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Learning in the Limit: Income Inference from Credit Extensions

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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.

CREDIT LIMITS ARE CENTRAL IN household consumption-savings decisions because they determine how much consumers can borrow to smooth consumption. As predicted by the workhorse economic models, for example, the buffer stock models, except for those households 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. Moreover, even for consumers far from being borrowing-constrained, credit limit extensions induce meaningful increases in total

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consumption.[1] Hence, the microlevel mechanisms through 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 impacting expectations.

Exploring how credit supply affects consumer expectations is challenging, as changes in beliefs surrounding real-world credit supply change must be identified. To address this difficulty, I collaborated with a large commercial bank in China to examine how consumers modify their expectations in response to credit expansion. This methodology combines 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 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 10 days before and after the experiments to study the effects of a limit increase on beliefs. The survey aimed to elicit beliefs about participants' future perspectives. It mainly focused on expectations about different components of consumer budget constraints (e.g., consumption, savings, income, and delinquency probability) and about future macroeconomic conditions.

I begin the analysis by studying the responses of unsecured debt and spending to credit limit extensions. I find a large consumption response to credit limit extensions. Specifically, each 1 Chinese yuan (CNY) increase in credit limit raises 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.[2]

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

[2] For example, estimated MPCL is between 0.2 and 0.6 in Agarwal et al. (2017) over 12 months, and 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).

Changes in expectations around increases in credit limits indicate how loosening borrowing constraints affects spending from consumers' perspective. Specifically, consumers update their income and spending expectations upward after receiving a higher credit limit. At the same time, 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 respects. 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 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. The results therefore point to 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 to capture variations in the degree of inference from limit extensions; the idea is that, at the extreme, if consumers believe the credit supply decision is purely random, they should not infer anything from it. To do so, 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 informed that the limit increase was sent to a randomly selected group of customers, conditional on having a good credit score. The latter message sought to weaken 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 about 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, and the consumption responses are approximately 30% smaller for T2 than for T1. Therefore, information about randomness in the credit expansion decision attenuates updates of income expectations and weakens the effects of limit extension on total consumption.

With information and credit 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, I find that income expectations have a significant effect on spending decisions. Each 1 CNY increase in income expectation over the next 12 months increases total spending by 0.22 CNY. Consequently, MPCL and MPB decrease by around 30% to 0.19 and 0.10, respectively, after controlling for expectations of future income changes. This

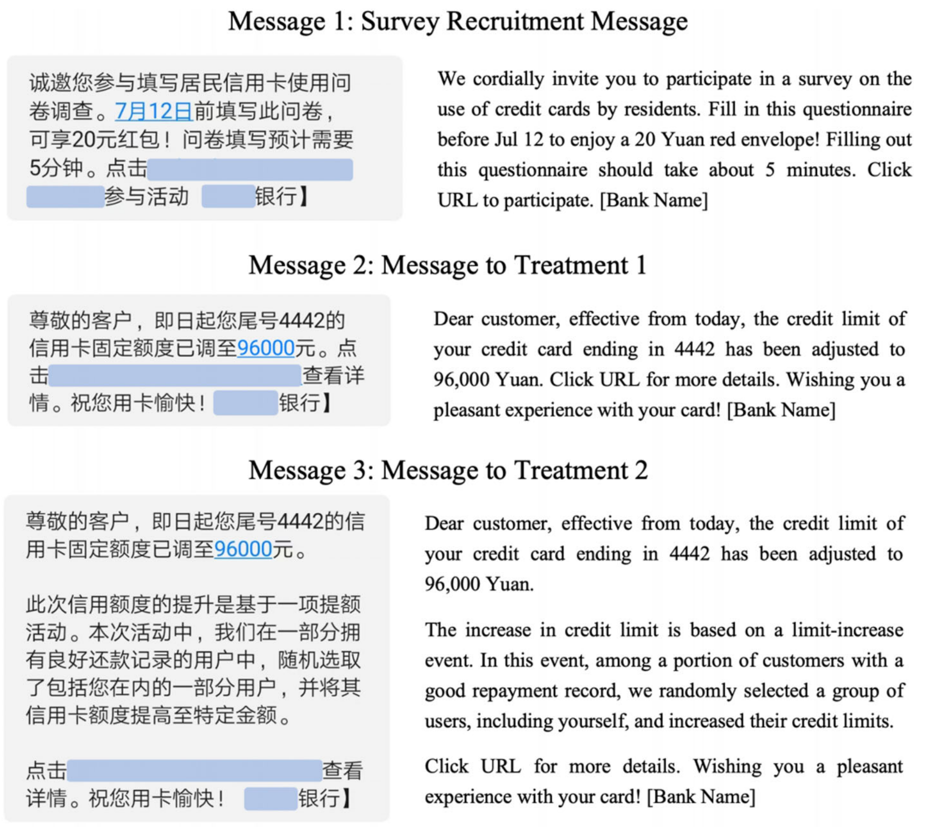

Figure 1. Messages sent to the participants. This figure shows the messages sent to participants. Message 1 is the survey recruitment message. Message 2 is the limit increase notice sent to Treatment group 1. Message 3 is the credit limit increase notice sent to Treatment group 2. In each panel, the left column shows the screenshot of the message, and the right column gives the English translation. (Color figure can be viewed at wileyonlinelibrary.com)

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 analysis, I examine whether macroeconomic expectations are likely to be 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 the expected macroeconomic outlook contribute to changes in income expectations, they do not fully account for the observed changes. 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, borrowers' financial sophistication can shape how they interpret and respond to credit supply decisions.

This study contributes largely to three strands of the 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, Notowidigdo, and Wang (2020), Aydin (2022), Chava et al. (2023), Cenzon (2024)). Recent work by Aydin (2022) provides a clean RCT-based estimate of the marginal propensity (MP) 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 helps fill 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, Phillips, and Cohen-Cole (2021)), reduce financial stress and boost productivity (Sergeyev, Lian, and Gorodnichenko (2023)), and enable mobility to higher-wage jobs (He and le Maire (2023); Van 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. (2019); Kuchler, Piazzesi, and Stroebel (2022)), and consumption (Rozsypal and Schlafmann (2023); Colarieti, Mei, and Stantcheva (2024); D'Acunto, Weber, and Yin (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 I provides a conceptual framework to illustrate how credit supply could affect income expectations and guide the empirical analysis. Section II describes the survey and experimental design, and provides a set of stylized facts about the setting. Section III documents the main results. Section IV concludes.

I. Conceptual Framework

A. Setup

This section presents a simple model to illustrate the main channels through which consumer spending changes 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 period t that has the form

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

where C_t is consumers' period-t consumption.[3] The discount rate for next-period utility is β. Consumers are endowed with an initial asset $A_0 = 0$ and receive income Y_t at the beginning of each period. The budget constraint t is given by

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

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 $A_1 < \psi$.[4]

B. Income Process

Income is stochastic and follows:

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

where $\alpha\, t$ 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

[3] The use of quadratic utility permits a closed-form solution given the linearity of the optimality conditions (see Jappelli and Pistaferri (2017) for details). However, it has the undesirable property that $u(C_t)$ is decreasing for large enough C_t. Therefore, an implicit assumption is that b has a value such that the range of C_t always gives $u' > 0$ and $u'' < 0$. Section V of the Internet Appendix validates the main propositions to calibrating a consumption-savings model with information content in credit supply. Internet Appendix may be found in the online version of this article.

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

persistence of the evolution of the states, and $\eta_t \sim N(0, \sigma_\eta^2)$ 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 estimated by banks that have rich cross-sectional information. At the beginning of t_1, consumers form priors of X_1 that follow $N(X^0, \sigma_0^2)$.

