Learning in the Limit: Income Inference from Credit Extensions

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Abstract

Combining a randomized controlled trial with administrative and survey data, I show that credit limit extensions significantly increase consumers' expectations about future personal income and macroeconomic growth. The increase in income expectations is associated with beliefs about higher future labor productivity rather than labor supply. By controlling for changes in expectations regarding future personal income, the consumption response to credit-limit extensions weakens by approximately 30%. These findings are consistent with consumers making inference of macroeconomic conditions from credit supply.

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I. Introduction

Credit limits play a crucial role in household consumption-savings decisions, because it underpins the extent to which consumers can borrow to smooth consumption. As predicted by the workhorse economic models, e.g., the buffer stock models, except for those close to being liquidity-constrained, credit limit variations should not significantly impact total spending. However, existing literature documents a large average spending response to changes in credit limits. Meanwhile, even for consumers far from being borrowing-constrained, credit limit extensions still induce nontrivial increases in total consumption.[1] Hence, the micro-level mechanisms by which credit limit extensions affect consumer spending remain unclear.

The standard estimation of spending responses to borrowing limit extensions relies on random or quasi-random variations in credit limits. An implicit assumption in these settings is that consumers in the field also treat credit-supply events randomly. However, banks' credit extension decisions are rarely random and are usually a function of economic conditions and consumer characteristics. An intriguing yet unanswered question is how consumers perceive banks' credit supply decisions. Do consumers always treat credit supply in the form of extended credit limits as random shocks only to their borrowing constraints, or do they believe credit supply is an endogenous outcome that contains information about which consumers are not fully informed? Motivated by this question, this study examines the effects of credit extensions on consumption through their effect on expectations.

Studying how credit supply affects consumer expectations is challenging, as belief changes around field credit supply events must be identified. To cope with this difficulty, I collaborated with a large commercial bank in China, focusing on how consumers modify their expectations in response to banks' credit expansion. This methodology combined a randomized controlled trial (RCT) with administrative and survey data. In this setup, the bank initially planned to increase the credit card limits of around 17,000 customers,

[1]See Gross and Souleles (2002), Agarwal et al. (2017), D'Acunto et al. (2020) Aydin (2022) for some examples.

following its usual internal underwriting process. However, the increased limit was delayed by 12 months in a randomly selected control group for experimental purposes. The remaining customers (the treated group) receive the planned credit-limit increase. Given that increases in credit supply are based on a bank's usual underwriting process, this setting provides an opportunity to identify the effects of limit extensions around a field credit supply event.

Two surveys were sent to approximately 70% of the participants in all groups within ten days before and after the experiments to study the effects of a limit increase on beliefs. The survey aimed to elicit beliefs about the participants' future perspectives. It mainly asked about expectations about different components of consumer budget constraints (e.g., consumption, savings, income, and delinquency probability) and their expectations about future macroeconomic conditions.

I begin the analysis by studying the responses to unsecured debt and spending to limit extensions. I find a large consumption response to limit extensions. Specifically, each CNY higher credit-limit increases total spending by 0.33 CNY and unsecured debt by 0.15 CNY over 12 months. These numbers are close to the estimated marginal propensity to consume out-of-limit change (MPCL) and the marginal propensity to borrow out-of-limit change (MPB) from previous literature.[1]

Changes in expectations around receiving higher credit-limits suggest how relaxed borrowing constraints affect spending from consumers' subjective perspectives. Specifically, I find that higher credit limits induce consumers to believe that their income and spending will be higher, and that the unemployment probability will be lower. Simultaneously, consumers become more optimistic about macroeconomic conditions, a finding also documented by Cenzon (2024). However, there are no significant changes in expectations regarding planned working hours, total savings, or default probability.

These findings are interesting in several ways. First, expectations about higher consumption and income, but not lower savings, suggest that increased credit limits make

[1] For example, estimated MPCL is between 0.2 and 0.6 in Agarwal et al. (2017) over 12 months; MPB is 0.11 at a 12-month horizon in Gross and Souleles (2002), between 0.08 and 0.3 in Agarwal et al. (2017, and 0.16 over nine months in Aydin (2022}.

consumers anticipate higher future consumption, which they believe is financed by increased income rather than by drawing down savings. This challenges the buffer stock model, which suggests that a higher credit limit reduces the need for precautionary savings, thereby increasing total consumption. In addition, unchanged expectations about working hours indicate that consumers do not believe that a relaxed borrowing constraint increases labor supply. In comparison, subjectively lower unemployment, higher hourly wages, and better macroeconomic conditions are consistent with consumers updating beliefs about the marginal product of labor, which tends to improve labor demand. Therefore, the results posit an *income-inference* channel through which credit-limit extensions affect consumption.

To isolate this possible belief channel in the credit supply, I use a random information treatment that varies the degree of inferencing from limit extensions. The basic idea is that, at the extreme, if consumers believe the credit supply decision is purely random, they should not infer anything from it. To accomplish this, I separated participants in the treatment group into two subgroups called T1 and T2. For both T1 and T2, participants received a notice about the increase in their credit limit (Figure 1), as bank customers would normally receive for such events; for T2, participants were also shown information that the limit increase was sent to a randomly selected group of customers, conditional on having a good credit score. It sought to weaken if at all, the amount of information consumers inferred from credit supply decisions.

Comparing the consumption responses of T1 and T2 sheds light on the existence of a belief channel in the credit supply. In particular, while expectations about other dimensions do not change much (e.g., default rate, wealth, and future credit limits), subjective beliefs about future consumption, income, and macroeconomic conditions for T2 become insignificant. The consumption responses are approximately 30% smaller for T2 than for T1. Therefore, information about randomness in the credit expansion decision attenuates income expectation updates and weakens limit extension's effects on total consumption.

With information and limit extension treatments, I can estimate the causal effect of exogenous changes in credit limits on spending while controlling for changes in income expectations. Over a 12-month horizon, each CNY higher credit limit increases total spending by 0.32 CNY and debt by 0.16 CNY without controlling for expectation changes. Additionally, income expectations have a significant effect on spending decisions. In particular, each CNY increase in expected income in the next 12 months increases total spending by 0.21. Consequently, MPCL and MPB decreases by around 30% to 0.24 and 0.11, respectively, after controlling for expectations of future income changes. This finding suggests that the income inference channel accounts for approximately 30% of the spending response to the limit extension.

To explore the potential heterogeneity in the strength of the income inference channel, I estimate the responses of income expectations for various consumer subsamples. Income expectations change more for consumers with lower socioeconomic status: those with lower income, less education, younger age, and more constrained borrowing limits. However, the effects are also significant, even for those with a higher socioeconomic status, offering an additional explanation for the large spending response to credit limit increases, even for unconstrained consumers. In addition, beliefs update more for those more uncertain about macroeconomic states and whose income covaries more with the aggregate economy. Although these results are informative, sample splits along one characteristic are likely correlated with splits along other characteristics. Therefore, the conclusions of this study are more suggestive.

This study contributes to the literature in two ways. First, it contributes to the literature on the effects of credit limit on borrowing and consumption (e.g., Zeldes, 1989; Ludvigson, 1999; Gross and Souleles, 2002; Agarwal et al., 2017; Guerrieri and Lorenzoni, 2017; Chava et al., 2020; D'Acunto et al., 2020; Gross et al., 2020; Aydin, 2022; Cenzon, 2024). A recent major progress was made by Aydin (2022), who provides a clean empirical estimation of the marginal propensity to borrow using an RCT in Turkey. Besides, Cenzon (2024) shows that consumers in the US become overly pessimistic about the macroeconomy after receiving negative credit limit shocks. Although previous literature mainly relies on the buffer-stock model to explain how credit limits affect consumption, the effect of credit expansion on consumer spending through changing beliefs remains an open question. The lack of evidence lies in the difficulty of combining RCT with observational and expected data. This study combines field credit supply events with survey data to provide a complete picture of how consumers change their beliefs about credit-limit extensions. The findings facilitate the direct testing of the effects of credit supply on consumers' beliefs. It also provides new insights into the macroeconomic models incorporating credit supply shocks.

In addition, many studies explore how relaxed borrowing constraints can affect consumption by increasing labor supply, thereby raising realized income. For example, Herkenhoff et al. (2021) show that relaxed borrowing constraints lead to longer unemployment duration and higher reemployment wages among unemployed workers. Sergeyev et al. (2023) suggest that tighter financial constraints increase stress levels and reduce labor productivity. He and Le Maire (2023) find that allowing homeowners to borrow against housing equity enables liquidity-constrained consumers to move to high-wage jobs and invest in valuable human and physical capital. Doornik et al. (2024) show that credit dedicated to investments in individual mobility increases formal employment rates and salaries. My analysis shows that active credit supply can increase macroeconomic and individual income expectations, even without increasing realized income.

This study also contributes to the growing body of literature that focuses on the role of beliefs in explaining consumers' spending-saving decisions (for reviews, see DellaVigna, 2009 and Benjamin, 2019). Ameriks et al. (2016) highlight recent advances by linking survey evidence with retirement choices. Manski (2004), Ameriks et al. (2020), Giglio et al. (2021), and Goronichenko and Yin (2024) study the relationship between investor beliefs and stock investments. Bucks and Pence (2008), Bailey et al. (2018), and Kuchler et al. (2022) analyze how beliefs affect mortgage-leverage choices. Rozsypal and Schlafmann (2023), Colarieti et al. (2024), and D'Acunto et al. (2024) study how subjective income expectations affect consumption. A related study by Soman and Cheema (2002) shows that the reported MPCL is larger when credit limit assignments is believed to reflect future earning potential. This study builds on the literature by conducting a quantitative survey matched with administrative and transaction-level data to explore consumer spending and borrowing decisions.

The remainder of this paper is organized as follows: Section II provides a conceptual framework to illustrate how credit supply could affect income expectations and guide the empirical analysis. Section III describes the survey and experimental design and provides a set of stylized facts about the setting. Section IV documents the main results. Section V concludes the paper.

II. Conceptual Framework

A. Setup

This section presents a simple model to illustrate the main channels through which consumers change their spending after credit constraint shocks. The model is stylized to build intuition. The model spans three periods: $t \in \{1, 2, 3\}$. There is a continuum of consumers with utility in *t* that has the form

$$u(C_t) = C_t - \frac{b}{2} C_t^2$$

where C_t is consumer consumption in period *t*. The consumer is endowed with an initial asset $A_0 = 0$ and receives income Y_t at the beginning of each period. The budget constraints in the three periods are

$$A_t = A_{t-1} + Y_t - C_t$$

where A_t represents total savings at the end of *t*. For simplicity, I set the discount factor and interest rate to zero. At the beginning of t_3, Y_3 is realized. The game ends afterward, and the agent consumes everything and ends the game with zero savings; that is, $A_3 = 0$. In addition, the consumer faces a borrowing limit L such that

$$A_t > -L.$$

Consumers can also choose to default at the end of period and start with zero assets at the beginning of the next period. For simplicity, I assume that consumers can choose to default only at the end of t_1. In doing so, the consumer incurs a monetary cost of ψ. Without other costs of default, default occurs when $A_1 < \psi$.[2]

B. Income Process

Income is stochastic and follows

$$Y_{t+1} = \alpha\, t + \beta\, X_{t+1},$$
$$X_{t+1} = \rho\, X_t + \eta_{t+1}.$$

$\alpha\, t$ is a deterministic trend. X_t summarizes the current systematic states (e.g., macroeconomic shocks to growth, productivity, and inflation). $\rho \in (0, 1)$ is the persistence of the evolution of the states. $\eta_t \sim N(0, \sigma_\eta^2)$ captures the systematic shocks to income. β gives the marginal effects of the systematic movements on individual income. For brevity, I assume $\beta = 1$ for the analysis.

