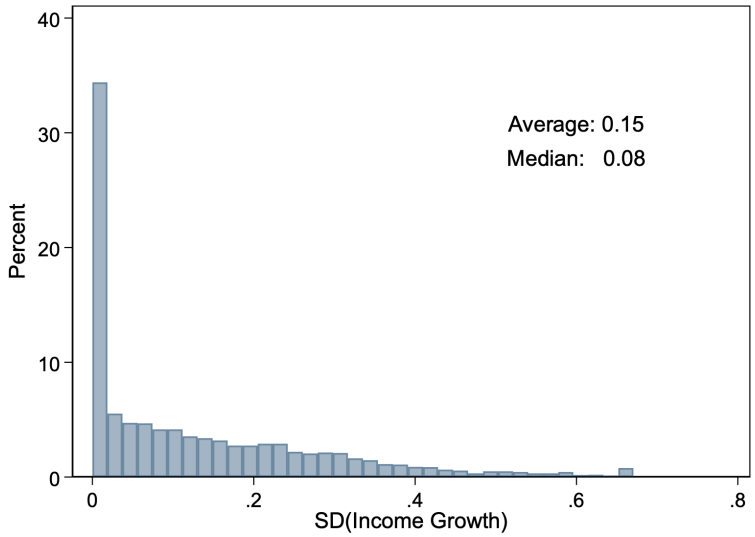


Figure A.6. Boom-Bust Household Cycles – Re-Calibration

This figure shows simulated paths from the structural model following a sequence of transitory income shocks. Red solid lines correspond to overreaction ($\theta = 2.54$). To simulate the case under Bayesian (blue dashed line), we first re-fit the SMM by calibrating the model with $\theta = 0$, which gives $\chi = 2.66$ and $\zeta = 0.42$. The top panels display the income shocks and expected income, and the bottom panels report changes in consumption and debt relative to no-shock average income, and percentage deviations of default relative to the no-shock baseline.

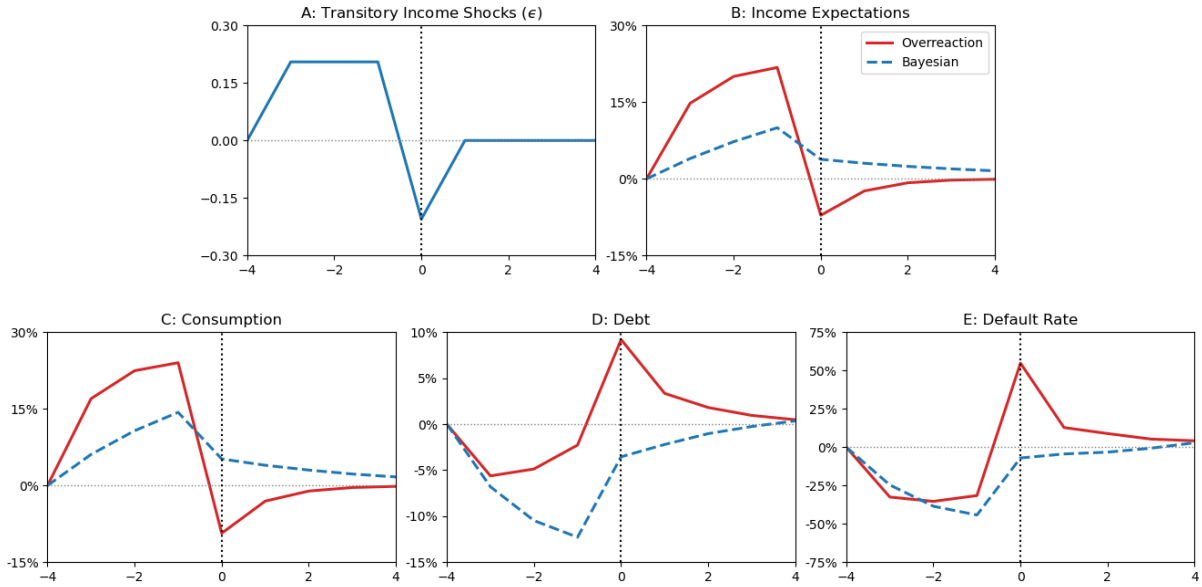


Figure A.7. Simulating Financial Crisis – Shocks

This figure plots the series of transitory income shocks when simulating Figure 7. The red solid line gives the shocks, which are manually picked so that the average debt-to-income ratio roughly matches that in the data. The black dashed line is the unexpected nonfarm payroll employment growth. The data is from Survey of Professional Forecasters. Unexpected nonfarm payroll employment growth is the realized value divided by the median forecasts made one year earlier minus one. We standardize both shocks to make the scale comparable.



TABLE A.1. Forecast Errors and Propensity to Misreport

In columns (1) - (4), Forecast Errors$_{t+1}$ is the dependent variable. Debt$_t$ is total unsecured borrowing at time t. Default$_t$ is an indicator for 90-day delinquency at time t. Liquidity$_t$ is liquid wealth relative to income. Credit Limit$_t$ is total credit limit. Income Reporting Errors$_t$ measures differences between reported and administrative income. Number of Banks$_t$ is the number of banks the subjects have accounts with. In columns (5) and (6), Shocks and Forecast Errors are the average income shocks and forecast errors for each individual. Survey %Completed is the percent of survey completed by the participants. All variables are measured in thousand CNY and winsorized at the 1% - 99% level within each wave.

	(1)	(2)	(3)	(4)	(5)	(6)
		Forecast Errors$_{t+1}$			Shocks	Forecast Error
Debt$_t$	-0.002	-0.003	-0.003	-0.003		
	(0.005)	(0.005)	(0.005)	(0.005)		
Default$_t$	0.002	0.002	0.002	0.002		
	(0.003)	(0.003)	(0.003)	(0.003)		
Liquidity$_t$		0.022	0.021	0.020		
		(0.084)	(0.084)	(0.083)		
Credit Limit$_t$		0.000	0.000	0.000		
		(0.000)	(0.000)	(0.000)		
Income Reporting Errors$_t$			-0.006	-0.006		
			(0.005)	(0.005)		
Number of Banks$_t$				0.060		
				(0.068)		
Survey %Completed					-0.065	0.120
					(0.086)	(0.204)
Individual FE	Yes	Yes	Yes	Yes	—	—
Industry × Wave FE	Yes	Yes	Yes	Yes	—	—
N Obs	26,449	23,504	23,504	23,504	6,280	6,280

Standard errors clustered at industry × wave in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.2. Data Comparison

Panel A reports summary statistics of the main sample. Panel B reports summary statistics of a 10% random subsample of all bank customers. All variables are winsorized at 1% - 99% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Survey Sample					Panel B: Overall Bank Sample				
	Mean	SD	p25	Median	p75	Mean	SD	p25	Median	p75
Age	39.88	9.03	34	39	46	41.45	9.77	33	41	48
Female	0.52	0.50	0	1	1	0.50	0.50	0	0	1
Spending	7.08	6.53	2.66	5.08	9.27	7.55	7.02	2.21	5.53	10.24
Income	13.02	12.85	4.53	8.37	16.42	14.28	14.49	3.99	9.11	21.34
Limit	81.33	117.12	15.00	30.00	100.00	87.24	137.35	12.50	36.00	120.00
Debt	4.75	9.40	0.00	0.00	4.99	4.11	10.79	0.00	0.00	5.34
Debt|Debt>0	11.79	11.68	2.89	7.85	17.02	9.75	12.73	2.46	8.53	19.20

TABLE A.3. Income Shocks, Forecast Errors, and Consumption Growth

$\Delta \log C_t$ is the growth in consumption between t and $t+1$. Shocks$_t$ - log is $\hat{s}^y_{i,t}$. Forecast Errors$_{t+1}$ - log is the difference between expected and realized income in log terms. High Util is one if utilization rate is above the median; High Liq is one if the consumers' liquidity is above median. Controls include Credit Limit, Liquidity, and Income Growth at time t. Level variables are in thousand CNY and all variables are winsorized at the 1-99% level within each wave.

	(1)	(2)	(3)	(4)
	$\Delta \log C_t$			
Shocks$_t$ - log	0.308***	0.231***	0.129***	0.331***
	(0.030)	(0.031)	(0.037)	(0.044)
Forecast Errors$_{t+1}$ - log		0.310***	0.292***	0.339***
		(0.029)	(0.037)	(0.029)
High Util$_t$			0.031	
			(0.049)	
Shocks$_t$ - log × High Util$_t$			0.194***	
			(0.053)	
High Liq$_t$				-0.026
				(0.056)
Shocks$_t$ - log × More Liq$_t$				0.205***
				(0.059)
Forecast Errors$_{t+1}$ - log × High Util$_t$			0.032	
			(0.036)	
Forecast Errors$_{t+1}$ - log × High Liq$_t$				-0.063*
				(0.032)
Industry × Wave FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	22,066	21,003	21,003	21,003

Standard errors clustered at industry × wave in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.4. Forecast Errors and Debt/Default Decisions – Heterogeneity by Utilization

ΔDebt_{t+1} is the change in total unsecured borrowing in period $t+1$. Default_{t+1} equals one if there is a 90-day delinquency on unsecured borrowing in $t+1$. Shocks_t is $Y_t - E_{t-1}[Y_t]$ implied by (4), where Y_t is the level of income. Forecast Errors_{t+1} is the difference between the subjective expectation of income and realized income in $t+1$. High Util_t is one if utilization rate is above the median in t, and zero otherwise. Controls include Liquidity, Credit Limit, and Income Growth in time t. All variables are measured in thousand CNY and winsorized at the 1% - 99% level within each wave.

	(1)	(2)	(3)	(4)
	ΔDebt_{t+1}		Default_{t+1}	
Shock_t	-0.030	-0.032	0.001	0.002
	(0.021)	(0.021)	(0.116)	(0.115)
Forecast Errors_{t+1}	0.042***	0.045***	0.649***	0.643***
	(0.014)	(0.014)	(0.153)	(0.156)
High Utilization	0.257	0.244	0.763***	0.767***
	(0.228)	(0.226)	(0.291)	(0.291)
High Utilization × Forecast Errors_{t+1}	0.058***	0.058***	0.391**	0.392**
	(0.019)	(0.019)	(0.194)	(0.194)
Shocks_{t+1}		-0.189**		0.033
		(0.089)		(0.113)
Industry × Wave FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N Obs	26,449	26,449	26,449	26,449

Standard errors clustered at industry × wave in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.5. Robustness with Different Fixed Effects

Forecast Errors$_{t+1}$ – Level is the difference between the subjective expectation of income and realized income in $t+1$. Forecast Errors$_{t+1}$ – log is the difference between the log of subjective income expectations and realized log income in $t+1$. Shocks$_t$ – log is the ϵ_t retrieved from fitting (4). Shocks$_t$ – Level is $Y_t - E_{t-1}[Y_t]$ implied by (4), where Y_t is the level of income in t. Surprises$_t$ – Level and Surprises$_t$ – log are respectively the negative of Forecast Errors$_t$ – Level and Forecast Errors$_t$ – log. Controls include Liquidity$_t$, Credit Limit$_t$, and Income Growth$_t$. All level variables are measured in thousand CNY and winsorized at the 1% - 99% level within each wave.

	Forecast Errors$_{t+1}$ – Level		Forecast Errors$_{t+1}$ – log	
	(1)	(2)	(3)	(4)
Shocks$_t$ – Level	0.289***			
	(0.031)			
Surprises$_t$ – Level		0.131***		
		(0.039)		
Shocks$_t$ – log			0.254***	
			(0.023)	
Surprises$_t$ – log				0.078***
				(0.025)
Fixed Effects	No	No	No	No
Controls	No	No	No	No
N Obs	26,449	15,644	25,407	14,354
R^2	0.01	0.01	0.02	0.00
	(5)	(6)	(7)	(8)
Shocks$_t$ – Level	0.442***			
	(0.053)			
Surprises$_t$ – Level		0.504***		
		(0.040)		
Shocks$_t$ – log			0.393***	
			(0.030)	
Surprises$_t$ – log				0.350***
				(0.028)
Fixed Effects		Industry × Wave, City × Wave, Individual		
Controls	Yes	Yes	Yes	Yes
N Obs	26,411	15,604	25,366	14,303
R^2	0.36	0.47	0.40	0.46
	(9)	(10)	(11)	(12)
Shocks$_t$ – Level	0.336***			
	(0.030)			
Surprises$_t$ – Level		0.210***		
		(0.023)		
Shocks$_t$ – log			0.321***	
			(0.025)	
Surprises$_t$ – log				0.121***
				(0.028)
Fixed Effects		Industry × Wave, City × Wave		
Controls	Yes	Yes	Yes	Yes
N Obs	26,530	16,523	25,558	15,406
R^2	0.12	0.13	0.14	0.11

Standard errors clustered at industry × wave in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.6. Income Surprises and Forecast Errors – Heterogeneity

Forecast Errors$_{t+1}$ is the difference between the subjective expectation of income and realized income in $t+1$. Shocks$_t$ is $Y_t - E_{t-1}[Y_t]$ implied by (4), where Y_t is the level of income. Young is defined as age smaller than 39. More volatile is one if average subjective income volatility is above the median, and zero otherwise. Government is one if the participants work in the government industry. Controls include Liquidity, Credit Limit, and Income Growth in time t. All level variables are measured in thousand CNY and winsorized at the 1% - 99% level within each wave.