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 noisy signal $s = X_1 + \epsilon$, where $\epsilon \sim N(0, \sigma_\epsilon^2)$.

Denote by $C_1^*(L, s)$ the optimal consumption at t_1. Let $m(L, s) \equiv \psi + C_1^*(L, s)$ be the income threshold below which consumers will default and $D_1 \equiv \max\{0,\ C_1^* - Y_1\}$ be the level of consumer borrowing. Assume that consumers who default max out on their credit limit (I verify this assumption in Section II.E). Banks earn interest only on repayment-contingent debt and lose δL on default, where $1-\delta$ is the recovery rate. Thus, banks' per-account expected profit is

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

Banks compete over L taking r, δ, and consumer consumption rule $C_1^*(L, s)$ as given à la Bertrand.[5] In equilibrium, consumers choose the offer with the highest credit limit, so credit supply is set such that (1) is zero. To facilitate analysis below, let the equilibrium schedule be $L = f(s)$.

D. Learning from Credit Limit Changes

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

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

Here, I focus on a separating equilibrium where credit limits reveal banks' information. Thus, f is invertible. I examine 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.

[5] 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 bps. In addition, Matcham (2025) shows that banks in the credit card market engage mainly in risk-based limit adjustments instead of rate adjustments.

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

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

where $K = \sigma_0^2/(\sigma_0^2 + \sigma_\epsilon^2)$ is the Kalman gain of the learning process, with $\hat{\sigma}^2 = \sigma_\epsilon^2 K$ the posterior uncertainty , and $\hat{X}_1$ the posterior beliefs. 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 is not entirely known to consumers, credit supply that incorporates banks' beliefs about X_t would change consumers' beliefs. Parameter θ captures the deviation from Bayesian learning. When $\theta > 0$, consumers overreact to signal surprises. This condition can be microfounded with diagnostic 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 via backward induction. In t_3, consumers consume everything available. The optimal consumption in t_2 can be written as

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

In t_1, optimal consumption depends on whether consumers are borrowing-constrained and whether 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 $\mathbb{E}_1[C_2^*]$ otherwise. When $\mathbb{E}_1[C_2^*] > Y_1 + L$, consumers are borrowing-constrained, in which case, they will consume $Y_1 + L$ regardless of the default choices. Therefore, optimal consumption in t_1 is

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

In equation (4), $Y_1 - \mathbb{E}_1[C_2^*] = A_1$ given a slack borrowing constraint and no default. Therefore, the consumption rule in t_1 follows the classic Hall (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

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

where Φ is the cumulative distribution function (CDF) of a standard normal distribution.

E.2. Bank

Given consumers' optimal decision rules (3) to (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 $0 \leq \theta < \bar{\theta}$, $f' > 0$. In particular, under Bayesian learning, $\theta = 0$ and $f' > 0$.*

The proof of Lemma 1 is in the Internet 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 θ 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 nondefaulters chooses optimal consumption equaling $\mathbb{E}_1[C_2^*]$. Consequently, expected value of the optimal consumption for those not currently constrained is

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

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

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

where $\Phi(\cdot)$ is the CDF of a standard normal distribution. The probability in (7) is denoted by Φ_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

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

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 the 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

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

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

As shown in equation (8), there are three channels through which credit limit extensions affect unconstrained consumers' current consumption. 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. In this case, a one-unit increase in credit limit signals to consumers that the bank believes their income will grow by g' units.

Equation (8) leads to the following proposition.

PROPOSITION 1: Under Bayesian learning, a higher credit limit increases posterior income expectations, and the effect of the income-inference channel is positive.

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, while more expected resources reduce default risk and profitability. Hence, banks increase credit limits to boost consumption further. Consumers correctly expect this strategy and update income expectations in the same direction as limit changes. Therefore, the income-inference channel is positive, and MPCL is larger than in the no-learning scenario.

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

A positive weight on the income-inference channel yields the following corollary.

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

II. Methodology

A. Data and Institutional Environment

The data used in this study come from a large commercial bank in China. The bank operates nationally and is among the top 10 commercial banks in the country, as ranked by total assets. By 2023, the bank's total assets amounted 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 United States.[6] 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 rewards 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 cashback rewards or transaction discounts. For unpaid amounts, debt is carried over to the next billing cycle at a daily interest rate of 5 bps.

Credit card use in China has grown significantly since 2016. A recent report shows that from 2016 to 2022, the total outstanding balances 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 forms of 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 as of 2023 (UnionPay (2023)).

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

B. Measuring Debt, Spending, and Income

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

Data from a single bank do not capture all of a consumer's 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. [7]

The account-aggregator service is promoted quarterly via notifications. In my 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, with total spending calculated 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 data set in Internet Appendix Table IA.I.

Income data are based on transaction histories. For employees, income is calculated from a consumer's social insurance contributions, as these payments typically represent a fixed fraction of total income.[8] Such contributions include 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 nonfinancial income.

To validate income accuracy, I compare the transaction-based estimates with government administrative records, available for 21% of the sample. Figure IA.1 in Internet Appendix depicts the results, with a regression R^2 of 0.96, confirming the effectiveness of this method. In addition, in Table IA.I, I verify that the income sample is representative of the full data set. In Table IA.II, I

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

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

Sample	Surveys	Groups	N Subjects Selected	N Subjects Collected	N Subjects Final
I	No	Control	2,700	2,700	2,534
		Treatment 1	3,200	3,200	3,026
		Treatment 2	1,600	1,600	1,532
II	Yes	Control	5,000	3,440	2,527
		Treatment 1	6,000	4,122	3,029
		Treatment 2	3,000	2,050	1,539

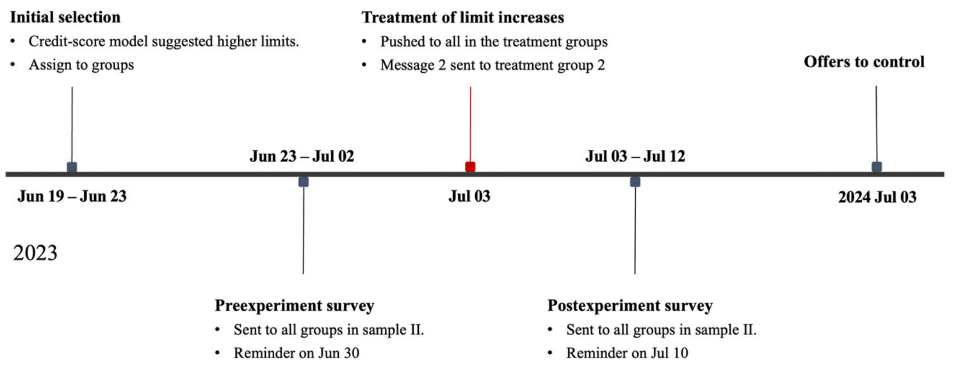

Figure 2. Timeline of the experiments and group assignment. This figure summarizes the experimental design. The top panel provides the timeline, and the bottom panel gives the assignment of the groups and the number of subjects at each stage of the experiment. (Color figure can be viewed at wileyonlinelibrary.com)

show that the borrowing and spending responses for the sample with available income and spending information are similar to those from the full sample.

C. Experimental Design

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

(i) *Sample construction*: From June 19 to 23, 2023, the bank selected a group of consumers (approximately 50,000 from 57 cities) to receive increased credit limits. These increases were based on the bank's credit scoring rules. From this group, 21,500 individuals were randomly selected as participants for this study and separated into two subsamples (I and II). In each subsample, subjects were further assigned to control group, treatment group 1 (T1), or treatment group 2 (T2). The number of participants in each group is presented in Figure 2.

