# Learning in the Limit: Income Inference from Credit Extensions

Xiao Yin

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**Abstract**

Combining a randomized controlled trial with administrative and survey data, this paper shows that credit limit extensions significantly increase total spending and income expectations. By controlling for changes in personal income expectations, the spending response to credit-limit extensions weakens by approximately 30%. For financially unconstrained consumers, expectation changes account for around two-thirds of the spending responses to limit extensions. These findings are consistent with consumers inferring future income from credit supply.

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Yin: University College London, Department of Economics and School of Management, xiao.yin@ucl.ac.uk.
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# I. Introduction

Credit limits are central in household consumption-savings decisions, because it determines how much 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 meaningful increases in total consumption. [1] Hence, the micro-level mechanisms by which credit limit extensions affect consumer spending are not well understood.

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 how credit extensions affect consumption by shaping expectations.

Exploring how credit supply affects consumer expectations is challenging, as belief changes surrounding real-world credit supply changes 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, following its usual internal underwriting process. However, the

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

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 of 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 0.25 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, consumers update their income and spending expectations upwards after receiving a higher credit limit. 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 consumers anticipate higher future consumption, which they believe is financed by

[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).

increased income rather than by drawing down savings. This challenges the buffer stock model, which suggests that a higher credit limit increases total consumption by reducing precautionary savings. In addition, unchanged expectations about working hours indicate that consumers do not believe that a relaxed borrowing constraint increases labor supply. In comparison, subjectively 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 aims at varying 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 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. 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. First of all, I find that income expectations have a significant effect on spending decisions. Each CNY increase in income expectation over the next 12 months increases total spending by 0.22. Consequently, MPCL and MPB decreases by around 30% to 0.19 and 0.10, 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.

In the final part of the results, I examine whether macroeconomic expectations are likely the sole driver of belief updates. Using survey responses that capture the perceived relationship between macroeconomic trends and personal income, I separate changes in income expectations into a macroeconomic component and a residual component. This analysis reveals that consumers infer more than just macroeconomic conditions from credit limit extensions. While shifts in expected macroeconomic outlook contribute to changes in income expectations, they do not fully account for the observed updates. Instead, consumers also incorporate private signals about their own future earnings, potentially drawing insights from banks' access to richer cross-sectional data or relying on heuristic reasoning.

It is important to note that the strength of the income-inference channel likely depends on the specific institutional environment. For example, in poorly developed banking markets consumers may always have more information than banks, while in highly concentrated markets banks may not need to act on the information they have. Similarly, the financial sophistication of borrowers can shape how they interpret and respond to credit supply decisions.

This study mainly contributes to three strands of literature. First, it advances research on the effects of credit limits on borrowing and consumption (e.g., Zeldes, 1989; Ludvigson, 1999; Gross and Souleles, 2002; Agarwal et al., 2017; Guerrieri and Lorenzoni, 2017; D'Acunto et al., 2020; Gross et al., 2020; Aydin, 2022; Chava et al., 2023; Cenzon, 2024). Recent work by Aydin (2022) provides a clean RCT-based estimate of the marginal propensity to borrow, and Cenzon (2024) finds that negative credit limit shocks induce macroeconomic pessimism. While most studies rely on the buffer-stock model as the underlying mechanism, the belief-driven effects of credit expansions remain underexplored. This study fills that gap by leveraging a field credit supply event and survey data to directly test how credit limit changes shape consumer expectations and spending, offering new insights for macroeconomic models incorporating credit supply shocks.

Second, this study complements research on borrowing constraints and labor income. Prior work shows that credit expansions can extend job search duration and increase reemployment wages (Herkenhoff et al., 2021), reduce financial stress and boost productivity (Sergeyev et al., 2023), and enable mobility to higher-wage jobs (He and Le Maire, 2023; Doornik et al., 2024). My findings reveal that credit expansions raise income expectations without necessarily increasing realized income, highlighting a belief-driven consumption channel.

Finally, this study contributes to the literature on the role of beliefs in financial decision-making (DellaVigna, 2009; Benjamin, 2019). Previous work explores how beliefs shape retirement choices (Ameriks et al., 2016), stock investments (Manski, 2004; Ameriks et al., 2020; Giglio et al., 2021; Gorodnichenko and Yin, 2024), mortgage-leverage decisions (Bucks and Pence, 2008; Bailey et al., 2018; Kuchler et al., 2022), and consumption (Rozsypal and Schlafmann, 2023; Colarieti et al., 2024; D'Acunto et al., 2024). Soman and Cheema (2002) show that MPCL increases when consumers perceive credit limit changes as signals of future earnings. This study builds on these insights by integrating survey data with administrative and transaction records to quantify the impact of belief updates on borrowing and spending.

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 spending after credit constraint shocks. It 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 consumers' period-$t$ consumption.[2] The discount rate for next-period utility is $\beta$. Consumers are endowed with an initial asset $A_0 = 0$ and receives income $Y_t$ at the beginning of each period. The budget constraint $t$ is

$$A_t = RA_{t-1} - C_t + Y_t,$$

where $A_t$ represents total savings at the end of $t$ and $R = 1 + r$ is the gross interest rate. For brevity, I set $\beta\, R = 1$. At the beginning of $t_3$, $Y_3$ is realized. The agent consumes everything and ends the game with zero savings; that is, $A_3 = 0$. In addition, consumers face 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, consumers incur a monetary cost with the net value of $\psi < 0$. Without other costs, default occurs when $A_1 < \psi$.[3]

## B. Income Process

Income is stochastic and follows

$$\begin{aligned} Y_{t+1} &= \alpha\, t + X_{t+1}, \\ X_{t+1} &= \rho\, X_t + \eta_{t+1}. \end{aligned}$$

[2] The use of quadratic utility permits close-form solution given the linearity of the optimality conditions (see Jappelli and Pistaferri (2017) for details). However, it has the undesired property that $u(C_t)$ is decreasing for large enough $C_t$. Therefore, an implicit assumption is that $b$ has the value such that the range of $C_t$ always gives $u' > 0$ and $u'' < 0$. Online appendix section V validates the main propositions through calibrating a consumption saving model with information content in credit supply.

[3] 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.

$\alpha t$ is a deterministic trend. $X_t$ summarizes the current systematic states (e.g., macroeconomic shocks and type-specific lifecycle trends). $\rho \in (0,1)$ is the persistence of the evolution of the states. $\eta_t \sim N(0, \sigma_\eta^2)$ captures the systematic shocks to income.

The key information friction is that consumers have noisy perceptions of the underlying state $X_t$ of their income. An example is inattention to current macroeconomic information (Mankiw and Reis, 2002; Reis, 2006; Coibion and Gorodnichenko, 2012). Alternatively, consumers could have noisy perception about their lifecycle income profile, which could be better inferenced by banks that have rich cross-sectional information. At the beginning of $t_1$, consumers form prior of $X_1$ that follows $N(X^0, \sigma_0^2)$.

### C. Bank

The banking market is perfectly competitive. A continuum of identical banks determines the borrowing limit $L$ at the beginning of $t_1$ before observing $Y_1$. Banks have flat priors and observe a noisy signal $s = X_1 + \epsilon$ and $\epsilon \sim N(0, \sigma_\epsilon^2)$.

Denote $C_1^*(L,s)$ as the optimal consumption at $t_1$. Let $m(L,s) \equiv \psi + C_1^*(L,s)$ as the income threshold below which consumers will default and $D_1 \equiv \max\{0, C_1^* - Y_1\}$ as the borrowing. Assume defaulters max out on their credit limit (verification in Section II.E). Banks earn interest only on repayment-contingent debt and lose $\delta L$ on default, where $1-\delta$ is the recovery rate. Thus the per-account expected profit is

$$\Pi(L,s) = r\,\mathbb{E}[\,D_1 \mathbf{1}\{Y_1 \geq m\} \mid s\,] - \delta L \Pr(\,Y_1 < m \mid s\,)\,. \tag{1}$$

Banks compete over $L$ *a la* Bertrand taking $r$, $\delta$, and consumer consumption rule $C_1^*(L,s)$ as given.[4] In equilibrium consumers choose the offer with the highest credit limit, so credit supply is set such that (1) is zero. For later use let the equilibrium schedule be $L = f(s)$.

### D. Learning from Credit Limit Changes

[4] The assumption that banks compete over credit limits but not interest rates is based on two motivations. First, in China, most credit cards have a daily interest rate of 5 basis points. In addition, Matcham (2025) shows that banks in the credit card market mainly engage in risk-based limit adjustments instead of rate adjustments.

After receiving credit limit $L$, consumers infer $X_1$ as perceived by banks. Specifically, consumers form subjective beliefs of $s$ as

$$\mathbb{E}_c[s] = f^{-1}(L) \equiv g(L).$$

Here I focus on a separating equilibrium where credit limits reveal banks' information. Thus, $f$ is invertible. I study when such condition exists in Section II.F. With rational learning, consumers can correctly infer the functional forms of $f$, and $E_c[s] = s$. In other words, rational learning implies that banks cannot change $L$ to oversignal their beliefs.

Given the supplied credit limit $L$, consumers' posterior of $X_1$ has the expected value

$$\hat{X}_1 = X^0 + (1+\theta)K[g(L) - X^0], \tag{2}$$

where $K = \sigma_0^2/(\sigma_0^2 + \sigma_\epsilon^2)$ is the Kalman gain of the learning process with $\hat{\sigma}^2 = \sigma_\epsilon^2 K$ being the posterior uncertainty. I use hat to denote posteriors. Note that Bayesian learning does not require banks to always achieve better predictability of $X_t$. As long as banks' signal contains additional information that are not entirely known to the consumers, credit supply that incorporates banks' beliefs about $X_t$ would change consumers' beliefs. $\theta$ captures the deviation from Bayesian learning. When $\theta > 0$, consumers overreact to signal surprises. It can be microfounded with diagnostic expectation with Kalman filtering over a normal distribution (Bordalo et al. 2019).