	(1)	(2)	(3)	(4)	(5)
	Forecast Errors$_{t+1}$				
Surprises$_t$	0.417***	0.310***	0.463***	0.438***	0.394***
	(0.053)	(0.048)	(0.043)	(0.068)	(0.072)
Surprises$_t$× Young	0.101**				
	(0.041)				
Surprises$_t$× More Volatile		0.207***			
		(0.032)			
Surprises$_t$× Government			-0.344***		
			(0.094)		
Surprises$_t$×(Year $\geq$ 2023)				0.060	
				(0.083)	
Surprises$_t$×(Shocks$_t$ $<$ 0)					0.078
					(0.058)
Individual FE	Yes	Yes	Yes	Yes	Yes
Industry × Wave FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
N Obs	15,644	15,644	15,644	15,644	15,644

Standard errors clustered at industry × wave in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.7. Robustness Checks

Each panel estimates the relationship between income shocks, forecast errors, and economic outcomes. ΔC_t is consumption changes, ΔB_{t+1} is the change in borrowing, and Default_{t+1} indicates default in period $t+1$. All regressions include individual and industry × wave fixed effects, and controls for credit limit, liquidity, and income growth at time t. Standard errors are clustered at industry × wave level. All variables are measured in thousand CNY and winsorized at the 1% - 99% level within each wave.

	(1)	(2)	(3)	(4)
	$\text{Forecast Errors}_{t+1}$	ΔC_t	ΔDebt_{t+1}	Default_{t+1}
	Panel A: Cluster at Individual Level			
Shocks_t	0.431***	0.166***	-0.015	0.003
	(0.021)	(0.023)	(0.019)	(0.116)
$\text{Forecast Errors}_{t+1}$		0.196***	0.065***	0.804***
		(0.013)	(0.009)	(0.143)
N Obs	26,449	26,449	26,449	26,449
	Panel B: Shocks over 2023-2025			
Shocks_t	0.413***	0.155***	0.017	-0.180
	(0.040)	(0.047)	(0.035)	(0.144)
$\text{Forecast Errors}_{t+1}$		0.255***	0.093***	0.953***
		(0.029)	(0.022)	(0.222)
N Obs	13,698	13,698	13,698	13,698
	Panel C: Small Reporting Errors			
Shocks_t	0.439***	0.188***	-0.099**	-0.099
	(0.074)	(0.040)	(0.045)	(0.170)
$\text{Forecast Errors}_{t+1}$		0.187***	0.060***	0.811***
		(0.024)	(0.021)	(0.228)
N Obs	12,040	12,040	12,040	12,040
	Panel D: Estimation with Subjective Beliefs			
Shocks_t	0.530***	0.246***	0.028	0.213
	(0.049)	(0.037)	(0.022)	(0.145)
$\text{Forecast Errors}_{t+1}$		0.130***	0.079***	0.815***
		(0.026)	(0.011)	(0.162)
N Obs	15,644	15,644	15,644	15,644

Standard errors clustered at industry × wave in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.7. Robustness Checks – Continued

Each panel estimates the relationship between income shocks, forecast errors, and economic outcomes. ΔC_t is consumption changes, ΔB_{t+1} is the change in borrowing, and Default_{t+1} indicates default in period $t+1$. All regressions include individual and industry × wave fixed effects, and controls for credit limit, liquidity, and income growth at time t. Standard errors are clustered at industry × wave level. All variables are measured in thousand CNY and winsorized at the 1% - 99% level within each wave.

	(1)	(2)	(3)	(4)
	$\text{Forecast Errors}_{t+1}$	ΔC_t	ΔDebt_{t+1}	Default_{t+1}
	Panel E: Sample with at least Ten Transactions per Month			
Shocks_t	0.367***	0.155***	-0.024	-0.059
	(0.050)	(0.021)	(0.015)	(0.102)
$\text{Forecast Errors}_{t+1}$		0.212***	0.066***	0.903***
		(0.012)	(0.006)	(0.133)
N Obs	29,876	29,876	29,876	29,876
	Panel F: Sample only using One Bank			
Shocks_t	0.403***	0.173***	-0.030	-0.089
	(0.055)	(0.040)	(0.022)	(0.176)
$\text{Forecast Errors}_{t+1}$		0.251***	0.073***	0.996***
		(0.033)	(0.015)	(0.182)
N Obs	19,177	19,177	19,177	19,177
	Panel G: In-Sample Shock Extraction			
Shocks_t	0.472***	0.151***	-0.032*	-0.076
	(0.030)	(0.019)	(0.017)	(0.133)
$\text{Forecast Errors}_{t+1}$		0.227***	0.077***	1.029***
		(0.017)	(0.009)	(0.135)
N Obs	26,449	26,449	26,449	26,449
	Panel H: Single Participants			
Shocks_t	0.451***	0.162***	0.007	0.084
	(0.062)	(0.045)	(0.029)	(0.203)
$\text{Forecast Errors}_{t+1}$		0.212***	0.073***	0.859***
		(0.034)	(0.013)	(0.209)
N Obs	9,069	9,069	9,069	9,069

Standard errors clustered at industry × wave in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.8. Income Shocks, Forecast Errors, and Transfers/Installments

This table reports regressions of Transfer, defined as total amount of cross-bank transfer, and Installment payment on mortgages and car loans on income shocks and forecast errors. All specifications control for Credit Limit, Liquidity, and Income Growth. Standard errors are clustered at industry × wave level. All level variables are measured in thousand CNY and winsorized at the 1% - 99% level within each wave.

	(1)	(2)	(3)	(4)
	ΔTransfer$_t$		ΔInstall$_t$	
Shocks$_t$	0.051	0.072	-0.002	-0.007
	(0.084)	(0.091)	(0.032)	(0.041)
Forecast Errors$_{t+1}$	0.004	0.000	-0.027	-0.007
	(0.023)	(0.029)	(0.021)	(0.022)
Credit Limit$_t$		-0.074		0.006
		(0.064)		(0.040)
Liquidity$_t$		0.003*		0.002**
		(0.002)		(0.001)
Income Growth$_t$		-0.223		-0.143
		(0.627)		(0.215)
Shocks$_{t+1}$		0.705		1.261***
		(0.474)		(0.319)
Industry × Wave FE	No	Yes	No	Yes
Individual FE	No	Yes	No	Yes
N Obs	26,449	26,449	26,449	26,449

Standard errors clustered at industry × wave in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.9. Income Shocks and Economic Behaviors - Long Sample

This table reports regressions of consumption, borrowing, and default on income shocks and household controls. ΔC_t denotes consumption changes, ΔB_{t+1} denotes changes in borrowing, and Default_{t+1} indicates default in period $t+1$. All regressions include individual and industry $\times$ period fixed effects, and controls for Credit Limit_t, Liquidity_t, and Income Growth_t. Standard errors are clustered at the industry $\times$ wave level. All level variables are measured in thousand CNY and winsorized at the 1% - 99% level within each wave.

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔC_t		ΔDebt_{t+1}		Default_{t+1}	
Shocks_t	0.254***	0.227***	0.015	-0.008	0.155	0.098
	(0.032)	(0.029)	(0.018)	(0.012)	(0.122)	(0.087)
Credit Limit_t	-0.000	-0.003	-0.008***	-0.012***	-0.000	-0.002*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Liquidity_t	-0.076	-0.085*	-0.484***	-0.531***	0.050	-0.027
	(0.137)	(0.044)	(0.136)	(0.097)	(0.143)	(0.077)
Income Growth_t	-1.789***	-0.773***	0.178	0.144	0.148	0.140
	(0.205)	(0.197)	(0.129)	(0.179)	(0.332)	(0.277)
Industry $\times$ Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Long Sample	No	Yes	No	Yes	No	Yes
N Obs	26,449	98,676	26,449	98,676	26,449	98,676

Standard errors clustered at industry $\times$ wave in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.11. Future Forecast Errors and Economic Choices

This table estimates the relationship between income shocks, forecast errors, and subsequent economic choices. ΔC_t is the change in consumption, ΔDebt_{t+1} is the change in borrowing, and Default_{t+1} is an indicator for default in period $t+1$. All regressions include individual and industry × wave fixed effects, and controls for credit limit, liquidity, and income growth at time t. Standard errors are clustered at the industry × wave level. All variables are measured in thousand CNY and winsorized at the 1%–99% level within each wave.

	(1)	(2)	(3)
	ΔC_t	ΔDebt_{t+1}	Default_{t+1}
Shocks_t	0.225***	-0.016	0.384**
	(0.066)	(0.052)	(0.187)
$\text{Forecast Errors}_{t+1}$	0.116***	0.079**	0.367**
	(0.042)	(0.036)	(0.182)
$\text{Forecast Errors}_{t+2}$	0.013	-0.012	-0.145
	(0.022)	(0.025)	(0.110)
Controls	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Industry × Wave FE	Yes	Yes	Yes
N Obs	10,421	10,421	10,421

Standard errors clustered at industry × wave in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

III Household Consumption Survey

Please read the following information carefully:

To better understand the households' consumption behaviors, we selected a certain number of active users to participate in a survey. The survey is expected to take about 5 minutes. If you choose to take the survey, you will be awarded a 10-CNY Red Pocket.

The data will be analyzed by third-party research scholars for scientific research purposes and will not be evaluated by this bank. We will not disclose participants' identifiable information in any respect. We will not, to any extent, change the types of financial products we provide, including credit scores, credit limits, deposit rates, etc., based on participants' answers. Therefore, please answer based on your actual opinion.

Please confirm if you would like to participate and complete the survey.

- Yes
- No

1. What was your total income over the past 12 months? _____

   Note: income includes wages, salaries, bonuses, commission, etc., excluding earnings from financial investment.

2. How many banks or financial platforms do you usually use for daily transactions?
   (a) 0
   (b) 1
   (c) 2
   (d) 3 or more

3. How many hours do you usually work per week? _____

For the following three questions, we would like to ask you about your income expectations over the next six months. Please consider the case if you do not have a job change.

Note: income includes wages, salaries, bonuses, commission, etc., excluding earnings from financial investment.

4. What would be the lowest possible level of total income you believe you would get over the next 6 months?

   _____

5. What would be the highest possible level of total income you believe you would get over the next 6 months?

6. What would your total income most likely be over the next 6 months?

   _____

For the following three questions, we would like to ask you about your income expectations over the next 12 months. Please consider the case if you do not have a job change.[1]

7. What would be the lowest possible level of total income you believe you would get over the next 12 months?

   _____

8. What would be the highest possible level of total income you believe you would get over the next 12 months?

9. What would your total income most likely be over the next 12 months?

   _____

For the following three questions, please answer if you are currently investing in the stock market.

10. What would be the lowest amount of income you believe you could earn from investing in the financial market in total over the next 6 months?

    Note: use negative number for a negative return. _____

11. What would be the highest amount of income you believe you could earn from investing in the financial market in total over the next 6 months?

    Note: use negative number for a negative return. _____

12. What would be the total amount of income you would most likely earn from investing in the financial market in the next 6 months?

    Note: use negative number for a negative return. _____

[1] Questions 7 - 9 were asked in 2023.

IV Example of Credit Report (English Translation)

CREDIT REFERENCE CENTER,
THE PEOPLE'S BANK OF CHINA

This report is for your understanding of your credit status only.

Personal Credit Report

(Personal Edition)

Report Number: 2015060100000332123				Report Date: 2015.06.01 10:05:15
Name of the Subject	**Type of Identification Document**	**Identification Document Number**	**Querying Institution**	**Reason for Inquiry**
Zhang Shiwu	Identity Card	110108******181X	Business Management Department, People's Bank of China	Self-inquiry (in person at counter)

Other Identification Information	
Document Type	**Document Number**
Passport	G30003516
Military Officer Certificate	M0938981

Anti-Fraud Warning	
The Information Subject has requested to set an anti-fraud warning. Contact number: 010—90000000/13900000000。	
Effective Date	**Expiration Date**
May 29, 2015	May 28, 2016

Dispute Information Notice
The Information Subject has raised three disputes regarding the content of the credit report, which are currently being processed. Please review the relevant information carefully.

