Social Debt Overhang and Conspicuous Consumption*

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Abstract

Debt owed to family and friends (FFD) is a key source of household finance in developing countries but often discourages conspicuous consumption due to social scrutiny. Using survey and proprietary data on Chinese households, we find higher FFD is associated with lower conspicuous consumption, unlike other debts. Social media amplifies this effect, but formalizing FFD with contracts or repayment schedules mitigates it. Evidence from China's consumption-oriented fiscal stimulus shows FFD reduces participation in such programs. These findings suggest that formalizing household financing channels can boost consumption, and thus economic growth, which is vital for countries with low consumption rates.

Keywords: informal finance, debt covenant, conspicuous good consumption, fiscal stimulus, Open-ended survey

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1 Introduction

Debt owed to family and friends (FFD) is a major component of household and entrepreneurial finance, especially in developing countries. For example, Ayyagari, Demirgüç-Kunt and Maksimovic (2010) find that the vast majority of firms in their sample, which are highly representative of the private sector in China, rely on informal, non-bank financing. According to our estimation, the total size of FFD on Chinese household balance sheets was around 70 billion USD in 2015, comparable in magnitude to the payday lending market in the United States (Morse, 2011; Bertrand and Morse, 2011). When access to formal credit is limited, households naturally turn to alternative credit channels as their primary source of borrowing (Fonseca, 2023). A large literature shows that different components of household consumption baskets, including both durable and nondurable goods, respond heterogeneously to shocks in income and debt (Baker, Farrokhnia, Meyer, Pagel and Yannelis, 2020; Yannelis and Amato, 2023; R. Baker, Farrokhnia, Meyer, Pagel and Yannelis, 2023). At the same time, consumption decisions are shaped not only by economic constraints but also by family, friends, and broader social networks (Angelucci, De Giorgi and Rasul, 2018). Importantly, debt overhang and debt adjustment have been identified as key mechanisms through which consumption becomes suppressed, particularly when income fluctuates (Colarieti, Mei and Stantcheva, 2024). Taken together, these insights suggest that FFD, as a form of "social debt," may exert a distinctive influence on household expenditure patterns, especially by constraining conspicuous consumption.

Theoretically, informal finance emerges as a second-best solution for households in developing countries because it addresses the moral hazard and information asymmetry issues associated with formal financing, which can result in credit rationing.[1] However, a factor that has not been sufficiently emphasized or empirically documented until now is that debt owed to family and friends (FFD) imposes certain hidden costs. FFD involves an "implicit covenant" that restricts borrowers from engaging in consumption, particularly conspicuous

[1]See Stiglitz (1990), Banerjee, Besley and Guinnane (1994), Prescott (1997), or Giné (2011).

purchases (Charles, Hurst and Roussanov, 2009). Such expenditures may signal to informal lenders that the borrower is misusing funds (Garber, Mian, Ponticelli and Sufi, 2024), potentially resulting in social stigma (Iyer, Khwaja, Luttmer and Shue, 2016; Bernstein, Colonnelli, Hoffman and Iverson, 2023) or increased repayment pressures.

Indeed, when households in China borrow from family and friends, typically at close to zero interest rates, these loans are often intended to support specific, pre-agreed purposes such as non-conspicuous consumption, start-ups, or self-run businesses.[2] Because these informal loans are based on mutual trust and social relationships, lenders generally expect borrowers to use the funds strictly for the intended purpose and to reciprocate by working harder or acting responsibly. Any deviation from this, such as spending on conspicuous goods including jewellery, luxury vacations, or even durable goods such as cars, can lead to non-pecuniary costs through social sanctions, strained relationships, or even early recall of the debt. As a result, households with outstanding family and friend debt (FFD) often face informal constraints on their consumption patterns and may delay conspicuous purchases, even if it means missing out on substantial government rebates or incentives provided during nationwide fiscal stimulus initiatives.

To test these hypotheses, we employ a novel dataset derived from survey data collected between 2013 and 2022 by a fintech firm, focusing on household balance sheets and consumption patterns. We also complement our survey dataset with actual consumption and social media data from Tencent Holdings, the largest social media company and the second-largest mobile payment provider in China.[3] For the survey dataset, the survey methodology integrates elements from both the U.S. Consumer Expenditure Survey (CEX) and the Panel Study of Income Dynamics (PSID). The dataset encompasses balance sheet and consumption

[2]See Akerlof (1982) or Lee and Persson (2016).

[3]The survey provides detailed demographic, consumption, and financial information, while Tencent's data offers granular insights into actual spending behavior and online social interactions, allowing for a comprehensive analysis of household consumption patterns in China. As of now, this survey firm has been partially acquired by Tencent, enabling closer integration between the survey data and Tencent's extensive social media and payment platform datasets. This acquisition enhances data consistency and allows for more comprehensive linking of household survey responses with actual consumption and social media activity.

data for over 9,000 households across 18 major cities in China, including Beijing, Shanghai, Guangzhou, and Shenzhen—the four largest cities in the country. Additionally, the survey gathers information on household liquid wealth, fintech debt balance, credit card balance, debt owed to family and friends (FFD), and income. We adopt this dataset due to its emphasis on high-frequency household balance sheet variables such as FFD and its extension of the sample with a longer time series, which mitigates the issues associated with inconsistent longitudinal data. This approach facilitates a more robust identification strategy for household fixed effects. In contrast, previous datasets predominantly focus on cross-sectional data and experience substantial sample attrition over time.[4]