## E. Optimality Conditions and Equilibrium

### *E.1. Consumers*

The consumer's optimal decision can be determined through backward induction. In $t_3$, consumers consume everything available. The optimal consumption in $t_2$ can be written as

$$C_2^* = \min\left\{\frac{RA_1 + Y_2 + \mathbb{E}_2[Y_3]}{2}, RA_1 + Y_2 + L\right\}. \tag{3}$$

In $t_1$, optimal consumption depends on if the consumers are borrowing constrained, and further if they choose to default. When $\mathbb{E}_1[C_2^*] < Y_1 + L$, consumers are not borrowing constrained. Under this scenario, optimal consumption in $t_1$ is $Y_1 + L$ if $Y_1 - \mathbb{E}_1[C_2^*] < \psi$, and is $\mathbb{E}_1[C_2^*]$ otherwise. When $\mathbb{E}_1[C_2^*] > Y_1 + L$, consumers are borrowing constrained, then they will consume $Y_1 + L$ regardless of the default choices. Therefore, optimal consumption in $t_1$ is

$$C_1^* = \begin{cases} \mathbb{E}_1[C_2^*] & if \quad Y_1 - \mathbb{E}_1[C_2^*] > \max\{\psi, -L\} \\ Y_1 + L & otherwise \end{cases}. \tag{4}$$

In equation (4), $Y_1 - \mathbb{E}_1[C_2^*] = A_1$ if under slack borrowing constraint and no default. Therefore, the consumption rule in $t_1$ follows the classic Hall's (1978) Martingale if consumers are not borrowing constrained and do not default. Otherwise, consumers spend all resources available.

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 of default is

$$\begin{aligned} \Phi_d &\equiv \Pr(Y_1 - C_1^* < \psi) \\ &= \Phi\left(\frac{\psi + C_1^* - \alpha - s}{\sigma_\eta}\right), \end{aligned} \tag{5}$$

where $\Phi$ is the CDF of a standard normal distribution.

*E.2. Bank*

Given consumers' optimal decision rules (3) – (5), banks choose $L$ such that (1) is zero. This yields the following lemma:

*Lemma 1: There exists* $\bar{\theta} > 0$ *such that for all* $\theta \in [0, \bar{\theta}]$, $f' > 0$. *In particular, under Bayesian learning* ($\theta = 0$), $f' > 0$.

The proof of Lemma 1 is in the online appendix section I. The intuition is as follows. On the zero-profit boundary, banks equate expected interest revenues from repayers with expected default losses. When the signal $s$ rises, the income distribution shifts right. Under Bayesian learning, consumption responds by less than one-for-one, so the end-of-period wealth increases. This lowers default risk while simultaneously raising expected repayments. Both forces increase profit at the current $L$. To restore zero profit, the bank must raise credit limits, implying $f'(s) > 0$. However, when $\theta$ is large enough, consumers update income expectations too much and end up consuming more than the realized income. Hence default risk dominates, and banks have to reduce credit limits to constrain spending.

### F. MPC out of Liquidity

Borrowing the language from Gross and Souleles (2002), I analyze a consumer's MPCL as the effect of a one-unit increase of $L$ 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 $t_1$ consumption is not constrained. Therefore, when not defaulting, $t_1$ consumption would be $\mathbb{E}_1[C_2^*]$.

In equilibrium, the default rate equals the fraction of consumers who choose to default. Meanwhile, defaulters max out total resources, and the non-defaulters chooses optimal consumption equaling $\mathbb{E}_1[C_2^*]$. Consequently, expected value of the optimal consumption for those not currently constrained is

$$C_1^* = \Phi_d(Y_1 + L) + (1 - \Phi_d)\mathbb{E}_1[C_2^*]. \tag{6}$$

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

$$P_2(not\ binding) = P\left(\frac{RA_1 + Y_2 + Y_3}{2} < RA_1 + Y_2 + L\right) = \Phi\left(\frac{2L + RA_1 - \alpha + \hat{X}_1}{\rho(1-\rho)\hat{\sigma}}\right), \tag{7}$$

where $\Phi(\cdot)$ is the standard normal CDF. (7) is denoted as $\Phi_L$. From (7), 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, or income volatility is smaller.

Combining (6) and (7) yields

$$\mathbb{E}_1[C_2^*] = C_2^{NC} - (1 - \Phi_L)(C_2^{NC} - C_2^C),$$

where $C_2^{NC} = \frac{RA_1 + \mathbb{E}_1[Y_2] + \mathbb{E}_1[Y_3]}{2}$ is the optimal level of $t_2$ consumption when borrowing limit is slack and $C_2^C = RA_1 + E_1[Y_2] + L$ 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 $C_1^*$ with respect to $L$, which yields

$$\frac{dC_1^*}{dL} = \underbrace{\frac{1}{\omega}\frac{\Phi_d}{1-\Phi_d}}_{default} + \underbrace{\frac{1}{\omega}\left[\frac{2\phi_L(C_2^{NC} - C_2^C)}{\rho(1-\rho)\hat{\sigma}} + (1-\Phi_L)\right]}_{precautionary} + \underbrace{\frac{1}{\omega}\,\chi(1+\theta)Kg'(L)}_{income-inference}. \tag{8}$$

$\omega = \left(\frac{1}{1-\Phi_d} + (C_2^{NC} - C_2^C)\left(\frac{\phi_d}{(1-\Phi_d)\sigma_\eta} + \frac{\phi_L R}{\rho(1-\rho)\hat{\sigma}}\right) + R\left(1 - \frac{\Phi_L}{2}\right)\right)$ and $\chi = \left(1 - \frac{\Phi_L}{2}\right)\rho(1 - \rho) + \frac{(C_2^{NC} - C_2^C)\phi_L}{\rho(1-\rho)\hat{\sigma}}$ are two positive numbers.

As shown in equation (8), 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. Lastly, the third term on the right-hand side of (8) captures an income inference channel. The sign of this channel depends on the relationship between $L$ and $s$. When $g' > 0$, banks will offer more credit if they forecast higher income 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.

Equation (8) gives the following proposition

*Proposition 1: Under Bayesian learning, higher credit limits increase posterior income expectations, implying a positive income-inference channel.*

The intuition behind Proposition 1 is as follows. From Lemma 1, rational consumers never increase consumption by more than the implied increase in income. In this case, consumption tracks expected income one-for-one or less, more expected resources reduce default risk and profitability. Hence, banks increase credit limit to boost consumption further. Consumers correctly expect this strategy and update income expectation to the same direction of limit changes. Therefore, income-inference channel is positive, and MPCL is larger compared with the no-learning situation.

By contrast, if consumers sufficiently overreact, characterized by a large enough $\theta$, then the belief update is too strong, leading to overconsumption. In that case, banks optimally pull back credit to prevent excessive default risk, creating a negative reaction and potentially reversing the MPCL.

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

*Corollary 1: With the income-inference channel, MPCL overestimates the role of precautionary savings in driving the spending responses to relaxed borrowing limits.*

## 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

[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.

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, 2023). 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 Debt, Spending, and Income

Debt data comes 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 balance, housing fund and social security contributions, etc. Given its comprehensive coverage, this dataset provides a complete view of consumers' borrowing behavior. Debt is then defined as the total unpaid balances at the end of the interest-free billing cycle.

Data from a single bank does not capture all spending history, as consumers often use multiple banks. To obtain a more complete picture of spending patterns, I use transaction histories from the bank's account-aggregator service. This service allows customers to link accounts from different financial institutions, providing a consolidated view of balances, transaction histories, and financial management such as bill reminders. [5]

The account-aggregator service is promoted quarterly via notifications. In my

[5] Using account aggregators has been a recent progress to study consumption behaviors (e.g., Baker, 2018; Baugh et al., 2021).

sample, 34% of participants opted in, while an additional 13% had only one bank as revealed by CRS. I use these two groups to analyze spending, calculating total spending as the sum of all purchase transactions in each period. Since sample coverage is incomplete, I confirm that this sample is representative of the full dataset (online appendix Table A.1).

Income data is retrieved based on transaction histories. For employees, income is calculated based on a consumer's social insurance contributions, as these payments typically represent a fixed fraction of total income.[4] This 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.

To validate income accuracy, I compare the transaction-based estimates with government administrative records, available for 21% of the sample. Figure A.1 (online appendix) shows the results, with a regression yielding an $R^2$ of 0.96, confirming the effectiveness of this method. Additionally, I verify that the income sample is representative of the full dataset (online appendix Table A.1). In addition, online appendix Table A.2 shows that the borrowing and spending responses for the sample with available income and spending information are similar to the whole sample.

## 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 of 2023, the bank selected a group of consumers (approximately 50,000 from 57 cities) and decided to increase their credit limits. These increases were based on the bank's credit scoring rules. Then, 21,500

[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.

individuals were randomly selected as participants for this study. Selected individuals were grouped into two subsamples (I and II). In each subsample, subjects were 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 of Figure 2.

2. **Pre-experiment survey**: On June 23, the participants in Sample II were invited to complete the survey through text messages. [6] 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 1 in Figure 1.

3. **Treatment**: On July 03, credit limits were automatically changed to the predetermined level for participants in T1 and T2 for both sample I and II. In addition, treated participants were informed about such changes through text messages (Figure 1 Message 2). At the same time, participants in T2 were informed that the changes were based on a research project (Message 3 in Figure 1). 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*.

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.

The main analysis is based on those who completed both surveys. In addition, I drop those who do not have at least 12 months of information available before the experiment, which

[6] Section IV in the online appendix reports the survey in English.

is about 5% of the whole sample. Besides, a random 30% of the participants were asked a series of hypothetical questions to elicit their perceptions of banks' credit supply rule (see section IV.F for details). To avoid hypothetical questions priming participants' beliefs, I exclude these participants for the main analysis. My final sample has 7,095 participants.

Mapped into equation (7), 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] Therefore, T1 and T2 enable the decomposition of MPCL.

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, 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% | ___% |

[6] The information treatment might affect expectations about the persistence of the limit increases. In Table 3, I show that the T2 does not have significantly lower expectations about future credit limit, and the expectations of future credit limit do not have significant effects on consumption behaviors.

| | |
|---|---|
| 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: 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.