I. Basic Personal Information

(1) Identification Information

Gender	**Date of Birth**	**Marital Status**	**Employment Status**
Male	1981.08.15	Married	Employed
Name of Data Reporting Institution	**Name of Data Reporting Institution**	**Name of Data Reporting Institution**	**Name of Data Reporting Institution**
Industrial and Commercial Bank of China	Industrial and Commercial Bank of China	Industrial and Commercial Bank of China	Industrial and Commercial Bank of China
Education	**Academic Degree**	**Nationality**	**Email Address**
Undergraduate	Bachelor's Degree	China	zhang15@hotmail.com
Name of Data Reporting Institution	**Name of Data Reporting Institution**	**Name of Data Reporting Institution**	**Name of Data Reporting Institution**
Industrial and Commercial Bank of China	Industrial and Commercial Bank of China	Industrial and Commercial Bank of China	Industrial and Commercial Bank of China
Mailing Address		**Registered Address**	
Room 301, Block A, International Enterprise Building, No. 35 Financial Street, Xicheng District, Beijing		Room C522, Building 7, North Chunxiao Garden, Chaoyang District, Beijing	
Name of Data Reporting Institution		**Name of Data Reporting Institution**	
Industrial and Commercial Bank of China		Industrial and Commercial Bank of China	

Reference Number	**Mobile Phone Number**	**Information Update Date**	**Name of Data Reporting Institution**
1	13811117777	2015.05.01	Industrial and Commercial Bank of China
2	13811112222	2015.01.22	Bank of China
3	13900000000	2014.02.01	Agricultural Bank of China
4	13300000000	2014.01.22	China CITIC Bank
5	18600000000	2013.11.12	China Construction Bank

(2) Spouse Information

Name	**Document Type**	**Document Number**	**Employer**	**Contact Number**
Li Jinhua	Foreigner Residence Permit	123560000008888	Finance Department, Samsung Electronics Beijing Branch	13800003333
Name of Data Reporting Institution				
Industrial and Commercial Bank of China				

(3) Residential Information

Reference Number	**Residential Address**	**Home Telephone**	**Residential Status**	**Information Update Date**

1	Room C555, Building 7, North District, Chunxiao Garden, Chaoyang District, Beijing	010—83234323	Mortgage	2015.05.01
2	Room 401, Building 2A, No. 20 Xueyuan Road Compound, Haidian District, Beijing	010—62123212	Collective Dormitory	2015.01.22
3	Room 603, Building 4, North Fuxingmen Street, Xicheng District, Beijing	010—59873232	Rented Apartment	2014.02.01
4	Room 201, Building 1, No. 64 Xijiaominxiang, Xicheng District, Beijing	010—59000011	Rented Apartment	2014.01.22
5	Room 701, Building 3, No. 10 Huayuan Road, Haidian District, Beijing	010—57889900	Rented Apartment	2013.11.12

Reference Number	Name of Data Reporting Institution
1	Industrial and Commercial Bank of China
2	Bank of China
3	Agricultural Bank of China
4	China CITIC Bank
5	China Construction Bank

(4) Employment Information

Reference Number	Employer	Type of Employer	Employer Address	Employer Telephone Number
1	Credit Reference Center, Corporate Department, People's Bank of China	Government Agency/Public Institution	Room 305, Block A, International Enterprise Building, No. 35 Financial Street, Xicheng District, Beijing	010—83233333
2	of Software Engineering, School of Information Science and Technology, Peking University	Government Agency/Public Institution	m 601, Science Building 3, No. 5 Yiheyuan Road, Haidian District, Beijing	010—62123333
3	Institute of Microelectronics, Chinese Academy of Sciences	Government Agency/Public Institution	No. 1 Qinghuayuan, Haidian District, Beijing	010—59875555
4	Beijing Weili Company	Individual or Private Enterprise	No. 3 Beitucheng West Road, Chaoyang District, Beijing	010—59006666
5	IBM Software Center	Foreign-funded Enterprise	No. 8 Beichen East Road, Chaoyang District, Beijing	010—57889900

Reference Number	Occupation	Industry	Position	Professional Title	Year Joined Current Employer	Information Update Date
1	Clerical and Related Personnel	Financial Industry	Mid-level Management	Intermediate	2008	2015.05.01
2	Professional and Technical Personnel	Scientific Research and Technical Services	Mid-level Management	Intermediate	2007	2015.01.22
3	Professional and Technical Personnel	Scientific Research and Technical Services	General Staff	Basic Level	2004	2014.02.01
4	Professional and Technical Personnel	Scientific Research and Technical Services	General Staff	Basic Level	2003	2014.01.22
5	Professional and Technical Personnel	Scientific Research and Technical Services	General Staff	Basic Level	2001	2013.11.12

Reference Number	Name of Data Reporting Institution
1	Industrial and Commercial Bank of China
2	Bank of China
3	Agricultural Bank of China
4	China CITIC Bank
5	China Construction Bank

II. Information Summary

(1) Credit Transaction Information Notice

Type of Business		Number of Accounts	Month of First Transaction Issuance
Loan	Personal Housing Loan	2	2007.09
	Personal Commercial Property Loan (including mixed-use property)	1	2007.09
	Other Types of Loans	2	2007.09
Credit card.	Credit Card	2	2007.09
	Quasi-Credit Card	1	2007.09
Other	--	3	2007.09
Total		11	--

(2) Summary of Credit Transaction Default Information

Summary of Recovered Claims		
Type of Business	Number of Accounts	Balance
Asset Disposal Services	1	10,000
Advance Payment Services	1	20,000

Total	2	30,000

Summary of Bad Debt Information	
Number of Accounts	Balance
1	170,000

Summary of Overdue (Overdraft) Information				
Account Type	Number of Accounts	Number of Months	Highest Single-Month Overdue/Overdraft Amount	Longest Overdue/Overdraft Period (Months)
Non-revolving Loan Account	3	6	5,500	2
Revolving Loan Account I	1	3	2,500	1
Revolving Loan Account II	2	6	5,500	2
Credit Card Account	2	4	5,500	4
Quasi-credit Card Account	--	--	--	--

(3) Summary of Credit Transactions, Credit Limits, and Liabilities (Unsettled/Active Accounts)

Summary of Non-revolving Loan Account Information				
Number of Managing Institutions	Number of Accounts	Total Credit Limit	Balance	Average Repayment Due in the Past 6 Months
2	3	1,010,000	551,000	6,000

Summary of Revolving Loan Account I Information				
Number of Managing Institutions	Number of Accounts	Total Credit Limit	Balance	Average Repayment Due in the Past 6 Months
1	3	20,000	12,000	2,000

Summary of Revolving Loan Account II Information				
Number of Managing Institutions	Number of Accounts	Total Credit Limit	Balance	Average Repayment Due in the Past 6 Months
2	3	610,000	50,000	8,000

Summary of Credit Card Account Information						
Number of Issuing Institutions	Number of Accounts	Total Credit Limit	Maximum Credit Limit per Institution	Minimum Credit Limit per Institution	Credit Utilized	Average Credit Utilized in the Past 6 Months
2	4	80,000	30,000	20,000	15,000	4,000

Summary of Quasi-credit Card Account Information						
Number of Issuing Institutions	Number of Accounts	Total Credit Limit	Maximum Credit Limit per Institution	Minimum Credit Limit per Institution	Overdraft Balance	Average Overdraft Balance in the Past 6 Months
3	4	95,000	30,000	5,000	12,000	2,000

Summary of Related Repayment Obligations					
For Individual					
Guarantee Obligation			Other Related Repayment Obligations		
Number of Accounts	Guaranteed Amount	Balance	Number of Accounts	Repayment Obligation Amount	Balance
1	200,000	100,000	3	900,000	500,000
For Enterprise					
Guarantee Obligation			Other Related Repayment Obligations		
Number of Accounts	Guaranteed Amount	Balance	Number of Accounts	Repayment Obligation Amount	Balance
1	200,000	100,000	3	900,000	500,000

(4) Summary of Non-Credit Transaction Information

Summary of Postpaid Service Arrears		
Type of Business	Number of Accounts	Outstanding Amount
Telecommunications Services	1	10,000
Utilities (Water, Electricity, Gas, etc.)	1	200

(5) Summary of Public Information

Public Information Summary		
Information Type	**Number of Records**	**Amount Involved**
Tax Arrears Information	1	10,000
Civil Judgment Information	1	10,000
Enforcement Information	1	10,000
Administrative Penalty Information	1	10,000

(6) Summary of Non-Financial Credit Transaction Information

Information Type	Number of Entries
Non-Financial Credit Transaction Information	1

(7) Summary of Disclosed Information

Summary of Public Information	
Information Type	**Number of Records**
Outstanding Payment Information	1
Judgment Information	1
Enforcement Information	1
Disciplinary Information	1

(8) Summary of Inquiry Records

Number of Institutions Inquired Within the Past Month		Number of Inquiries Within the Past Month			Number of Inquiries Within the Past Two Years		
Loan Approval	Credit Card Approval	Loan Approval	Credit Card Approval	Self-Inquiry	Post-Loan Management	Guarantor Qualification Review	Special Merchant Real-Name Verification
0	0	0	0	3	7	1	1

Dispute and Explanation Information	
Dispute Mark	**Date Added**
Credit transaction information is currently under dispute resolution.	2014.07.22

3. Credit Transaction Information Details

(1) Information on Claims Under Recovery

Account 1

Managing Institution	Type of Business	Date of Claim Receipt	Original Creditor	Original Debt Business Type	Claim Amount	Repayment Status at the Time of Claim Transfer
Cinda Asset Management Company	Asset Disposal	2007.11.09	Industrial and Commercial Bank of China	Loan	400,000	6

As of January 8, 2011		
Account Status	**Balance**	**Most Recent Repayment Date**
Collection	20,000	2011.01.08

Account 2

Managing Institution	Type of Business	Date of Claim Receipt	Original Creditor	Original Debt Business Type	Claim Amount	payment Status at the Time of Claim Transfer
Shouchuang Guarantee Company	Subrogated Debt Repayment	2007.11.08	ICBC Leasing	Financial Leasing	10,000	2

As of January 20, 2011				
Account Status			**Account Closure Date**	
Closed			2011.01.20	
Special Transaction Type	**Date of Occurrence**	**Number of Months Changed**	**Transaction Amount**	**Detailed Record**
Guarantor (Third Party) Subrogation	2011.01.20	0	10,000	This loan was repaid in the amount of 10,000 yuan by XX Company.

(2) Non-revolving Loan Account

Account 1 (Credit Agreement Identifier: ICBCZH121211)

Managing Institution	Account Identifier	Opening Date	Maturity Date	Loan Amount	Account Currency
Industrial and Commercial Bank of China, Beijing Branch	ICBCZH00001	2010.01.22	2020.01.19	360,000	Renminbi
Type of Business	**Type of Guarantee**	**Number of Repayment Periods**	**Repayment Frequency**	**Repayment Method**	**Joint Borrower Indicator**
Personal Commercial Housing Loan	Mortgage	180	Month	Equal Principal Installments	Primary Borrower

As of May 25, 2015

Account Status	Balance	Most Recent Repayment Date
Bad Debt	166,000	2013.04.05

Repayment Record from July 2010 to May 2015

	1	2	3	4	5	6	7	8	9	10	11	12
2015	B	B	B	B	B							
	16,200	16,300	16,400	16,500	16,600							
2014	B	B	B	B	B	B	B	B	B	B	B	B
	16,200	16,200	16,200	16,200	16,200	16,200	16,200	16,200	16,200	16,200	16,200	16,200
2013	3	4	5	6	7	B	B	B	B	B	B	B
	16,200	16,200	16,200	16,200	16,200	16,200	16,200	16,200	16,200	16,200	16,200	16,200
2012	N	N	N	N	N	N	N	N	N	N	1	2
	0	0	0	0	0	0	0	0	0	0	16,200	16,200
2011	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2010							N	N	N	N	N	N
							0	0	0	0	0	0

Account 2 (Credit Agreement Identifier: BOCBJ12362414 **) (Transferred from another institution)**

Managing Institution	Account Identifier	Opening Date	Maturity Date	Loan Amount	Account Currency
Bank of China, Beijing Branch	BOCBJ00100	2010.09.22	2025.09.21	500,000	US Dollars
Type of Business	**Type of Guarantee**	**Number of Repayment Periods**	**Repayment Frequency**	**Repayment Method**	**Joint Borrower Indicator**
Personal Commercial Housing Loan	Mortgage	180	Month	Equal Principal Installments	None

As of May 5, 2015

Account Status	Five-tier classification	Balance	Remaining repayment periods	Repayment due this month	Repayment date	Actual repayment this month	Most recent repayment date
Overdue	Substandard	400,000	125	5,000	2015.05.05	0	2015.03.05

Current number of overdue periods	Total current overdue amount	Principal overdue for 31–60 days	Principal overdue for 61–90 days	Principal overdue for 91–180 days	Overdue for more than 180 days; principal remains unpaid.
2	6,100	1,000	0	0	0

Latest repayment record after May 5, 2015.

Five-tier classification	Balance	Repayment Date	Repayment Amount	Current Repayment Status
Normal	394,000	2015.05.31	6,100	N

Repayment record from September 2010 to May 2015.

	1	2	3	4	5	6	7	8	9	10	11	12
2015	N	N	N	1	2							
	0	0	0	3,000	6,100							
2014	N	N	N	N	N	N	D	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2013	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2012	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2011	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2010									N	N	N	N
									0	0	0	0

Special Transaction Type	Date of Occurrence	Number of Months Changed	Transaction Amount	Detailed Record
Guarantor (third party) repayment	2014.07.05	0	20,000	This loan was repaid by XX Company in the amount of 20,000 yuan.