We first demonstrate that the presence of debt owed to family and friends (FFD) on household balance sheets significantly reduces consumption of conspicuous goods. Under the core (or relatively narrow) definition of conspicuous good consumption, households with an additional RMB of FFD consume 10 cents less on conspicuous goods compared to households without FFD, while their consumption of other goods remains unaffected. In fact, there is a positive but statistically insignificant increase in other consumption (non-conspicuous consumption). Under a broader definition of conspicuous good consumption, households with an additional RMB of FFD consume 15 cents less on conspicuous goods compared to those without FFD, again without reducing their consumption of other goods. We find no significant substitution effect, indicating that the reduction in conspicuous good consumption does not statistically increase other forms of consumption; rather, these consumption opportunities are largely forgone. Furthermore, we show that the impact of FFD is distinct from that of arm's-length forms of debt, such as home mortgages, fintech debt, or other types of debt.[5] Home mortgages and other debts do not have an aggregate effect on either

[4]The mean values of household balance sheet variables, including both debt and asset/income variables, in our sample are between 10% to 30% higher than the corresponding values found in commonly used government-sponsored university-conducted household surveys, such as the China Household Finance Survey (CHFS) and China Family Panel Studies (CFPS). This trend is similarly observed when comparing our data to direct government surveys, including those by the National Bureau of Statistics of China (NBS) and the financial stability report of the People's Bank of China (PBOC). This discrepancy may be attributable to our survey's focus on households from major urban centers.

[5]Arm's length debt has been shown to have a significant impact on various aspects of household behavior.

conspicuous or other types of consumption. In contrast, fintech debt positively influences conspicuous consumption while negatively affecting other forms of consumption.

To further establish causality, we employ an instrumental variable approach, using the characteristics of a household's social networks, specifically, the average number of close relatives or friends within a community, as the instrument.[6] These social network characteristics influence the likelihood and amount of FFD while being less likely to directly affect consumption patterns. Our analysis shows that the average number of close relatives and friends (CFR) has no significant correlation with household balance sheet variables. Moreover, the size of the social network, as proxied by the total number of social media contacts, cannot predict FFD or conspicuous consumption. This suggests that having more friends, or a larger social network, does not mechanically lead to higher FFD or greater conspicuous consumption. Only close friends and family influence the availability of FFD credit. This result is robust to both the traditional instrumental variable approach with two-way fixed effects and the long-difference specification in Dinerstein, Koustas, Yannelis and Earnest (2024), which compares how a household's outcome changes from half a year after the household's FFD borrowing to half a year before the FFD borrowing. Taken together, these findings suggest that the exclusion restriction for our instrumental variable is likely satisfied. We find that CFR functions as a strong instrument for FFD, with the predicted variation significantly and negatively impacting conspicuous consumption. The economic magnitude of this effect is similar to the estimates derived from the panel regression approach in the previous section, indicating that our panel regression with fixed effects does not suffer from significant bias.

We also collect the number of social media posts in a given quarter by each household and

For example, Fonseca and Matray (2021), Fonseca and Van Doornik (2022), and Fonseca and Matray (2024) show that credit expansion can have profound effect on inequality and labor outcome. Therefore, we control for bank debt in order to isolate the effect of FFD.

[6]We use the WeChat social media dataset to identify, for each household, the number of individuals they interacted with on at least 10 days within a given month, as long as the WeChat algorithm classifies these conversations as non-work-related; we define this measure as close friends and relatives (CFR). Alternatively, we use survey data in which households report the number of CFR they have. Both measures yield similar results.

study its relationship with FFD. Since the literature has documented that social media is a way to communicate information, signal one's wealth (Jensen Schau and Gilly, 2003; Berger and Ward, 2010; Belk, 2013), and share one's feelings, we hypothesize that if FFD serves as a "disciplinary mechanism" for conspicuous consumption and wealth signaling, higher FFD would lead to fewer social media posts. We indeed find that households with high FFD post less on social media. Moreover, we find that households with higher FFD post less on social media regarding consumption, but do not post less regarding their feelings or sentiments. This again verifies that FFD not only decreases conspicuous consumption but also reduces posting that could be related to social signaling.[7]

We also hypothesize that the presence of FFD affects the passthrough of fiscal policies aimed at promoting consumption. We use China's Shopping Coupon Distribution Program as a natural experiment to identify the negative causal relationship between FFD and conspicuous good consumption. This program was a post-COVID-19 government stimulus initiative designed to incentivize households to increase spending in order to boost aggregate consumption and stimulate economic growth. Our findings demonstrate that the presence of FFD on household balance sheets significantly diminishes the fiscal multiplier effect of shopping coupons. Specifically, for every dollar offered through the coupon program, we estimate the fiscal multiplier to be approximately 0.008. However, FFD reduces the fiscal multiplier for conspicuous consumption to 0.005, while showing no effect on other types of goods consumption. Furthermore, we observe no interaction effects from other forms of household debt, such as home mortgages, fintech debt, or other debts. These results suggest that developing more formal channels for household finance could lead to increased consumption. This is particularly crucial for countries where low consumption rates hinder economic growth.