(ii) *Preexperiment survey*: On June 23, 2023, the participants in Sample II were invited to complete the survey through text messages.[9] The survey was completed before July 2. A reminder text to complete the surveys was sent on June 30. The recruitment text is displayed in Figure 1, Message 1.

(iii) *Treatment*: On July 3, 2023, 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 (see Figure 1, Message 2). At the same time, participants in T2 were informed that the changes were based on a research project (See Figure 1, Message 3). The following information was disclosed:

> *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*.

(iv) *Postexperiment survey*: On July 3, 2023, after receiving the treatment notice, the participants in Sample II were invited to complete another survey through text messages. The survey was completed before July 12. A reminder to fill out the surveys was sent on July 10.

(v) *Limit changes to control*: The new credit limits for the control group, as determined in step 1, were pushed on July 3, 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 amounts to about 5% of the full sample. In addition, a random 30% of 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 from the main analysis. My final sample contains 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 $g'(L)$ exogenously.[10] T1 and T2 therefore 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 (e.g., Coibion et al.

[9] Section IV of the Internet Appendix reports the survey in English.

[10] The information treatment might affect expectations about the persistence of the limit increases. In Table III, I show that T2 does not have significantly lower expectations about future credit limits, and those expectations do not significantly affect consumption behaviors.

(2024); Gorodnichenko and Yin (2024)) and is usually used to avoid antagonizing participants. Specifically, in the preexperiment 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 postexperiment 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% and 10%	___%
Decreases by between 0% and 5%	___%
Stays roughly the same	___%
Increases by between 0% and 5%	___%
Increases by between 5% and 10%	___%
Increases by between 10% and 20%	___%
Increases by between 20% and 50%	___%
Increases by more than 50%	___%

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

> Over the next 12 months, conditional on not being unemployed, what level of total income are you most likely to earn?
>
> Note: income includes wages, salaries, bonuses, commission, etc., excluding earnings from financial investment.
>
> Please assign a probability to the percentage change in the total income you are most likely to earn over the next 12 months, conditional on not being unemployed. (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% and 10%	___%
Decreases by between 0% and 5%	___%
Stays roughly the same	___%
Increases by between 0% and 5%	___%
Increases by between 5% and 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.

C.1. Demand Effects and Selective Responses

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. In addition, 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 may 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 (see Table IA.III). As these consumers lack direct borrowing ties with the bank, they have less incentive to manipulate their responses.

To alleviate selective response problems, the survey was designed to be brief and highly incentivized. The preexperiment survey had only 15 mandatory questions (plus three additional questions for 30% of participants), and the postexperiment survey had 10 mandatory questions. Both took less than 7 minutes to complete on average, and participants received 20 CNY—equivalent to an hourly rate exceeding 171 CNY, well above the 95$^{\text{th}}$ percentile for Chinese urban residents. As a result, the response rate was high, reaching nearly 70%.

C.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 IA.IV shows that survey participants had lower spending, income, and credit limits, and higher debt, compared to the broader customer base. This suggests that survey respondents had greater need for credit on average. However, the differences were modest: the absolute log differences between the characteristic averages are less than 10%, indicating that the sample is broadly representative of the Chinese urban population.

D. Summary Statistics

Table I presents summary statistics based on preexperiment 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% of respondents hold a college degree. The average outstanding interest-incurring debt is 7,200 CNY, rising to 17,500 CNY for those with positive preexperiment debt. This result indicates that approximately 40% of participants hold unsecured debt, which is at the lower bound of the 40% to 80% range found in U.S. studies (Gross and Souleles (2002); Zinman (2009); Fulford (2015)). I further find that 19% carry both positive liquid wealth and positive credit card debt (coholders). Moreover, if hand-to-mouth is defined as those with liquid assets less than two months of income, 32% of respondents are hand-to-mouth.

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

Compared to the unsurveyed sample, survey respondents were generally more likely to be younger and less wealthy, and to have lower income. However, these differences were not particularly large, the absolute log differences between the characteristic averages are less than 10%.

III. Results

A. Spending Responses to Credit Limit Extensions

First, I present results on the experiment's consumption dynamics. Motivated by Proposition 1, suppose that the credit limit affects consumption only through the precautionary motive, as the buffer stock model typically suggests. Then, spending dynamics should be similar 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 from those in T1 after informing T2 about the randomness in supply decisions.

Figure 3 plots the evolution of changes in unsecured debt and total spending around the experiment. Panels A and B depict the results for Sample I; Panels C and D depict the results for those that completed the surveys in Sample II. I

Table I
Summary Statistics

This table gives summary statistics. Panels A and B, respectively, summarize Samples I and II. Liq. Wealth and Tot. Wealth are liquidity wealth and total wealth from surveys scaled by annualized income. $\mathbb{E}[\Delta Y\%]$ is expected income growth from preexperiment 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% and 99% levels.

		Age	Female	College	Income	Spending	Debt	Debt | Debt > 0	Limit	Δ Limit	Liq. Wealth	Tot. Wealth	$\mathbb{E}[\Delta Y\%]$
Panel 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	2,534	2,534	2,534	1,000	1,198	2,534	1,078	2,534	2,534			
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	3,026	3,026	3,026	1,244	1,450	3,026	1,207	3,026	3,026			
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	1,532	1,532	1,532	592	690	1,532	611	1,532	1,532			
	p-values	0.73	0.31	0.42	0.94	0.39	0.65	0.63	0.16	0.29			
Panel 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	2,527	2,527	2,527	1,023	1,186	2,527	1,096	2,527	2,527	1,023	1,023	1,023
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	3,029	3,029	3,029	1,203	1,449	3,029	1,241	3,029	3,029	1,203	1,203	1,203

(Continued)

Table I—*Continued*

Panel B: With Surveys													
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	1,539	1,539	1,539	590	686	1,539	654	1,539	1,539	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

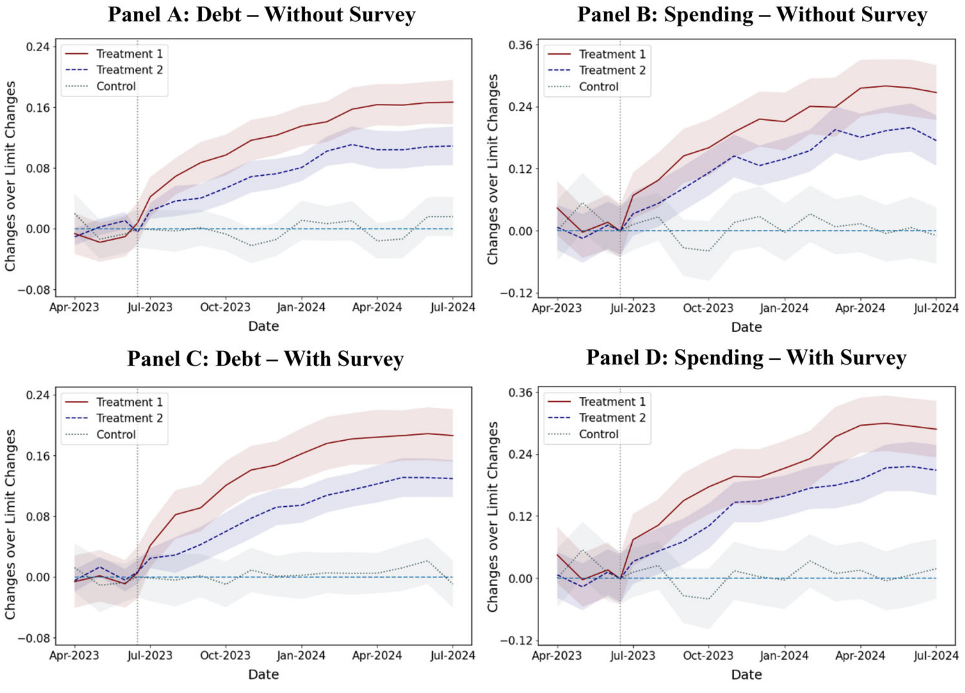

Figure 3. Evolution of debt and spending. This figure plots the evolution of total unsecured debt and spending on both sides of the experimental period, residualized by date fixed effects. Panels A and B are based on Sample I and Panels C and D are based on those who completed the surveys in Sample II. 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 time of treatment is zero. (Color figure can be viewed at wileyonlinelibrary.com)

scale changes around the experiment by the predetermined limit changes and thus the magnitudes can be interpreted as marginal propensities. In both plots, solid red and dashed blue lines correspond to T1 and T2, respectively, 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. As can be seen, the spending response of T2 is significantly smaller than that of T1. The divergence in the evolution of debt and spending between T1 and T2 indicates that credit limit extensions affect factors other than instant borrowing capacity.[11]