Institution Statement	Date Added
The customer authorized XX Company to repay the loan. Due to the company's failure to make timely payments, there were multiple overdue incidents.	2014.08.12
Personal Statement	**Date Added**
I was unable to make timely repayments due to being abroad; this was not a malicious default.	2014.09.12
Dispute Mark	**Date Added**
This transaction is currently under dispute resolution.	2013.10.10
Special Note	**Date Added**
The disputed information is indeed incorrect, but due to technical reasons, it cannot be corrected at this time.	2013.10.25

Account 3 (Credit Agreement Identifier: AAAAA011111 **)**

Managing Institution	Account Identifier	Opening Date	Maturity Date	Loan Amount	Account Currency
Beijing Housing Provident Fund Management Center	AAAAA00001	2007.12.02	2012.12.01	200,000	Renminbi
Type of Business	**Type of Guarantee**	**Number of Repayment Periods**	**Repayment Frequency**	**Repayment Method**	**Joint Borrower Indicator**
Personal Housing Provident Fund Loan	Mortgage	60	Month	Installment with Equal Principal and Interest	None

As of August 10, 2011

Account Status	Transfer-out Month
Transfer-out	2011.08

Repayment Record from July 2010 to August 2011

	1	2	3	4	5	6	7	8	9	10	11	12
2011	N	N	N	N	N	N	N	#				
	0	0	0	0	0	0	0					
2010							N	1	2	3	N	N
							0	100	200	300	0	0

Account 4 (Credit Agreement Identifier: PSBOC011105)

Managing Institution	Account Identifier	Opening Date	Maturity Date	Loan Amount	Account Currency
Postal Savings Bank of China, Beijing Branch	PSBOC00005	2011.09.29	--	10,000	Renminbi
Type of Business	**Type of Guarantee**	**Number of Repayment Periods**	**Repayment Frequency**	**Repayment Method**	**Joint Borrower Indicator**
Commercial Student Loan	Credit/Unsecured	--	Irregular	Lump-sum Principal and Interest Payment at Maturity	None

As of May 15, 2015

Account Status	Account Closure Date
Settled	2015.05.15

Repayment Record from September 2011 to May 2015

	1	2	3	4	5	6	7	8	9	10	11	12
2015	N	N	N	N	C							
	0	0	0	0	0							
2014	B	B	B	N	N	N	N	N	N	N	N	N
	900	1,000	1,100	0	0	0	0	0	0	0	0	0
2013	N	N	N	N	1	2	3	4	5	6	B	B
	0	0	0	0	100	200	300	400	500	600	700	800
2012	N	1	N	N	N	N	N	N	N	N	N	N
	0	100	0	0	0	0	0	0	0	0	0	0
2011									N	N	N	N
									0	0	0	0

Special Transaction Type	Date of Occurrence	Number of Months Changed	Transaction Amount	Detailed Record
Early Settlement	2015.05.15	7	500	--

(3) Revolving Loan Account I

(Due to the large number of such accounts, only the most recent N accounts are shown in this report.)

Account 1 (Credit Agreement Identifier: BOC0255220 **)**

Managing Institution	Account Identifier	Opening Date	Maturity Date	Loan Amount	Account Currency
Bank of China, Xidan Branch	BOC0244220	2014.08.22	2016.08.21	500,000	US Dollars
Type of Business	**Type of Guarantee**	**Number of Repayment Periods**	**Repayment Frequency**	**Repayment Method**	**Joint Borrower Indicator**
Personal Consumer Loan	Mortgage	24	Month	Equal Principal Installments	None

As of May 5, 2015

Account Status	Five-tier classification	Balance	Remaining repayment periods	Repayment due this month	Repayment date	Actual repayment this month	Most recent repayment date
Overdue	Substandard	40,000	14	5,000	2015.05.05	0	2015.03.05

Current number of overdue periods	Total current overdue amount	Principal overdue for 31–60 days	Overdue Principal: 61–90 Days	Overdue Principal: 91–180 Days	Overdue for more than 180 days; principal remains unpaid.
2	6,100	1,000	0	0	0

Repayment Record: August 2014 to May 2015

	1	2	3	4	5	6	7	8	9	10	11	12
2015	N	N	N	1	2							
	0	0	0	6,000	6,100							
2014								N	N	N	N	N
								0	0	0	0	0

Account 2 (Credit Agreement Identifier: BOC0255220 **)**

Managing Institution	Account Identifier	Opening Date	Maturity Date	Loan Amount	Account Currency
China Merchants Bank, Beijing Branch	CMB00009	2011.09.22	2016.09.21	500,000	US Dollars
Type of Business	**Type of Guarantee**	**Number of Repayment Periods**	**Repayment Frequency**	**Repayment Method**	**Joint Borrower Indicator**
Personal Consumer Loan	Mortgage	60	Month	Installment with Equal Principal and Interest	None

As of May 5, 2015

Account Status	Five-tier classification	Balance	Remaining repayment periods	Repayment due this month	Repayment date	Actual repayment this month	Most recent repayment date
Normal	Normal	40,000	16	5,000	2015.05.05	5,000	2015.05.05

Current number of overdue periods	Total current overdue amount	incipal overdue for 31–60 days	verdue Principal: 61–90 Days	verdue Principal: 91–180 Days	verdue for more than 180 days; principal remains unpaid.
0	0	0	0	0	0

Repayment Record from September 2011 to May 2015

	1	2	3	4	5	6	7	8	9	10	11	12
2015	N	N	N	N	N							
	0	0	0	0	0							
2014	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2013	#	N	N	N	N	N	1	N	N	1	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2012	N	N	N	N	N	#	N	N	N	N	N	N
	0	0	0	0	0		0	0	0	0	0	0
2011									#	#	#	#

(4) Revolving Loan Account II

Account 1 (Credit Agreement Identifier: CGBXY0007 **)**

Managing Institution	Account Identifier	Opening Date	Maturity Date	Account Credit Limit	Account Currency
Guangfa Bank, Beijing Branch	CGB0007	2013.07.22	2019.01.31	70,000	US Dollars
Type of Business	**Type of Guarantee**	**Number of Repayment Periods**	**Repayment Frequency**	**Repayment Method**	**Joint Borrower Indicator**
Personal Consumer Loan	Mortgage	--	Month	Interest settled periodically, Principal repaid at maturity	None

As of May 5, 2015												
Account Status	**Five-tier classification**	**Balance**		**Remaining repayment periods**	**Repayment due this month**	**Repayment date**	**Actual repayment this month**	**Most recent repayment date**				
Overdue	Substandard	30,000		79	5,000	2015.05.05	0	2015.03.05				
Current number of overdue periods	**Total current overdue amount**	**Principal overdue for 31–60 days**		**Principal overdue for 61–90 days**		**Principal overdue for 91–180 days**		**Overdue for more than 180 days; principal remains unpaid.**				
2	6,100	1,000		0		0		0				
Repayment record from July 2013 to May 2015												
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
2015	N	N	N	1	2							
	0	0	0	6,000	6,100							
2014	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2013							N	N	N	N	N	N
							0	0	0	0	0	0

Account 2 (Credit Agreement Identifier: CQXY2225631 **)**

Managing Institution	**Account Identifier**	**Opening Date**	**Maturity Date**	**Account Credit Limit**	**Account Currency**
Chongqing XX Microloan Company	CQ2225631	2012.10.09	--	30,000	Renminbi
Type of Business	**Type of Guarantee**	**Number of Repayment Periods**	**Repayment Frequency**	**Repayment Method**	**Joint Borrower Indicator**
Personal Consumer Loan	Credit/Unsecured	--	Irregular	Interest settled periodically, principal repaid flexibly	None

As of April 28, 2015												
Account Status				**Account Closure Date**								
Settled				2015.04.28								
Repayment record from October 2012 to April 2015												
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
2015	N	N	N	C								
	0	0	0	0								
2014	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2013	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2012										N	N	N
										0	0	0

(5) Credit Card Account

Account 1 (Credit Agreement Identifier: CGFBXY11111**Card ending in 1365)**

Issuing Institution	**Account Identifier**	**Opening Date**	**Account Credit Limit**	**Shared Credit Limit**	**Currency**	**Type of Business**	**Type of Guarantee**
Guangfa Bank Credit Card Center	CGFB001	2010.01.22	160,000	160,000	Renminbi	Credit Card	Credit/Unsecured

As of May 31, 2015												
Account Status				**Balance**				**Most Recent Repayment Date**				
Bad Debt				135,500				2014.08.05				
Repayment Record from July 2010 to May 2015												
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
2015	B	B	B	B	B							
	13,100	13,200	13,300	13,400	13,500							
2014	N	N	N	N	N	N	1	2	3	4	5	6
	0	0	0	0	0	0	12,500	12,600	12,700	12,800	12,900	13,000
2013	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0

2012	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2011	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2010							N	N	N	N	N	N
							0	0	0	0	0	0

Account 2 (Credit Agreement Identifier: AAAXY003 **)**

Issuing Institution	Account Identifier	Opening Date	Account Credit Limit	Shared Credit Limit	Currency	Type of Business	Type of Guarantee
Industrial and Commercial Bank of China, Credit Card Center	AAA003	2009.05.22	16,000	160,000	Renminbi	Credit Card	Credit/Unsecured

As of April 12, 2015

Account Status	Balance	Credit Utilized	Outstanding balance of large-sum special installment not yet billed	Remaining installment periods	Average credit utilized over the past 6 months	Maximum credit utilized
Normal	255,500	135,500	110,000	11	90,000	150,000

Statement date	Repayment due this month	Actual repayment this month	Most Recent Repayment Date	Current number of overdue periods	Total current overdue amount
2015.04.12	24,500	0	2015.03.10	1	24,550

Large-sum special installment information

Large-sum special installment limit	Installment limit effective date	Installment limit expiration date	Amount utilized in installments
120,000	2015.09.12	2016.09.11	120,000

Latest repayment record after April 12, 2015

Balance	Repayment Date	Repayment Amount	Current Repayment Status
230,950	2015.04.25	24,550	N

Repayment record from July 2010 to April 2015

	1	2	3	4	5	6	7	8	9	10	11	12
2015	N	N	N	N								
	0	0	0	0								
2014	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2013	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2012	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2011	#	#	#	#	#	#	#	#	#	#	N	N
											0	0
2010							N	N	N	N	N	N
							0	0	0	0	0	0

Explanation of special events

No statement was issued for this account in May 2015.

Special Transaction Type	Date of Occurrence	Number of Months Changed	Transaction Amount	Detailed Record
Personalized Installment	2012.07	5	10,000	--

Institution Statement	Date Added
The overdue status of this card is extremely serious.	2012.12.15
Personal Statement	**Date Added**
I was unable to make timely repayments due to being abroad, resulting in the current overdue status. This is not a malicious default.	2013.07.02
Dispute Mark	**Date Added**
This transaction is currently under dispute resolution.	2013.07.22

Account 3 (Credit Agreement Identifier: ICBCXY003 **)**

Issuing Institution	Account Identifier	Opening Date	Account Credit Limit	Shared Credit Limit	Currency	Type of Business	Type of Guarantee
Industrial and Commercial Bank of China, Credit Card Center	ICBC0002	2009.05.28	50,000	50,000	Renminbi	Credit Card	Credit/Unsecured

As of May 10, 2015

Account Status	Account Closure Date
Account Closure	May 10, 2015

Repayment Record from July 2010 to May 2015

	1	2	3	4	5	6	7	8	9	10	11	12

2015	N	N	N	N	C							
	0	0	0	0	0							
2014	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2013	N	N	N	N	N	N	1	2	N	N	N	N
	0	0	0	0	0	0	100	200	0	0	0	0
2012	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2011	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2010							N	N	N	N	N	N
							0	0	0	0	0	0

Account 4 (Credit Agreement Identifier: CMBXY003 **)**

Issuing Institution	Account Identifier	Opening Date	Account Credit Limit	Shared Credit Limit	Currency	Type of Business	Type of Guarantee
China Merchants Bank Credit Card Center	CMB005	2009.05.28	30,000	50,000	Renminbi	Credit Card	Credit/Unsecured
As of May 28, 2015, the account status is 'Not Activated.'							