[7]We also find that social media alters the nature of conspicuous consumption. Although restaurant expenditures are typically not categorized as conspicuous consumption, they can potentially be considered as such when combined with social media. This is supported by Atkin, Colson-Sihra and Shayo (2021), who demonstrate that food choices can reveal social identity. This suggests that social media platforms can transform ordinary consumption into a form of conspicuous consumption by amplifying its visibility and social significance.

We develop a simple theoretical framework to formalize the interactions between borrowers and their informal lenders, typically family and friends, and to generate corresponding testable implications. Borrowers choose between conspicuous and non-conspicuous consumption given an existing level of informal debt, while lenders impose sanctions based on observed conspicuous consumption.[8] Borrower utility follows a CES specification over consumption types, augmented by status gains from signaling through conspicuous consumption and disutility from lender-imposed sanctions. In this setup, conspicuous consumption serves as a signal of income that shapes lenders' beliefs, while sanctions arise when such spending exceeds a threshold determined by inferred income and outstanding debt. The resulting social feedback loop captures how informal debt can discipline conspicuous consumption, potentially leading to lower visible spending compared with other forms of borrowing.

The model generates several testable predictions. First, as lenders place more weight on verifiable income, the suppressing effect of FFD on conspicuous consumption weakens. Second, social-media visibility amplifies sanction risk, when posts are harder to hide from FFD lenders, increases in debt discourage conspicuous consumption posting and, in turn, conspicuous spending. Third, contract formalization mitigates social sanctions and improves income signaling, relaxing the debt–to–consumption penalty and permitting more conspicuous consumption. We test these implications by (i) using job instability (income volatility, job turnover) as a proxy for low verifiability, and (ii) measuring lender–borrower social overlap as a proxy for high visibility/monitoring. Consistent with the theory, we find that lower verifiability and higher social visibility make the FFD effect more negative.

Moreover, for the third prediction, the theoretical setup implies that if the FFD comes with a written contract, positive interest rate, or pre-determined repayment date, then the implicit covenant can be lifted: such "formal FFD" does not reduce conspicuous good con-

[8]Endogenizing the borrower's choice between informal and formal debt would not alter the qualitative disciplining mechanism of informal borrowing. The key difference lies in the equilibrium composition of debt: borrowers with a stronger preference for conspicuous consumption or higher aversion to social sanctions would optimally shift toward formal credit, while those more tolerant of social monitoring would continue to rely on informal sources. Hence, formal credit access affects the amount of informal debt but not the underlying logic by which informal debt constrains conspicuous consumption.

sumption, only "informal FFD" does. We indeed empirically confirm this in our paper that written contract, positive interest rate, and pre-determined repayment date alleviate the negative effect of FFD on conspicuous consumption. This result is consistent with that of Lee and Persson (2016), who show theoretically that "formalizing" the informal finance can decrease many of its shadow costs. Most of the time, friend-and-family borrowers and lenders seal the debt contract with just a "handshake" because of the social collateral borrowers post. However, a more formally complete debt contract implicitly specifies a richer set of contingencies in which the borrowers are exempt from pecuniary and non-pecuniary sanctions, thus relaxing the implicit covenant.

We complement our main analysis with results from an open-ended survey that was conducted in addition to the main survey in 2018 and 2019. As Haaland, Roth, Stantcheva and Wohlfart (2024) suggests, open-ended surveys can sometimes reveal the mechanisms behind economic agents' behavior better than the "revealed preference" approach, as the latter is often limited. The survey included questions such as, "Have you ever experienced any form of pressure, criticism, or sanction from your bank/P2P/Fintech/FFD lender after you borrowed? If so, can you describe what happened?" and "Do you ever hide or avoid sharing certain purchases on social media because you have borrowed from family or friends? Why or why not?" Using LLMs to assist our analysis, we find that FFD lenders mainly impose sanctions through criticism or verbal abuse, whereas other debts, such as fintech or P2P loans, primarily result in harassment or intimidation. In contrast, banks mainly impose sanctions through legal or formal actions. Households are much more comfortable making luxury purchases after repaying FFD loans, and they often avoid sharing such purchases on social media due to fear of sanctions or feelings of guilt. The open-ended survey enriches and corroborates our main analysis.

This paper contributes to the existing literature on informal financing and non-bank financing. Agrawal, Catalini and Goldfarb (2014) demonstrate that friend-and-family financing is provided online for new artists in the US, facilitating financial support from friends

and relatives with fewer social frictions. Notably, the rise of non-bank financial institutions, including fintech lenders, has provided an increasingly important alternative source of credit for firms in both developed and emerging markets over the past two decades (Acharya, Khandwala and Öncü, 2013; Irani, Iyer, Meisenzahl and Peydro, 2021; Acharya, Cetorelli and Tuckman, 2024). Fonseca (2023) shows that households turn to payday lending when formal credit channels become more restrictive. Our paper is the first to empirically show that FFD on the balance sheet can limit households' consumption of conspicuous goods. Previous studies have primarily focused on whether financing from family and friends makes households less likely to undertake risky projects to avoid jeopardizing intrafamily consumption insurance.