The key information friction is that consumers have noisy perceptions of the underlying economic state X_t. One possibility is inattention to current macroeconomic information (Mankiw and Reis, 2002; Reis, 2006; Coibion and Gorodnichenko, 2012). At the beginning of t_1, the consumer forms prior of X_1 that follows $N(X^0, \sigma_0^2)$.

C. Banks

The banking market is assumed to be perfectly competitive. A continuum of identical banks determines the borrowing limit L at the beginning of t_1 before observing Y_1. Banks observe a noisy signal $\tilde{s} = \tilde{X}_1 + \epsilon$ and $\epsilon \sim N(0, \sigma_\epsilon^2)$.

Banks face a constant rate of return r on the credit cards. With perfect competition, banks set L such that the default rate on credit limit is equal to r, under banks' belief $\tilde{s}$. For now, let banks' credit supply decisions be

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

$$L = f(\tilde{s}). \quad (1)$$

D. Learning from Credit Limit Changes

After receiving credit limit L, consumers infer $\tilde{X}_1$ as perceived by banks via Bayesian learning. Specifically, consumers form subjective beliefs of $\tilde{s}$ as

$$E_c[\tilde{s}] = f^{-1}(L) \equiv g(L).$$

With rational learning, consumers can correctly infer the functional forms of f, and $E_c[\tilde{s}] = \tilde{s}$. In other words, rational learning implies that banks cannot change L to oversignal their beliefs.

With the supplied credit limit L, the consumer's posterior expectation of $\tilde{X}_1$ has the expected value

$$\hat{X}_1 = X^0 + K[g(L) - X^0], \quad (2)$$

where $K = \frac{\sigma_0^2}{\sigma_0^2 + \sigma_\epsilon^2}$ is the Kalman gain of the learning process. Note that Bayesian learning does not require banks to achieve better predictability of X_t. As long as banks' signal precision is not zero and consumers are not perfectly informed about X_t, credit supply that incorporates banks' beliefs about X_t would change consumers' beliefs.

E. Optimality Condition and Equilibrium

The solution of the model is standard given a three-period setup and quadratic utility. The consumer's optimal decision can be determined through backward induction. The optimal decision in period three is straightforward. Consumers consume only everything available. The optimal consumption in t_2 and t_1 can be written as follows:

$$C_2^* = min\left\{\frac{A_1 + Y_2 + E_2[Y_3]}{2}, A_1 + Y_2 + L\right\},$$

$$C_1^* = \begin{cases} Y_1 + L & if\ Y_1 - C_1^* < \psi \\ min\{E_1[C_2^*], Y_1 + L\} & otherwise \end{cases} . \quad (3)$$

Suppose that consumers do not default and consumption in t_1 is not binding; then, the consumption rule in t_1 is the classic Hall (1978) Martingale rule. Otherwise, consumers spend all available resources.

At the end of t_1, consumers default if $Y_1 - C_1^* < \psi$. From the banks' perspective at the beginning of t_1, the probability such that $Y_1 - C_1^* < \psi$ is

$$\begin{aligned}\Phi_d &\equiv \Pr(Y_1 - C_1^* < \psi) \\ &= \Phi\left(\frac{\psi + C_1^* - \alpha - \hat{X}_1}{\hat{\sigma}\,\rho}\right),\end{aligned} \tag{4}$$

where $\hat{\sigma}^2 = \sigma_0^2\sigma_\epsilon^2/(\sigma_0^2 + \sigma_\epsilon^2)$ is the consumer's posterior variance of X_1 after receiving the credit supply. Φ is the CDF of a standard normal distribution.

In equilibrium, the consumer follows consumption rule (3) under subjective belief (2), given credit supply rule (1). The bank sets a credit limit such that the default probability (4) is equal to r.

F. MPC out of Liquidity

Borrowing the language from Gross and Souleles (2002), I analyze consumer *i*'s MPCL as the effect of a one-unit increase in L on C_1^*. When borrowing is binding both before and after a credit shock, MPCL is equal to one. Extensive literature documents that MPCL is large, even with slack borrowing limit. To analyze MPCL for financially unconstrained consumers, consider the case in which

$$C_1^* = min\{E_1[C_2^*], Y_1 + L\}$$

In equilibrium, the default rate equals the fraction of consumers who choose to default. Consequently, the average consumption of these consumers is:

$$\bar{C}_1^* = r(Y_1 + L) + (1 - r)E_1[C_2^*]. \tag{5}$$

Given that the future income is normal. The probability that consumption in the second period does not bind is.

$$P_2(not\ binding) = P\left(\frac{A_1 + Y_2 + Y_3}{2} < A_1 + Y_2 + L\right) = \Phi\left(\frac{2L + A_1 - \alpha + \hat{X}_1}{\rho(1-\rho)\hat{\sigma}}\right), \quad (6)$$

where $\Phi(\cdot)$ is the standard normal CDF. (6) is denoted as Φ_L. From (6), the probability of a slack borrowing limit is larger if savings are higher, the credit limit is larger, the income shock in period one is larger, and income volatility is smaller.

Combining (5) and (6) yields

$$E_1[C_2^*] = \tilde{C}_2 - (1 - \Phi_L)(\tilde{C}_2 - \bar{C}_2),$$

where $\tilde{C}_2 = \frac{A_1 + E_1[Y_2] + E_1[Y_3]}{2}$ is the optimal level of t_2 consumption when there is no borrowing limit and $\bar{C}_2 = A_1 + E_1[Y_2] + L$ is the highest level of t_2 consumption when the borrowing limit binds in t_2.

The MPCL for the average consumer that is currently unconstrained is then derived by differentiating $\bar{C}_1^*$ with respect to L, which yields

$$\frac{d\bar{C}_1^*}{dL} = \underbrace{\frac{1}{\omega}\frac{r}{1-r}}_{default} + \underbrace{\frac{1}{\omega}\left[\frac{2\phi_L(\tilde{C}_2 - \bar{C}_2)}{\rho(1-\rho)\hat{\sigma}} + (1 - \Phi_L)\right]}_{precautionary} + \underbrace{\frac{1}{\omega}\chi K g'(L)}_{income-inference}. \quad (7)$$

$\omega = 1 + 1/(1-r) - \Phi_L/2 + (\tilde{C}_2 - \bar{C}_2)\phi_L/(\rho(1-\rho)\hat{\sigma})$ and $\chi = \omega - \frac{1}{1-r} + [1 - \rho(1-\rho)]\ \Phi_L/2$ are two positive numbers.

As shown in (7), there are three channels through which credit limit extensions affect the current consumption of unconstrained consumers. The first term captures the increase in consumption for those who choose to default. The second term represents a conventional precautionary channel. Through this channel, an increase in credit limit increases current consumption by reducing the probability of a binding constraint and increasing future debt capacity. In addition, the third term on the right-hand side of (7) captures an income inference channel. The sign of the income-inference channel depends on the relationship between L and $\hat{X}_1$. Suppose $g' > 0$, the bank will offer more credit if it perceives a better current economic status in the future. Then, a one-unit increase in credit limit signals to consumers that the bank believes their income will grow by g' units.

Corollary 1: assuming $d\bar{C}_1^*/d\hat{X}_1 < 1$, i.e., the marginal propensity to consume out of macroeconomic expectations is smaller than one. Then credit supply increases with $\tilde{s}$, i.e., $f'(\tilde{s}) > 0$.

Corollary 1 then gives the following proposition.

Proposition 1: when $d\bar{C}_1^*/d\hat{X}_1 < 1$, a higher credit limit increases posterior income expectations, and the income-inference channel in (7) is positive.

Detailed Corollary 1 and Proposition 1 proofs are provided in the online appendix section I. The intuition is straightforward. In equilibrium, the credit limit is set such that the default rate (4) equals to r. From (4), when $\hat{X}_1$ is larger, the default threshold becomes smaller, given more resources. Simultaneously, $\bar{C}_1^*$ increases, which reduces resources and increases the probability of default. When $\partial\bar{C}_1^*/\partial\hat{X}_1 < 1$, the increases in consumption in response to the expectation changes is less than one-to-one. Consequently, total resources increase and the default probability decreases with the same credit limit level. Suppose that the MPCL is positive. Then, banks set a higher L to increase consumption to a level such that the default rate holds at r. Therefore, $f'(\tilde{s}) > 0$. Meanwhile, given $f'(\tilde{s}) > 0$, the MPCL is positive.

A positive weight of the income-inference channel yields the following proposition:

Proposition 2: The unconditional level of MPCL is larger than that when controlling for the effects of credit expansion on income expectations.

III. Methodology

A. Data and Institutional Environment

The data used in this study are obtained from a large commercial bank in China. The bank operates nationally and is among the top ten commercial banks in the country, as ranked by total assets. By 2023, the bank's total assets will amount to over \$1 trillion, with over 50 million active customers and 80 million active credit cards outstanding. With its large customer base, the sample strongly represents consumers across the demographic distribution of China's population.

Most people in China use Alipay or Weixin Pay as payment methods for daily transactions. Such payment tools usually require users to link their accounts with bank or credit cards, similar to PayPal and Apple Pay in the US.[3] The credit cards used in this study are similar to those used in other countries. In general, each credit card is assigned a credit limit, and consumers can accumulate balances below this limit every month and use the card as a payment method. Consumers earn different discounts and cashback when purchasing certain goods or services. At the end of each billing cycle, a minimum repayment is required (usually 10% of the current balance). Beyond this amount, consumers can choose to repay any proportion of their current balance. Consumers who repay all accumulated balances do not incur any interest and enjoy rewards from cashback or transaction discounts. For unpaid amounts, debt is carried over to the next billing cycle at a daily interest rate of five basis points.

Credit card use in China has grown significantly since 2016. A recent report showed that from 2016 to 2022, the total outstanding balance of credit cards in China grew from 3.6 trillion CNY to 8.7 trillion CNY (UnionPay, 2020). At the same time, the total credit limit increased from 9.1 trillion CNY to 22.3 trillion CNY. Credit cards and other personal credit from commercial banks in China are the most common methods for consumption-based unsecured debt. Similar products from FinTech platforms and consumption debt companies, including Alibaba's Huabei, have recently gained market share. However, the total market share of these companies remains relatively small, accounting for approximately 20% of all consumption-based credit debt by 2023 (UnionPay, 2023).