(6) Quasi-credit Card Account

Account 1 (Credit Agreement Identifier: PSBCXY003**)**

Issuing Institution	Account Identifier	Opening Date	Account Credit Limit	Shared Credit Limit	Currency	Type of Guarantee
Postal Savings Bank Credit Card Center	PSBC0002	2010.01.22	30,000	30,000	Renminbi	Credit/Unsecured

As of May 31, 2015

Account Status	Balance	Most Recent Repayment Date
Bad Debt	10,000	2014.08.05

Repayment Record from July 2010 to May 2015

	1	2	3	4	5	6	7	8	9	10	11	12
2015	5	6	7	B	B							
	10,000	10,000	10,000	10,000	10,000							
2014	N	N	N	N	N	N	N	N	1	2	3	4
	0	0	0	0	0	0	0	0	10,000	10,000	10,000	10,000
2013	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2012	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2011	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2010							N	N	N	N	N	N
							0	0	0	0	0	0

Account 2 (Credit Agreement Identifier: AAA8845213 **) (Card ending in 1465)**

Issuing Institution	Account Identifier	Opening Date	Account Credit Limit	Shared Credit Limit	Currency	Type of Guarantee
Industrial and Commercial Bank of China, Credit Card Center	AAA003	2009.05.22	16,000	160,000	Renminbi	Credit/Unsecured

As of May 19, 2015

Account Status	Overdraft Balance	Average Overdraft Balance in the Past 6 Months	Maximum Overdraft Balance	Statement date	Actual repayment this month	Most recent repayment date	Overdraft balance unpaid for over 180 days
Normal	1,000	1,000	2,000	2015.05.19	0	2015.02.20	0

Repayment Record from June 2013 to May 2015

	1	2	3	4	5	6	7	8	9	10	11	12
2015	N	N	1	2	3							
	0	0	800	900	1,000							
2014	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0

2013	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2012	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2011	N	N	N	N	N	N	N	N	N	N	N	N
	0	0	0	0	0	0	0	0	0	0	0	0
2010							N	N	N	N	N	N
							0	0	0	0	0	0

Special Transaction Type	Date of Occurrence	Number of Months Changed	Transaction Amount	Detailed Record
Other	2012.07	0	1,000	--

(7) Information on Related Repayment Responsibilities

Personal loans with related repayment responsibilities

Account 1

Managing Institution	Type of Business	Opening Date	Maturity Date	Type of Responsible Person	Repayment Obligation Amount	Currency	Guarantee Contract Number
Industrial and Commercial Bank of China, Beijing Branch	Personal Consumer Loan	2011.05.15	2016.05.14	Guarantee	200,000	Renminbi	AAAAAAAA0001

Primary Borrower	Primary Borrower Identification Type	Primary Borrower Identification Number
Zhang San	Identity Card	110109198312030021
As of May 25, 2015		
Balance	**Five-tier classification**	**Repayment Status**
100,000	Normal	N

Account 2

Managing Institution	Type of Business	Opening Date	Maturity Date	Type of Responsible Person	Repayment Obligation Amount	Currency	Guarantee Contract Number
Industrial and Commercial Bank of China, Beijing Branch	Credit Card	2011.05.15	--	Guarantee	20,000	Renminbi	AAAAAAAA0001

Primary Borrower	Primary Borrower Identification Type	Primary Borrower Identification Number
Wang Wu	Identity Card	3101181977010110023
As of May 25, 2015		
Balance	**Five-tier classification**	**Repayment Status**
10,000		N

Enterprise loan with associated repayment obligations

Account 1

Managing Institution	Type of Business	Opening Date	Maturity Date	Type of Responsible Person	Repayment Obligation Amount	Currency	Guarantee Contract Number
China Construction Bank, Beijing Branch	Fixed asset loan	2011.05.15	2016.05.14	Accounts receivable debtor	200,000	Renminbi	--

Primary Borrower	Primary Borrower Identification Type	Primary Borrower Identification Number
A Beijing-based company	Institutional credit code	12011819008808
As of May 25, 2015		
Balance	**Five-tier classification**	**Number of overdue months**
100,000	Substandard	2

(8) Credit Agreement Information

Credit Agreement 1

Managing Institution	Credit Agreement Identifier	Effective Date	Maturity Date	Purpose of credit limit
China Construction Bank	CCB2222321	2015.05.01	2019.01.31	Non-revolving loan limit
Credit Limit	**Credit limit**	**Credit limit identifier**	**Credit Utilized**	**Currency**
40,000	100,000	CCB55555	40,000	Renminbi

Credit Agreement 2

Managing Institution	Credit Agreement Identifier	Effective Date	Maturity Date	Purpose of credit limit
Bank of China	BOC22223	2014.10.01	2019.01.31	Revolving Loan Limit
Credit Limit	**Credit limit**	**Credit limit identifier**	**Credit Utilized**	**Currency**
40,000	100,000	PSBOC3333	40,000	US Dollars

Credit Agreement 3

Managing Institution	Credit Agreement Identifier	Effective Date	Maturity Date	Purpose of credit limit
Postal Savings Bank of China, Beijing Branch	PSBOC00001	2011.09.29	2015.12.28	Revolving Loan Limit
Credit Limit	**Credit limit**	**Credit limit identifier**	**Credit Utilized**	**Currency**
10,000			10,000	Renminbi

Credit Agreement 4

Managing Institution	Credit Agreement Identifier	Effective Date	Maturity Date	Purpose of credit limit
Bank of China, Xidan Branch	BOC0255220	2010.02.01	2020.01.31	Revolving Loan Limit
Credit Limit	**Credit limit**	**Credit limit identifier**	**Credit Utilized**	**Currency**
1,200,000			0	US Dollars

Credit Agreement 5

Managing Institution	Credit Agreement Identifier	Effective Date	Maturity Date	Purpose of credit limit
Guangfa Bank, Beijing Branch	CGBXY0007	2012.02.01	2019.01.31	Credit Card Shared Limit
Credit Limit	**Credit limit**	**Credit limit identifier**	**Credit Utilized**	**Currency**
70,000	100,000	PSBOC3333	40,000	US Dollars

Credit Agreement 6

Managing Institution	Credit Agreement Identifier	Effective Date	Maturity Date	Purpose of credit limit
Bohai Bank Beijing Branch	BHXY4432122	2010.02.01	2020.01.31	Revolving Loan Limit
Credit Limit	**Credit limit**	**Credit limit identifier**	**Credit Utilized**	**Currency**
1,200,000			1,200,000	US Dollars

IV. Details of Non-Credit Transaction Information

Postpaid Record

Account

Institution Name	Type of Business	Service Activation Date	Current Payment Status	Current Outstanding Amount	Accounting Period (Year/Month)
China Tietong Gansu Branch	Fixed-Line Postpaid	2009.08.17	Outstanding Charges	10,000	2015.05

Payment records from June 2013 to May 2015

	1	2	3	4	5	6	7	8	9	10	11	12
2015	N	N	N	1	2							
2014	N	N	N	N	N	N	N	N	N	N	N	N
2013						N	N	N	N	N	N	N

Account

Institution Name	Type of Business	Service Activation Date	Current Payment Status	Current Outstanding Amount	Accounting Period (Year/Month)
Beijing Tap Water Company	Tap Water Charges	2013.08.17	Outstanding Charges	200	2015.06

Account

Institution Name	Type of Business	Service Activation Date	Current Payment Status	Current Outstanding Amount	Accounting Period (Year/Month)

China Unicom Gansu Branch	Postpaid Mobile Phone	2012.08.17	Normal	0	2015.05

Payment records from June 2013 to May 2015

	1	2	3	4	5	6	7	8	9	10	11	12
2015	N	N	N	N	N							
2014	N	N	N	N	N	N	N	N	N	N	N	N
2013						N	N	N	N	1	N	N

V. Public Information Details

(1) Tax Arrears Record

Reference Number	Supervising Tax Authority	Total Amount of Tax Arrears	Tax Arrears Statistics Date
1	Dongcheng District Local Taxation Bureau, Beijing	500	2012.03.17
2	Jingyuan County National Tax Bureau, Gansu Province	700	2011.05.11

(2) Civil Judgment Record

Reference Number	Filing Court	Cause of Action	Date of Filing	Method of Case Closure
1	People's Court of Xuanwu District, Beijing	--	2011.09.11	Judgment
2	People's Court of Dongcheng District, Beijing	--	2009.05.09	Judgment

Reference Number	Judgment/Mediation Outcome	Effective Date of Judgment/Mediation	Litigation Subject	Litigation Amount
1	The defendant, Zhang Shiwu, shall compensate the plaintiff, Li Si, Renminbi 500,000.	2011.07.09	House Sale Dispute	500,000
2	The defendant, Zhang Shiwu, shall compensate the plaintiff, Wang Wu, Renminbi 200,000.	2010.10.11	House Sale Dispute	200,000

(3) Record of Compulsory Enforcement

Reference Number	Enforcement Court	Cause of Enforcement	Date of Filing	Method of Case Closure
1	People's Court of Xicheng District, Beijing	--	2012.09.11	Enforcement Case Closed
2	People's Court of Xuanwu District, Beijing	--	2011.05.09	Enforcement Case Closed

Reference Number	Case Status	Date of Case Closure	Enforcement Target	Enforcement Target Value	Enforced Target	Enforced Target Amount
1	Execution Completed	2012.09.15	Real Estate	420,000	House Sale Dispute	420,000
2	Execution Completed	2011.10.11	Real Estate	220,000	House Sale Dispute	220,000

(4) Administrative Penalty Records

Reference Number	Penalizing Authority	Penalty Details	Penalty Amount	Effective Date	Expiration Date	Administrative Reconsideration Result
1	Xining Local Taxation Bureau, Qinghai Province	Ordered to make corrections within a specified period; confiscation of illegal gains	400	2012.08	2015.07	--
2	Hunan Provincial Construction Management Service Center	Temporary suspension or revocation of permit; temporary suspension or revocation of license		2010.07	2013.07	

(5) Housing Provident Fund Contribution Records

Contribution Location	Contribution Date	Initial Contribution Month	Contribution Month	Contribution Status	Monthly Contribution Amount	Individual Contribution Rate	Employer Contribution Rate
Tongliao City, Inner Mongolia Autonomous Region	2007.01.01	2007.01	2008.12	Contribution	1,000	12%	12%
Contributing Entity							**Information Update Date**
Nurumusu Township Management Station, Horqin Left Middle Banner							2013.07

Contribution Location	Contribution Date	Initial Contribution Month	Contribution Month	Contribution Status	Monthly Contribution Amount	Individual Contribution Rate	Employer Contribution Rate
Beijing	2006.07.01	2006.01	2006.12	Contribution	1,000	12%	12%
Contributing Entity							**Information Update Date**
Bank of Beijing							2014.07

(6) Minimum Living Allowance Assistance Record

Reference Number	Personnel Category	Location	Employer	Household Monthly Income	Application Date	Approval Date	Information Update Date
1	Employed Staff	Beijing	--	200	1995.01.08	1995.03.08	2008.03.15

(7) Professional Qualification Record

Reference Number	Professional Qualification Name	Level	Date Obtained	Maturity Date	Date Revoked	Issuing Authority	Authority Location
1	Accounting Professional Qualification Certificate	Professional Qualification Certificate Issued by Provincial or Municipal Authority	2009.03	2017.05	--	Jiangxi Provincial Department of Finance	Urban District, Nanchang City, Jiangxi Province
2	Accounting Professional Qualification Certificate	Professional Qualification Certificate Issued by Provincial or Municipal Authority	2007.05	2029.03	--	Beijing Municipal Department of Finance	Chaoyang District, Urban District, Beijing

(8) Administrative Award Record

Reference Number	Awarding Authority	Award Details	Effective Date	Expiration Date
1	Local Taxation Bureau of Baiyin City, Gansu Province	Outstanding Taxpayer	2010.06	2014.06
2	Hunan Provincial Construction Management Service Center.	Not available.	2009.05	2013.05

VI. Non-Financial Credit Transaction Information.

Record 1.

Type of Business	Credit Transaction Number.	Opening Date	Maturity Date	Current Outstanding Amount.	Currency	Creditor Name.
Postpaid Mobile Phone	CU101	2013.08.17			Renminbi	China Unicom Gansu Branch.

Repayment date	Overdue Amount.	Number of Overdue Days.	Outstanding Interest Amount.	Payment Amount.	Actual Repayment Date.	Current Payment Status.	Information Update Date
--	0	--	--	200	2015.05.15	Normal	2015.05

Record 2.

Type of Business	Credit Transaction Number.	Opening Date	Maturity Date	Current Outstanding Amount.	Currency	Creditor Name.
Commercial Trade Credit Transaction.	AA1000023	2012.08.17	2018.09.09	20,000	US Dollars	Beijing AA Trading Co., Ltd.

Repayment date	Overdue Amount.	Number of Overdue Days.	Outstanding Interest Amount.	Payment Amount.	Actual Repayment Date.	Current Payment Status.	Information Update Date
2015.04.15	10,000	100	--	10,000	2015.01.15	Abnormal.	2015.05.20

7. Public Information

(1) Judgment Information

Record 1.

Type of Litigation	Litigation Status	Case Number	Cause of Action	Date of Filing	Filing Court	Court of Judgment
Civil	Defendant	(2011) Jing Min - Chu Zi No. 00056	--	2011.09.11	Beijing Xuanwu District People's Court	Beijing Xuanwu District People's Court

Date of Case Closure	Method of Case Closure	Litigation Subject	Litigation Amount	Start Date of Exit Restriction	Date of Exit Restriction Lifted
2011.07.09	Judgment	House Sale Dispute	500,000	--	--

Judgment/Mediation Outcome	Amount Payable by Judgment/Mediation	Effective Date of Judgment/Mediation	Information Update Date
The Defendant, Zhang Shiwuwu, shall compensate the Plaintiff, Li Si, in the amount of Renminbi 400,000.	--	2011.07.09	2011.10.10

Record 2.

Type of Litigation	Litigation Status	Case Number	Cause of Action	Date of Filing	Filing Court	Court of Judgment
Civil	Defendant	(2010) Jing Min - Chu Zi No. 00116	--	2010.09.11	Beijing Dongcheng District People's Court	Beijing Dongcheng District People's Court

Date of Case Closure	Method of Case Closure	Litigation Subject	Litigation Amount	Start Date of Exit Restriction	Date of Exit Restriction Lifted
2010.10.11	Judgment	House Sale Dispute	200,000	--	--

Judgment/Mediation Outcome	Amount Payable by Judgment/Mediation	Effective Date of Judgment/Mediation	Information Update Date
The defendant, Zhang Shiwu, shall compensate the plaintiff, Wang Wu, Renminbi 200,000.	--	2010.11.01	2010.12.30

(2) Enforcement Information

Record 1.