*1. Demand effects and selective responding*

The use of surveys provides valuable insights into consumer beliefs about credit supply but comes with challenges. Survey demand effects may arise if participants adjust responses based on perceived intentions. Additionally, response rates are never perfect, and selection bias may occur if response likelihood varies systematically by participant characteristics.

Several design features in this study mitigate these concerns. Since the survey was distributed through a bank, participants might have been tempted to signal better creditworthiness. To prevent this, the survey began with an explicit disclaimer:

> *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 framing aimed to minimize strategic response behavior. I further verify this concern by comparing survey responses from consumers who primarily borrow from other banks (online appendix Table A.3). As these consumers lack direct borrowing ties with the bank, they have less incentive to manipulate their responses.

To alleviate selective responding problems, the survey was designed to be brief and highly incentivized. The pre-experiment survey required only 15 core questions (plus three additional questions for 30% of participants), and the post-experiment survey had 10 mandatory questions. Both took under seven minutes to complete, and participants received 20 CNY — equivalent to an hourly rate exceeding 171 CNY, well above the 95th percentile for urban Chinese residents. As a result, the response rate was high, reaching nearly 70%.

*2. External validity of the experiment*

Since the experiment was based on a one-time credit supply event, the selected sample might differ from the broader Chinese population, raising concerns about external validity. To assess representativeness, I compare sample demographics with a 10% random sample from the bank's full customer database. As one of China's largest banks, its customer base is broadly representative of urban residents.

Table A.4 shows that survey participants had lower spending, income, and credit limits, and higher debt compared to the broader customer base. This suggests that respondents had a greater need for credit. However, the differences were modest — the absolute log differences between the averages of the characteristics are less than 10%, indicating that the sample is broadly representative of the Chinese urban population.

### D. Summary Statistics

Table 1 presents summary statistics based on pre-experiment characteristics. Panel A describes the unsurveyed sample (Sample I), while Panel B covers the surveyed sample (Sample II). For the surveyed sample, the average age is 38, with 43% female participants. About 50% hold a college degree. The average outstanding interest-incurring debt is 7,200 CNY, rising to 17,500 CNY for those with positive pre-experiment debt. This indicates that approximately 40% of participants hold unsecured debt, which falls at the lower bound of the 40%–80% range found in U.S. studies (Gross & Souleles, 2002; Zinman, 2009; Fulford, 2015). In the sample, 19% carry both positive liquid wealth and positive credit card debt (co-holders). Meanwhile, if hand-to-mouth is defined as those with liquid asset less than two months of income, 32% of the subjects are hand-to-mouth.

The average credit limit increase is about 13,100 CNY, which is economically significant: 16% of the pre-experiment total credit limit and 9% of annual income. The *p* values comparing control and treatment groups show no significant differences across any dimensions. This confirms the effectiveness of randomization.

Compared to the unsurveyed sample, survey respondents were generally more likely to younger, less wealthy, and have lower income. However, these differences were not particularly large: the absolute log differences between the characteristics averages are less than 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 1, 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 3 plots the evolution of the changes in unsecured debt and total spending around the experiment. Panels A and B give the results for Sample I; panels C and D give those that completed the surveys in Sample II. I scale the changes around the experiment by the pre-determined limit changes. Thus, the magnitudes give an interpretation 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. 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 credit limit extensions affect factors other than instant borrowing capacity.[7]

I continue to estimate the effects of credit limits on spending. Table 2 presents the results. Columns (1) – (5) give the results for changes in debt for the unsurveyed sample. Column (1) reports the first-stage estimate of the treatments on credit limits. Columns (2) and (3) present the intent-to-treat (ITT) estimates. These specifications compare the average changes in credit limits and debt between the treatment groups and the control group using ordinary least square (OLS). Columns (4) and (5) give the marginal propensity (MP) estimates, which calculate the treatment effects of the change in credit limits on the change in unsecured debt using two-stage-least-squares (2SLS), in which the randomized experimental assignments are used as an instrumental variable (IV) for the change in credit limits. Without additional controls, these numbers equal to the ratio of the ITT estimates and the first-stage estimates. Consequently, the MP estimates for T1 give the interpretations of MPB.

From Panel A, on average, credit limit was 13.3 thousand CNY higher for T1. This resulted in a higher debt of around 1.5 thousand CNY over six months and 2.0 thousand CNY over 12 months. Columns (4) and (5) give the MP estimates. For each CNY higher credit limit, debt increased by 0.116 over six months and 0.151 over 12 months. Meanwhile,

[7] Online appendix Figure A.2 plots the evolution for all participants in Sample II including non-respondents.

each CNY higher credit limit increased T1 spending by 17.9 cents over six months and 24.8 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 increased the borrowing of T2 by 7.2 cents over six months and 10 cents over 12 months, and increased the spending by 12.8 cents over six months and 17.3 cents over 12 months. Differences in the spending responses between T1 and T2 indicate a belief channel affecting spending responses to limiting changes.

As the survey response rate is not perfect and sending surveys might prime consumer expectations, comparing the spending responses of the surveyed and unsurveyed samples sheds light on whether the survey sample results are subjective to selection issues or survey demand effects. From Panel B of Table 2, spending and debt responses are generally slightly larger for the surveyed sample. This is expected given that survey participants generally have less wealth (i.e., more liquidity constrained). However, the differences in MPB and MPCL between the two samples are economically insignificant, indicating that selection bias and survey demand are unlikely to be a serious issue.

**B. Expectation Responses to Limit Changes**

Informing that the credit supply decisions involve randomization attenuates 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 MP estimates of the limit changes on expectations are presented in Table 3. The results from T1 show that a higher credit limit significantly increases subjective expectations about future consumption and income, and marginally but insignificantly lower probability of being unemployment. Each one-thousand CNY higher credit limit increase consumption expectation by 286 CNY and income expectation by 349 CNY. However, there were no significant changes in subjective labor supply, as captured by the number of hours likely to work. At the same time, expectations about future borrowing capacity and default probability remain unchanged, as captured by the one-year and five-year changes in the expectations of total credit limit or default probability. For T2, when informed about the randomization of credit supply, expectations about consumption and income 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 higher marginal productivity of labor instead of 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 suggest that mechanisms suggested by a buffer-stock model is not the only motivation for consumers to expect higher spending after a higher credit limit. Buffer-stock model predicts that higher credit limits boost consumption by reducing precautionary savings. However, as Table 3 shows, subjective beliefs about total wealth do not decrease, implying that precautionary motives are not the only subjective driver of credit limit-induced consumption changes.

A potential concern with bank-distributed surveys is that consumers might misreport creditworthiness to appear lower-risk. This is unlikely here for two reasons: (1) the survey explicitly stated that banks would not handle the data, and (2) while reported income is higher, subjective default risk beliefs remain unchanged, making strategic misreporting improbable.

Credit limit shocks significantly affect income expectations, but the extent of inference from credit supply should vary across individuals. This heterogeneity can be better explored through the distribution of belief changes. Figure 4 shows that in both the control group and T2, belief changes are more closely distributed around zero, while in T1, shifts in income and consumption expectations skew more to the right. However, belief changes are not uniformly positive—around 45% of participants reported zero or negative future income expectations. Thus, the large average belief changes stem from substantial shifts among some consumers rather than uniform adjustments across all participants.[8]

I continue to study expectations regarding the macroeconomic conditions. Previous studies have shown that credit supply is procyclical (Bassett et al., 2014; Boons et al., 2023; Weitzner and Howes, 2023; Fishman et al., 2024), 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 so, participants in T1 should update their beliefs about the macroeconomy after receiving limit shocks. To explore this conjecture, I use the following two questions:

> *How much will the overall Chinese economy/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 columns (9) and (10) in Table 3. After the experiment, participants in T1 increased their expectations of GDP growth over the next 12 months by a total of 0.40 percentage points and decreased their expectations of unemployment rates by 1.90 percentage points. This translates to 0.31 percentage points higher GDP growth expectation and 1.49 percentage points lower unemployment rate expectations for each 10 thousand CNY higher credit limit. In contrast, there were no significant changes in expectations regarding the macroeconomy for T2.

[8] Online appendix Figure A.3 shows the distribution of log changes.

These results support the idea that consumers view credit supply as procyclical—interpreting credit limit increases as signals of economic expansion. Moreover, T2 findings confirm that when participants are informed that limit changes are random (conditional on good payment history), their macroeconomic expectations remain unchanged.

**C. Decomposing the Effects of Limit Extensions on Spending**

Researchers have been using arguably exogenous changes in credit limit to estimate MPCL and MPB. However, as shown, when consumers infer information from bank credit supply events, the estimated marginal propensity effects do not directly map to the conventional marginal effects of borrowing limits on consumption. That is, more IVs are needed to control for the changes in expectations.

To empirically test the mechanism highlighted by the model, I use a 2SLS approach to separately identify the effects of belief updating and credit limit changes on spending behavior. This maps directly to the structure implied by equation (8), in which MPCL reflects both the inference-based channel and the residual channel. My approach follows Beutel and Weber (2023), Coibion et al. (2024), and Gorodnichenko and Yin (2024). The first-stage regression is

$$x_i^h = a_0^h + a_1^h \times T1_i + a_2^h \times T2_i + error_i, \tag{9}$$

where $x_i^h = \{\Delta Limit_i, \Delta\mathbb{E}[Y_i]\}$, and $T1_i$ and $T2_i$ are respectively dummies if $i$ is in the corresponding treatment group. Specification (9) is estimated for the realized changes in credit limit, $\Delta Limit_i$, and the changes in income expectations around the experiment $\Delta\mathbb{E}[Y_i]$. The second stage regression is given by

$$y_i = \alpha_0 + \alpha_L \Delta Limit_i + \alpha_E \Delta\mathbb{E}[Y_i] + error_i, \tag{10}$$

where $y_i \in \{\Delta B_i, C_i\}$. This specification instruments the changes in credit limit and changes in income expectation with the two treatment dummies. Relevance requires that T1 and T2 change credit limits and expectations differentially. This is satisfied as T1 and T2 changes $\Delta Limit_i$ similarly, whereas, as evident by columns (1) of Table 4, only T1 has significant impacts on $\Delta\mathbb{E}[Y_i]$. Note that credit limit changes also affect expectations about future consumption and macroeconomy. Therefore, exclusion restriction requires that these expectations change spending only through changing personal income expectations and the main effects of limit change.