I next estimate the effects of credit limits on spending. Table II presents the results. Columns (1) to (5) report results for changes in debt for the unsurveyed sample. Column (1) reports the first-stage estimate of the treatments on credit limits, while columns (2) and (3) present the intent-to-treat (ITT) estimates.

[11] Figure IA.2 plots the evolution for all participants in Sample II, including nonrespondents.

Table II

Borrowing and Spending Responses

This table assesses the effects of credit limit increases on nondurable 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 change in credit limit. All variables are in thousand CNY. All variables are winsorized at the 1% and 99% levels. Standard errors clustered at industry $\times$ city level are in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Panel A: Without Survey										
		OLS		IV			OLS		IV	
	ΔL	Δ *B-6M*	Δ *B-12M*	Δ *B-6M*	Δ *B-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)		
$\Delta L \times$ *T1*				0.116***	0.151***				0.179***	0.248***
				(0.039)	(0.038)				(0.022)	(0.036)
$\Delta L \times$ *T2*				0.072***	0.101***				0.128***	0.173***
				(0.027)	(0.027)				(0.023)	(0.037)
First-stage *F*				2,632.44	2,632.44				1,223.86	1,223.86
N	7,092	7,092	7,092	7,092	7,092	3,338	3,338	3,338	3,338	3,338

(*Continued*)

Table II—*Continued*

Panel B: With Survey										
		OLS		IV			OLS		IV	
	ΔL (11)	Δ *B-6M* (12)	Δ *B-12M* (13)	Δ *B-6M* (14)	Δ *B-12M* (15)	ΔL (16)	*C-6M* (17)	*C-12M* (18)	*C-6M* (19)	*C-12M* (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)		
$\Delta L \times T1$				0.122***	0.166***				0.190***	0.259***
				(0.018)	(0.019)				(0.018)	(0.030)
$\Delta L \times T2$				0.080***	0.107***				0.126***	0.180***
				(0.018)	(0.017)				(0.022)	(0.032)
First-stage F				2,466.56	2,466.56				1,159.99	1,159.99
N	7,095	7,095	7,095	7,095	7,095	3,321	3,321	3,321	3,321	3,321

These specifications compare the average changes in credit limits and debt between the treatment groups and the control group using ordinary least squares (OLS). Columns (4) and (5) report the 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 are equal to the ratio of the ITT estimates and the first-stage estimates. The MP estimates for T1 can therefore be interpreted as MPBs.

Panel A shows that, on average, credit limits were 13,300 CNY higher for T1. This results in an increase in debt of around 1,500 CNY over six months and 2,000 CNY over 12 months. Turning to the MP estimates, for each 1 CNY increase in credit limit, debt increased by 0.116 over six months and 0.151 over 12 months. Meanwhile, each 1 CNY increase in 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 MPB and MPCL documented in 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 1 CNY increase in credit limit increased borrowing of T2 by 7.2 cents over six months and 10 cents over 12 months, and increased 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 credit limit changes.

Because the survey response rate is not perfect and sending surveys to consumers may prime consumer expectations, comparing the spending responses of the surveyed and unsurveyed samples sheds light on whether the survey sample results are subject to selection issues or survey demand effects. From Panel B of Table II, spending and debt responses are generally slightly larger for the surveyed sample. This is in line with expectations given that survey participants generally have lower wealth (i.e., are 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

The finding that 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

Table III

The Effects of Treatments on Beliefs

$\Delta\mathbb{E}$ [C], $\Delta\mathbb{E}$ [Y], $\Delta\mathbb{E}$ [W], and $\Delta\mathbb{E}$ [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. $\mathbb{E}$ [u] and $\mathbb{E}$ [p(d)] are the expected unemployment probability and delinquent probability over the 12 months after the experiment. $\Delta\mathbb{E}$ [L]–1Y and $\Delta\mathbb{E}$ [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 change in credit limit. All variables are winsorized at the 1% and 99% levels. Standard errors clustered at industry $\times$ city level are in parentheses. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

	$\Delta\mathbb{E}$ [C] (1)	$\Delta\mathbb{E}$ [Y] (2)	$\Delta\mathbb{E}$ [W] (3)	$\Delta\mathbb{E}$ [Hrs] (4)	$\mathbb{E}$ [u] (5)
$\Delta L \times T1$	0.286**	0.349***	0.001	0.000	−0.222
	(0.117)	(0.045)	(0.001)	(0.000)	(0.151)
$\Delta L \times T2$	−0.045	0.023	−0.001	0.000	−0.052
	(0.110)	(0.058)	(0.001)	(0.000)	(0.193)
	$\mathbb{E}$ [d] (6)	$\Delta\mathbb{E}$ [L]–$1Y$ (7)	$\Delta\mathbb{E}$ [L]–$5Y$ (8)	$\Delta\mathbb{E}$ [GDP] (9)	$\Delta\mathbb{E}$ [UR] (10)
$\Delta L \times T1$	−0.001	0.748	0.376	0.310***	−1.494***
	(0.151)	(0.887)	(1.314)	(0.056)	(0.351)
$\Delta L \times T2$	−0.005	1.012	1.105	0.044	−0.282
	(0.193)	(0.953)	(1.496)	(0.032)	(0.366)
First-stage F	2,466.56				
N	7,095	7,095	7,095	7,095	7,095

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 III. The results from T1 show that a higher credit limit significantly increases subjective expectations about future consumption and income, and marginally but insignificantly decreases probability of facing unemployment. Each 1,000 CNY increase in credit limit raises consumption expectation by 286 CNY and income expectation by 349 CNY. However, there are 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 the default probability remain unchanged, as captured by the one-year and five-year changes in total credit limit and default probability expectations. For T2, when informed about the randomization of credit supply, expectations about consumption and income become insignificant.

The results in Table III suggest that consumers believe they will consume more in the future following an increase in their credit limit, consistent with empirical findings in the literature. In addition, higher consumption is believed to be financed by more income in the future due to a higher marginal productivity of labor instead of drawing down savings, increasing default frequency, or increasing labor supply. Indifferent responses to credit limit growth suggest that information treatment attenuates consumption responses by erasing consumers' updated expectations about future earnings growth rather than informing them about a less persistent increase in credit limits.