Enforcement Court	Enforcement Case Number	Cause of Enforcement	Method of Case Closure	Case Status	Listed or Not List of Dishonest Persons Subject to Enforcement
Beijing Xicheng District People's Court	(2012) Jing Min-Chuzi No. 01041	--	Enforcement Case Closed	Execution Completed	No

Date of Enforcement Filing	Date of Enforcement Completion	Enforcement Target	Enforcement Target Amount	Enforced Target	Enforced Target Amount	Information Update Date
2012.09.11	2013.09.15	Real Estate	420,000	House Sale Dispute	420,000	2013.10.01

Record 2.

Enforcement Court	Enforcement Case Number	Cause of Enforcement	Method of Case Closure	Case Status	Listed or Not List of Dishonest Persons Subject to Enforcement
Beijing Xuanwu District People's Court	(2011) Jing Min-Chuzi No. 01041	--	Enforcement Case Closed	Execution Completed	No

Date of Enforcement Filing	Date of Enforcement Completion	Enforcement Target	Enforcement Target Amount	Enforced Target	Enforced Target Amount	Information Update Date
2011.05.09	2013.09.15	Real Estate	220,000	House Sale Dispute	220,000	2013.10.01

(3) Certification Information

Record 1.

Certification Category	Certification Document Number	Certification Details	Effective Date	Maturity Date	Date Revoked	Certification Status	Certifying Authority Name
Reward Information	INCTX123012	Outstanding Taxpayer	2010.06	2014.06	--	--	Baiyin City Local Taxation Bureau, Gansu Province

Record 2.

Certification Category	Certification Document Number	Certification Details	Effective Date	Maturity Date	Date Revoked	Certification Status	Certifying Authority Name
Professional Qualification	ACC000001	Accounting Professional Qualification Certificate	2009.03	2017.05			Beijing Municipal Finance Bureau

(4) Disciplinary Information

Record 1.

Category of Disciplinary Action	Disciplinary Decision Document Number	Details of Disciplinary Action	Effective Date	Maturity Date	Status of Disciplinary Action	Name of Disciplinary Authority
--	INCTX124212	Ordered to rectify within a specified period; confiscation of illegal gains	2012.08	2015.07	--	Xining Local Taxation Bureau, Qinghai Province

Record 2.

Category of Disciplinary Action	Disciplinary Decision Document Number	Details of Disciplinary Action	Effective Date	Maturity Date	Status of Disciplinary Action	Name of Disciplinary Authority
Temporary suspension or revocation of license certificate	CN000124512	Temporary suspension or revocation of license Certificate; temporary suspension or revocation License	2010.07	2013.06	Expired	Hunan Provincial Construction Management Service Center

(5) Arrears Information

Record 1.

Category of Arrears	Arrears Certificate Number	Amount Due	Amount Paid	Tax Arrears Amount	Most Recent Payment Date	Supervisory Authority Name
Tax Arrears	CN12485442333	--	--	500	2012.03.17	Dongcheng District Local Taxation Bureau, Beijing

Record 2.

Category of Arrears	Arrears Certificate Number	Amount Due	Amount Paid	Tax Arrears Amount	Most Recent Payment Date	Supervisory Authority Name

Tax Arrears	CN12485442333	--	--	700	2011.05.11	Jingyuan County National Taxation Bureau, Gansu Province

(4) Other Public Information

Record 1.

Information Type	Information Description	Institution Name	Information Update Date
List or Directory Information	--	Local Taxation Bureau of Baiyin City, Gansu Province	2010.06.13

Record 2.

Information Type	Information Description	Institution Name	Information Update Date
Information Published by Authoritative Media	**--**	**Hunan Provincial Construction Management Service Center.**	**2009.05.14**

8. Other Non-Public Information

Record 1.

Institution Name	Type of Business	Item Name	Contribution Date	Initial Contribution Month
Tongliao City Housing Provident Fund Center, Inner Mongolia Autonomous Region	Housin	--	2007.01.01	2007.01

Contribution Month	Contribution Status	Amount Due	Amount Paid	Individual Contribution Rate	Employer Contribution Rate
2008.12	Contribution	1,000	1,000	12%	12%

Employer	Information Update Date
Nurumusu Township Management Station, Horqin Left Middle Banner	2013.07

Record 2.

Institution Name	Type of Business	Item Name	Contribution Date	Initial Contribution Month
Beijing Housing Provident Fund Center	Housing Provident Fund	--	2006.07.01	2006.01

Contribution Month	Contribution Status	Amount Due	Amount Paid	Individual Contribution Rate	Employer Contribution Rate
2008.12	Contribution	1,000	1,000	12%	12%

Employer	Information Update Date
Bank of Beijing	2014.07

9. Personal Statement

Reference Number	Statement Content	Date Added
1	My ID card was lost. Any new transactions after November 2013 were not conducted by me.	2013.11.14

10. Dispute Annotation

Reference Number	Annotation Content	Date Added
1	Other identification documents are currently under dispute processing.	2015.04.15

11. Inquiry Records

Institutional Inquiry Record Details

Reference Number	Inquiry Date	Querying Institution	Reason for Inquiry
1	2015.05.31	Industrial and Commercial Bank of China	Loan Approval
2	2015.04.14	China Merchants Bank	Credit Card Approval
3	2014.11.16	Industrial and Commercial Bank of China	Special Merchant Real-Name Verification
4	2014.10.10	Ping An Property & Casualty Insurance	Pre-Insurance Review
5	2013.09.10	Bank of Communications Financial Leasing Co., Ltd.	Financing Approval

Personal Inquiry Record Details

Reference Number	Inquiry Date	Querying Institution	Reason for Inquiry
1	2015.05.14	The undersigned.	Self-inquiry (Internet Personal Credit Information Service Platform).
2	2014.11.14	The undersigned.	Self-inquiry (Commercial Bank Online Banking).
3	2014.01.10	Business Management Department, People's Bank of China	Self-inquiry (in person at counter)

Report Notes.

1. This report is issued by the Credit Reference Center of the People's Bank of China and is generated based on information recorded in the personal credit system as of the report date. Except for inquiry records, all other information is provided by relevant institutions. The Credit Reference Center does not guarantee its authenticity or accuracy, but undertakes to remain objective and neutral throughout the entire process of information aggregation, processing, and integration.
2. In the credit transaction information section of this report, summary information with 'business type' marked as 'other' does not include 'asset disposal' or 'advance payment' transactions.
3. If there is no 'Summary of Credit Transaction Default Information' in this report, it indicates that the Information Subject has had no overdue records in the past five years.
4. For agreements with a credit limit, the Information Subject's available limit should be estimated based on the credit limit, credit limit information, and balance provided in the 'Credit Agreement Information.'
5. Since different types of accounts may share a credit limit, the aggregated total may exceed the sum of the individual details. Therefore, the total credit limit cannot be calculated simply by adding the total credit limits from the summaries of sub-accounts under revolving limits, Revolving Loan Accounts, Credit Card Accounts, and Quasi-credit Card Accounts.
6. In this report, 'non-revolving loans' refer to loan services in which the credit institution grants the Borrower a certain credit limit that is non-revolving. The disbursement method may be either a one-time disbursement or multiple disbursements.
7. In this report, 'revolving loan' refers to a credit limit granted by a credit institution to the borrower, within which the borrower may borrow multiple times and use the funds repeatedly during the specified period. 'Revolving Loan Account I' generally refers to the situation where, under a revolving credit limit, the borrower's multiple loans are managed separately through different accounts, with each loan repaid individually. 'Revolving Loan Account II' generally refers to the situation where, under a revolving credit limit, the borrower's multiple loans are managed collectively through a single account, with the loans repaid together.
8. In the credit transaction details of this report, the maturity date of a revolving loan account refers to the expiration date of the credit limit for that account.
9. In the credit transaction details section of this report, lending accounts (excluding recovery information) display repayment information for the past five years, including the current repayment status and the current total overdue amount (for quasi-credit card accounts, this refers to the overdraft balance). If the current repayment status is "#" or the current total overdue amount is "--", both indicate that the specific value is unknown.
10. For 'small-amount, high-frequency' transactions processed through self-service channels, financial institutions will consolidate and report the relevant accounts, which will be displayed in the credit transaction details section of this report. In such cases, the repayment method for the account is 'no distinction of repayment method', the repayment frequency is uniformly set to 'monthly', the number of repayment periods is calculated on a monthly basis, and the repayment information is observed and updated monthly.
11. In this report, quasi-credit card accounts with overdrafts exceeding 60 days are consolidated in the information summary under 'Overdue (Overdraft) Information Summary.'
12. A repayment period shown as '--' in this report indicates that the account is not on an installment repayment plan.
13. This report does not display default behaviors that ended more than five years ago, nor does it display tax arrears records, records of compulsory enforcement, civil judgment records, administrative penalty records, or telecommunications arrears records from over five years ago.
14. Institutional notes are special explanatory information added by data-providing institutions regarding specific transactions.
15. A personal statement is a brief note attached by the information subject to the credit report, for which the information subject is responsible for its authenticity.
16. A dispute annotation is added by the Credit Reference Center to indicate which information in the credit report the information subject disputes.
17. Sections marked in red in this report indicate the possible presence of default information; sections marked in pink indicate negative public information. Sections marked in yellow indicate key information that requires special attention.
18. Except for the amounts displayed in their respective currencies under 'Enterprise Loans with Relevant Repayment Responsibilities,' all amounts in this report are denominated in Renminbi.
19. This report contains personal privacy information. Inquirers should use it in accordance with the law and ensure its proper safekeeping. The Credit Reference Center will not assume any responsibility for personal information leakage caused by improper use.
20. This report consolidates information submitted by data providers under different identification documents of the Information Subject.

Compilation Notes

Explanation of Repayment Status for Non-revolving Loan Accounts, Revolving Loan Account I, and Revolving Loan Account II:

* – No Repayment History This Month; data with a repayment cycle longer than one month is indicated by this symbol. If the repayment frequency is irregular and there is no repayment activity in the current month, * is used; this symbol is also used if no repayment is required in the month the account is opened.

N – Normal (the borrower has repaid the full amount due for the month on time).

1 – Overdue 1–30 days. 2 – Overdue 31–60 days. 3-Overdue for 61-90 days.

4 – Overdue 91–120 days; 5 – Overdue 121–150 days;

6 – Overdue 151–180 days. 7 – Overdue more than 180 days.

B-Bad debt (indicates that the borrower has not repaid the loan for an extended period).

M-Repaid after the agreed repayment date but before the end of the month (indicates that the borrower has cleared all overdue amounts, but did not repay by the due date of the month).

D-Guarantor repayment (indicates that the loan has been repaid by the guarantor, including both full and partial repayments by the guarantor). Z-Repayment by asset transfer (indicates that the loan has been repaid through asset transfer; refers only to the portion repaid in this manner).

C-Settled (the borrower's loan has been fully repaid, with a loan balance of 0). Including normal settlement, early settlement, settlement by asset offset, guarantor repayment settlement, and similar situations); G–Ended (termination of the account in any form other than settlement);

#–Account has been opened, but the status for the month is unknown.

Explanation of repayment status for credit card accounts and quasi-credit card accounts:

(1) Credit Card Account:

*–No repayment history this month, i.e., not used this month;

N–Normal, meaning the minimum repayment amount for the month has been fully paid, or the account is within the interest-free period after overdraft;

1 – Overdue 1–30 days. 2 – Overdue 31–60 days. 3-Overdue for 61-90 days.

4–Overdue 91–120 days; 5 – Overdue 121–150 days;

6–Overdue 151–180 days; 7 – Overdue more than 180 days.

C–Account closed; G–Ended;

#-Account has been opened, but the status for the current month is unknown.

A-The credit card did not issue a statement this month due to an adjustment of the billing date.

(2) Quasi-credit Card Account:

*-No repayment history this month, i.e., no overdraft this month;

N-Normal, meaning the quasi-credit card overdraft has been repaid.

1-Overdraft for 1–30 days (Normal, not overdue); 2-Overdraft for 31–60 days (Normal, not overdue); 3-Overdraft for 61–90 days.

4-Overdraft for 91–120 days; 5-Overdraft for 121–150 days.

6-Overdraft for 151–180 days; 7-Overdraft for more than 180 days.

C - Account Closed; G - Terminated;

#–Account has been opened, but the status for the month is unknown.

Explanation of Repayment Status for Postpaid Services:

Telecommunications Services:

* - Service is active, but no payment is required this month;

N - Normal (the user has paid all service fees for the month on time, including users within the grace period); 0 - Payment overdue beyond the grace period but less than 1 month;

1 - Payment overdue beyond the grace period for 1 month but less than 2 months;

2 - Payment overdue beyond the grace period for 2 months but less than 3 months;

3 - Payment overdue beyond the grace period for 3 months but less than 4 months;

4 - Payment overdue beyond the grace period for 4 months but less than 5 months;

5 - Payment overdue beyond the grace period for 5 months but less than 6 months;

6 - Payment overdue beyond the grace period for more than 6 months;

C - Normal account closure (account closed after settlement); G - Ended (account closed not through normal settlement);

- Unknown: No data for this period.