Panel A of Table 4 summarizes the results. The first-stage *F*-statistics are all well above 10, indicating strong impacts of treatments on expectations and credit limits. From columns (3) and (4), both income expectations and borrowing limits have significant effects on borrowing. Each CNY higher income expectation increases debt by 12.7 cents over six months and 17.9 cents over 12 months. Controlling for the changes in income expectation, each CNY higher credit limit increases debt by 7.7 cents over six months and 10.3 cents over 12 months.

The results are similar for spending. From columns (5) and (6), the MPC out of income expectation is 19.6 cents over six months and 24.5 cents over 12 months. For rational and unconstrained agents, these numbers also suggest whether the perceived income changes are permanent or transitory. For a permanent income change, the MPC should be one. For a one-time shock, the MPC should be equal to the annuity factor, which is less than 0.05 if the annual interest rate on saving is 5%. However, an average MPC of around 0.2 is possible for a transitory but persistent shock. That is, income shocks have an AR1 process with non-trivial rate of depreciation. Meanwhile, behavioral biases like present bias (Maxted, 2024) or rule-of-thumb are also possible (McDowall, 2023) for consumption to respond to transitory income shock stronger.

Controlling for the expectation changes, each CNY higher credit limit increases total spending by 12.3 cents over six months and 17.7 cents over 12 months. Mapped to equation (8), the 0.259 MPCL for T1 from Table 2 column (20) gives the unconditional MPCL, while the 0.177 MPCL from Table 4 column (10) gives the MPCL controlling for expectation changes. This indicates that changes in income expectations account for approximately 32% of MPCL.

While the information treatment to T2 aims at exogenously varying the degree of inferencing from credit supply, additional information about bank credit supply might affect consumer perceptions about other dimensions of bank-lending strategies or the banking sector. As an alternative strategy, I exclude T2 from my sample and employ location-by-treatment interactions to separately identify the effects of credit-limit changes and the changes in expectations on consumers' spending. This strategy is often used when treatment changes the outcome variables indirectly through variables other than the variable of interests (Kling et al., 2007; Abdulkadiroglu et al., 2014; Kline and Walters, 2016).

In particular, the first and second stages are respectively

$$x_i^h = b_0^h + b_1^h \times T1_i + b_2^h \times T1_i \times P_i + b_3^h \times P_i + error_i^h, \tag{9'}$$

$$y_i = \beta_0 + \beta_L \times \Delta Limit_i + \beta_E \times \Delta\mathbb{E}[Y_i] + \beta_3^h \times P_i + error_i, \tag{10'}$$

where $P_i$ is a dummy variable that is equal to one if $i$ lives in a province with high average income volatility before the experiment. I define a province as having high average income volatility if the average individual monthly income volatility over the three years before the experiment is in the upper two terciles. Therefore, this specification instruments $\Delta Limit_i$ and $\Delta\mathbb{E}[Y_i]$ by the treatment dummy and the treatment-high-uncertainty interaction. Controlling for the high-uncertainty province fixed effects makes sure that the instruments only use exogenous variations from $T1_i$.

Relevance of the location-by-treatment strategy requires that the consumers' degree of learning varies across $P_i$, and this degree of variation is different from that of $\Delta Limit_i$. This is likely as $\Delta Limit_i$, which is randomized, is not expected to be different across provinces. Whereas, through Bayesian learning, the degree of inference should be larger when ex ante uncertainty is higher.

The results are in Panel B of Table 4. Consistent with the conjecture, the treatment of higher credit limits is not statistically different between high- and low-uncertainty provinces, while expectation changes are only significant for provinces in the upper two uncertainty terciles. The differential effects of the two IVs permit the identification of $\Delta Limit_i$ and $\Delta\mathbb{E}[Y_i]$. Columns (9) – (12) give the estimates of specification $(10')$. The results are similar to those in Panel A.

In summary, the spending responses and survey results suggest that after receiving credit limit expansions, consumers update their expectations about their personal income, and higher income expectations induce them to increase spending in addition to relaxed borrowing constraints.

**D. Heterogeneity of MPB and MPCL**

This section examines how the income-inference channel affects MPCL across consumer subgroups. I split the sample by consumer characteristics to analyze variations in income expectations and MPCL. However, since these splits correlate across characteristics, the results should be considered suggestive. I focus on 12-month MPB for greater statistical power after segmentation.[9]

First, I analyze how limit-extension impact spending across liquidity levels. Studies show that credit supply significantly affects even consumers with high liquidity buffers (D'Acunto et al., 2020; Aydin, 2022), challenging the standard buffer-stock model. I test whether liquidity levels influence responses to limit extensions, with and without controlling for expectation changes.[10]

Liquidity constraints are based on the utilization ratio, defined as the ratio of unsecured debt over total credit limit, where higher values indicate greater constraints. In Table 5, columns (1) – (6), show that more constrained consumers exhibit stronger income expectation responses, possibly due to heightened attention to bank notifications. However, despite larger expectation changes, their MPC out of income expectations is lower (columns 3 and 6), possibly due to financial constraints impeding the ability to consume future income.

MPB from T1 captures the unconditional effect of each additional CNY in credit. MPB is 0.246 for the more constrained group and 0.099 for the less constrained group (columns 2 and 5). When accounting for expectation changes (columns 3 and 6), MPB declines to 0.163 and 0.033, respectively. Note that the estimates unconditional on $\Delta E[Y]$

[9] The results for 12-month spending responses are in the online appendix Table A.5.
[10] Table A.6 in the online appendix shows that the experiment had insignificantly different effects on limit changes for the different treatments and different characteristics groups.

for T1 give the total MPB and the coefficients in front of $\Delta L$ conditional on $\Delta E[Y]$ gives the MPB controlling for expectation changes. Therefore, one minus the ratio of the two estimates give the weight of income-inference in total MPB. This implies that the income-inference channel explains 67% of MPB for the more constrained group but only 33% for the less constrained group. This result highlights that belief-based responses play a relatively larger role for less constrained consumers. In these cases, the effect of credit supply operates less through liquidity and more through subjective expectations, helping to explain why unconstrained households still respond strongly to limit increases.

I extend this analysis to uncertainty measures, as learning should be greater for those with more uncertain income expectations. To test this, I split the sample by subjective pre-experiment macroeconomic uncertainty. Columns (7) and (10) show that learning from limit extensions is more than twice as strong for high-uncertainty consumers. Consequently, MPB weakens more after controlling for income expectations in the high-uncertainty group compared to the low-uncertainty group.

Next, I examine heterogeneity by prior experience, which is defined as the number of bank-initiated limit increases before the experiment. I classify participants with fewer past limit extensions as less experienced. Columns (13) – (18) show that less experienced consumers adjust their expectations more than experienced ones. A potential reason is that less experienced consumers also have higher prior uncertainty, leading to stronger reactions to signals. Another possibility is that individuals tend to overreact to noisier, more volatile signals when forming subjective beliefs (Ba et al., 2024; Augenblick et al., 2025). Less experienced consumers, being less calibrated in linking limit increases to future income, may perceive extensions as noisier and overreact accordingly.

### E. Types of Information Inferred

The findings indicate that consumers make inference from credit limit extensions, and macroeconomic expectation is an important component. However, this finding does not conclude that macroeconomic fluctuations are the only information consumers learn about. For example, banks that are equipped with rich cross-sectional data and advanced statistical tools might be able to extract high-dimensional information about the consumers including life-cycle movements and so on (Brunnermeier et al., 2024). Otherwise, individuals might have behavioral biases and associate a fraction of limit extension with income changes as a rule-of-thumb. In this section, I provide further evidence about if macroeconomic movements are the only types of information consumers learn from credit supply.

I decompose changes in income expectations into a macro component, $\Delta\mathbb{E}[Y_i - M]$, and a residual component, $\Delta\mathbb{E}[Y_i - O]$. To do so, I first measure subjective income sensitivity to macroeconomic movements with the following two questions:

> 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?

Let the answers to these two questions be $S_{G,i}$ and $S_{U,i}$. These two variables measure subjective beliefs about how movements of GDP and unemployment affect individual incomes. Defining expected changes in GDP and unemployment as $\Delta\mathbb{E}[GDP_i]$ and $\Delta\mathbb{E}[UR_i]$, then $\Delta\mathbb{E}[Y_i - M]$ is derived as

$$\Delta\mathbb{E}[Y_i - M] = \Delta\mathbb{E}[GDP_i] \times S_{G,i}/0.05 - \Delta\mathbb{E}[UR_i] \times S_{U,i}/0.1. \tag{10}$$

$\Delta\mathbb{E}[Y_i - M]$ gives the changes in income expectation due to changes in macroeconomic factors. $\Delta\mathbb{E}[Y_i - O]$ is then derived as $\Delta\mathbb{E}[Y_i] - \Delta\mathbb{E}[Y_i - M]$.[11]

Columns (1) and (2) of Table 6 show that there is a strong positive relationship between $\Delta\mathbb{E}[Y_i - M]$ and $\Delta\mathbb{E}[Y_i]$. However, this relationship is far from being perfect. The $R^2$ is 0.255 from a univariate regression and 0.274 if residualized by demographics. Therefore, macroeconomic fluctuation roughly explains 26% of the change in expectations.

While macroeconomic expectations only accounts for 26% of the variations of total income expectations, it's possible that the residuals are just measurement errors that do not affect choices. To test this conjecture, I re-estimate specification (8′) and (9′) while having $\Delta Limit_i$, $\Delta\mathbb{E}[Y_i - M]$, and $\Delta\mathbb{E}[Y_i - O]$ on the right-hand side. This requires another

[11] One caveat is that $\Delta E[Y_i - M]$ measures macroeconomy-driven expectation changes only through GDP growth and unemployment rate. There might be other macroeconomic sources that affect subjective income expectations, including inflation, industrial production, etc.