In sum, the findings above suggest that the mechanisms proposed by the buffer stock model are not the only reason for consumers to expect higher spending after an increase in credit limit. Buffer stock model predicts that higher credit limits boost consumption by reducing precautionary savings. However, as Table III 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 may misreport creditworthiness to appear lower-risk. This is unlikely in the current context for two reasons: (i) the survey explicitly stated that banks would not handle the data, and (ii) while reported income is higher, subjective beliefs about default risk 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 changes in belief. Figure 4 shows that in both the control group and T2, changes in belief are more closely distributed around zero, while in T1, shifts in income and consumption expectations skew more to the right. However, changes in belief are not uniformly positive—around 45% of participants reported zero or negative future income expectations. Thus, the large average changes in belief stem from substantial changes among some consumers rather than uniform adjustments across all participants.[12]

I next study expectations regarding macroeconomic conditions. Previous studies show that credit supply is procyclical (Bassett et al. (2014); Boons, Ottonello, and Valkanov (2023); Weitzner and Howes (2023); Fishman, Parker, and Straub (2024)), and that consumers are imperfectly informed about macroeconomic conditions (Coibion and Gorodnichenko (2012); Nakamura and Steinsson (2018); Andre et al. (2022)). Consequently, credit supply may serve as a signal that consumers use to update their beliefs about the current state of the macroeconomy. If so, participants in T1 should update their beliefs about the macroeconomy after receiving credit limit shocks. To explore this possibility, I ask 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 III. After the experiment, participants in T1 increased their expectations of GDP growth over the next 12 months by 0.40 percentage points and decreased their

[12] Figure IA.3 shows the distribution of log changes.

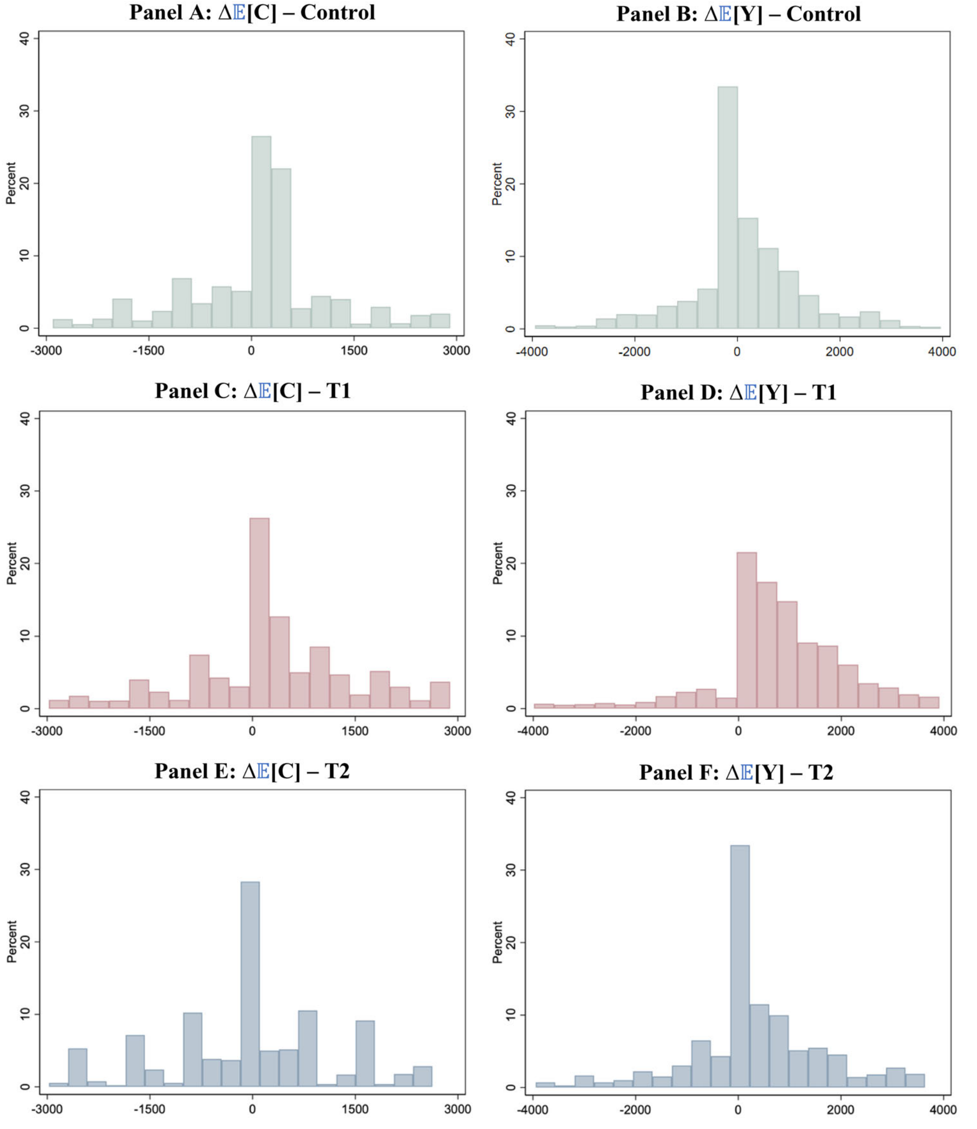

Figure 4. Distributions of belief changes. This figure shows the changes in consumption expectations (left column) and income expectations (right column) using the sample completing both surveys (sample II). Panels A and B correspond to the control group, Panels C and D to treatment group 1, and Panels E and F to treatment group 2. The distributions are based on samples winsorized at the 5% level. (Color figure can be viewed at wileyonlinelibrary.com)

expectations of the unemployment rates by 1.90 percentage points. These effects translate to 0.31 percentage points higher GDP growth expectations and 1.49 percentage points lower unemployment rate expectations for each 10,000 CNY increase in credit limit. In contrast, there are no significant changes in expectations regarding the macroeconomy for T2.

Overall, these results suggest that consumers view credit supply as procyclical—interpreting credit limit increases as signals of economic expansion. In line with this, the T2 findings indicate that when participants are informed that limit changes are random (conditional on good payment history), their macroeconomic expectations do not change.

C. Decomposing the Effects of Credit Limit Extensions on Spending

Prior studies have used arguably exogenous changes in credit limit to estimate MPCL and MPB. However, as shown above, when consumers infer information from bank credit supply events, the estimated MP 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 specification is

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

where $x_i^h = \{\Delta Limit_i, \Delta\mathbb{E}[Y_i]\}$, and $T1_i$ and $T2_i$ are dummies indicating whether i is in the corresponding treatment group. Specification (9) yields estimates for realized changes in the credit limit, $\Delta Limit_i$, and changes in income expectations around the experiment $\Delta\mathbb{E}[Y_i]$. The second-stage regression specification 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 changes in credit limit and changes in income expectations with the two treatment dummies. Relevance requires that changes in credit limits and expectations differ across T1 and T2. This is satisfied as T1 and T2 observe similar effects on $\Delta Limit_i$, but, as column (1) of Table IV shows, only T1 observes significant effects on $\Delta\mathbb{E}[Y_i]$. Note that credit limit changes also affect expectations about future consumption and macroeconomic conditions. Therefore, the exclusion restriction requires that these expectations affect spending only through changes to personal income expectations and the main effects of changes in credit limits.

Panel A of Table IV presents the results. The first-stage *F*-statistics are all well above 10, indicating strong effects of treatment on expectations and credit limits. From columns (3) and (4), both income expectations and borrowing limits significantly affect borrowing. Each 1 CNY increase in income expectation increases debt by 12.7 cents over six months and 17.9 cents over 12 months.