V Transitory and Permanent Shocks

In this appendix, we decompose income innovations into their permanent and transitory components following Pistaferri (2001) and adapt the approach to our setting where subjective expectations may violate rational expectations.

We assume that the logarithm of income, $y_{i,t}$, for individual i at time t follows

$$y_{i,t} = X_{i,t}\Omega + \Gamma_i\Pi + p_{i,t} + \varepsilon_{i,t},$$
$$p_{i,t} = p_{i,t-1} + \zeta_{i,t},$$

where $X_{i,t}$ collects observable time-varying characteristics (the same set of controls as in equation (4) in the main text), Ω denotes their coefficients, Γ_i represents time-invariant individual attributes with corresponding loadings Π, $p_{i,t}$ is the permanent component of income following a random walk with innovation $\zeta_{i,t}$, and $\varepsilon_{i,t}$ is the transitory component. Both innovations $\zeta_{i,t}$ and $\varepsilon_{i,t}$ are mean-zero and mutually uncorrelated. Taking first differences yields

$$\Delta y_{i,t} = \Delta X_{i,t}\Omega + \zeta_{i,t} + \Delta\varepsilon_{i,t}.$$

Under rational expectations, agents' forecasts equal the conditional mean given their information set $\mathcal{I}_{i,t}$, implying $E_{i,t}[\zeta_{i,t+1}] = E_{i,t}[\varepsilon_{i,t+1}] = 0$. The transitory and permanent innovations can then be expressed as

$$\varepsilon_{i,t} = -E_{i,t}[\Delta y_{i,t+1}] + \Delta X_{i,t+1}\Omega,$$
$$\zeta_{i,t} = \Delta y_{i,t+1} - E_{i,t-1}[\Delta y_{i,t}] - \varepsilon_{i,t}. \tag{A.1}$$

This decomposition requires that expectations satisfy rational expectations to ensure $E_{i,t}[\zeta_{i,t+1}] = E_{i,t}[\varepsilon_{i,t+1}] = 0$. Since survey evidence indicates that households in our data over-extrapolate recent income news, we rely on the model-based forecast $E_t[\Delta y_{i,t+1}]$ from the income process in equation (4), estimated on a large administrative panel. The assumption is that this "objective" forecast approximates the conditional mean under rational expectations given observable variables.

If households hold private information beyond the econometrician's observables, part of what we label as a "shock" may reflect private signals or temporary inattention rather than pure surprises. To mitigate this concern, we test and confirm that the innovation sequence exhibits no serial dependence. In Figure A.8, we verify that the shocks are not autocorrelated, ensuring internal consistency while acknowledging that subjective beliefs may violate these moment conditions.

Table A.10 reports the variance decomposition of income shocks. Roughly two-thirds of the variation in income shocks is transitory at the six-month horizon, a natural consequence of the short frequency.

Table A.11 presents regressions including both estimated components simultaneously. Both

permanent and transitory shocks significantly affect income expectations with a similar magnitude. This finding is consistent with the model's prediction: individuals cannot perfectly distinguish between permanent and transitory innovations and tend to interpret short-lived income changes as partially persistent.

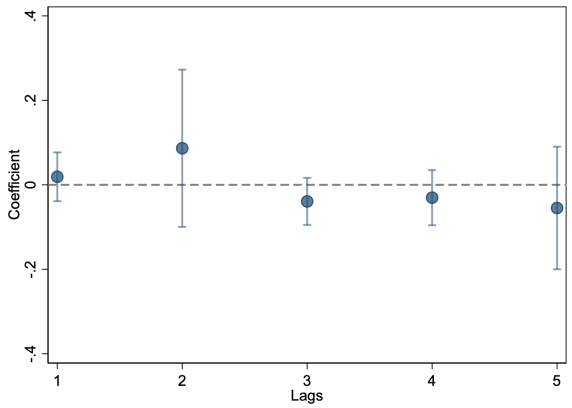
In addition, in column (3), we calculate the signal-to-noise ratio for each individual, and find that the degree of extrapolation is larger for those with a higher signal-to-noise ratio. This is consistent with our Proposition 1 that, given overreaction, the degree of overreaction is larger for those whose income is more driven by persistent shocks, that is, when income is a stronger signal of the underlying state.

Our result differs from Blundell et al. (2008), who find that transitory shocks have little effect on consumption, largely because transitory variation in the PSID data reflects measurement error. In our administrative data, short-term income fluctuations are real and economically meaningful, making it plausible that both types of shocks influence beliefs and spending.

Figure A.8. Autocorrelation of Permanent and Transitory Shocks

This figure gives the coefficients of regressing permanent and transitory income shocks on its lags. The left panel focuses on the transitory shocks and the right panel focuses on the permanent shocks. The segments give the 95 percent confident intervals, with standard errors clustered at individual level. All regressions control for individual fixed effects.

Panel A: Transitory Shocks



Panel B: Permanent Shocks

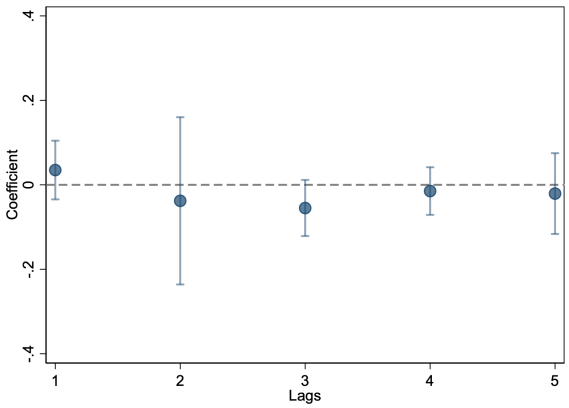


TABLE A.10. Variance Decomposition of Persistent and Transitory Income Shocks

$\Delta y_t - E[\Delta y_t]$ is the unexpected income growth. ζ is the persistent income shock. ε is the transitory income shock. The decomposition is based on equation (A.1).

	(1) $Var(\Delta y_t - E[\Delta y_t])$	(2) $Var(\zeta)$	(3) $Var(\varepsilon)$	(4) $2Cov(\zeta, \varepsilon)$
Level	0.129	0.035	0.085	0.009
Percent	100.00%	27.13%	65.89%	6.98%

TABLE A.11. Permanent and Transitory Income Shocks, Forecast Errors, and Consumption Growth

Dependent variables are forecast errors (log) in columns (1)–(4) and consumption growth $\Delta \log C_{t+1}$ in columns (5)–(6). ε_t and ζ_t denote transitory and permanent income shocks. All level variables are winsorized at 1%–99% level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Forecast Errors$_{t+1}$ – log				$\Delta \log C_{t+1}$	
ε_t	0.226***	0.276***			0.211***	0.226***
	(0.024)	(0.026)			(0.037)	(0.036)
ζ_t	0.182***	0.266***			0.520***	0.444***
	(0.064)	(0.070)			(0.110)	(0.114)
Shock$_t$-log			0.276***	0.245***		
			(0.027)	(0.027)		
Shock$_t$-log× High Var Ratio			0.122***	0.094**		
			(0.034)	(0.038)		
Shock$_t$-log× High Var(ε)				0.059**		
				(0.028)		
Forecast Errors$_{t+1}$ – log					0.349***	0.319***
					(0.028)	(0.031)
Industry × Wave FE	No	Yes	Yes	Yes	No	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	No	Yes
N Obs	24,993	24,991	25,407	25,407	20,615	20,613
R^2	0.30	0.37	0.37	0.37	0.19	0.20

Standard errors clustered at industry × wave in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

VI Model Solution, Estimation, and Simulation

VI.A Solving the Model

The solution follows Carroll and Toche (2009) while under subjective expectations. We use value function iteration (VFI) to solve the model. Denote posterior expectation as $\hat{z}$ and $\tilde{x} \equiv x/\hat{z}$ for any variable x. Consequently, for the state variable $\tilde{a}$, the procedure of solving the model is as follows:

1. Discretize the state for current perceived wealth-to-permanent income $\tilde{a}$ into $n_m = 200$ grid points over $-\tilde{l}$ and $\tilde{a}_{max} = 30$. The maximum value is set to roughly match two times the maximum in the data, which is around 15 times income.
2. Approximate $\epsilon_{i,t}$ using five discrete values.
3. Given each $\tilde{a}$, use VFI to solve for $V^{ND}(\tilde{a})$, $V^{D}(\tilde{a})$, and $V(\tilde{a})$ until $V(\tilde{a})$ converges.
4. For $V^{ND}(\tilde{a})$ and $V^{D}(\tilde{a})$, solve for the policy function for consumption $\tilde{c}^{ND}(\tilde{a})$ and $\tilde{c}^{D}(\tilde{a})$. Get the policy function for default $d(\tilde{a})$ based on (13) and consumption $\tilde{c}(\tilde{a}) = (1-d(\tilde{a}))\tilde{c}^{ND}(\tilde{a}) + d(\tilde{a})\tilde{c}^{D}(\tilde{a})$.
5. Linearly interpolate to get the optimal policy functions $\tilde{c}^{*}(\tilde{a})$ and $d^{*}(\tilde{a})$.

When simulating the choices, we get the level of consumption by multiplying the policy functions with posterior of $\hat{z}$. We then solve for wealth accumulation using realized income.

VI.B Estimation

The estimation consists of two stages. In the first stage, we rely on our income and beliefs microdata. We pin down the parameters associated with the income process such as the degree of extrapolation θ and the marginal rate of garnishment. In the second stage, we use the simulated method of moments (SMM) to get the estimates of the two default related parameters χ and λ.

First Stage: The first-stage estimation requires the use of income and survey data. We first set the time frequency t to six months to be consistent with the survey frequency. For the parameters governing the income process, α, σ_ϵ^2, and σ_η^2, we residualize all individual incomes by age quintiles, year, education, occupation industry, city, and gender fixed effects, and estimate the process in (1) using the method of moments. After residualization, α is set to 0. When solving the model, we measure consumption and saving with respect to the level of average income.

The average annualized interest rate on deposits in the data is around 3%. We therefore set $r_s = 1.5\%$. We use various interest rates and fees on the credit card borrowing from the bank to determine r_b. The average daily interest rate on credit card debt is 5 basis points. After accounting for a 45 days interest-free period, a 2.5% reward rate, and 0.5% of debt-related fees, we set r_b to 5% per six months. We set a uniform credit limit for all consumers ($l = 1.4$) so that the average credit limit to average income in the model matches the average total credit limit to annual income in the data (60%).

We compute the marginal garnishment rate ν from the bank's database—it is about 5%, which

roughly corresponds to one third of the average monthly income in the data.[2] We set the discount rate $\beta = 0.95^{0.5}$, so that the annual rate is 0.95, and $\gamma = 2$. Finally, we calculate θ to match the regression coefficient of forecast errors on income shocks, which yields $\theta = 2.54$.

Second Stage: We use SMM to estimate χ and λ. The targeted moments are the average wealth-consumption ratio and average default rate. The intuition is as follows. The stigma cost χ directly affects consumers' willingness to default. A higher χ indicates a higher cost of default and hence a lower default rate. Meanwhile, when λ is small, default decisions are close to deterministic: only households with sufficiently low wealth choose default. As a result, high consumption is concentrated among a small group of very low-wealth households, and most agents retain buffers, leading to a higher average wealth-to-consumption ratio.

The SMM procedure searches for the set of parameters that minimize the weighted deviation between the actual and simulated moments,

$$(m - \hat{m}(\Theta))' \widehat{W} (m - \hat{m}(\Theta)), \tag{D1}$$

where $\hat{W}$ is the variance-covariance matrix of the data moments. The calculation of the empirical moments is straightforward and is based on the main sample of analysis. The weight matrix $\widehat{W}$ adjusts for the possibility that some moments are more precisely estimated than others. We calculate $\widehat{W}$ as the inverse of the variance-covariance matrix of the empirical moments based on 100,000 bootstrap draws with replacements.

For simulated moments, we focus on the steady-state distribution. Specifically, given χ, λ, and the parameters in the first stage, we simulate 20000 individuals with initial wealth uniformly distributed between $-\tilde{l}$ and $\tilde{a}_{max}$ for 1000 periods. We then keep the data from period 501 to 1000 as the simulated sample. With this solution algorithm, we calibrate the model by adjusting the targeted parameters in each moment calculation iteration. We minimize (D1) using the L-BFGS-B method in Python's scipy package, with bounds $(0.1, 10.0)$ and $(0.05, 1.0)$ respectively for χ and λ,

The standard errors are obtained using the delta-method and the empirical variance-covariance matrix. The formula for the variance-covariance matrix of the SMM estimators is

$$(G' W^{-1} G)^{-1} + (G' \tilde{W}^{-1} G)^{-1}.$$

The first term captures the error coming from the estimation of data moments, where W is the variance-covariance matrix of data moments. The second term comes from the noise when estimating the simulated moments. $\tilde{W}$ is the variance-covariance matrix of moments in simulated moments. G is the Jacobian matrix around the SMM estimate.