IV that affect $\Delta\mathbb{E}[Y_i - O]$ and $\Delta\mathbb{E}[Y_i - M]$ differentially than ex-ante income volatility. I use macroeconomic uncertainty as the third IV. Specifically, I let $MU_i = 1$ if the consumers answered *not confident* to the following question:

> How confident are you in evaluating whether the overall economy is functioning effectively at the moment?

Presumably, consumers should update beliefs about the macroeconomic growth more if they are less confident about evaluating the aggregate economy.

The first-stage results are in columns (3) and (4) of Table 6. As expected, treated consumers with higher macroeconomic uncertainty changes $\Delta\mathbb{E}[Y_i - M]$ more than $\Delta\mathbb{E}[Y_i - O]$. Columns (5) – (8) give the second-stage results. While the estimates of MPB and MPCL are similar when controlling for $\Delta\mathbb{E}[Y_i]$ alone or $\Delta\mathbb{E}[Y_i - M]$ and $\Delta\mathbb{E}[Y_i - O]$ together, MPC out of $\Delta\mathbb{E}[Y_i - M]$ and $\Delta\mathbb{E}[Y_i - O]$ are in general both significantly positive.

The results suggest that while macroeconomic movement is a key driver of income expectations, it is not the sole factor. Banks may have access to advanced information beyond macroeconomic trends, particularly through rich cross-sectional data. Even without directly forecasting income, banks can infer patterns using statistical analysis. For instance, they may extend credit limits based on life-cycle consumption trends, which, given the cointegration of consumption and income, can signal income changes. Additionally, behavioral biases, such as motivated beliefs or over-optimism, may lead consumers to attribute positive news to their earning potential, even without a direct link between credit limit increases and income growth.

### F. Subjective Sensitivity of Income Expectations to 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 questions 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.

> Suppose 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.

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, $\lambda$, as

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

Mapped to (2), $\lambda = g'(L)$ is the subjective 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 5 plots the distribution of $\lambda$. 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. Average $\lambda$ is 0.86 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 0.86-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 0.86. Given that the posterior income expectation is 0.35, the average consumer's Kalman gain of the learning process is around 0.41.

Equation (8) shows that change in income expectations after receiving limit extensions should move positively with the signal sensitivity of income growth $\lambda$. In Panel B of Figure 5, I split the sample by $\lambda$ into four groups and then plot the average change in income expectations by $\lambda$-groups within each treatment group. Participants in T1 have a larger change in income expectations after the experiment, and this change increases with $\lambda$. Income changes are also near zero, especially when $\lambda$ is close to zero. At the same time, there is no apparent association between $\lambda$ and changes in income expectation for the other two groups.

In sum, Figure 5 indicates consumers believe that limit extensions are positively associated with banks' beliefs about future income growth. In turn, consumers with uncertain income beliefs adjust their income expectations upwards in response to a positive credit supply shock.

### G. 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 6 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, industry fixed effects, and city fixed effects. In all four panels, the *x*-axis are the limit changes as proposed by the bank before the 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. The similar association of realized income between the two groups indicates limit extensions do no increase total income. Panels A and B indicate that when banks actively offer increased credit limits to consumers, they are, to some degrees, 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.[12]

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

[12] Note that this does not necessarily imply that banks at this time achieve better predictability of consumer future income changes. It just suggests that consumers are not fully aware of the information about income changes contained in credit supply decisions. In Table A.7 of online appendix section III, I show that prior income expectations have a much higher predictive ability of future income changes than limit changes.

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. However, forecast errors no longer co-moves with credit supply for T1 after the credit supply event.

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 the values implied by the credit decisions. The adjusted expectations affect spending, even if limit extensions do not increase realized income.[13]

### H. Discussion

The results show that credit supply shocks significantly impact income expectations. This section explores how beliefs respond to credit limit extensions. A caveat is that, with a one-time cross-sectional data, assessing the degree of reaction is hard. Therefore, I view this exploration as more agnostic.

Note that Figure 6 shows that the limit extensions do not cause higher income. Therefore, expectation changes seem to come from an information channel. To assess whether belief updating is consistent with Bayesian learning, I calibrate the implied parameters from the observed effects of credit limit changes on income expectations. Survey responses suggest an average signal sensitivity $g' \approx 0.86$, which implies $(1 + \theta)K = 0.41$.[14] This number could be consistent with Bayesian learning, i.e., $\theta = 0$ and $K \in (0,1)$.

However, if consumers were rational learners ($\theta = 0$), a $K \approx 0.5$ implies that credit supply must be nearly as predictive of future income as their prior expectations. To assess this, I compare $R^2$s from predicting future income using credit supply versus prior

[13] Online appendix Figure A.4 and Figure A.5 show the plot for log changes and for macroeconomic expectations.

[14] Online appendix III estimates the relationship between limit changes and income changes using data from 2015 to 2024 and finds an objective measure of $g' = 0.68$.

expectations (Table A.7, online appendix III). Assuming independent noise in these signals, the results suggest a rational Kalman gain of $K = 0.22$. This leads to $\theta = 0.90$, indicating a 90% overreaction to signal surprises relative to Bayesian learning.[15] The estimate of $\theta$ is broadly in the range of estimates in Bordalo et al. (2019), D'Acunto et al. (2024), and Chodorow-Reich et al. (2024). Relatedly, the findings in Table 5 suggest that overreaction may be tempered by experience: consumers who have seen more credit supply decisions in the past may learn to better calibrate their response to the signal.

This finding has implications for household credit cycles. Recent research shows that expansionary credit conditions often precede economic deterioration rather than improvement (Lopez-Salido et al., 2017; Mian & Sufi, 2017).[16] Belief overreaction to credit supply may explain this discrepancy. When lending standards loosen during economic booms, over-extrapolative consumers with incomplete information get too optimistic about credit expansions as signals of sustained future income growth. This over-extrapolation amplifies the link between credit supply and expected income. When misbeliefs are corrected, consumption declines, creating boom-bust cycles.[17]

## I. Limit Extensions and Labor Supply

Previous literature finds several channels through which more credit boosts income, including entrepreneurship, better job matching, and labor mobility (Herkenhoff et al., 2021; Sergeyev et al., 2023; He and Le Maire, 2023; Doornik et al., 2024). Table A.8 examines the impact of credit limit extensions on labor supply at the extensive margin using four proxies: job change, self-employment, relocation, and unemployment. Across all columns, no significant relationship suggests a lack of extensive-margin labor supply adjustments.[18]

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[15] See online appendix III for the calibration details.
[16] Figure A.6 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.
[17] See D'Acunto et al. (2024) about how over-extrapolation of income surprises can lead to aggregate boom-bust household credit cycles.
[18] The credit shock here may be too small to have a significant effect, as it represents only 10% of annual income for a sample including many creditworthy individuals, unlike the larger interventions mostly for constrained borrowers in other studies (e.g., Herkenhoff et al., 2021; He and Le Maire, 2023).

## 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. I find that consumers revise upwards beliefs about future personal income after credit extensions. Approximately 30% of MPCL can be attributed to shifts in income expectations. The findings are consistent with consumers being imperfectly-informed about future income and infer related information from 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 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.[19]

[19] In the online appendix, section VII, I use survey questions on SurveyMonkey to show that hypothetical limit extensions have similar effects on expectations over different components of budget constraints, implying 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

诚邀您参与填写居民信用卡使用问卷调查。7月12日前填写此问卷，可享20元红包！问卷填写预计需要5分钟。点击 参与活动 银行】

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

尊敬的客户，即日起您尾号4442的信用卡固定额度已调至96000元。点击 查看详情。祝您用卡愉快！ 银行】

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

尊敬的客户，即日起您尾号4442的信用卡固定额度已调至96000元。

此次信用额度的提升是基于一项提额活动。本次活动中，我们在一部分拥有良好还款记录的用户中，随机选取了包括您在内的一部分用户，并将其信用卡额度提高至特定金额。

点击 查看详情。祝您用卡愉快！ 银行】

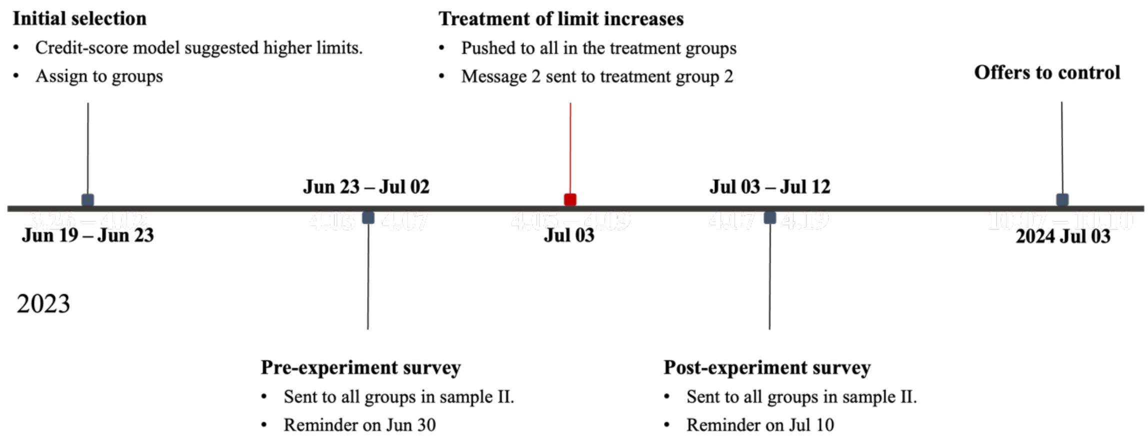
Dear customer, effective from today, the credit limit of your credit card ending in 4442 has been adjusted to 96,000 Yuan.

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.