B. Measuring Income, Debt, and Spending

1. Income

I follow the steps that the bank uses to classify income. Individual income is classified based on regular inflows. The bank classifies income into two main categories: salary and

[3] Consumers can temporarily accumulate positive balances, called changes, in WeChat or Alipay wallet. This money can then be used for transactions and cannot be observed by the bank.

business cash flow. Salary is the periodic monthly income inflows, bonuses, and commissions if consumers work as employees. The bank calculates this number in two ways. First, the number is directly labeled as salary if income is paid through direct deposits to this bank. Otherwise, the bank can identify monthly income if the consumer's social security insurance is paid through the bank, which is usually a fixed portion of the consumer's income.[4] Income from business operations is the difference between the total inflow and outflow when these transactions are categorized as business operations. This is usually the main source of income for the self-employed population. Given the income information requirements for the analysis, the sample is restricted to those whose income information is available at the bank. This restriction reduces the sample size by approximately 35%.

When all incomes in my sample are aggregated, the split of the two components is 70.16% from salaries and 29.84% from business operations. To verify that these figures are accurately computed at the individual level, I match the income computed at the consumer-year level from the bank to individual-level data from the administrative government agency. The results of this comparison are shown in Panel A of Figure A.1. in the online appendix. The results show a very strong relationship between income from the bank and that from the administrative agency. Fitting a regression between the two yields an R^2 of 0.86.

2. *Unsecured debt*

Debt data are taken from the Credit Reference Center of the People's Bank of China (the official credit registry) based on the reference reports retrieved by the bank. The Credit

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[4] In China, social security payments have six components, that is, five types of insurance and a housing provident fund. The types of insurance are paid with a fixed proportion of workers' monthly income. One insurance is for retirement savings, which is similar to the retirement saving plan in other countries. The monthly contribution is 8% of the total income. However, the income base is usually capped at the two tails of the income distribution. The numbers differ for different geographic areas but are usually at 30% and 300% or 40% and 400% of the previous year's average income in that area. The uncapped distribution is wide enough to cover most of the workers in China. In the analysis, I remove the consumers in the capped region. This only causes around 7% drop in the sample.

Reference Center aggregates personal credit information from all financial institutions. Therefore, the study of debt behavior is expected to capture consumers' overall borrowing outlook.

3. Spending

The main analysis is based on interest-incurring debt owing to complete coverage. In addition, I calculate total spending as the sum of all purchasing transactions in a given period. This measure has several advantages and limitations. First, because the data is from a single provider, there are issues covering all the spending histories of the participants. The buffer-stock model suggests that the consumption response to limit increases for high liquidity consumers is also positive, but debt needs are generally close to zero for these individuals. In this case, testing the mechanisms by which limit extensions affect spending requires focusing on the consumption patterns from those that do not incur more debt.

To deal with the sample-coverage problems associated with using data from one financial institution, I leverage the finding that many consumers use only one bank for daily transactions[5] and focus on consumers who use this bank as their main bank for daily transactions. The sample is selected based on two criteria. First, participants were asked the following survey question:

How many banks have you used for transaction purposes over the past year?

The participants that answered *one* were included.

Following Gonang and Noel (2019), the second criterion requires that at least 15 spending transactions, on average, are conducted each month over the 12 months before the survey. The two criteria ensure that the consumers use only one bank for transaction purposes, and this bank is the one the participants are referring to.

The effectiveness of the sample selection method is verified using two tests. First, I elicit total past consumption in the pre-experiment survey with the following question:

[5] Nelson (2022) shows that, depending on their FICO scores, at least 80% to over 90% of the consumers in the US hold only one primary credit card account.

What was the total amount of your spending during the past 12 months (excluding investment and purchases of durable goods, including housing, cars, etc.)?

I then compare this number with the total spending based on the sum of all purchasing transactions for the selected sample. Panel B of Figure B.1 in the online appendix shows the binned scatterplots of the two. A regression between the two yielded an intercept of zero, a slope of 0.98, and an $R^2$of 0.64. This indicates a high correlation between the two measures, particularly when the survey measure of consumption is generally noisy.

The second test examines changes in cross-bank transfers before and after the experiment. If the participants started to use this bank more after the experiment, I would see a positive change in the net inflow transfer for the treatment group. Table A.1 in the online appendix shows that the changes in transfers are insignificant from zero, indicating that changes in banking relationship is unlikely a concern.

C. Experimental Design

The experimental procedure is illustrated in Figure 2. It consists of five steps. Specifically,

1. **Sample construction**: From June 19 to 23, the bank selected a group of consumers (approximately 50000 from 57 cities) and decided to increase their credit limits. This increase was based on banks' credit scoring rules. Then, 17000 individuals were randomly selected as participants for this study. Selected individuals were grouped into two subsamples (I and II). In each subsample, subjects are assigned to either a control group, treatment group 1 (T1), or treatment group 2 (T2). The number of participants in each group is presented in the table in Figure 2.

2. **Pre-experiment survey**: On June 23, the participants in Sample II were invited to complete the survey through text messages (Section III. A in the online appendix reports the survey in English). The survey was completed before July 02. A reminder text to complete the surveys was sent on June 30. The recruitment text is shown in Message I in Figure 1.

3. **Treatment**: On July 03, credit limits were changed to the predetermined level for participants in T1 and T2 for both samples. In addition, treated participants were informed about such changes through text messages (Figure 1 Message II) . At the same time, participants in T2 were informed that the changes were based on a research project. Additional information disclosed is as follows:

   The increase in credit limit is part of our routine credit assessment initiative. This initiative randomly selected a group of users among a group of customers with good repayment record, including yourself, and increased their credit limits (*see Message 3 in Figure 1).*

4. **Post-experiment survey**: On July 03, after receiving the treatment notice, the participants in Sample II were invited to complete another survey through text messages. The survey was completed before Jul 12. A reminder to fill out the surveys was sent on July 10.

5. **Limit changes to control**: The new credit limits for the control group, as determined in step 1, were pushed on July 03, 2024.

My main analysis is based on those who completed both surveys and satisfied the filters in Section II.B. This gives 5500 participants. In addition, I check for noticeable differences in the pre-experiment summary statistics and spending responses between the surveyed (Sample II) and unsurveyed (Sample I) samples.

Mapped into equation (5), the treatment effect on T1 estimates the total effect of the credit limit on consumption. The information treatment to T2 seeks to vary exogenously. $g'(L)$.[6] T1 and T2, therefore enable the decomposition of the income-inference channel in (7).

Prior expectations are elicited as point estimates, and posterior beliefs are elicited using subjective probability distributions. This way of asking the same questions in different formats draws on previous literature (for example, see Coibion et al., 2022,

[6] The information treatment might affect expectations about the persistence of the limit increases. In Table, I show that the T2 do not have significantly lower expectations about future credit limit, and the expectations of future credit limit do not have significant effects on consumption behaviors.

Gorodnichenko and Yin 2024, etc.) and is usually used to avoid antagonizing the participants. Specifically, in the pre-experiment survey, consumption expectations were elicited using the following questions:

> Over the next 12 months, how much would you most likely spend on average every month (excluding investments and purchases of durable goods, including housing and cars)?

In the post-experiment survey, consumption expectations were elicited with the following question:

> Please assign probability to the percentage change in your total spending over the next 12 months (excluding investments and purchases of durable goods, including housing and cars).
>
> Note: the sum has to sum to 100%

Decreases by more than 50%	___%
Decreases by between 20% and 50%	___%
Decreases by between 10% and 20%	___%
Decreases by between 5% to 10%	___%
Decreases by between 0% to 5%	___%
Stays roughly the same	___%
Increases by between 0% to 5%	___%
Increases by between 5% to 10%	___%
Increases by between 10% and 20%	___%
Increases by between 20% and 50%	___%
Increases by more than 50%	___%

Similarly, I elicit income expectations with the following two items:

> Over the next 12 months, conditional on not being unemployed, what level of total income are you most likely to earn?
>
> Note: income includes wages, salaries, bonuses, commission, etc., excluding earnings from financial investment.

> Please assign a probability to the percentage change in the total income you are most likely to earn over the next 12 months, conditional on not being unemployed.
>
> Note: Note: income includes wages, salaries, bonuses, commission, etc., excluding earnings from financial investment. The sum has to sum to 100%

Decreases by more than 50%	___%
Decreases by between 20% and 50%	___%

Decreases by between 10% and 20%	___%
Decreases by between 5% to 10%	___%
Decreases by between 0% to 5%	___%
Stays roughly the same	___%
Increases by between 0% to 5%	___%
Increases by between 5% to 10%	___%
Increases by between 10% and 20%	___%
Increases by between 20% and 50%	___%
Increases by more than 50%	___%

I ask similar questions to elicit expectations about wealth, default probability, unemployment probability, short- and long-term credit limits, and beliefs about the macroeconomy.

4. Demand effects and selective responding

The use of surveys helps study consumer beliefs about credit supply. However, survey collection has several potential problems. For example, receiving a survey might induce participants to respond or behave differently based on anticipation of the survey senders' intentions (*survey demand effects*). In addition, because taking a survey is time-consuming, the response rate is always less than perfect. If the decision to respond to the survey varies systematically according to the participants' characteristics, the treatment effects will suffer from selection bias.

Several survey design features aim to eliminate the potential confounding effects of completing the surveys. For example, because the survey is sent through a bank, participants may want to use the survey answers to signal better creditworthiness. To avoid the development of such strategic motives, the survey started with some preliminary information,

> *This survey is in collaboration with third-party research scholars. The surveys will only be analyzed for scientific research purposes and will not be evaluated by this bank. We will not disclose participants' personal information in any respect. We will not, to any extent, change the types of financial products we provide, including credit scores, credit limits, deposit and borrowing interesting rates, etc., based on the participants' personal answers. Please answer the survey based on your true*

thoughts.

This explicit framing was designed to minimize the possibility of consumers providing answers that depart from their true beliefs in the hope of obtaining better services from the bank if they provide distorted expectations. I further check this concern by showing that the responses are similar for consumers whose borrowing relationship is with *other* banks, both before and after the experiments in online appendix Table A.2. As these consumers do not borrow from the bank, they are expected to have less incentive to cater to the bank in the sample.

Another concern is the loss of sample representativeness due to selective responses to the survey. To avoid this problem, the survey was designed to minimize the time required to complete the survey with a very large payment. Only 15 questions in the pre-experiment survey and 10 in the post-experiment survey had to be answered by all participants, and three additional questions in the pre-experiment survey were sent to 30% of the participants. The average time to complete the survey was less than seven minutes for both surveys, and the compensation was 20 CNY. This is equivalent to an hourly rate of more than 171 CNY, higher than the 95^{th} percentile for all urban residences in China. Ultimately, the response rate was very high, close to 70%.

5. External validity of the experiment

Because the experiment is based on a one-time credit supply event, the selected consumers may be systematically different from the average Chinese consumer. The potentially selective sample casts doubt on the external validity of the experiment.