Second, our work contributes to the growing literature on the economic impact of social media. While prior studies have focused on social media's effects on asset prices (Chen, De, Hu and Hwang, 2014), information transmission (Bailey, Cao, Kuchler and Stroebel, 2018), political coordination (Enikolopov, Makarin and Petrova, 2020), and individual welfare (Allcott, Braghieri, Eichmeyer and Gentzkow, 2020), the other side of the causality, specifically, its influence on consumption, remains less explored. Whereas previous literature demonstrates how social media can shape investors' beliefs and economic decisions, our results complement this work by showing that household balance sheets can also influence social media behavior, and that social media itself can alter the nature of consumption, shifting it from normal to conspicuous.

This paper also relates to the existing literature on consumption and fiscal stimulus passthrough. We show that when a household borrow from its peers, it can have negative effect on the household's consumption. While Mian and Sufi (2012) document a reversal effect of the CARS program and conclude that the effect of the stimulus was temporary. Our paper makes an incremental contribution by studying the effect of FFD on household balance sheets, which is common in developing countries, and showing that the negative effect of FFD on shopping coupons take-up is economically large and statistically significant, which

reduces the fiscal multiplier during the Covid-19 crisis. Bertrand and Morse (2016) show that consumption, especially visible consumption, "trickles down" from high-income groups to middle-income groups. Our findings echo this result by showing that visible consumption also responds to debt.

Finally, this paper relates to the vast literature on debt covenants. Chava and Roberts (2008) use a regression discontinuity design to show that a firm's capital investment declines sharply after it violates a covenant, because the creditors can threaten to take control. Roberts and Sufi (2009) show that the net debt issuance of a firm declines following debt covenant violations. Falato and Liang (2016) find evidence that violation of loan covenants can lead to severe job cuts at firms. Our paper uncovers an implicit debt covenant associated with FFD, i.e., a restriction on conspicuous-good consumption. Borrowers accept this implicit covenant when they obtain funds from family or friends. However, ex post, the covenant can constrain their consumption choices, preventing them from fully benefiting from shopping voucher subsidies or similar incentives designed to encourage consumption.

2 Household Consumption and Debt Survey

We use a consulting/fintech firm's household survey database, complemented by Tencent Holdings' social media and consumption spending dataset, as our main data source. The survey provides detailed demographic, consumption, and financial information, while Tencent's data offers granular insights into actual spending behavior and online social interactions, allowing for a comprehensive analysis of household consumption patterns in China. The survey dataset includes balance sheet data for more than 30,000 household, and we keep observations with more than four quarters of observation. This leaves us with 9,000 households from 18 major cities in China, including the four largest cities in China, Beijing, Shanghai, Guangzhou, and Shenzhen.[9] The balance sheet data includes quarterly survey of

[9]The motivation for the consulting/fintech firm to collect comprehensive household balance sheet data is multifaceted. Firstly, understanding household financial behavior is critical for these firms to offer tailored

household wealth variables and debt variables. Specifically, the fintech firm survey household regarding their borrowing from family and friends from 2013 till 2025, and we use the sample period 2013 to 2022 accordingly. The survey data include detailed information on FFD, such as the quarterly RMB standing of FFD, an indicator for whether the FFD had a written contract, a pre-agreed maturity date by which the borrower must repay the debt, and whether the family and friends charged the borrower a positive interest rate. In addition to FFD information, the survey also includes information about the household's liquid wealth, home mortgage balance, fintech borrowing balance, income, as well as social media posting behavior.[10]

Table 1 presents the summary statistics for household balance sheet variables, focusing on consumption, debt, and wealth descriptors. For consumption descriptors, conspicuous consumption (narrow/core) represents the quarterly RMB amount spent on consumption categories considered conspicuous according to Charles, Hurst and Roussanov (2009), including clothes and jewellery. Conspicuous consumption (broad) extends the narrow/core definition to also include iPhone, sports/sports equipment, entertainment expenses, travel

financial products and services. By analyzing detailed data on household wealth, debt, borrowing habits, and financial agreements, these firms can gain valuable insights into consumer needs and preferences. This data allows them to develop more effective financial solutions, improve risk assessment models, and enhance their strategic decision-making processes. Additionally, the data can be used to identify emerging trends and opportunities in the financial market, enabling these firms to stay competitive and innovative. Moreover, detailed household financial data is essential for developing their digital lending algorithms and expanding their customer base by offering personalized financial products. Furthermore, the firm leverage this data to provide evidence-based advisory services to clients in the financial sector and technology sector, helping them navigate the complexities of the Chinese market and make informed investment decisions. Beyond their internal use, these firms also monetize the data by selling it to big tech firms. Big tech firms, with their vast resources and advanced analytics capabilities, can utilize this data to enhance their own products and services, particularly in areas such as targeted advertising, credit scoring, and market analysis. Overall, the collection of such granular data empowers these firms to better serve their clients, achieve sustainable business growth, and create additional revenue streams through data sales. The cost for the survey company to collect data from each household per survey ranges from 15 RMB to 60 RMB, with an average cost of about 35 RMB. Approximately 80% of this cost is provided to the survey respondent as an incentive. The profit per household per survey is approximately 12 RMB. As of now, this survey firm has been partially acquired by Tencent, enabling closer integration between the survey data and Tencent's extensive social media and payment platform datasets. This acquisition enhances data consistency and allows for more comprehensive linking of household survey responses with actual consumption and social media activity.