Table IV

The Effects of Limit Changes on Borrowing and Spending

This table reports the effects of credit limit increases and income expectation changes on spending and borrowing. Panel A reports results for specifications (9) and (10). Panel B excludes *T2*, and reports results for specifications (9') and (10'). ΔL 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. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Panel A: Treatment as IV						
	$\Delta\mathbb{E}[Y]$ (1)	ΔL (2)	ΔB–6M (3)	ΔB–12M (4)	C–6M (5)	C–12M (6)
T1	4.450***	12.742***				
	(0.558)	(0.315)				
T2	0.302	13.371***				
	(0.780)	(0.548)				
ΔL			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)
First-stage *F*			67.56	67.56	29.23	29.23
N	7,095	7,095	7,095	7,095	3,321	3,321
Panel B: Interaction as IV						
	$\Delta\mathbb{E}[Y]$ (7)	ΔL (8)	ΔB–6M (9)	ΔB–12M (10)	C–6M (11)	C–12M (12)
T1	0.030	12.162***				
	(0.839)	(0.436)				
T1 × *P*	6.539***	0.796				
	(0.920)	(0.544)				
ΔL			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)
First-stage *F*			44.67	44.67	16.84	16.84
N	5,556	5,556	5,556	5,556	2,635	2,635

Controlling for changes in income expectations, each 1 CNY increase in credit limit raises 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 to income expectations is 19.6 cents over six months and 24.5 cents over 12 months. For rational, unconstrained agents, these values have implications for whether the perceived income changes are permanent or transitory. For a permanent income change, the MPC should be one, whereas 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%. An average MPC of around 0.2 is possible for a transitory but persistent shock, implying that income shocks follow an AR1 process with nontrivial rate of depreciation. Meanwhile, behavioral biases like present bias (Maxted (2024)) or rule-of-thumb bias are also possible (McDowall (2023)) for consumption to respond to a transitory income shock stronger.

Controlling for changes in expectations, each 1 CNY increase in credit limit raises 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 II column (20) gives the unconditional MPCL, while the 0.177 MPCL from Table IV column (10) gives the MPCL controlling for expectation changes. These results indicate that changes in income expectations account for approximately 32% of MPCL.

While the information treatment for T2 aims to exogenously vary the degree of inferences made from changes in bank credit supply, additional information about bank credit supply may 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 changes in expectations on consumers' spending. This strategy is often used when treatment affects the outcome variables indirectly through factors other than the variable of interest (Kling, Liebman, and Katz (2007); Abdulkadiroğlu, Angrist, and Pathak (2014); Kline and Walters (2016)).

In particular, the first and second stages are, respectively,

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

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

where P_i is a dummy variable 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. This specification therefore instruments $\Delta Limit_i$ and $\Delta\mathbb{E}[Y_i]$ by the treatment dummy and the interaction between treatment and high-uncertainty-province dummies. Controlling for high-uncertainty province fixed effects makes sure that the instruments only use exogenous variation from $T1_i$.

Relevance of the location-by-treatment strategy requires that the extent of consumer learning varies across P_i, and that this degree of variation is different than that of $\Delta Limit_i$. This is likely as $\Delta Limit_i$, which is randomized, is not expected to differ across provinces, whereas, as a result of Bayesian learning, the degree of inference should be larger when ex ante uncertainty is higher.

The results are reported in Panel B of Table IV. As expected, the treatment of higher credit limits is not statistically different between high- and low-uncertainty provinces, while expectation changes are significant only 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) to (12) report the estimates of specification (10′). As can be seen, the results are similar to those in Panel A.

In summary, the spending responses and survey results suggest that after receiving credit limit increases, consumers update their expectations about their personal income, and the higher income expectations induce them to increase spending above and beyond the effects of relaxed borrowing constraints.

D. Heterogeneity of MPB and MPCL

In this section, I examine how the income-inference channel affects MPCL across consumer subgroups. I split the sample by consumer characteristics to analyze variation 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.[13]

First, I analyze how the effect of an increase in credit limit on spending varies across liquidity levels. Studies show that credit supply even has a significant effect on consumers with high liquidity buffers (D'Acunto et al. (2020); Aydin (2022)), challenging the standard buffer stock model. I examine whether liquidity levels influence responses to limit extensions, with and without controls for changes in income expectation.[14]

Liquidity constraints are based on the utilization ratio, that is, the ratio of unsecured debt to total credit limit, with higher values indicating greater constraints. Table V, columns (1) to (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 1 CNY increase in credit limit. 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 $\Delta E[Y]$ for T1 give the total MPB and the coefficients for ΔL conditional on $\Delta E[Y]$ give the MPB controlling for expectation changes. Therefore, one minus the ratio of the two estimates gives 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 such cases, the effect of credit supply operates less through

[13] Results for 12-month spending responses are provided in Table IA.V.

[14] Table IA.VI in the Internet Appendix shows that the experiment had no significantly different effects on credit limit changes for different treatments and different characteristic groups.

Table V

Heterogeneity in Debt Responses

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

	More Constrained			Less Constrained		
	$\Delta\mathbb{E}$ [Y] (1)	Δ *B–12M* (2)	Δ *B–12M* (3)	$\Delta\mathbb{E}$ [Y] (4)	Δ *B–12M* (5)	Δ *B–12M* (6)
$\Delta L \times T1$	0.440***	0.246***		0.276***	0.099***	
	(0.050)	(0.026)		(0.059)	(0.018)	
$\Delta L \times T2$	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)
$\Delta\mathbb{E}$ [Y]			0.187**			0.238**
			(0.085)			(0.093)
Weight of $\Delta\mathbb{E}$ [Y]			33.74%			66.67%
First-stage F		1,315.12	62.27		1,151.35	17.56
N	3,543	3,543	3,543	3,552	3,552	3,552
	High Uncertainty			**Low Uncertainty**		
	$\Delta\mathbb{E}$ [Y] (7)	Δ *B–12M* (8)	Δ *B–12M* (9)	$\Delta\mathbb{E}$ [Y] (10)	Δ *B–12M* (11)	Δ *B–12M* (12)
$\Delta L \times T1$	0.483***	0.198***		0.218***	0.135***	
	(0.052)	(0.026)		(0.057)	(0.019)	
$\Delta L \times T2$	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)
$\Delta\mathbb{E}$ [Y]			0.178**			0.185
			(0.071)			(0.122)
Weight of $\Delta\mathbb{E}$ [Y]			43.43%			37.37%
First-stage F		1,309.12	60.02		1,161.02	16.54
N	3,597	3,597	3,597	3,498	3,498	3,498
	Less Experience			**More Experience**		
	$\Delta\mathbb{E}$ [Y] (13)	Δ *B–12M* (14)	Δ *B–12M* (15)	$\Delta\mathbb{E}$ [Y] (16)	Δ *B–12M* (17)	Δ *B–12M* (18)
$\Delta L \times T1$	0.434***	0.207***		0.264***	0.125***	
	(0.059)	(0.027)		(0.049)	(0.018)	

(*Continued*)

Table V—*Continued*

	Less Experience			More Experience		
	$\Delta\mathbb{E}$ [Y] (13)	Δ B–$12M$ (14)	Δ B–$12M$ (15)	$\Delta\mathbb{E}$ [Y] (16)	Δ B–$12M$ (17)	Δ B–$12M$ (18)
$\Delta\ L \times T2$	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)
$\Delta\mathbb{E}$ [Y]			0.207**			0.139
			(0.094)			(0.094)
Weight of $\Delta\mathbb{E}$ [Y]			43.48%			29.60%
First-stage F		1,272.08	43.39		1,192.01	24.83
N	3,611	3,611	3,611	3,484	3,484	3,484

liquidity and more through subjective expectations, which helps explain why unconstrained households still respond strongly to limit increases.

I extend this analysis to uncertainty measures, as learning should be greater for consumers with more uncertain income expectations. To test this conjecture, I split the sample by subjective preexperiment macroeconomic uncertainty. Columns (7) and (10) show that learning from credit 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.