To assess the sample's representativeness, I compare the demographics of the sample and a 3% random sample from the bank database covering all customers. As the bank is one of the largest banks in China, its customer base should be representative of the overall number of Chinese urban residents. Table A.3 presents the results. In general, the participants in the sample have less spending, income, savings, credit limits, and more debt. In other words, the surveyed participants seemed to need more credit. However, these differences were not excessively large. For all characteristics, the differences were less than 10%. Therefore, the sample was broadly representative of the entire Chinese urban population.

D. Summary Statistics

Table 1 provides summary statistics based on the pre-experiment characteristics. Panels 1, 2, and 3 describe the control, T1, and T2 groups. The average age of the participants is approximately 38 years, and approximately 42% are female. About half of the participants have a college degree. The average outstanding interest-incurring debt is about 7 thousand CNY and around 16.5 CNY, conditional on holding a positive amount of debt before the experiment. A simple calculation indicates that approximately 40% of participants hold positive unsecured debt. This proportion is at the lower bound of the 40%–80% range found in previous studies using US data (Gross and Souleles, 2002; Zinman, 2009; Fulford, 2015). The average increase in the credit limit is around 12 thousand CNY. This magnitude is economically significant. This is approximately 14% of the pre-experiment average total credit limit and 10% of the average pre-experiment annual income. Columns (7) and (12) provide *t*-statistics for the differences between the control and treatment groups. All samples are balanced with no statistical differences among any of the dimensions. This indicates the effectiveness of randomization.

Despite the high response rate, an imperfect response rate indicates that samples with and without surveys may differ in many dimensions. Table A.4. in the online appendix presents the summary statistics of the unsurveyed sample. Generally, more males completed the survey. Those who completed the survey were more likely to be younger, less educated, earning less, and less wealthy. However, the differences were not particularly significant, with the differences in magnitude mostly within 10%.

IV. Results

A. Spending Responses to Limit Extensions

First, I present the results of the consumption dynamics of the experiment. As guided by Proposition 2, suppose that the credit limit affects consumption only through the precautionary motive, as usually suggested in the buffer stock model. Then, one should expect similar spending dynamics for both treatment groups because the realized changes in credit limits are statistically indifferent between the two groups. However, if the supply of credit limits affects consumer beliefs, then the consumption response of those in T2 should be different after informing them about the randomness in supply decisions.

Figure 2 plots the evolution of the changes in unsecured debt and total spending around the experiment. I scale the changes around the experiment by the pre-determined limit changes. Thus, the magnitudes give an interpretation in terms of marginal propensity. The *x*-axis is the date. In both plots, the solid red and the dashed blue lines represent T1 and T2, and the dotted gray line represents the control group. The shaded regions are two times the standard errors. Both debt and spending are residualized by date-fixed effects. As shown, the sharp increase in spending right after the experiment for the two treatment groups indicates the experiment's effectiveness. Besides, the spending response of T2 is significantly smaller than that in T1. A divergence in the evolution of debt and spending between T1 and T2 indicates that changes in credit limit affect factors other than instant borrowing capacity.

I continue to study the average treatment effects (ATE) of credit limits on spending. Table 2 presents the intent-to-treat (ITT) estimates of the experiments. The estimates are scaled using the average changes in credit limits in the sample. In this case, the numbers in Table 2 show the interpretations of MPB and MPCL. That is, each CNY's average changes in borrowing and spending have higher credit limits. Panels A and B provide the six-month and 12-month responses, respectively. As shown, each CNY higher credit limit increases the borrowing of T1 by 12.4 cents over six months and by 16.2 cents over 12 months. At the same time, each CNY higher credit limit increases T1 spending by 29.7 cents over six months and 33.2 cents over 12 months. These estimates are close to the documented MPB and MPCL in the previous literature, which is usually in the range of 0.09 to 0.20 for MPB (Gross and Souleles, 2002; Agarwal et al., 2017; Aydin, 2022) and 0.2 to 0.6 for MPCL (Agarwal et al., 2017). Spending responses were larger than debt responses. This is consistent with both the buffer-stock model and credit-limit-changing beliefs. For example, in the buffer-stock model, even for consumers with high liquidity, a larger credit limit reduces the precautionary motive and increases consumption by reducing total savings.

For comparison, each CNY higher credit limit increases the borrowing of T2 by 8.5 cents over six months and 11.4 cents over 12 months. At the same time, each CNY higher credit limit increases the spending of T2 by 20 cents over six months and 23.2 cents over 12 months. The differences between T1 and T2 significantly differ from zero, indicating that the belief channel affects spending responses to limiting changes.

As the survey response rate is not perfect, comparing the spending responses of the surveyed and unsurveyed samples sheds light on whether the survey sample results are subjective to selection issues. From Figure B.2 in the online appendix, spending responses are generally slightly smaller for the unsurveyed sample because these consumers have relatively more liquidity. However, the differences were insignificant, with responses only approximately 13% greater. Additionally, the patterns of the two samples were similar.

B. Expectation Responses to Limit Changes

Informing that the credit supply decisions involve randomization, attentuates consumption responses to limit extensions. This indicates that credit supply affects consumption decisions, in addition to relaxing instantaneous borrowing constraints. In this section, I use survey data from Sample II to examine the effects of credit supply on consumers' subjective beliefs about the various components of their budget constraints.

The ITT estimates of the limit changes in expectations are presented in Table 3. Similar to the estimations of MPB and MPCL, I scale all estimates using the average changes in credit limits. For changes in wealth and credit limits, the units are each thousand CNY increase in the credit limit. The results from T1 show that a higher credit limit significantly increases subjective expectations about future consumption and income, marginally increasing expected liquid savings and lower expected unemployment rates. However, there were no significant changes in subjective labor supply, as captured by the number of hours likely to work. At the same time, future borrowing capacity remains unchanged, as captured by the one-year and five-year changes in the total credit limit or default probability. For T2, when informed about the randomization of credit supply, expectations about consumption, income, savings, and unemployment become insignificant.

The results in Table 3 suggest that consumers believe they will consume more in the future in response to a higher credit limit, consistent with the empirical findings in the literature. In addition, higher consumption is believed to be financed by more income in the future due to either higher marginal productivity of labor or lower unemployment risk, but not by drawing down savings, increasing default frequency, or increasing labor supply. Indifferent responses to subjective limit growth suggest that information treatment attenuates consumption responses by erasing consumers' updates about future earnings ability rather than indirectly informing them of a less persistent increase in credit limits.

The findings show that, from the consumer perspective, the reason for more spending after a higher credit limit is inconsistent with the buffer-stock model. In the buffer-stock model, a higher credit limit increases consumption by reducing savings, because higher credit limit alleviates precautionary motives by increasing the ability to smooth consumption. However, as Table 3 shows, subjective beliefs about total wealth do not decrease. The results suggest that the precautionary motive is unlikely to be the sole reason the supply of credit lines affects consumption.

One concern with sending out surveys through banks is that consumers might want to misreport creditworthiness to signal a lower-risk type. This is unlikely in the present study for two reasons. First, the disclosure information in the survey explicitly informed the participants that the bank would not analyze the data. Second, as Table 3 shows, although income is reported higher, subjective beliefs about default rates are not lower. Therefore, it is improbable that consumers will signal lower risk. An additional test focuses on the expectation changes and debt responses of participants whose relationships are with other banks. If consumers use the survey to misreport income strategically, those who do not use this bank for daily transactions will have less incentive to misreport. In the online appendix Table A.2, I restrict the sample to consumers who used credit cards only at other banks before and after the experiment. These results are similar to those obtained using the entire sample. This finding suggests that the reported higher income is unlikely to result from strategic misreporting catering to banks.

Credit limit shocks have a significant effect on income expectations. However, the behavior of inferencing from the credit supply should be heterogeneous and largely depends on many factors. Heterogeneity in belief changes is also evident in the direct exploration of the distributions of the changes. Figure 4 shows the histogram of expectation changes separately for the three groups. As shown, for both the control group and T2, the changes in beliefs are more symmetric around zero. For T1, expectation changes concerning consumption and income are more distributed in the positive region. However, belief changes are not entirely positive, with approximately 45% of the participants having a negative or zero change in belief in future income after the experiment. Therefore, the large average belief change is due to many consumers having large belief changes instead of everyone having similar changes.

C. Macroeconomic Expectations

In this section, I continue to study expectations regarding the macroeconomic conditions. Previous studies have shown that credit supply is procyclical (Bassett et al., 2014; Fishman et al., 2020; Boons et al., 2023; Weitzner and Howes, 2023), and consumers are imperfectly informed about macroeconomic conditions (Coibion and Gorodnichenko, 2012; Nakamura and Steinsson, 2018; Andre et al., 2022). Consequently, credit supply can serve as a noisy signal for consumers to update their beliefs about the current macroeconomic state. If consumers infer information about the macroeconomy, then the participants in T1 should update their beliefs about the macroeconomic variables after receiving limit shocks.

To explore this conjecture, I use the following question:

> *How much will the overall Chinese economy and unemployment rate change (as a percentage relative to the current level) in the next year?*

I use the overall growth rate of the Chinese economy to approximate GDP growth. The results are summarized in Table 4. After the experiment, participants in T1 increased their expectations of GDP growth over the next 12 months by 4.6% and decreased their expectations of unemployment rates by 20.8%. The latter is the percentage change in the unemployment rate. Therefore, suppose the ex-ante expectation of the unemployment rate was 5%. Then, T1's expectation of the unemployment rate became approximately one percentage point lower after the experiment. In contrast, there were no significant changes in expectations regarding the macroeconomy for T2. These results are consistent with consumers' belief that credit supply is procyclical, such that positive changes in credit limits result from an expansionary economy. This is consistent with the findings on the cyclicality of credit supply. In addition, as is evident from T2, when participants are informed that the limit supply decisions are random conditional on having a good payment history, expectations remain constant after receiving changes in the credit limit.

When consumers believe that the credit supply is associated with an expansionary aggregate economy, those who think that a booming period affects their income to a greater extent experience larger changes in income expectations. However, recent literature has documented that expansionary credit conditions are usually associated with future deterioration rather than improved economic conditions (Lopez-Salido et al., 2017; Mian and Sufi, 2017). Figure A.3 in the online appendix provides further evidence in the US that periods with higher credit limit growth are also those with higher subjective future income growth but lower realized future GDP growth. Recent literature on the extrapolative expectation formation process may explain this apparent inconsistency. Suppose lending standards are looser during booming periods; the credit supply reacts positively to the current economic shocks. Consumers with incomplete information about the current state of the economy update their beliefs accordingly in response to credit expansion. With extrapolative expectation formation process (e.g., Bordalo et al., 2018; D'Acunto et al., 2024), this positive news is over-extrapolated to the future, amplifying the positive relationship between current credit supply decisions and expected future income. When misbeliefs are resolved, consumption growth decreases, inducing a boom-then-bust pattern.