[10] Although the consulting firm surveyed households' social media posting behavior, our analysis primarily relies on Tencent's social media posting data to examine household social media activity.

expenses, and restaurants (excluding cooking at home).[11] All consumption covers quarterly RMB spending across all consumption categories, excluding vehicle-related consumption. We present vehicle consumption, which includes car purchases and maintenance costs, as a standalone category. Following Charles, Hurst and Roussanov (2009), we classify car purchases as conspicuous consumption but analyze them separately; thus, they are excluded from both our narrowly and broadly defined measures of conspicuous consumption.

For FFD descriptors, FFD represents the RMB amount of debt from family and friends in quarter t. Conditional on FFD equal to one, the Contract, Interest, and Maturity variables indicate whether the FFD has a written contract, a positive interest rate, or a pre-determined repayment date, respectively. The Any variable denotes whether the FFD has any of these three features. The mean values of Contract, Interest, Maturity, and Any are conditional on FFD equal to one.

Regarding other debt descriptors, home mortgage debt balance and fintech lender debt balance are measured at a quarterly level in RMB. Fintech lenders include P2P lenders (Morse, 2015), Ant Financial, JingDong BaiTiao, or other online lenders besides banks. The Other category captures the debt balance of households, excluding home mortgage, FFD, and fintech lenders.

Lastly, wealth descriptors encompass liquid wealth, which measures household wealth in cash or a checking account in RMB, and income, representing the survey respondent's monthly income in RMB. For household income, we aggregate the variable to the quarterly level.

The mean FFD is around 20,000 RMB. The mean liquid wealth in the survey is 251,000

[11] There are two reasons for classifying these consumption categories as conspicuous consumption. First, in the China sample, these categories exhibit a strong correlation with clothing and jewelry consumption, particularly following the rise of social media in 2015. Second, they meet the "reference group" criteria outlined by Charles et al. (2009). These results are detailed in the later part of the analysis. Additionally, we specifically highlight the iPhone as a conspicuous consumption item because it is regarded as a premium smartphone in China. In contrast, other cellphone consumption does not demonstrate a similar correlation with jewelry and clothing as the iPhone does. It is only in 2024 that the conspicuous nature of the iPhone begins to gradually diminish. See https://www.scmp.com/opinion/china-opinion/article/3275082/why-apples-iphone-losing-its-shine-china. We tentatively categorize the consumption of all non-iPhone electronic products under home appliances.

RMB, the mean household mortgage balance is 217,000 RMB, the mean fintech balance is 7,000 RMB, and the mean income is 37,000 RMB per quarter. The mean conspicuous consumption level is around 3000 RMB according to a narrow definition, and the amount is 8,600 RMB for a broad level definition. The mean consumption for all consumption is around 28,000 RMB.

How representative are the households in this survey? We compare the mean values of the household balance sheet variables in our sample with those from the National Bureau of Statistics of China (NBS) and the financial stability report of the People's Bank of China (PBOC). The household in our dataset has higher income, more saving, higher debt level, and higher consumption level, and the magnitude are between 10% to 30% for various variables, potentially reflecting the facts that we are only surveying the 18 largest cities in China. This is also similarly true when we compare our summary statistics to the ones from government sponsored university organised surveys such as the China Family Panel Study (CFPS) conducted biennially by Peking University and the China Household Finance Survey (CHFS) conducted by Southwestern University of Finance and Economics.[12] In figures A.1 in the Appendix, we also show the histogram of income, liquid wealth, debt, and other variables, the distribution patterns are similar to what we observe in US database such as CEX and PSID.

Figure 1 compares the pre-trend of average covariates for households that borrow from family and friends (FFD) with those that do not, over the four years preceding the borrowing event. The analysis shows that average liquid wealth, income, total debt level, and home ownership are similar between households that borrow FFD and those that do not. Similarly, when comparing these average covariates for households that borrow FFD with those that take on a mortgage. The results indicate that average liquid wealth, income, total debt level, and home ownership are also similar between these two groups. Therefore, we find

[12]These datasets conduct surveys usually at a two-year frequency. We choose not to use these datasets for our main analysis because of their low frequency and the fact that they do not include a focused survey regarding FFD.

no evidence that households borrowing from FFD are in greater or lesser financial distress compared to those that do not borrow FFD or those that take on other types of debt such as a mortgage.

We also complement our survey dataset with actual consumption and social media posting data from Tencent Holdings, the largest social media company and the second-largest mobile payment provider in China. Tencent's flagship "super-app," WeChat (Weixin), bundles messaging, social feeds ("Moments"), and a ubiquitous mobile wallet (WeChat Pay). In urban China, QR-code payments via WeChat Pay are accepted at supermarkets, restaurants, street vendors, and on public transport; users also pay utility bills, order taxis/food delivery, and shop inside WeChat "mini-programs." Because social interactions and payments occur on the same platform and identity, WeChat links a household's social graph to a large share of everyday consumption, both online and offline. We are able to match payment and social media data for approximately 7,800 households out of a total of 9,000 during the sample period from 2014 to 2022. Among these, we have reliable consumption data for about 2,100 households.