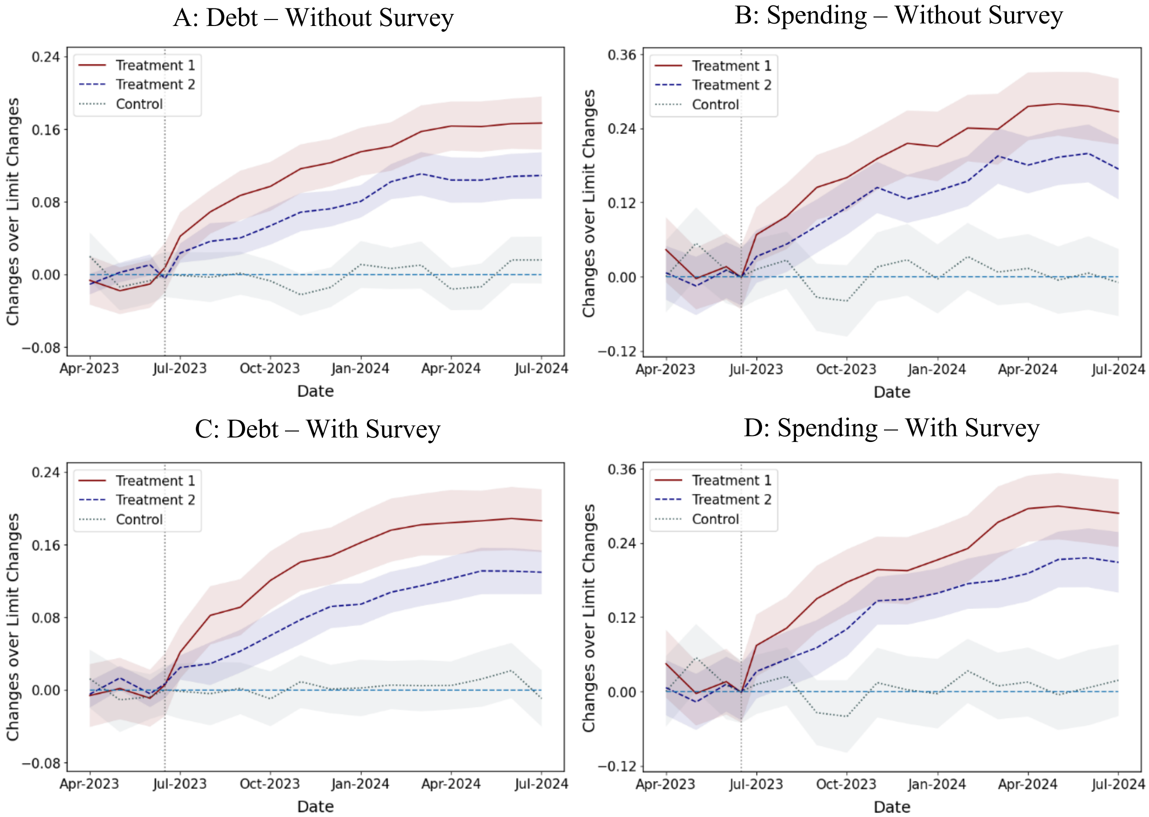
Figure 2: Timeline of the Experiments and Group Assignment




| Sample | Surveys | Groups | N Subjects Selected | N Subjects Collected | N Subjects Final |
|---|---|---|---|---|---|
| I | No | Control | 2700 | 2700 | 2534 |
| | | Treatment 1 | 3200 | 3200 | 3026 |
| | | Treatment 2 | 1600 | 1600 | 1532 |
| II | Yes | Control | 5000 | 3440 | 2527 |
| | | Treatment 1 | 6000 | 4122 | 3029 |
| | | Treatment 2 | 3000 | 2050 | 1539 |

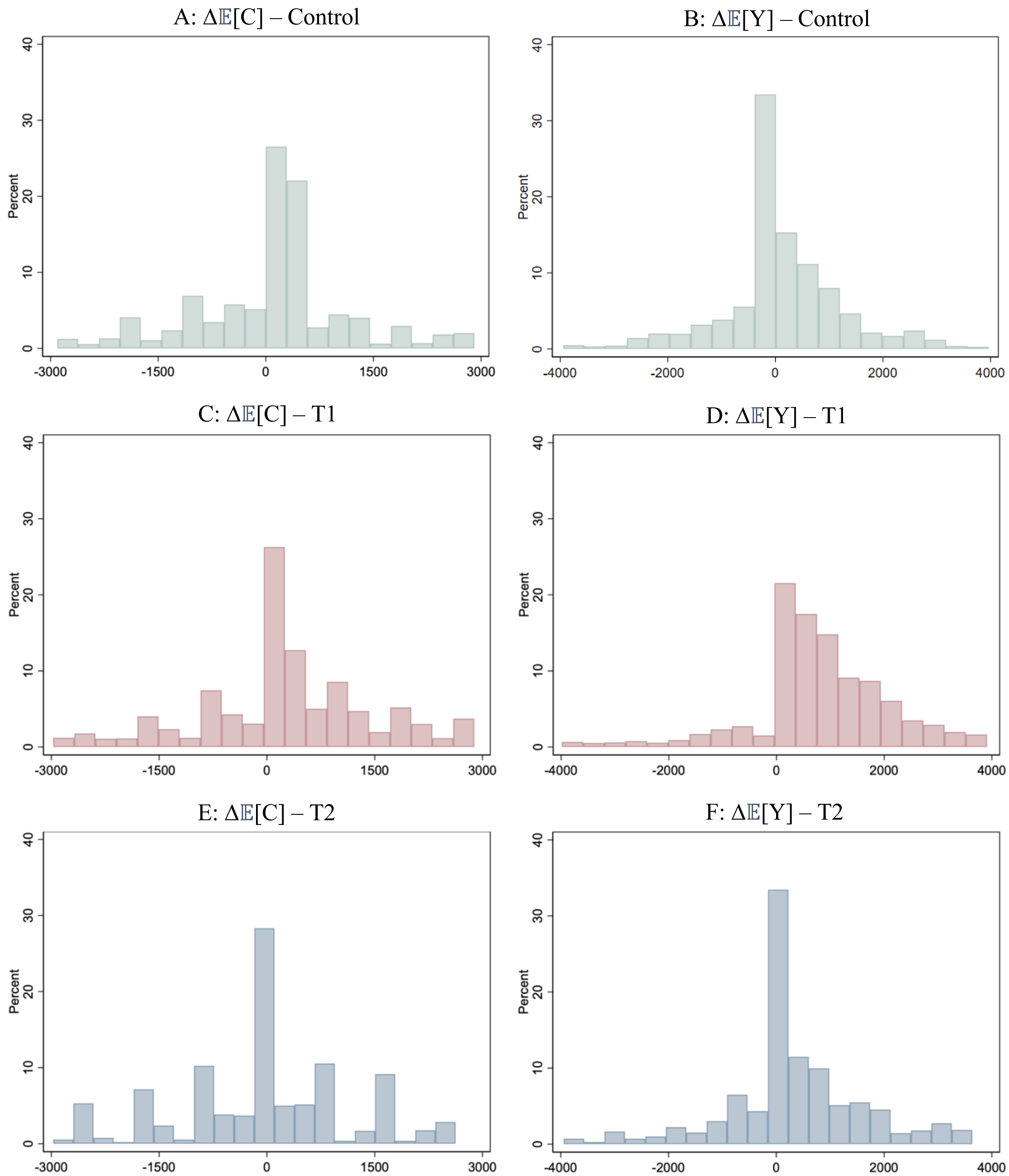
Note: this figure plots the experimental design. The top panel gives the timeline, and the bottom panel gives the assignment of the groups and the number of subjects at each stage of the experiment.

Figure 3. Evolution of Debt and Spending



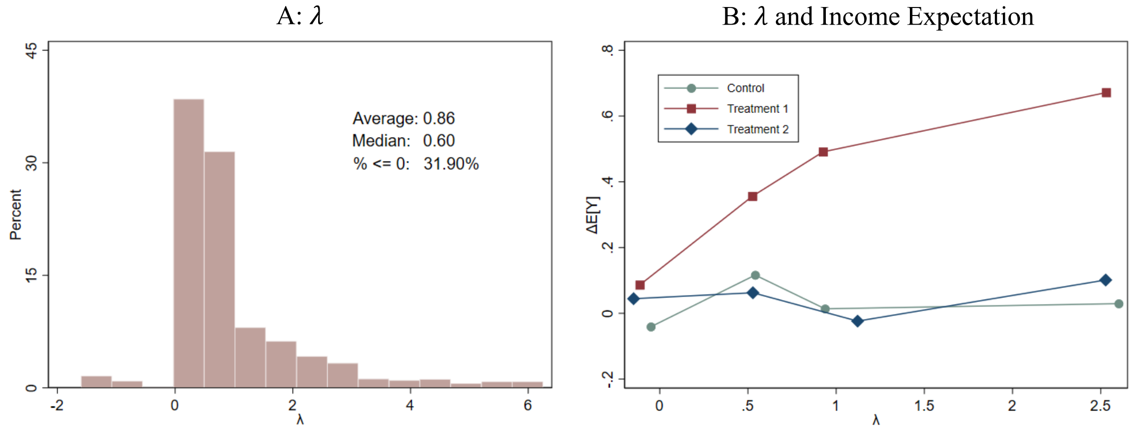

Note: This figure plots the evolution of total unsecured debt and spending on both sides of the experimental period, residualized by date fixed effects. Panels A and B are based on Sample I and panels C and D are based on those who completed the surveys in Sample II. In each panel, the x-axis gives the 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