D. Limit Extensions and Labor Supply

The literature proposes several channels through which more available credit increases realized income, including more entrepreneurial activities, better labor market matches, and labor mobility (Herkenhoff et al., 2021; Sergeyev et al., 2023; He and Le Maire, 2023; Doornik et al., 2024). Table 3 shows that consumers do not plan to adjust the labor supply at the intensive margin by working more hours, conditional on not changing jobs. In Table 5, I examine whether limit extensions in my setting affect labor supply through the extensive margin. I considered three dummy variables: job change, becoming self-employed, and changing residence. The three variables are proxies for labor mobility, entrepreneurship, and housing locks. The estimates in Table 5 are multiplied by 100 for interpretability. Across all columns, no significant relationship is consistent with the lack of extensive-margin adjustment of labor supply.

The lack of similar findings could be because the increases in total available credit are insufficient to induce significant changes in the labor supply at the extensive margin. For example, credit access in Doornik et al. (2024) is designed to increase labor mobility. Meanwhile, borrowing against the credit line is equivalent to one year of income in He and Le Maire (2023) but is around 10% of the annual income in this study. Furthermore, the effects in Herkenhoff et al. (2021), Sergeyev et al. (2023), and He and Le Maire (2023) mostly focus on credit-constrained borrowers. However, my sample focuses largely on creditworthy borrowers. Section IV.H demonstrates that belief updating is strong for unconstrained consumers.

E. Income Expectations around Credit Limit Extensions

In this section, I study the association between credit limit extensions, consumer income expectations, and realized income changes around the experiments. This helps shed light on the extent to which credit supply is correlated with income expectation and whether credit supply changes through an information channel or because it increases realized income. Given that those in T2 received additional information, I focus on those in T1 and the control group to imply a static relationship.

Figure 5 shows the binned scatter plots of consumer income-change expectations and realized income changes versus predetermined limit changes. All the variables are residualized by age, degree, gender, income, savings, total spending, industry fixed effects, and city fixed effects. In all four panels, the *x*-axes are the limit changes as proposed by the bank before random assignment. These numbers are positive for all participants before residualization. Panel A shows that the pre-experiment expectations about income changes over the next 12 months are not significantly correlated with the proposed limit changes, as is the case for both the control and treatment groups. Panel B shows that realized income changes are positively correlated with the proposed limit changes for both the control and treatment groups and the associations are similar for the two groups. Panels A and B indicate that when banks actively offer increased credit limits to consumers, they are, to some degree, informed about consumer income changes in the near future. However, consumers are not perfectly informed about this income growth as correlated with the limit extension.

Panel C plots consumer expectations after the experiment. Because the control group did not receive the offer, there was no change in their expectations. In the treatment group, there was a positive relationship between expectations and proposed limit changes. This finding confirms previous results. Panel D plots the consumer expectation errors after the experiment. Expectation errors are defined as the difference between post-experiment expectations and realized income. From the plot, expectation errors are negatively correlated with the proposed limit changes for the control group but insignificantly correlated with the proposed limit changes for the treatment group.

In summary, the results are consistent with the model described in Section II. Consumers are imperfectly informed about income changes, whereas credit supply is correlated with future income. After receiving limit extensions, consumers shift their income expectations closer to their true values.

These findings are not evidence that banks are more informed about individual income changes. As long as banks have non-random beliefs about consumer near-term income (e.g., by analyzing macroeconomic cycles) and consumers are imperfectly informed about income changes, credit supply, which is a noisy signal about income changes, affects consumer income expectations. However, one caveat of this study is that its findings are based on a single-limit supply event. While the field experiment is designed around a routine limit supply event, it is still possible that the associations between limit changes, realized income changes, and pre-and post-event expectations differ at other times, especially when inattention varies around business cycles.

F. Subjective Sensitivity between Income Expectations and Credit Limit Extensions

As a direct test of the income inference channel, I elicit consumer subjective beliefs about credit supply as a function of bank-perceived future income growth. I rely on the following two items from the survey:

> Suppose banks increase their credit card limit by 5000 CNY this month. This means that banks expect total income to change by ___ over the next 12 months.
>
> Note: use a negative number for decreases.
>
> Suppose that banks increase their credit card limit by 10000 CNY this month. This means that banks expect total income to change by ___ over the next 12 months.
>
> Note: use a negative number for decreases.

These questions were sent to a random sample of 30% of participants. Suppose the answers to the two questions are respectively x_1 and x_2, I then calculate the consumers' subjective beliefs about the credit limit sensitivity to bank-perceived income growth, λ, as

$$\lambda = \frac{x_2 - x_1}{5000}$$

Mapped to (2), $\lambda = g'(L)$ is the marginal relationship between credit limit and bank beliefs about consumers' future income growth. When $\lambda = 1$, consumers believe that the bank's supply of credit limit moves one-for-one with the bank's prediction about their future income changes.

Figure 6 plots the distribution of λ. It shows a large heterogeneity in the beliefs about the sensitivity of credit supply to bank-perceived income growth. Around 35% of the consumers believe $\lambda \leq 0$. However, most of the participants believe credit-limit extensions are associated with higher income growth in the future. The economic significance of λ is large. Its average is 0.81, and the median is 0.60. Thus, for a 1-CNY increase in the credit limit, consumers, on average, believe the bank expects their income to increase by 0.81-CNY over the next 12 months. From a Bayesian-learning perspective, Panel A of Figure 6 suggests that consumers, on average, learn about their future income from credit limit extension as a signal of income changes, with a signal sensitivity of 0.81. Given that the posterior income expectation is 0.33, the average consumer's Kalman gain of the learning process is around 0.41.

Equation (7) shows that change in income expectations after receiving limit extensions should move positively with the signal sensitivity of income growth λ. In Panel B of Figure 7, I split the sample by λ into four groups and then plot the average change in income expectations by λ-groups within each treatment group. Participants in T1 have a larger change in income expectations after the experiment, and this change increases with λ. Income changes are also near zero, especially when λ is close to zero. At the same time, there is no apparent association between λ and changes in income expectation for the other two groups.

In summary, the results in Figure 6 indicate that consumers believe that limit extensions are positively associated with banks' beliefs about future income growth. Consistent with Bayesian learning, consumers with uncertain income beliefs adjust their income expectations upwards in response to a positive credit supply shock.

G. The Effects of Limit Extensions on Spending

To further progress and establish causal relationships, I use exogenous variations in beliefs and limit extensions to study how increases in credit limits affect spending and debt conditional on income changes. My approach is a two-stage least squares estimation, following Beutel and Weber (2023), Coibion et al. (2024), and Goronichenko and Yin (2024). The first-stage regression analysis is as follows:

$$x_i^h = a_0^h + \sum_{k=1}^{2} a_k^h \times \mathbb{I}\{i \in Treat_k\} + \ b_0^h \times Prior_i^{\mathrm{E}[\Delta Y]} + \\ \sum_{k=1}^{2} b_k^h \times \ \mathbb{I}\{i \in Treat_k\} \ \times \ Prior_i^{\mathrm{E}[\Delta Y]} + \ Controls_i + error_i^h \quad (8)$$

where $x_i^h = \{\Delta Limit_i, Posterior_i^{\mathrm{E}[\Delta Y]}\}$, $Prior_i^{\mathrm{E}[\Delta Y]}$ is the prior expectations of the changes in income expectation. Specification (8) is estimated for $\Delta Limit_i$ and the posterior expectations of income changes.

The second stage regression is given by

$$y_i = \alpha_0 + \beta_L \Delta Limit_i + \beta_E Posterior_i^{E[\Delta Y]} + \beta_P \ Prior_i^{\mathrm{E}[\Delta Y]} + \ Controls_i + error_i, \ (9)$$

where $y_i = \{\Delta C_i, \Delta B_i\}$. The set of controls is based on the pretreatment variables and include gender, age, indicators for full-time employees, indicators for having at least a college degree, total credit limit, and total income.

The results are summarized in Table 6. Panels A and B show the six-month and 12-month responses, respectively. The first-stage F-statistics are all above 100, indicating the strong impact of treatments on expectations. Focusing on Panel B, column (1) gives the effects of $\Delta Limit_i$ on total unsecured debt 12 months after the experiment, without controlling for any expectation changes. The estimate is based on the control group and T1, which received no additional information. Therefore, this provides the total effect of the active limit extension on borrowing. The estimate of 0.159 is the same as the scaled ITT estimate for T1 (Table 2). From column (2), I include $Posterior_i^{E[\Delta Y]}$. The estimates in front of $\Delta Limit_i$ is weakened by around 30% to 0.113. Meanwhile, for each CNY with a higher expected income in the next 12 months, the total debt increased by 0.089 CNY. This finding suggests that changes in income expectations account for approximately 30% of the debt responses to credit limit extensions.

Columns (13) and (14) present the spending results. The results are qualitatively similar. From column (13), for each CNY with a higher expected income in the next 12 months, total spending increases by 0.210 CNY. This number also suggests whether consumers believe an income change is permanent or transitory. For a permanent income change, the MPC should be one. For a one-time shock, the MPC should be roughly equal to the annuity factor, which should be less than 0.05 if the annual interest rate on saving is 5% for consumers that are not borrowing-constrained. However, an average MPC of around 0.21 is possible for a one-time shock if some consumers are liquidity-constrained or perceive the shock to be persistent but not permanent.

The estimated coefficients show the *total* effects of limit extensions and changes in personal income expectations on borrowing and spending. In other words, if the information treatment changes beliefs about personal income but also other beliefs related to personal income (that is, cross-learning), β_E captures the direct effect via $\mathrm{E}[\Delta Y]$ and indirect effects via other beliefs. Specifically, I show that information treatments affect not only $\mathrm{E}[\Delta Y]$ but also macroeconomic expectations. If macroeconomic expectations are the source of income changes, then controlling for changes in macroeconomic expectations, the effects of $\mathrm{E}[\Delta Y]$ will be attenuated.

To unbundle these effects, I follow Goronichenko and Yin (2024) and instrument $\Delta Limit_i$, $Posterior_i^{\mathrm{E}[\Delta Y]}$, as well as macroeconomic expectations using a modified specification of equation (8) that includes prior macroeconomic expectations interacting with the treatment indicator variables. This approach requires IVs to induce differential changes in expectations and the implied uncertainty. To construct a single measure of macroeconomic expectations, I use the first principal components of the expected changes in GDP and the unemployment rate.[7]

The results are shown in Columns (11) and (15) of Table 6. The first-stage *F*-statistics were above 200, indicating reasonably strong first-stage results and a lack of collinearity in the treatment effects. Even if controlling for changes in macroeconomic expectations, estimates of β_L hardly changes. Macroeconomic expectations have a significant impact on spending. In addition, the estimated effects of $\mathrm{E}[\Delta Y]$ on spending and borrowing gets significantly smaller. Therefore, updating the macroeconomic conditions

[7] In the online appendix Table A.4., I verify that the results are similar if controlling for the two variables separately.

seems to be an important reason for people to update their income. Nonetheless, β_E, though not statistically significant due to large standard errors, are not entirely insignificant economically. For example, from column (15), each CNY higher $\mathrm{E}[\Delta Y]$, conditional on macroeconomic expectations, increases spending by 8.1 cents. Therefore, factors other than macroeconomic conditions (e.g., life-cycle components) could affect expectations of individual income after receiving higher credit limits.