It is important to note that since we can only match the exact personal identifier for the household head, the consumption patterns captured may only partially reflect those of the household head. Therefore, our matched dataset likely underestimates total household consumption for three reasons. First, because there are two major mobile payment firms in China, Tencent (WeChat Pay) and Alipay, we are only able to capture around 45% of all mobile transactions. Second, households may also use cash or credit cards for consumption, which are not recorded in our dataset. Third, the household head might not be the only person making purchases for the household.

Another limitation is that we are unable to assign Tencent's WeChat Pay data to precise consumption categories. For example, if a household shops at Uniqlo or Zara, it is most likely that the spending is related to clothing. However, it is more difficult to categorize purchases at stores like Walmart, which sell both clothing and groceries. Therefore, we

primarily use the survey data for the consumption regressions, while employing Tencent's actual consumption data as a robustness check.

Using a conservative approach suggested by Tencent, we are able to obtain a cautious estimate of certain consumption categories, such as clothing/shoes, travel/vacation, sports, entertainment, restaurants, transportation, pets, health, and alcohol/tobacco.

3 FFD and conspicuous good consumption

3.1 FFD and consumption

In many countries, borrowing from family and friends is very common and not limited to low income households or households in a liquidity crisis. Many households prefer borrowing from family and friends because they can borrow without paying interest, and the procedure is much less complicated than borrowing from a bank. When there is a lack of financial literacy among households, there is also a greater risk that banks exploit their clients,[13] which makes FFD an even more attractive financing option. Moreover, households do not need physical collateral to borrow from family and friends.

However, households may feel social pressure to avoid certain forms of consumption when they have family and friend debt (FFD) outstanding. In the Chinese context, borrowing from family and friends typically occurs at close to zero interest rates and is often intended to support specific goals such as non-conspicuous consumption needs or entrepreneurial ventures. Because these informal loans are based on mutual trust and social relationships, lenders generally expect borrowers to use the funds strictly for the pre-agreed purpose. Any deviation from this, such as spending on luxury items or leisure activities, can lead to social disapproval or strained relationships, reinforcing the expectation that borrowed money is used responsibly. This dynamic creates informal constraints on consumption patterns beyond purely

[13] See Munnell, Tootell, Browne and McEneaney (1996); Cohn, Fehr and Maréchal (2014); Gurun, Matvos and Seru (2016).

financial considerations. Conspicuous good consumption is usually not urgent; many studies such as Caballero (1990) and Leahy and Zeira (2005) show that durable and conspicuous good consumption such as cars are postponed during the trough of a business cycle. Luxury purchases such as vacations or jewellery, can therefore lead to non-pecuniary costs through social sanctions and can even trigger early recall of the FFD, as many social norms implicitly require borrowers to pay back FFD before enjoying luxury consumption.[14] Finally, there is no household bankruptcy law in China before 2021, making FFD non-dischargeable.[15] Signaling to family and friend lenders that the borrower is constrained may increase the chance of FFD relief. Conversely, the purchase of conspicuous consumption may make it difficult for the borrower to seek relief from FFD. Consequently, households may forgo the purchase of conspicuous consumption, even when they can get a large rebate from the government, in order to postpone the repayment of FFD. Therefore, we hypothesize that FFD on household balance sheet reduce conspicuous good consumption but not other forms of consumption.

To test this hypothesis, we estimate the following panel regression:

$$Conspicuous_Consumption_{iT} = \alpha_T + \beta_T FFD_{iT} + \gamma_T^{HV} HV_{iT} + \epsilon_{iT} \ , \tag{1}$$

$Conspicuous_Consumption_{iT}$ is the amount of conspicuous good consumption of household i in quarter T. FFD is the RMB amount of debt owed to family and friends in a given quarter T. The regression coefficient β_T measures the marginal effect of FFD on conspicuous consumption. Quarter fixed effects, city fixed effects, or household fixed effects are included in different specifications to help establish causality.

HV is a vector of household balance sheet debt variables as well as income/wealth variables. We include household wealth variable, such as liquid wealth and income as control variables. We also include the balances on home mortgages and fintech debt to contrast

[14]See Besley, Coate and Loury (1993); Besley and Coate (1995)); Karlan, Mobius, Rosenblat and Szeidl (2009)

[15]The first household bankruptcy law in China was passed and the pilot program was conducted in Shenzhen in 2021.

the effects of these arms-length debt variables with the effect of FFD. The effects of these arms-length debt variables are theoretically ambiguous. High bank debt balances may coincide with high wealth and good financial health, or alternatively, burdensome debt service. Specifically, anecdotal evidence[16] suggests that household borrow from fintech debt specifically to finance their conspicuous consumption.