I next examine heterogeneity by prior experience, which is defined as the number of bank-initiated credit limit increases before the experiment. I classify participants with fewer past credit limit increases as less experienced. Columns (13) to (18) show that less experienced consumers adjust their expectations more than experienced consumers. 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, Bohren, and Imas (2024); Augenblick, Lazarus, and Thaler (2025)). Less experienced consumers, being less calibrated in linking credit limit increases to future income, may perceive extensions as noisier and therefore overreact.

E. Types of Information Inferred

The findings above indicate that consumers draw inferences from credit limit changes, with macroeconomic expectation as an important component. However, this result does not suggest that macroeconomic conditions are the only variables that 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 consumers, including their lifecycle stage (Brunnermeier, Lamba, and Segura-Rodriguez (2024)). Moreover, individuals with behavioral biases may link a credit limit increase as a signal about earnings potential following a rule of thumb. In this section, I provide evidence on whether consumers also learn about personal income growth from credit supply in addition to about macroeconomic conditions.

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 using 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?

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

$$\Delta\mathbb{E}\left[Y_i - M\right] = \Delta\mathbb{E}\left[GDP_i\right] \times S_{G,i}/0.05 - \Delta\mathbb{E}\left[UR_i\right] \times S_{U,i}/0.1, \qquad (11)$$

where $\Delta\mathbb{E}[Y_i - M]$ gives the change in income expectations due to changes in macroeconomic factors. Therefore, $\Delta\mathbb{E}[Y_i - O]$ is then derived as $\Delta\mathbb{E}[Y_i] - \Delta\mathbb{E}[Y_i - M]$.[15]

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

While macroeconomic expectations account only for 26% of the variation in total income expectations, it is possible that the residuals are just measurement errors that do not affect choices. To test this conjecture, I estimate specifications (8′) and (9′) after including $\Delta Limit_i$, $\Delta\mathbb{E}[Y_i - M]$, and $\Delta\mathbb{E}[Y_i - O]$ on the right-hand side. This requires another IV that affects $\Delta\mathbb{E}[Y_i - O]$ and $\Delta\mathbb{E}[Y_i - M]$ differentially than ex ante income volatility. I use macroeconomic uncertainty as the third IV. Specifically, I set $MU_i = 1$ if consumers answered *not confident* to the following question:

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

[15] One caveat is that $\Delta E[Y_i - M]$ measures changes in macroeconomic expectations captured by changes in GDP growth and the unemployment rate. There might be other macroeconomic factors that affect subjective income expectations, including inflation, industrial production, etc.

Table VI

Decomposing Expectation Changes

$\Delta\mathbb{E}$ [*Y*] and $\boldsymbol{\Delta}\mathbb{E}$ [*Y–M*] are, respectively, the changes in income expectations and the changes in income expectations driven by macroeconomic expectations. $\boldsymbol{\Delta}\mathbb{E}$ [*Y–O*] is the difference between $\boldsymbol{\Delta}\mathbb{E}$ [*Y*] and $\boldsymbol{\Delta}\mathbb{E}$ [*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 consumers answered "not confident" to the question eliciting their confidence in evaluating the macroeconomy. All variables are winsorized at the 1% and 99% levels. Standard errors clustered at industry $\times$ city level are in parentheses. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

	$\Delta\mathbb{E}$ [*Y*] (1)	$\Delta\mathbb{E}$ [*Y*] (2)	$\Delta\mathbb{E}$ [*Y–M*] (3)	$\Delta\mathbb{E}$ [*Y–O*] (4)
$\Delta\mathbb{E}$ [*Y–M*]	1.592***	1.861***		
	(0.068)	(0.056)		
T1			−1.563***	4.237***
			(0.277)	(0.755)
T1 $\times$*P*			1.846***	3.686***
			(0.293)	(0.693)
T1 $\times$ *MU*			3.211***	−8.747***
			(0.240)	(0.720)
Residualized	No	Yes		
R^2	0.255	0.274		
N	5,556	5,556	5,556	5,556
	Δ *B–6M* (5)	Δ *B–12M* (6)	*C–6M* (7)	*C–12M* (8)
Δ *L*	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)
First-stage *F*	30.75	30.75	12.74	12.74
N	5,556	5,556	2,635	2,635

Presumably, consumers should update beliefs about 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 VI. As expected, treated consumers with higher macroeconomic uncertainty change $\Delta\mathbb{E}[Y_i - M]$ more than $\Delta\mathbb{E}[Y_i - O]$. Columns (5) to (8) report the second-stage results. While the estimates of MPB and MPCL are similar when controlling for $\Delta\mathbb{E}[Y_i]$ alone or for both $\Delta\mathbb{E}[Y_i - M]$ 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 generally both significantly positive.

The results suggest that while macroeconomic expectations are a key driver of income expectations, they are not the sole factor. Banks may have access to 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 increase credit limits based on life-cycle consumption trends, which, given the cointegration of consumption and income, can signal income changes. In addition, behavioral biases such as overoptimism 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 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 5,000 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 10,000 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, λ, according to

$$\lambda = \frac{x_2 - x_1}{5,000}.$$

Mapped to (2), $\lambda = g'(L)$ is the subjective marginal relationship between credit limits and bank beliefs about consumers' future income growth. When $\lambda = 1$, consumers believe that a 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 λ. It shows large heterogeneity in beliefs about the sensitivity of credit supply to bank-perceived income growth. Around 35% of the consumers believe $\lambda \leq 0$. However, most participants believe credit limit extensions are associated with higher income growth in the future. The average λ is 0.86 and the median is 0.60. Thus, for a 1 CNY increase in the credit limit, consumers on average believe that 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, on average, consumers learn about their future income from credit limit increases, 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 income expectations after receiving a credit limit increase should move positively with the signal sensitivity of income growth λ. In Panel B of Figure 5, I split the sample by λ into four groups and then plot the average change in income expectations by λ-groups within each treatment group. Participants in T1 have a larger change in income expectations after

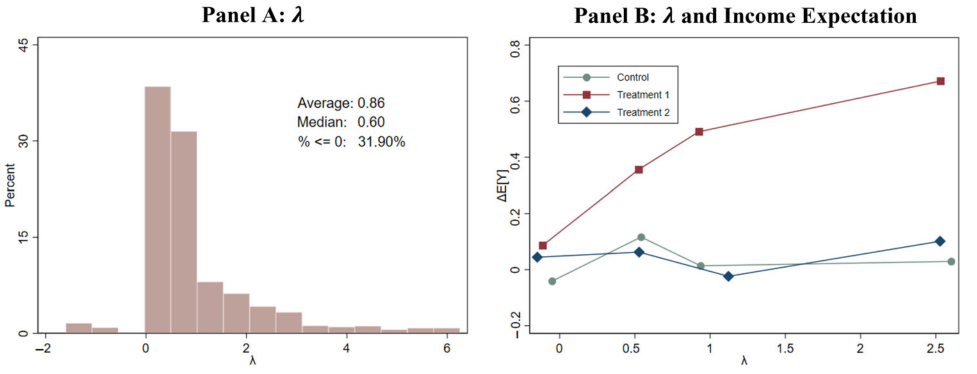

Figure 5. Subjective sensitivity of income changes to limit extensions. Panel A shows the distribution of consumer subjective beliefs about the sensitivity of income growth as perceived by the bank to credit limit increases, λ. The distribution is cut at the 1% level. Panel B plots changes in income expectations for each 1 CNY higher predetermined increase in credit limit. The estimates are conditional on four λ groups. Splits of the λ groups are conditional on the treatment groups. (Color figure can be viewed at wileyonlinelibrary.com)

the experiment, and this change increases with λ. Income expectation changes are also near zero, especially when λ is close to zero. At the same time, there is no apparent association between λ and changes in income expectations for the other two groups.