Information treatment can change consumption by affecting beliefs about the other dimensions. One possibility is that informing the participants about the randomization of the experiment made them believe that the limit changes were less persistent. In columns (12) and (16), I use a similar strategy to control the expected total credit limit over five years. The results show that the effects of the expected total credit limit over five years are close to zero. Simultaneously, the estimated effects of limit changes, income expectations, and macroeconomic expectations hardly changed. This finding indicates that a subjective, less persistent credit limit does not seem to be the reason for participants having lower consumption responses after receiving the information treatment.

In summary, the spending responses and survey results findings suggest that after receiving credit limit expansions, consumers update their expectations about the macroeconomic state and personal income, and rosier income expectations induce them to increase spending in addition to relaxed borrowing constraints, even without increasing realized income.

H. Heterogeneity of Changes in Income Expectations

This section examines whether investors with different characteristics exhibit the same sensitivity to expected changes in their limit extensions. I estimate the ATE in income expectations for the different subsamples of participants in Table 7. Columns (1) – (8) present the results by pre-experiment subjective beliefs, and columns (9) – (16) provide estimates by demographics. One caveat is that the subsample splits along one characteristic and can correlate with another. Therefore, these results should be viewed as suggestive.

When consumers change their income expectations after credit supply shocks by making inferences about the aggregate economy, expectation changes should depend on consumers' uncertainty about the aggregate economy and their sensitivity to how macroeconomic movements affect individual income. In the former case, even if credit supply contains information about aggregate economic states, inferences from credit supply should be minimal for consumers with low uncertainty about economic states. For the latter, inferences should depend on how much individual income is affected by macroeconomic shocks. In other words, expectation changes should also be small for someone whose unemployment probability and personal income have zero covariability with the aggregate unemployment probability and GDP growth. Testing the heterogeneity of income expectation changes due to macroeconomic uncertainty and income sensitivity to macroeconomic movements effectively informs this macroeconomic inference channel.

To construct a measure of macroeconomic uncertainty, I use the following question.

> How confident are you about evaluating whether the overall economy is functioning effectively?

This question measures how confident participants were about their current economic state. If income inference is due to consumers' updated perceptions of the current macroeconomic state from credit supply, then expectation changes should be larger for those less confident in evaluating macroeconomic performance. To test this conjecture, I define those who answer *very confident* as having low macroeconomic uncertainty and the rest as having high macroeconomic uncertainty.

I rely on the following two questions to measure income sensitivity to macroeconomic movements.

> Suppose China's overall economy grows by 5% relative to its current level over the following year. How would this affect the total income in the next year?

> Suppose that the unemployment rate in China decreases by 10% relative to the current level in the following year. How would this affect the total income in the next year?

These two questions provide subjective beliefs about how movements in the GDP and unemployment affect individual incomes. I also define participants as having high growth sensitivity if their answers to the first question are above the median and high unemployment sensitivity if their answers to the second question are below the median. I then studied the expectation changes separately for these groups.

The results are shown in Columns (1) and (6) of Table 8. Those in T1, who report high macroeconomic uncertainty, higher growth, or unemployment rate sensitivity also have a larger change in income expectations. In addition, columns (7) and (8) split the sample by λ. Consistent with Figure 6, the results show that those with a higher λ have a larger change in income expectations.

Columns (9) to (16) split the sample by age, education, income, and credit line utilization rate. The results show that income changes are larger for those with lower socioeconomic status (younger age, lower income, lower education, and tighter borrowing constraints). However, the effects are significant even for those with a relatively higher socioeconomic status.

V. Conclusion

Traditional studies on the macroeconomic effects of credit supply often assume that economic agents possess full-information rational expectations, leaving the impact of credit supply on beliefs largely unexplored. This study attempts to understand how changes in credit supply causally impact subjective beliefs and how these altered beliefs influence consumer spending and borrowing behaviors. In particular, credit limit extensions boost consumers' beliefs about macroeconomic growth and future personal income. Specifically, approximately 30% of increased consumption following higher credit limits can be attributed to a shift in income expectations. Income updates are stronger for those with more uncertain assessments of the underlying macroeconomic conditions. The findings are consistent with consumers being inattentive to macroeconomic states and making inferences about active credit-supply decisions.

Further research is needed to comprehensively understand the macroeconomic implications of lenders and borrowers with access to different sets of information. Additionally, this study touches on the nuances of banks' credit supply decisions, which may vary depending on the statistical precision achieved with different borrower characteristics. For instance, credit supply decisions grounded in statistical analysis may disproportionately favor individuals for whom banks can make more accurate predictions (Fuster et al., 2022). This aspect raises interesting questions about the potential asymmetric impacts of monetary policies across various industries, influenced by banks' ability to make statistical inferences. Future research could explore the distributional effects of monetary policy in scenarios in which banks depend on statistical analysis to make credit supply decisions, further illuminating the complex dynamics in credit markets. Additionally, this study uses a one-time credit limit event in one country. Future research could examine how credit limit changes affect the expectations of other countries.[2]

[2] In the online appendix, section IV, I use survey questions on SurveyMonkey to show that hypothetical limit extensions also raise expectations about future spending and income, but not default, saving, and working hours if focusing on US consumers. In addition, changes in spending and income expectations turn insignificant if the hypothetical limit extensions are told to be random. This implies that the income-inference channel is likely to exist also in the US.

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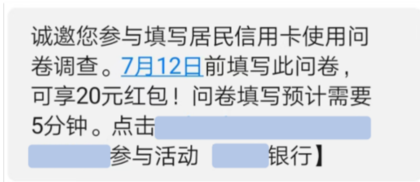
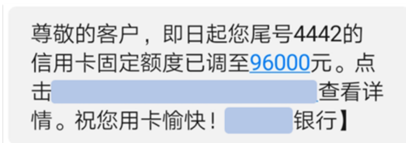
Figure 1: Messages Sent to the Participants

Message 1: Survey Recruitment Message



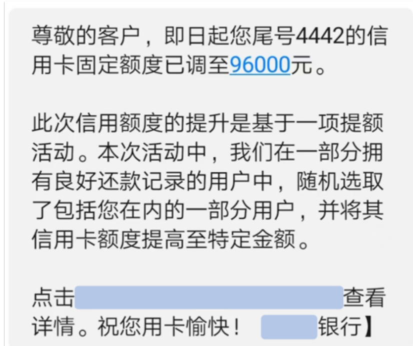
We cordially invite you to participate in a survey on the use of credit cards by residents. Fill in this questionnaire before Jul 12 to enjoy a 20 Yuan red envelope! Filling out this questionnaire should take about 5 minutes. Click URL to participate. [Bank Name]

Message 2: Message to Treatment 1



Dear customer, effective from today, the credit limit of your credit card ending in 4442 has been adjusted to 96,000 Yuan. Click URL for more details. Wishing you a pleasant experience with your card! [Bank Name]

Message 3: Message to Treatment 2



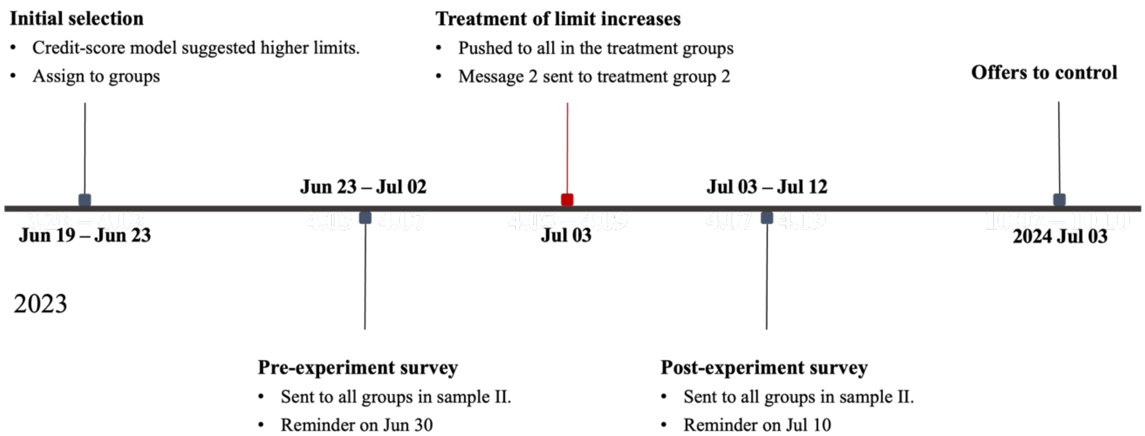
Dear customer, effective from today, the credit limit of your credit card ending in 4442 has been adjusted to 96,000 Yuan.

The increase in credit limit is based on a limit-increase event. In this event, among a portion of customers with a good repayment record, we randomly selected a group of users, including yourself, and increased their credit limits.

Click URL for more details. Wishing you a pleasant experience with your card! [Bank Name]

Note: this figure gives the messages sent to the participants. Message 1 is the survey recruitment message. Message 2 is the limit increase notice sent to Treatment group 1. Message 3 is the limit increase notice sent to Treatment group 2. For each panel, the left column gives the screenshot of the messages, and the right column gives the English translation.

Figure 2: Timeline of the Experiments and Group Assignment



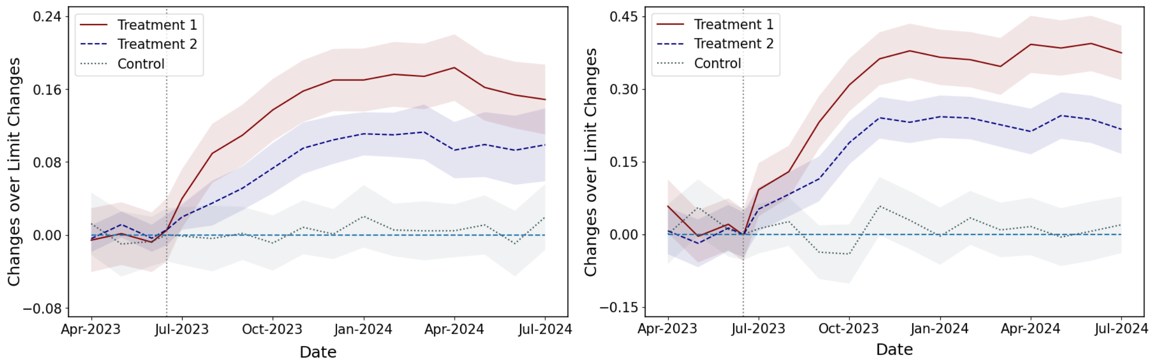
Sample	Surveys Sent	Groups	# Subjects Selected	# Subjects Final
I	No	Control	2000	1950
		Treatment 1	2400	2331
		Treatment 2	1200	1159
II	Yes	Control	5000	2701
		Treatment 1	6500	3356
		Treatment 2	3000	1643

Note: this figure plots the experimental design. The top panel gives the timeline, and the bottom panel gives the assignment of the groups.