Table 2 presents the results. In general, FFD is negatively associated with both broadly and narrowly defined conspicuous consumption, with varying degrees of significance. For example, a coefficient of -0.06 for FFD in Specification (f) suggests that households with one more RMB of FFD outstanding consume 6 cents less in terms of narrowly defined conspicuous consumption compared to households without FFD. The t-statistic of -3.81 (in parentheses) indicates that this relationship is statistically significant at the 1% level. Similarly, a coefficient of -0.15 for FFD in Specification (a) implies that households with one more RMB of FFD outstanding consume 15 cents less in terms of broadly defined conspicuous consumption compared to households without FFD. The t-statistic of -5.53 indicates that this relationship is also statistically significant at the 1% level. These results are consistent with our hypothesis that FFD decreases household's conspicuous consumption. Figure 2 also shows the main results when we use an alternative specification, where the independent variable is a dummy variable that equals one if the household has taken a FFD in quarter T.[17] Taking on FFD has a significant negative impact on conspicuous consumption in RMB terms, particularly for items such as clothing and iPhones, but does not affect non-conspicuous consumption.

Liquid wealth and income generally have positive associations with consumption. For instance, in Specification (b), a coefficient of 0.01 for liquid wealth indicates that a one RMB increase in liquid wealth is associated with a 1 cent increase in broadly defined conspicuous

[16]The following South China Morning Post discusses how Chinese younger generation use fintech debt to finance smartphone and clothes purchases, which we classify as conspicuous consumption. https://www.scmp.com/tech/big-tech/article/3185463/too-easy-borrow-debt-plagues-young-people-despite-chinas-scrutiny.

[17]The indicator equals one as long as the household has not repaid the FFD.

consumption. The t-statistic of 4.24 shows that this relationship is statistically significant at the 1% level. Likewise, a coefficient of 0.04 for income in Specification (b) suggests that a one RMB increase in income is associated with a 4 cent increase in broadly defined conspicuous consumption. The t-statistic of 3.95 indicates that this relationship is statistically significant at the 1% level.

The associations between consumption and mortgage, fintech debt, and other debt vary across specifications. For instance, a coefficient of 0.03 for fintech debt in Specification (b) implies that a one RMB increase in fintech debt is associated with a 3 cent increase in broadly defined conspicuous consumption. The t-statistic of 2.32 indicates that this relationship is statistically significant at the 5% level. Meanwhile, a coefficient of -0.02 for fintech debt in Specification (h) suggests that a one RMB increase in fintech debt is associated with a 2 cent decrease in other consumption (non-conspicuous consumption). The t-statistic of -2.12 indicates that this relationship is statistically significant at the 5% level.

Moreover, as a placebo/parallel trend test, we alternatively define pseudo-treatment periods as two quarters, four quarters, and eight quarters before a household actually takes on FFD. We then re-conduct the analysis using these pseudo-treatments in our regression specification (1). If households were already in distress or there was a pre-existing trend of conspicuous consumption decline, our placebo tests would capture these effects. However, we find no treatment effects from these alternative pseudo-treatments, suggesting that the parallel trend assumption is likely satisfied.[18]

3.2 Consumption By Category

We check consumption by category when the household has FFD on balance sheet using the same regression (1). Table 3 Panel A of the table shows the results for various categories of conspicuous consumption, including clothing and shoes (1a), jewelry/handbags/watches (1b), cars (1c), iPhones (1d), travel/vacation (1e), sports (1f), entertainment (movie/KTV)

[18]Moreover, we conduct a robustness check by excluding households that have never taken FFD, using only those that staggeredly take FFD for the analysis. The results, presented in Table A.5, remain similar.

(1g), and restaurants (1h). In general, FFD is negatively associated with consumption across these categories, with varying degrees of significance.[19]

For example, a coefficient of -0.02 for FFD in the clothing and shoes category (1a) suggests that households with one more RMB of FFD outstanding consume 2 cents less compared to households without FFD. The t-statistic of -2.13 indicates that this relationship is statistically significant at the 5% level.

Panel B of the table presents the results for various categories of other consumption (non-conspicuous consumption), including rent (2a), transportation (2b), utilities (2c), pet (2d), education (2e), health (2f), alcohol/tobacco (2g), food expenses excluding restaurants (2h), home appliances (2i), and miscellaneous (2j). We tentatively categorize the consumption of all non-iPhone electronic products under home appliances. The associations between FFD and consumption in these categories are mostly positive, but not statistically significant at the 10%, 5%, or 1% levels. For example, a coefficient of 0.03 for FFD in the rent category (2a) implies that households with one more RMB of FFD outstanding consume 3 cents more compared to households without FFD. However, the t-statistic of 0.42 indicates that this relationship is not statistically significant.

3.3 Social Media Posting

One significant change in consumer behavior is that wealth signaling is no longer limited to conspicuous consumption of physically visible goods but also includes posting about various consumption patterns on social media (Jensen Schau and Gilly, 2003; Berger and Ward, 2010; Belk, 2013). Therefore, we aggregate Tencent's social media postings on a quarterly basis. We hypothesize that if FFD indeed has an effect on conspicuous consumption, it should also reduce the number of social media posts by households.

[19]In later analysis (Appendix Table A.7), we show that (1c), iPhones (1d), travel/vacation (1e), sports (1f), entertainment (movie/KTV) (1g), and restaurants (1h) are plausibly conspicuous consumption because their consumption share become more correlated with clothing, shoes, jewelry, and other conspicuous consumption after the arise of social media in 2015. A large quantity of social media posting regarding consumption is also related to these consumption categories. Moreover, these cconsumption categories also satisfy the Charles, Hurst and Roussanov (2009) test, later discussed in the robustness checks section.