In sum, Figure 5 indicates that consumers believe that credit limit increases 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 Increases

In this section, I study the association between credit limit increases, 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 expectations and whether credit supply changes through an information channel or because it increases realized income. Given that consumers in T2 received additional information, I focus on those in T1 and the control group to imply a static relationship.

Figure 6 shows binned scatter plots of consumer expected income changes and realized income changes versus predetermined credit limit changes. All of the variables are residualized by age, degree, gender, industry fixed effects, and city fixed effects. In all four panels, the x-axis corresponds to credit 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 preexperiment expectations about income changes over the next 12 months are not significantly correlated with the proposed credit limit changes, as is the case for both the control and treatment groups.

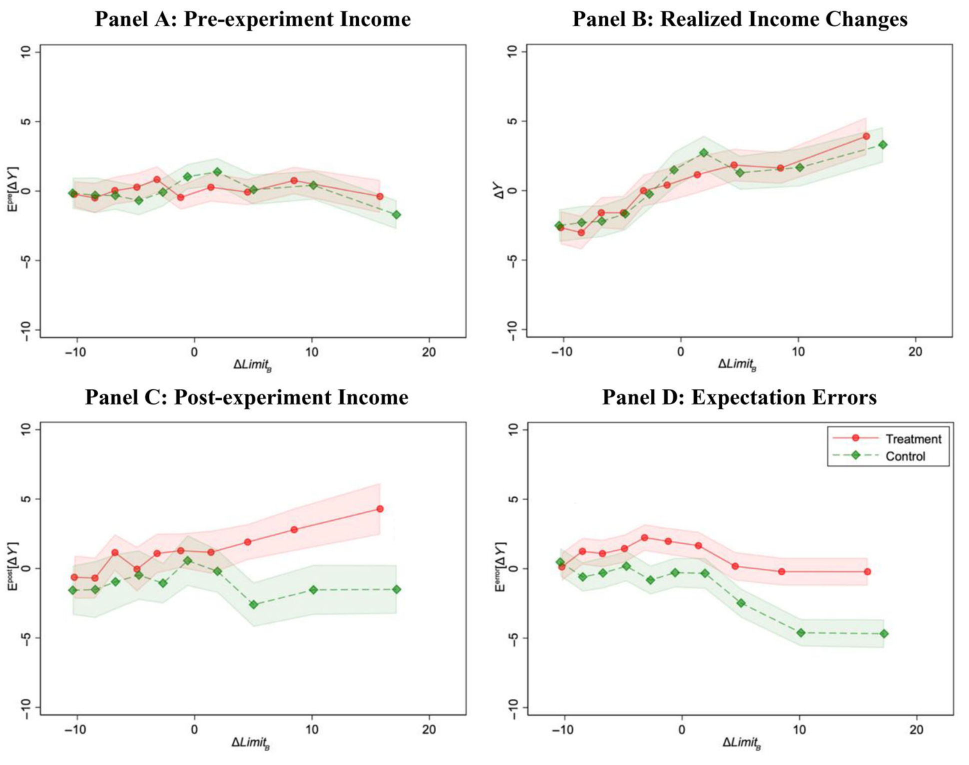

Figure 6. Expectations and realizations of income changes. This figure plots consumer expectations and realized income changes versus the predetermined credit limit changes focusing on the control and treatment group 1. The x-axis corresponds to credit limit changes as proposed by the bank before the random assignment, and the y-axis is consumer preexperiment expected income changes, realized income changes 12 months around the experiment, postexperiment expected income changes, and expectation errors after the experiment, in Panels A, B, C, and D, respectively. Expectation errors are defined as the differences between postexperiment expectations and income realizations. All variables are residualized by age, degree, gender, industry fixed effects, and city fixed effects. Units are in thousand CNY. (Color figure can be viewed at wileyonlinelibrary.com)

Panel B shows that realized income changes are positively correlated with the proposed credit 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 not increase total income. Panels A and B indicate that when banks actively offer increased credit limits to consumers, to some degree, the banks are informed about changes in consumer income in the near future. However, consumers are not perfectly informed about this income growth as correlated with the credit limit increase.[16]

[16] 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

Panel C plots consumer expectations after the experiment. Because the control group did not receive the offer, there was no change in their expectations. In the treatment group, there was a positive relationship between expectations and proposed credit limit changes. This finding confirms the results above. Panel D plots consumer expectation errors after the experiment. Expectation errors are defined as the difference between postexperiment expectations and realized income. From the plot, expectation errors are negatively correlated with the proposed credit limit changes for the control group. However, forecast errors no longer comove with credit supply for T1 after the credit supply event.

In sum, 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 credit limit increases, consumers shift their income expectations closer to the values implied by the credit decisions. The adjusted expectations affect spending, even if credit limit extensions do not increase realized income.[17]

H. Discussion

The results show that credit supply shocks significantly impact income expectations. In this section, I explore how beliefs respond to credit limit increases. A caveat is that, with cross-sectional data, assessing the degree of reaction is hard. I therefore view this exploration as more agnostic.

Note that Figure 6 shows that credit limit increases do not lead to 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 of $g' \approx 0.86$, which implies $(1+\theta)K = 0.41$.[18] This number could be consistent with Bayesian learning, that is, $\theta = 0$ and $K \in (0, 1)$.

However, if consumers were rational learners ($\theta = 0$), $K \approx 0.5$ would imply that credit supply must be nearly as predictive about future income as their prior expectations. To assess this, I compare R^2 s from predicting future income using credit supply versus prior expectations (Table IA.VII). 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.[19] The estimate of θ is broadly in the range of estimates in Bordalo et al. (2019), D'Acunto, Weber, and Yin (2024), and Chodorow-Reich, Guren, and McQuade (2024). Related, the findings in Table V suggest that overreaction may be tempered by experience: consumers

information about future income changes contained in credit supply decisions. In Table IA.VII, I show that prior income expectations have a much higher ability to predict future income changes than credit limit changes.

[17] Figures IA.4 and IA.5 show the plot for log changes and for macroeconomic expectations.

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

[19] See Internet Appendix Section III for the calibration details.

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 (López-Salido, Stein, and Zakrajšek (2017); Mian, Sufi, and Verner (2017)).[20] Belief overreaction to credit supply may explain this discrepancy. When lending standards loosen during economic booms, overextrapolative consumers with incomplete information get too optimistic about credit expansions as signals of sustained future income growth. This overextrapolation amplifies the link between credit supply and expected income. When misbeliefs are corrected, consumption declines, creating boom-bust cycles. [21]

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, Phillips, and Cohen-Cole (2021); Sergeyev, Lian, and Gorodnichenko (2023); He and le Maire (2023); Van Doornik et al. (2024)). Table IA.VIII 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.[22]

IV. 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 beliefs about future personal income upward 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.

[20] Figure IA.6 provides further evidence in the United States that periods with higher credit limit growth are also those with higher subjective future income growth but lower realized future GDP growth.

[21] See D'Acunto, Weber, and Yin (2024) about how overextrapolation of income surprises can lead to aggregate boom-bust household credit cycles.

[22] 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, Phillips, and Cohen-Cole (2021); He and le Maire (2023)).

Further research is needed to comprehensively understand the macroeconomic implications of lenders and borrowers with access to different sets of information. In addition, 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. In addition, this study uses a one-time credit limit event in one country. Future research could examine how credit limit changes affect expectations in other countries.[23]

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[23] In the Internet Appendix, Section VII, I use survey questions on SurveyMonkey to show that hypothetical credit limit increases have similar effects on expectations over different components of budget constraints, implying that the income inference channel is likely to also exist in the United States.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.