Figure 3. Evolution of Debt and Spending

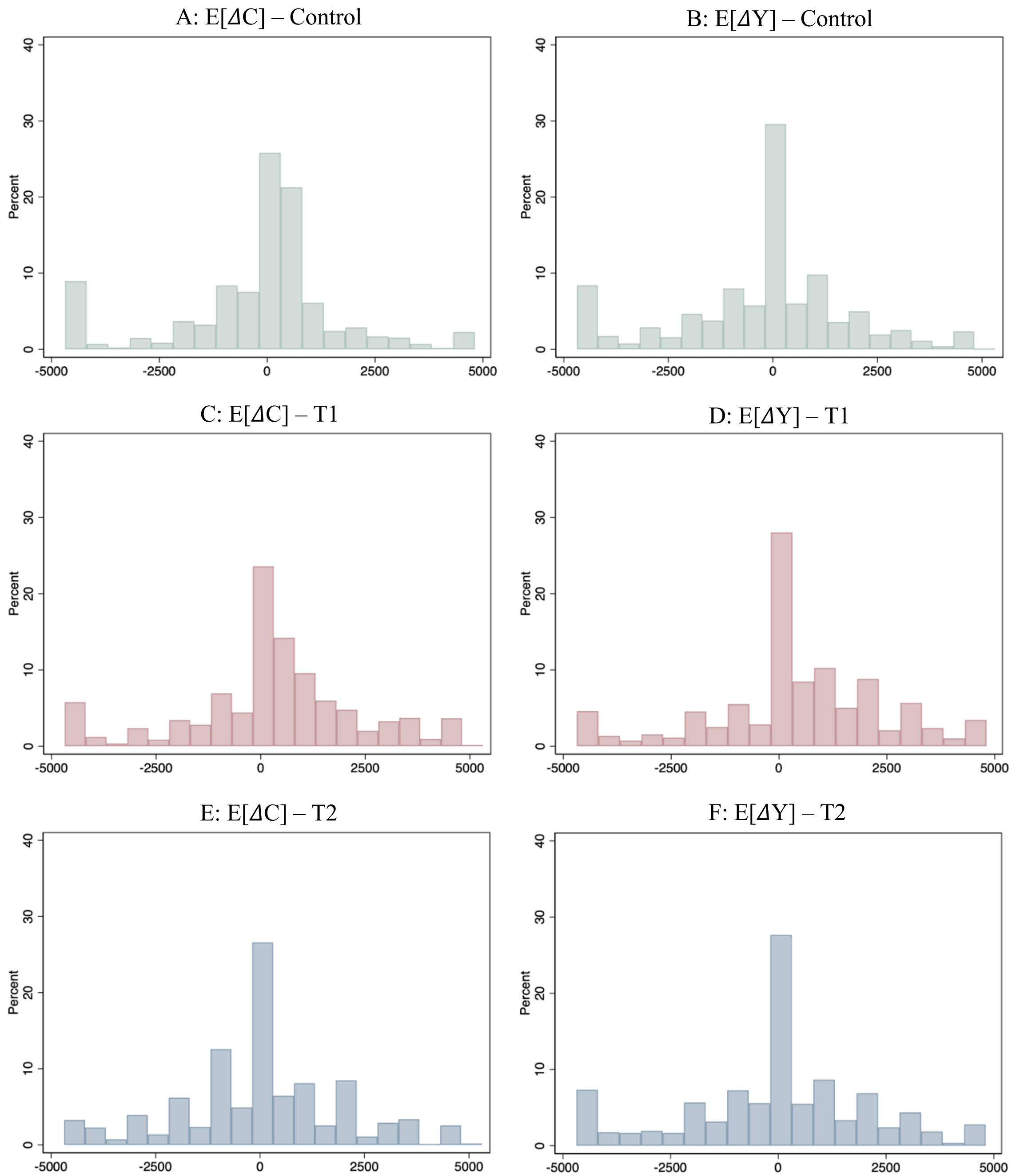
A: Debt

B: Spending



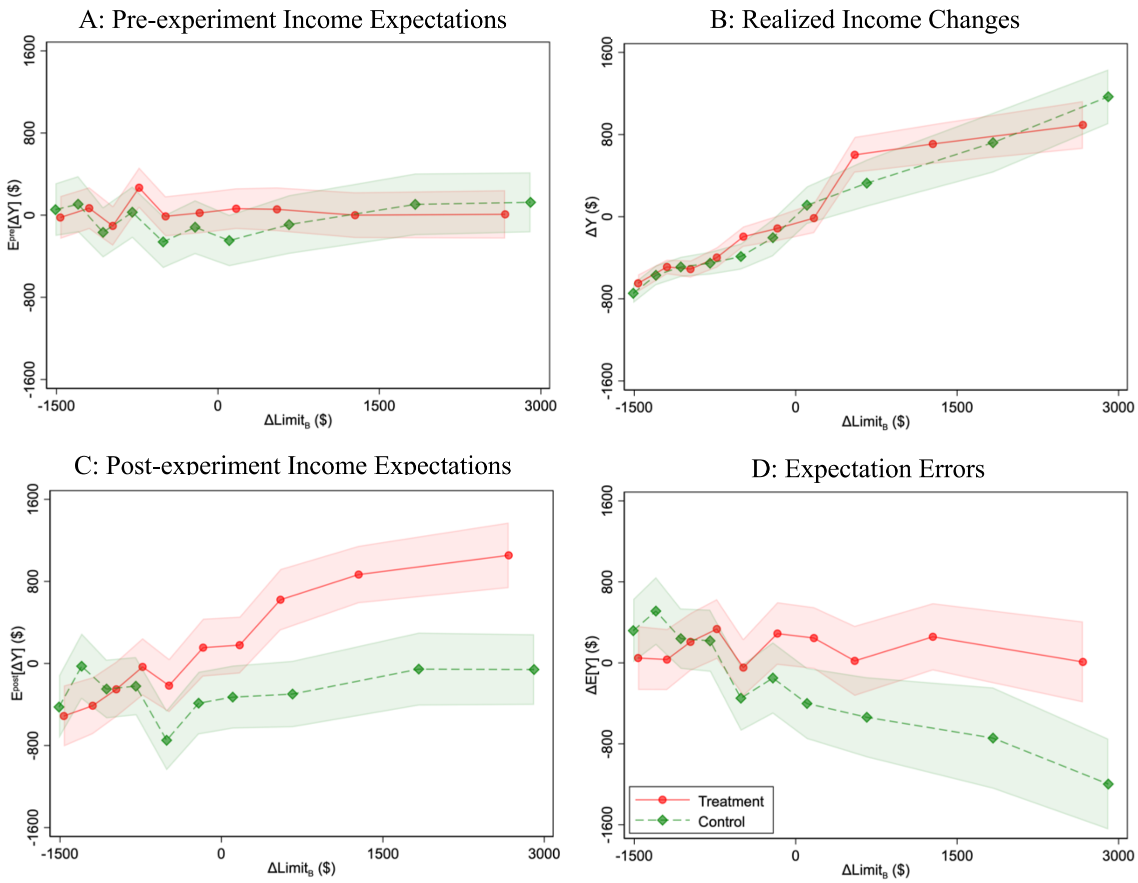
Note: This figure plots the evolution of total non-durable debt and spending on both sides of the experimental period for Sample II. In each panel, the x-axis gives the dates. The solid red line shows the evolution of T1, the blue dashed line shows the evolution of T2, and the gray dotted line shows the evolution of the control group. The gray vertical line gives the time of the treatment. All lines are vertically shifted so that the value for the control group at the treatment time is 0.

Figure 4. Distributions of Belief Changes



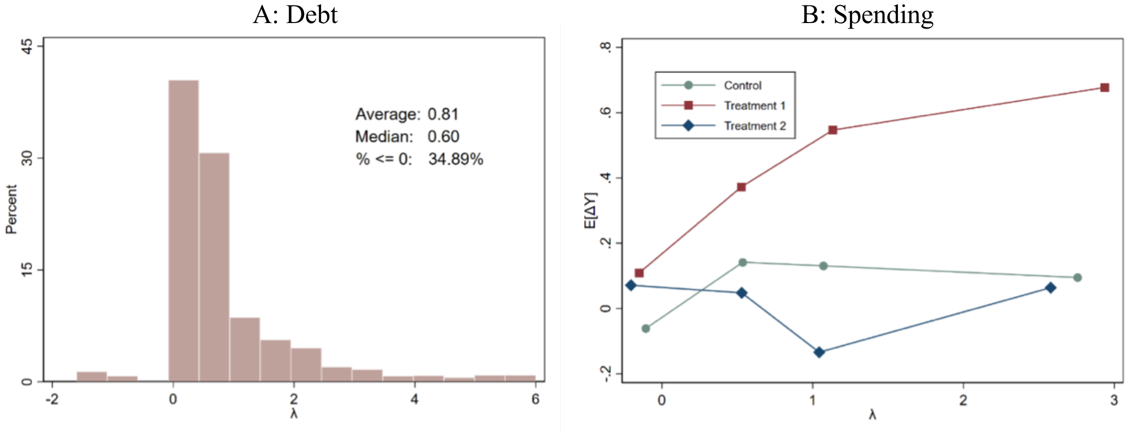
Note: This figures plots the expected changes in consumption (left column) and income (right column) using the sample receiving the post-experiment surveys (sample II). Panels A and B give the control group; panels C and D give the treatment group 1; panels E and F give the treatment group 2. The illustration is based on samples winsorized at 5% level.

Figure 5. Expectations and Realizations of Income Changes



Note: This figure plots consumer expectations and realized income changes versus the pre-determined limit changes focusing on control and treatment 1. The *x*-axis is the limit changes as proposed by the bank before the random assignment. the *y*-axis of the four panels is consumer pre-experiment expected income changes, realized income changes 12 months around the experiment, post-experiment expected income changes, and expectation errors after the experiment, respectively. expectation errors are defined as the differences between post-experiment expectation and income realizations. All variables are residualized by age, degree, gender, income, saving, total spending, industry fixed effects, city fixed effects.

Figure 6. Subjective Sensitivity of Income Changes to Limit Extensions



Note: Panel A plots the distribution of consumer subjective beliefs about the sensitivity of income growth as perceived by the bank to credit extension, λ. The plot is cut at 1% level. The right plot gives the changes in income expectations for each CNY higher pre-determined increase in credit limit. The estimates are conditional on four λ groups. Splits of λ groups are conditional on treatment groups and limit-increase deciles.