[2]This number is slightly smaller than the estimate of around 9% from DeFusco et al. (2024) in the U.S., conditional on being garnished for delinquent debt.

We compute $\tilde{W}$ by bootstrapping the simulated sample using SMM-estimated parameters. We start with simulated data (20,000 individuals for 500 periods). We then draw 20,000 individuals from this sample with replacement and compute the moments. We repeat this procedure 100 times and use these 100 sets of moments to compute the variance-covariance matrix $\tilde{W}$.

We estimate G using the following technique. For the j^{th} parameter $\hat{\theta}_j \in \{\hat{\chi}, \hat{\lambda}\}$, we simulate the model, holding the other parameter constant and change $\hat{\theta}_j$ to $\hat{\theta}_j + \iota$ and $\hat{\theta}_j - \iota$. From this we get four new moments wc_L, wc_H, d_L, and d_H. Then the j^{th} column of G will be $[wc_H - wc_L, d_H - d_L]/(2\iota)$. We set $\iota = 0.001$ for estimating G.

VI.C Simulation Details: Aggregate Household Debt Cycle

Given the estimated parameters, we simulate 20,000 individuals for 1,000 semiannual periods using subjective expectation $\hat{z}_{i,t}$ and the optimal policy functions $\tilde{c}^*(\tilde{a})$ and $d^*(\tilde{a})$ obtained in Section VI. The first 500 periods are discarded, and the remaining 500 periods are used as the steady-state distribution for all subsequent experiments.

We compute three simulation cases:

1. **Benchmark (Extrapolative Expectations).** In the benchmark simulation, consumers form expectations according to $\theta = 2.54$. At period $t_0 = 901$, we introduce a sequence of three consecutive positive transitory income shocks, each equal to one-half of the standard deviation of ϵ_t, followed by one negative transitory income shocks equal to one-half of the standard deviation of ϵ_t. After period $t_0 + 4$, shocks revert to their steady-state distributions.
2. **Bayesian Learning.** The same shock sequence and timing are applied with $\theta = 0$. All other parameters, initial steady-state distributions, and random seeds are identical to the benchmark case.
3. **No-Shock Baseline.** The baseline simulation uses the same parameterization and random draws as the benchmark case, but without any exogenous shock to income. This simulation provides the counterfactual path for computing percentage deviations.

For each case, we record the cross-sectional averages of income, income expectations, consumption, debt, and default for each period t. The response for variable $x_{i,t} \in \{y_{i,t}, E[y_{i,t}], d_{i,t}\}$ at horizon h is defined as

$$Dx(h) = \frac{\bar{x}^{shock}_{t_0+h} - \bar{x}^{baseline}_{t_0+h}}{\bar{x}^{baseline}_{t_0+h}}, \tag{A.2}$$

where $\bar{x}^{shock}_{t_0+h}$ and $\bar{x}^{baseline}_{t_0+h}$ denote period-$t_0 + h$ cross-sectional means under the shock and no-shock simulations, respectively. The response for variable $x_{i,t} \in \{c_{i,t}, b_{i,t}\}$ at horizon h is defined as

$$Dx(h) = \frac{\bar{x}^{shock}_{t_0+h} - \bar{x}^{baseline}_{t_0+h}}{\bar{y}^{baseline}_{t_0+h}}, \tag{A.3}$$

VI.D Simulation Details: Unsecured Debt around the Global Financial Crisis

Given the estimated parameters, we simulate the aggregate unsecured debt and default dynamics during the Global Financial Crisis (GFC) using the same model structure and parameters as in Section VI. GDP is from FRED. Unsecured debt is Consumer Loans: Credit Cards and Other Revolving Plans, All Commercial Banks. Delinquency is Delinquency Rate on Credit Card Loans, All Commercial Banks. Labor share is the Share of Labour Compensation in GDP. Share of credit card holders with positive debt is from 2004 Survey of Consumer Finance.

To replicate the debt and default dynamics observed during the Global Financial Crisis, we simulate 20,000 individuals for 1,000 semiannual periods using the optimal policy functions from the estimated model. After reaching the stationary distribution (burn-in of 500 periods), we manually choose a sequence of 20 aggregate transitory income shocks ϵ_t starting in period 900, corresponding roughly to 2004-2013. These shocks are manually fine-tuned so that, under extrapolative expectations ($\theta = 2.54$), the simulated path of the aggregate unsecured-debt-to-income ratio roughly matches the empirical data.

Formally, we iteratively adjust ϵ_t to minimize the difference between the model-implied and observed debt ratios over this period. For each candidate sequence of shocks, we simulate the model forward and compute the implied paths of aggregate debt and default, integrating micro-level choices over the simulated distribution of agents.

Once the sequence of ϵ_t that reproduces the empirical debt dynamics is found, we fix these shocks and re-simulate the model under rational learning ($\theta = 0$). This comparison isolates the role of extrapolative expectations in amplifying borrowing and default during the boom-bust cycle.

VII Testing Alternative Biased Expectation Formation

Our specification of income expectation formation process (1) adapts the conventional buffer-stock model with an observed permanent income shocks. While a natural extension to allow sub-optimal expectation formation is to introduce deviation from the Bayesian benchmark, the literature has documented many other subjective expectation formation processes that can potentially explain expectation anomalies in the data. In this section, other than Bayesian and overreaction, we replicate the core forecast-error regression under the following four competing models:

1. Diagnostic Kalman Filtering: This income process follows Bordalo et al. (2019). The difference between overreaction and diagnostic Kalman filtering is the reference distribution agents overreact to. That is, if we denote $\hat{z}_t$ as the posterior under Bayesian and $\hat{z}_t^\theta$ the subjective posterior, then in overreaction, the posterior of the permanent component is

$$\hat{z}_t^\theta = \hat{z}_{t-1}^\theta + (1+\theta)\kappa(y_t - \alpha - \hat{z}_{t-1}^\theta)$$

While in diagnostic Kalman filtering, it is

$$\hat{z}_t^{\theta} = \hat{z}_{t-1} + (1+\theta)\kappa(y_t - \alpha - \hat{z}_{t-1})$$

That is, in the language of Bordalo et al. (2019), the reference distribution is the Bayesian prior distribution due to the kernel-of-truth assumption. While in our case, the reference distribution is the subjective prior distribution.

2. Full-Information Rational Expectation (FIRE): Here we assume that people observe the permanent component z_t, so log income is essentially an AR(1) process.
3. Over-Persistence: We assume that people observe the permanent component z_t, so log income is essentially an AR(1) process. However, as in Afrouzi et al. (2023) and Rozsypal and Schlafmann (2023), we assume that the true log income process is $y_{t+1} = y_t + \epsilon_t$ with $= 0.5$ but people believe that $= 0.99$.
4. Learning about Long-Run Growth: Here we assume individual income process follows

$$\begin{aligned} y_{i,t} &= \alpha_i + z_{i,t} + \epsilon_{i,t} \\ z_{i,t} &= z_{i,t-1} + \eta_{i,t}, \end{aligned} \tag{A.4}$$

That is, agents are also different in their long run income growth rate α_i. Then, as in Guvenen (2007), agents learn about α_i and $z_{i,t-1}$ simultaneously through Kalman filtering. Note that in an infinite-horizon environment, the Kalman gain over α_i is zero. So we set a constant Kalman gain of 0.0723 for α_i and 0.1667 for $z_{i,t-1}$. These values equal the Kalman gain for people starting at age 21 with prior uncertainty of α_i that is equal to two times the standard deviation of $\epsilon_{i,t}$ at age 39, which is the mean age in our sample.

Table A.12 first reproduces the regression results in columns (1) and (2), regressing next-period forecast errors on current-period income shocks and then shows the estimated coefficients on simulated data under the different expectation formation processes. It shows that, apart from overconfidence and diagnostic Kalman filtering, none of the other specifications can generate our results.

While both overreactive Kalman learning and diagnostic Kalman filtering can match the one-period forecast-error regression, they make different predictions about persistence. Under diagnostic Kalman filtering as in Bordalo et al. (2019), overreaction is always relative to the Bayesian prior, so expectation distortions do not carry over across periods as agents always start a period as Bayesian. As a result, income shocks predict forecast errors only at horizon $t+1$; beyond that, Bayesian orthogonality reasserts itself. In contrast, under overconfidence (or, equivalently, diagnostic learning with a subjective prior as the reference distribution), belief distortions persist across periods. This implies that income shocks

predict forecast errors at longer horizons, with effects that decay geometrically.

In Figure A.9, we test this implication by regressing forecast error in time $t+1$ on income shocks in t, $t-1$, ..., $t-4$. As shown, diagnostic Kalman filtering only results in a positive relationship of income shocks and forecast errors in the previous period. Beyond that, Bayesian orthogonality applies and income shocks do not predict forecast errors further in the future. However, in overreaction, the relationship between income shocks and forecast errors weakens only geometrically with horizon. Meanwhile, the calibration seems to match our data counterpart closely. Therefore, we choose overconfidence, or diagnostic Kalman filtering with subjective prior as the reference distribution, as our preferred specification.

TABLE A.12. Income Shocks and Forecast Errors – Alternative Processes

This table reports regressions results of forecast error in $t+1$ on income shocks in t assuming the same income process but different expectation formation processes. Columns (1) and (2) are respectively the Bayesian and overreaction case as in the main analysis. Column (3) uses the diagnostic expectations over Kalman filtering as in Bordalo et al. (2019), Column (4) assumes agents have full information rational expectations. In column (5), we assume the true persistence $\rho = 0.5$ while agents believe that $\rho = 0.99$. In column (6), we assume agents are endowed with a fixed α_i, and learn about α_i and $z_{i,t}$ through Bayesian learning over realized income at the same time, we use a constant Kalman gain of 0.0723 for α_i and 0.1667 for $z_{i,t}$. These are the kalman gain at age 38 for someone starting with prior uncertainty of α_i that is two times the standard deviation of the income shocks and prior uncertainty for $z_{i,t}$ that is one time the standard deviation of the income shocks.

	Bayesian	Overreaction	Diagnostic Kalman Filter	FIRE	Over-Persistence	Long-Run Growth
	(1)	(2)	(3)	(4)	(5)	(6)
Shocks_t	-0.026	0.431	0.417	-0.031	0.019	0.022
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.001	0.154	0.148	0.001	0.000	0.000
Nobs						100,000

Figure A.9. Forecast Errors and Lagged Income Shocks

This figure plots the regression coefficients of regressing Forecast Errors in $t+1$ on income shocks in t to $t-4$. The blue line uses data when agents are Bayesian. The red line assumes agents overreact to signal surprises. The green line assumes agents have diagnostic expectations as in Bordalo et al. (2019). The black line gives the data counterpart. Shaded regions denote the 95% confidence intervals.

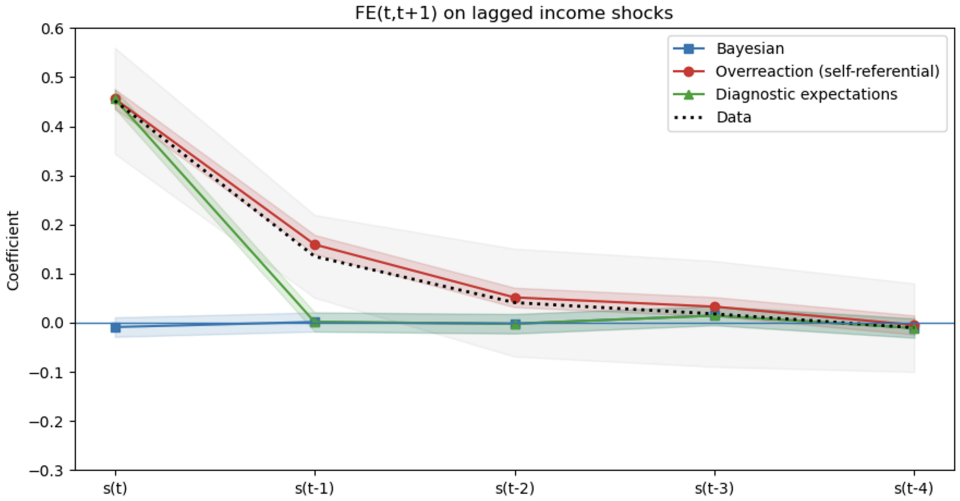


Figure A.10. Boom-Bust Cycles - Alternative Specifications

This figure replicates the exercise in Figure 6 under different expectation formation process. Diagnostic Expectations follows Bordalo et al. (2019), in which overreaction is with respect to the Bayesian signal surprises. Long-Run Growth assumes agents are endowed with a fixed α_i, and learn about α_i and $z_{i,t}$ through Bayesian learning over realized income at the same time. We use a constant Kalman gain of 0.0723 for α_i and 0.1667 for $z_{i,t}$. These are the Kalman gains at age 38 for someone starting at age 21 with prior uncertainty of α_i that is two times the standard deviation of the income shocks and prior uncertainty for $z_{i,t}$ that is one time the standard deviation of the income shocks. Over-persistence assumes the true persistence $\rho = 0.5$ while agents believe that $\rho = 0.99$. FIRE assumes agents have full information rational expectations.