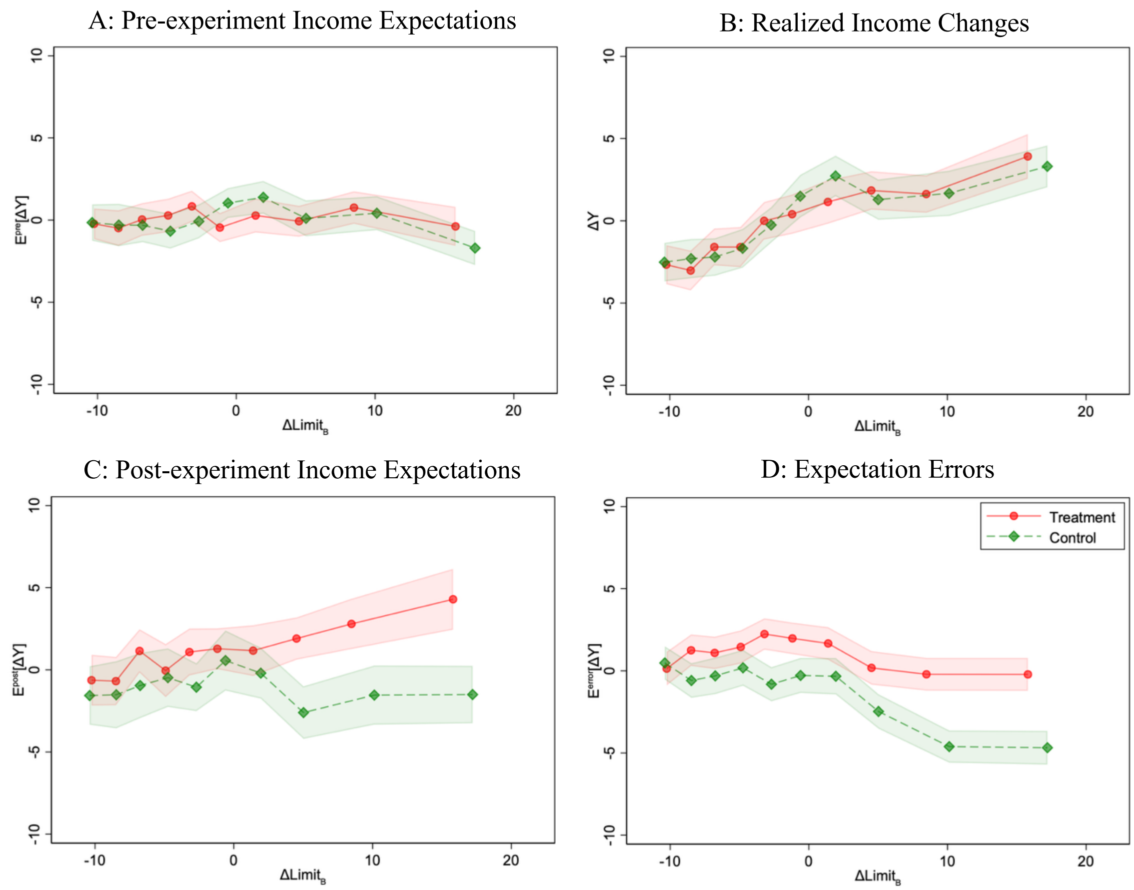

Note: This figure plots the changes in consumption expectations (left column) and income expectations (right column) using the sample completing both surveys (sample II). Panels A and B give the control group; panels C and D give the treatment group 1; panels E and F give the treatment group 2. The illustration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

Figure 5. 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, $\lambda$. 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 $\lambda$ groups. Splits of $\lambda$ groups are conditional on treatment groups.

Figure 6. 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, industry fixed effects, and city fixed effects. Units are in thousand CNY.

## Table 1: Summary Statistics

| | | Age | Female | College | Income | Spending | Debt | Debt\|Debt>0 | Limit | ΔLimit | Liq. Wealth | Tot. Wealth | $\mathbb{E}[\Delta Y\%]$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | A. Without Surveys | | | | | | | |
| Control | Mean | 39.41 | 0.46 | 0.48 | 12.08 | 7.80 | 6.94 | 16.31 | 91.57 | 13.59 | | | |
| | SD | 10.57 | 0.50 | 0.50 | 9.78 | 3.08 | 11.57 | 12.72 | 100.05 | 9.87 | | | |
| | N | 2534 | 2534 | 2534 | 1000 | 1198 | 2534 | 1078 | 2534 | 2534 | | | |
| T1 | Mean | 39.33 | 0.47 | 0.49 | 12.21 | 7.94 | 6.69 | 16.77 | 88.68 | 13.33 | | | |
| | SD | 9.94 | 0.50 | 0.50 | 8.39 | 3.17 | 10.08 | 9.26 | 98.16 | 9.14 | | | |
| | N | 3026 | 3026 | 3026 | 1244 | 1450 | 3026 | 1207 | 3026 | 3026 | | | |
| T2 | Mean | 39.15 | 0.44 | 0.48 | 12.22 | 7.79 | 6.67 | 16.44 | 94.85 | 13.78 | | | |
| | SD | 9.96 | 0.50 | 0.50 | 9.85 | 3.23 | 12.04 | 14.02 | 118.06 | 9.78 | | | |
| | N | 1532 | 1532 | 1532 | 592 | 690 | 1532 | 611 | 1532 | 1532 | | | |
| | *p*-values | 0.73 | 0.31 | 0.42 | 0.94 | 0.39 | 0.65 | 0.63 | 0.16 | 0.29 | | | |
| | | | | | | B. With Surveys | | | | | | | |
| Control | Mean | 38.73 | 0.43 | 0.51 | 10.63 | 6.84 | 7.23 | 17.45 | 86.50 | 13.05 | 0.88 | 4.70 | 4.23 |
| | SD | 10.65 | 0.50 | 0.50 | 9.02 | 1.94 | 11.38 | 15.02 | 100.92 | 9.81 | 1.38 | 5.55 | 17.81 |
| | N | 2527 | 2527 | 2527 | 1023 | 1186 | 2527 | 1096 | 2527 | 2527 | 1023 | 1023 | 1023 |
| T1 | Mean | 38.35 | 0.42 | 0.49 | 11.19 | 6.82 | 7.42 | 18.18 | 84.26 | 12.74 | 0.89 | 4.72 | 4.26 |
| | SD | 10.07 | 0.49 | 0.50 | 7.58 | 2.10 | 10.67 | 9.49 | 90.00 | 8.99 | 1.35 | 6.42 | 15.03 |
| | N | 3029 | 3029 | 3029 | 1203 | 1449 | 3029 | 1241 | 3029 | 3029 | 1203 | 1203 | 1203 |
| T2 | Mean | 38.72 | 0.43 | 0.50 | 10.95 | 6.81 | 7.00 | 17.44 | 89.59 | 13.37 | 0.84 | 4.48 | 4.14 |
| | SD | 10.32 | 0.50 | 0.50 | 9.60 | 2.10 | 11.97 | 16.75 | 115.71 | 9.82 | 1.29 | 5.33 | 14.23 |
| | N | 1539 | 1539 | 1539 | 590 | 686 | 1539 | 654 | 1539 | 1539 | 590 | 590 | 590 |
| | *p*-values | 0.32 | 0.82 | 0.41 | 0.31 | 0.96 | 0.48 | 0.34 | 0.23 | 0.10 | 0.70 | 0.69 | 0.99 |

Note: This table gives the summary statistics. Panel A and Panel B respectively summarize Sample I and Sample II. Liq. Wealth and Tot. Wealth are respectively liquidity wealth and total wealth from surveys scaled by annualized income. $\mathbb{E}[\Delta Y\%]$ is expected income growth from pre-experiment surveys. The units of the variables excluding Age, Female, and College are in thousands of CNY. *p*-values give the joint test that the averages of the two treatment samples are zero. All variables are winsorized at the 1% - 99% level.

Table 2: Borrowing and Spending Responses

| | A: Without Survey | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | OLS | | IV | | | OLS | | IV | |
| | ΔL | ΔB-6M | ΔB-12M | ΔB-6M | ΔB-12M | ΔL | C-6M | C-12M | C-6M | C-12M |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| T1 | 13.333*** | 1.546*** | 2.018*** | | | 13.310*** | 2.381*** | 3.305*** | | |
| | (0.460) | (0.492) | (0.459) | | | (0.503) | (0.291) | (0.473) | | |
| T2 | 13.782*** | 0.993*** | 1.390*** | | | 13.710*** | 1.759*** | 2.372*** | | |
| | (0.598) | (0.351) | (0.330) | | | (0.639) | (0.334) | (0.530) | | |
| ΔL × T1 | | | | 0.116*** | 0.151*** | | | | 0.179*** | 0.248*** |
| | | | | (0.039) | (0.038) | | | | (0.022) | (0.036) |
| ΔL × T2 | | | | 0.072*** | 0.101*** | | | | 0.128*** | 0.173*** |
| | | | | (0.027) | (0.027) | | | | (0.023) | (0.037) |
| 1st-stage *F* | | | | 2632.44 | 2632.44 | | | | 1223.86 | 1223.86 |
| N | 7092 | 7092 | 7092 | 7092 | 7092 | 3338 | 3338 | 3338 | 3338 | 3338 |
| | B: With Survey | | | | | | | | | |
| | | OLS | | IV | | | OLS | | IV | |
| | ΔL | ΔB-6M | ΔB-12M | ΔB-6M | ΔB-12M | ΔL | C-6M | C-12M | C-6M | C-12M |
| | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) | (19) | (20) |
| T1 | 12.742*** | 1.549*** | 2.112*** | | | 12.609*** | 2.392*** | 3.272*** | | |
| | (0.315) | (0.220) | (0.223) | | | (0.322) | (0.223) | (0.399) | | |
| T2 | 13.371*** | 1.071*** | 1.435*** | | | 13.139*** | 1.660*** | 2.370*** | | |
| | (0.548) | (0.235) | (0.216) | | | (0.556) | (0.307) | (0.433) | | |
| ΔL × T1 | | | | 0.122*** | 0.166*** | | | | 0.190*** | 0.259*** |
| | | | | (0.018) | (0.019) | | | | (0.018) | (0.030) |
| ΔL × T2 | | | | 0.080*** | 0.107*** | | | | 0.126*** | 0.180*** |
| | | | | (0.018) | (0.017) | | | | (0.022) | (0.032) |
| 1st-stage *F* | | | | 2466.56 | 2466.56 | | | | 1159.99 | 1159.99 |
| N | 7095 | 7095 | 7095 | 7095 | 7095 | 3321 | 3321 | 3321 | 3321 | 3321 |