Table 1: Summary Statistics

	Mean	SD	N	Mean	SD	Diff	*t*-stats	N	Mean	SD	Diff	*t*-stats	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Panel 1: Control			Panel 2: T1					Panel 3: T2				
Age	37.91	10.25	1888	37.62	9.50	-0.29	-0.74	2275	37.83	9.75	-0.08	-0.16	1337
Female	0.43	0.50	1888	0.41	0.49	-0.02	-1.01	2275	0.42	0.49	-0.01	-0.52	1337
College	0.46	0.50	1888	0.47	0.50	0.02	0.92	2275	0.47	0.50	0.01	0.52	1337
Income	9.69	8.74	1888	9.48	6.99	-0.21	-0.65	2275	9.83	8.65	0.15	0.35	1337
Saving	139.05	149.84	1888	139.91	138.71	0.86	0.15	2275	146.14	139.33	7.09	0.97	1337
Debt	7.40	13.37	1888	7.01	10.10	-0.39	-0.79	2275	7.07	13.40	-0.33	-0.54	1337
Debt|Debt>0	16.54	15.76	831	16.99	8.81	0.45	0.54	937	16.39	16.25	-0.15	-0.15	535
Limit	88.25	112.19	1888	87.33	111.53	-0.92	-0.81	2275	89.18	116.89	0.94	0.65	1337
ΔLimit	12.01	9.09	1888	11.73	8.20	-0.29	-0.82	2275	12.40	8.94	0.39	0.87	1337
							Survey						
Spending	7.77	13.57	1888	7.94	12.92	0.17	0.32	2275	8.09	11.09	0.32	0.48	1337
Income	9.61	9.60	1888	9.54	7.75	-0.07	-0.19	2275	9.95	10.88	0.34	0.73	1337
Liquid Wealth	155.59	266.48	1888	150.71	188.84	-4.88	-0.53	2275	154.00	233.84	-1.59	-0.14	1337
Total Wealth	431.39	900.12	1888	426.85	678.23	-4.54	-0.14	2275	443.92	725.35	12.53	0.31	1337

Note: This table gives the summary statistics based on the sample with the surveys (sample II). The units of the variables excluding Age, Female, and College are in thousands of CNY. The column Diff gives the differences in the average values between the given group and the control group. t-stats are the associated *t*-statistics, testing the significance of the differences in the means. All variables are winsorized at 1% - 99% level.

Table 2: Borrowing and Spending Responses

	Panel A: 6 Months			
	ΔB	ΔB	ΔC	ΔC
	(5)	(6)	(7)	(8)
T1	0.124***	0.121***	0.297***	0.292***
	(0.013)	(0.015)	(0.040)	(0.045)
T2	0.085***	0.083***	0.200***	0.198***
	(0.012)	(0.013)	(0.044)	(0.044)
Difference	0.039***	0.038***	0.097***	0.094**
	(0.014)	(0.018)	(0.051)	(0.049)
Controls	No	Yes	No	Yes
N	5500	5500	5500	5500
	Panel B: 12 Months			
	ΔB	ΔB	ΔC	ΔC
	(5)	(6)	(7)	(8)
T1	0.162***	0.159***	0.332***	0.321***
	(0.015)	(0.016)	(0.046)	(0.051)
T2	0.114***	0.114***	0.232***	0.235***
	(0.012)	(0.013)	(0.044)	(0.044)
Difference	0.047***	0.045***	0.100**	0.106*
	(0.015)	(0.017)	(0.049)	(0.058)
Controls	No	Yes	No	Yes
N	5500	5500	5500	5500

Note: This table assesses the effects of credit extension on non-durable debt and spending. Panel A is the six-month changes and panel B is the 12-month changes. T1 and T2 are respectively the two treatment group identifiers. Coefficients are divided by the pre-determined average increase in credit limit to give an interpretation of marginal propensity. In each column, Difference is the difference in the estimates between T1 and T2. Controls include gender, province fixed effects, industry fixed effects, a dummy variable labeling if the participants are younger than 38, and a dummy variable for having at least a college degree. All variables are winsorized at the 1% - 99% level. Standard errors clustered at city level are in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 3: The Effects of Treatments on Beliefs

	E[ΔC]	E[ΔY]	E[ΔW]	E[ΔHrs]
	(1)	(2)	(3)	(4)
T1	0.277**	0.381***	0.001	0.000
	(0.136)	(0.080)	(0.002)	(0.000)
T2	-0.030	0.079	-0.002	0.000
	(0.102)	(0.100)	(0.002)	(0.000)
Controls	Yes	Yes	Yes	Yes
N	5500	5500	5500	5500

	E[u]	E[p(d)]	E[ΔL] - 1Y	E[ΔL] - 5Y
	(5)	(6)	(7)	(8)
T1	-0.283*	-0.064	0.943	0.474
	(0.156)	(0.170)	(0.874)	(2.042)
T2	-0.020	0.133	0.958	0.695
	(0.214)	(0.209)	(0.707)	(3.044)
Controls	Yes	Yes	Yes	Yes
N	5500	5500	5500	5500

Note: E[ΔC], E[ΔY], E[ΔW], E[ΔHrs] are respectively the difference between expected total spending, total income, total wealth, and hours to work every week over the 12 months after and before the experiment. E[u] and E[p(d)] are the expected unemployment probability and delinquent probability over the 12 months after the experiment. E[ΔL]-1Y and E[ΔL]-5Y are the expected growth rate of one-year and five-year credit limits. T1 and T2 are respectively the two treatment group identifiers. Coefficients are divided by the pre-determined average increase in credit limit to give an interpretation of marginal propensity. All variables are winsorized at the 1% - 99% level. Standard errors clustered at city level are in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 4: The Effects of Treatments on Macroeconomic Beliefs

	E[ΔGDP]	E[ΔGDP]	E[ΔUnemp Rate]	E[ΔUnemp Rate]
	(1)	(2)	(3)	(4)
T1	0.049***	0.046***	-0.208***	-0.231***
	(0.018)	(0.017)	(0.065)	(0.063)
T2	0.015	0.017	-0.047	-0.054
	(0.022)	(0.021)	(0.070)	(0.072)
Controls	No	Yes	No	Yes
N	5500	5500	5500	5500

Note: E[ΔGDP] and E[ΔUnemp Rate] are respectively the expected growth rate of macroeconomy and the unemplyment rate. T1 and T2 are respectively the two treatment group identifiers. Coefficients are divided by the pre-determined average increase in credit limit to give an interpretation of marginal propensity. All variables are winsorized at the 1% - 99% level. Standard errors clustered at city level are in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 5: Treatments and Labor Supply Adjustment

	Job Change (1)	Job Change (2)	Self-empolyed (3)	Self-empolyed (4)	Change Residence (5)	Change Residence (6)
T1	-0.358	-0.696	0.823	0.785	0.632	0.667
	(0.822)	(0.808)	(0.830)	(0.800)	(0.621)	(0.646)
T2	-0.038	-0.107	0.332	0.467	0.225	0.207
	(0.924)	(0.908)	(0.887)	(0.899)	(0.721)	(0.726)
Controls	No	Yes	No	Yes	No	Yes
N	5500	5500	5500	5500	5500	5500

Note: Job Change, Self-employed, and Change Residence are respectively dummy variables for being unemployed, having a job change, being self-employed, and having changed place of living during the 12 months after the experiment. T1 and T2 are respectively the two treatment group identifiers. Coefficients are divided by the pre-determined average increase in credit limit to give an interpretation of marginal propensity. All estimates are multiplied by 100. Control variables are winsorized at the 1% - 99% level. Standard errors clustered at city level are in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 6: The Effects of Limit Changes on Borrowing and Spending

	Panel A: 6 Months							
	ΔB	ΔB	ΔB	ΔB	ΔC	ΔC	ΔC	ΔC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔLimit	0.143***	0.102***	0.098***	0.097***	0.227***	0.160***	0.157***	0.155***
	(0.032)	(0.031)	(0.035)	(0.037)	(0.043)	(0.047)	(0.051)	(0.054)
E[ΔY]		0.102***	0.032	0.030		0.232***	0.097	0.091
		(0.039)	(0.041)	(0.043)		(0.064)	(0.068)	(0.072)
E[Macro Growth]			0.091***	0.089***			0.104***	0.100***
			(0.027)	(0.029)			(0.033)	(0.034)
E[ΔL] - 5Y				0.002				0.005
				(0.083)				(0.091)
First-stage *F*	713.21	334.28	297.84	132.17	713.21	334.28	297.84	132.17
N	4163	5500	5500	5500	4163	5500	5500	5500
	Panel B: 12 Months							
	ΔB	ΔB	ΔB	ΔB	ΔC	ΔC	ΔC	ΔC
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
ΔLimit	0.159***	0.113***	0.110***	0.109***	0.321***	0.236***	0.234***	0.231***
	(0.039)	(0.039)	(0.039)	(0.041)	(0.059)	(0.064)	(0.066)	(0.069)
E[ΔY]		0.089***	0.031	0.030		0.210***	0.081	0.077
		(0.041)	(0.043)	(0.045)		(0.069)	(0.075)	(0.084)
E[Macro Growth]			0.087***	0.084***			0.112***	0.108***
			(0.028)	(0.031)			(0.033)	(0.035)
E[ΔL] - 5Y				0.005				0.009
				(0.077)				(0.094)
First-stage *F*	713.21	334.28	297.84	132.17	713.21	334.28	297.84	132.17
N	4163	5500	5500	5500	4163	5500	5500	5500

Note: This table reports the IV estimates of equation (7) and (8). Panels A and B respectively focuses on the six-month and 12-month response. *Δ*B and *Δ*C are respectively the changes in unsecured borrowing 12 months after the experiment and spending over the 12 months after the experiment. *Δ*Limit is the realized change in credit limit, E[*Δ*Y] is the changes income expectation in the next 12 months. E[Macro Growth] is the first principal component of expected growth rates of GDP and unemployment rate. E[*Δ*L] - 5Y is the expected 5-year growth rate of credit limit. All variabels are winsorized at 1% and 99% level. Standard errors clustered at city level are in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 7: Heterogeneity in Income Expectation Changes

	Macro Uncertainty		Growth Sensitivity		Unemployment Sensitivity		Subj. Income Sensitivity	
	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T1	0.199	0.446***	0.132	0.500***	0.099	0.569***	0.218*	0.497***
	(0.151)	(0.148)	(0.163)	(0.131)	(0.194)	(0.141)	(0.132)	(0.155)
T2	0.077	0.089	0.049	0.107	0.029	0.138	0.053	0.099
	(0.160)	(0.139)	(0.142)	(0.129)	(0.158)	(0.140)	(0.153)	(0.170)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2122	3378	2568	2932	2437	3063	2750	2750

	Age		Education		Income		Utilization Rate	
	Low	High	Low	High	Low	High	Low	High
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
T1	0.397**	0.254*	0.402**	0.232*	0.431**	0.230	0.396**	0.301*
	(0.161)	(0.133)	(0.171)	(0.140)	(0.202)	(0.139)	(0.205)	(0.182)
T2	0.077	0.062	0.052	0.087	0.043	0.097	0.060	0.088
	(0.144)	(0.157)	(0.182)	(0.179)	(0.162)	(0.233)	(0.200)	(0.211)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2750	2750	2950	2550	2750	2750	2750	2750

Note: This table reports the changes in subjective income expectation around the experiment. The left-hand side variables are E[ΔY]. Sample split are based on the pre-experiment sample median. All variabels are winsorized at 1% and 99% level. Standard errors clustered at city level are in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$