Note: This table assesses the effects of credit extension on non-durable debt and spending. Panel A focuses on Sample I and Panel B focuses on Sample II. T1 and T2 are respectively the two treatment group identifiers. ΔL is the changes in credit limit. All variables are in thousand CNY. All variables are winsorized at the 1% - 99% level. Standard errors clustered at industry×city level are in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 3: The Effects of Treatments on Beliefs

| | ΔE[C] | ΔE[Y] | ΔE[W] | ΔE[Hrs] | E[u] |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ΔL × T1 | 0.286** | 0.349*** | 0.001 | 0.000 | -0.222 |
| | (0.117) | (0.045) | (0.001) | (0.000) | (0.151) |
| ΔL × T2 | -0.045 | 0.023 | -0.001 | 0.000 | -0.052 |
| | (0.110) | (0.058) | (0.001) | (0.000) | (0.193) |
| | E [d] | ΔE[L] -- 1Y | ΔE[L] -- 5Y | ΔE[GDP] | ΔE[UR] |
| | (6) | (7) | (8) | (9) | (10) |
| ΔL × T1 | -0.001 | 0.748 | 0.376 | 0.310*** | -1.494*** |
| | (0.151) | (0.887) | (1.314) | (0.056) | (0.351) |
| ΔL × T2 | -0.005 | 1.012 | 1.105 | 0.044 | -0.282 |
| | (0.193) | (0.953) | (1.496) | (0.032) | (0.366) |
| 1st-stage *F* | | | 2466.56 | | |
| N | 7095 | 7095 | 7095 | 7095 | 7095 |

Note: ΔE[C], ΔE[Y], ΔE[W], ΔE[Hrs] 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. ΔE[L]-1Y and ΔE[L]-5Y are the expected growth rate of one-year and five-year credit limits. T1 and T2 are respectively the two treatment group identifiers. ΔL is the changes in credit limit. All variables are winsorized at the 1% - 99% level. Standard errors clustered at industry×city level are in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 4: The Effects of Limit Changes on Borrowing and Spending

| | A: Treatment as IV | | | | | |
|---|---|---|---|---|---|---|
| | $\Delta\mathbb{E}[Y]$ | $\Delta L$ | $\Delta$B-6M | $\Delta$B-12M | C-6M | C-12M |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| T1 | 4.450*** | 12.742*** | | | | |
| | (0.558) | (0.315) | | | | |
| T2 | 0.302 | 13.371*** | | | | |
| | (0.780) | (0.548) | | | | |
| $\Delta L$ | | | 0.077*** | 0.103*** | 0.123*** | 0.177*** |
| | | | (0.022) | (0.023) | (0.018) | (0.030) |
| $\Delta\mathbb{E}[Y]$ | | | 0.127* | 0.179** | 0.196*** | 0.245** |
| | | | (0.070) | (0.074) | (0.045) | (0.098) |
| 1st-stage $F$ | | | 67.56 | 67.56 | 29.23 | 29.23 |
| N | 7095 | 7095 | 7095 | 7095 | 3321 | 3321 |
| | B: Interaction as IV | | | | | |
| | $\Delta\mathbb{E}[Y]$ | $\Delta L$ | $\Delta$B-6M | $\Delta$B-12M | C-6M | C-12M |
| | (7) | (8) | (9) | (10) | (11) | (12) |
| T1 | 0.030 | 12.162*** | | | | |
| | (0.839) | (0.436) | | | | |
| T1 × P | 6.539*** | 0.796 | | | | |
| | (0.920) | (0.544) | | | | |
| $\Delta L$ | | | 0.079*** | 0.111*** | 0.122*** | 0.182*** |
| | | | (0.027) | (0.025) | (0.029) | (0.035) |
| $\Delta\mathbb{E}[Y]$ | | | 0.118** | 0.151** | 0.198*** | 0.245*** |
| | | | (0.056) | (0.058) | (0.075) | (0.087) |
| 1st-stage $F$ | | | 44.67 | 44.67 | 16.84 | 16.84 |
| N | 5556 | 5556 | 5556 | 5556 | 2635 | 2635 |

Note: This table reports the effects of limit extension and income expectation changes on spending and borrowing. Panel A reports results for specification (8) and (9). Panel B exludes T2, and reports reults for specification (9') and (10'). $\Delta L$ is the realized change in credit limit, $\Delta\mathbb{E}[Y]$ is the changes in income expectations. P is a dummy variable that equals one if the consumers are in a province with average income volatility in the top two terciles. All variables are winsorized at the 1% and 99% level. Standard errors clustered at industry×city level are in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 5: Heterogeneity in Debt Responses

| | More Constrained | | | Less Constrained | | |
|---|---|---|---|---|---|---|
| | ΔE[Y] | ΔB-12M | ΔB-12M | ΔE[Y] | ΔB-12M | ΔB-12M |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ΔL × T1 | 0.440*** | 0.246*** | | 0.276*** | 0.099*** | |
| | (0.050) | (0.026) | | (0.059) | (0.018) | |
| ΔL × T2 | 0.018 | 0.167*** | | 0.028 | 0.040** | |
| | (0.070) | (0.023) | | (0.064) | (0.018) | |
| ΔL | | | 0.163*** | | | 0.033 |
| | | | (0.032) | | | (0.024) |
| ΔE[Y] | | | 0.187** | | | 0.238** |
| | | | (0.085) | | | (0.093) |
| Weight of ΔE[Y] | | | 33.74% | | | 66.67% |
| 1st-stage *F* | | 1315.12 | 62.27 | | 1151.35 | 17.56 |
| N | 3543 | 3543 | 3543 | 3552 | 3552 | 3552 |
| | High Uncertainty | | | Low Uncertainty | | |
| | ΔE[Y] | ΔB-12M | ΔB-12M | ΔE[Y] | ΔB-12M | ΔB-12M |
| | (7) | (8) | (9) | (10) | (11) | (12) |
| ΔL × T1 | 0.483*** | 0.198*** | | 0.218*** | 0.135*** | |
| | (0.052) | (0.026) | | (0.057) | (0.019) | |
| ΔL × T2 | 0.060 | 0.122*** | | -0.017 | 0.091*** | |
| | (0.067) | (0.020) | | (0.065) | (0.022) | |
| ΔL | | | 0.112*** | | | 0.094*** |
| | | | (0.028) | | | (0.024) |
| ΔE[Y] | | | 0.178** | | | 0.185 |
| | | | (0.071) | | | (0.122) |
| Weight of ΔE[Y] | | | 43.43% | | | 37.37% |
| 1st-stage *F* | | 1309.12 | 60.02 | | 1161.02 | 16.54 |
| N | 3597 | 3597 | 3597 | 3498 | 3498 | 3498 |
| | Less Experience | | | More Experience | | |
| | ΔE[Y] | ΔB-12M | ΔB-12M | ΔE[Y] | ΔB-12M | ΔB-12M |
| | (13) | (14) | (15) | (16) | (17) | (18) |
| ΔL × T1 | 0.434*** | 0.207*** | | 0.264*** | 0.125*** | |
| | (0.059) | (0.027) | | (0.049) | (0.018) | |
| ΔL × T2 | 0.053 | 0.128*** | | -0.008 | 0.087*** | |
| | (0.074) | (0.025) | | (0.069) | (0.017) | |
| ΔL | | | 0.117*** | | | 0.088*** |
| | | | (0.035) | | | (0.020) |
| ΔE[Y] | | | 0.207** | | | 0.139 |
| | | | (0.094) | | | (0.094) |
| Weight of ΔE[Y] | | | 43.48% | | | 29.60% |
| 1st-stage *F* | | 1272.08 | 43.39 | | 1192.01 | 24.83 |
| N | 3611 | 3611 | 3611 | 3484 | 3484 | 3484 |

Note: This table reports the changes in subjective income expectation around the experiment. The left-hand side variables are ΔB - 12M. Constrained is based on utilization ratio, defined as if the ratio of unsecured debt balance to total credit limit is below the median. Uncertainty is subjective pre-experiment macroeconomic uncertainty. Experience is the number of bank-initiated credit limit increases. Sample split are based on the pre-experiment sample median. All variabels are winsorized at the 1% and 99% level. Standard errors clustered at industry×city level are in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 6: Decomposing Expectation Changes

| | $\Delta\mathbb{E}$[Y] | $\Delta\mathbb{E}$[Y] | $\Delta\mathbb{E}$[Y-M] | $\Delta\mathbb{E}$[Y-O] |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\Delta\mathbb{E}$[Y-M] | 1.592*** | 1.861*** | | |
| | (0.068) | (0.056) | | |
| T1 | | | -1.563*** | 4.237*** |
| | | | (0.277) | (0.755) |
| T1 × P | | | 1.846*** | 3.686*** |
| | | | (0.293) | (0.693) |
| T1 × MU | | | 3.211*** | -8.747*** |
| | | | (0.240) | (0.720) |
| Residualized | No | Yes | | |
| $R^2$ | 0.255 | 0.274 | | |
| N | 5556 | 5556 | 5556 | 5556 |
| | $\Delta$B - 6M | $\Delta$B - 12M | C - 6M | C - 12M |
| | (5) | (6) | (7) | (8) |
| $\Delta$Limit | 0.080*** | 0.112*** | 0.123*** | 0.181*** |
| | (0.027) | (0.026) | (0.027) | (0.032) |
| $\Delta\mathbb{E}$[Y-M] | 0.185 | 0.261** | 0.215* | 0.281** |
| | (0.125) | (0.120) | (0.127) | (0.136) |
| $\Delta\mathbb{E}$[Y-O] | 0.103** | 0.126** | 0.205*** | 0.267*** |
| | (0.048) | (0.051) | (0.063) | (0.076) |
| 1st-stage $F$ | 30.75 | 30.75 | 12.74 | 12.74 |
| N | 5556 | 5556 | 2635 | 2635 |

Note: $\Delta\mathbb{E}$[Y] and $\Delta\mathbb{E}$[Y-M] are respectively the changes in income expectations, changes in income expectations driven by macroeconomic expectations. $\Delta\mathbb{E}$[Y-O] is the difference between $\Delta\mathbb{E}$[Y] and $\Delta\mathbb{E}$[Y-M]. P is a dummy variable that equals one if the consumers are in a province with average income volatility in the top two terciles. MU is a dummy variable that equals one if the consumers answered "not confident" to the question eliciting their confidence in evaluating the macroeconomy. All variables are winsorized at the 1% and 99% level. Standard errors clustered at industry×city level are in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.