We indeed find that the household with higher FFD reduces their social media posting. Table 4 presents the estimates of the coefficient β_T in percent and their t-statistics (in parentheses) for the social media posting regression. The baseline regression in Specification (1) is given by:

$$Ln(Social_Media_{iT}) = \alpha_T + \beta_T Ln(FFD_{iT}) + \gamma_T^{HV} HV_{iT} + \epsilon_{iT} \ ,$$

where $Social_Media_{iT}$ indicates the number of social media posts in quarter T. Other dependent variables include $Consumption_Post_{iT}$ that represents the number of social media posts in quarter T related to any forms of consumption. $Sentiment_Post_{iT}$ indicates the number of social media posts in quarter T unrelated to any forms of consumption.

For example, a coefficient of -0.18 for FFD in column (a) suggests that a 1% increase in FFD is associated with an approximately 0.18% decrease in the number of social media posts. The t-statistic of -9.19 indicates that this relationship is statistically significant at the 1% level. This could imply that households with more debt owed to family and friends are less likely to share their activities on social media, possibly due to fear of social sanctions or concerns about their public image as we hypothesized.

The table also shows the results for different specifications, including the inclusion of quarter fixed effects (FE), city FEs, and household FEs. In general, FFD is negatively associated with social media posts, especially for consumption-related posts but not for sentiment-related posts. This indeed suggests that FFD only affect posting related to consumption, but not related to general posting about household's other activities.

Liquid wealth, income, mortgage, fintech debt, and other debt also have varying associations with social media posts across different specifications, but none of them are statistically significant. Figure 3 also shows the main results when we use an alternative specification, where the independent variable is a dummy variable that equals one if the household has taken a FFD in quarter T. The results are also qualitatively similar.[20]

[20]Again, we conduct a robustness check by excluding households that have never taken FFD, using only

3.4 Instrumental Variables

To address potential endogeneity concerns associated with our panel regression analysis, we use IV regressions to strengthen our main results. We use a household's characteristics of social networks, the number of close relatives or friends in a community, to serve as instruments. This characteristic may influence the likelihood and amount of FFD but are less likely to directly affect consumption patterns. We define CFR as the average number of close relatives or friends the household has. We employ two different approaches to define this variable. First, in our survey, we directly ask the household head how many close relatives or friends they have.[21] Alternatively, we utilize the WeChat social media dataset to identify, for each household, the number of individuals with whom they have interacted on at least 10 days within a given month, provided that the WeChat algorithm classifies these conversations as non-work-related. The first measure is subject to considerable subjectivity, while the second measure contains a substantial amount of noise. Nevertheless, both approaches yield similar results, and we primarily report the results based on the first measure.[22]

We use a long-difference regression following Dinerstein, Koustas, Yannelis and Earnest (2024) to compare changes in household outcomes from six months before to six months after the household adopts the FFD. We estimate this specification using two-stage least squares (2SLS) regression.

$$C_i = \beta \text{ FFD }_i + \lambda X_i + \epsilon_i$$

$$\text{FFD }_i = \gamma \text{ CFR }_i + \pi X_i + \mu_i$$

We also randomly assign a placebo FFD borrowing date to households in the control group. Our results are robust to approximately 200 rounds of random assignment of these

those that staggeredly take FFD for the analysis. The results, presented in Table A.6, remain similar.

[21] We provide respondents with general guidelines for defining a close relative or friend, such as maintaining mutual contact at least once per week and sharing a meal together at least once per month. However, we do not strictly enforce these criteria, allowing respondents the flexibility to interpret the question as they see fit.

[22] Results using the second (survey-based) measure are available upon request.

placebo FFD dates. This identification strategy aims to estimate the local average treatment effect (LATE), specifically for borrowers whose borrowing decisions are influenced by the availability of FFD. If FFD borrowing in our sample is driven by financial distress or other specific household characteristics, we may expect our IV estimates to diverge from those obtained using a standard difference-in-differences approach. Furthermore, our exclusion restriction assumes that the number of friends and family members a household has does not directly affect overall consumption—or specifically, conspicuous consumption. Instead, these variables influence conspicuous consumption only through their effect on FFD borrowing. Table 5 shows that, aside from FFD, other household balance sheet variables are uncorrelated with CFR.

Table 6 presents the results of the two-stage regression analysis. In the first stage, CFR is shown to have a significant positive effect on the likelihood of receiving FFD, with a coefficient exceeding 2500 and a t-statistic of 5.38. This indicates that households with a greater number of close friends and relatives are substantially more likely to borrow from family and friends. The F-test for instrument strength yields a value of 25.17, significant at the 1% level, confirming that CFR is a strong predictor of FFD.

The second stage examines the effect of FFD on various types of consumption: conspicuous consumption, expenditure on clothes, expenditure on iPhones, and non-conspicuous consumption. The coefficient for FFD on conspicuous consumption is -0.19, significant at the 1% level (t = -2.61), suggesting that borrowing from family and friends is associated with a reduction in conspicuous consumption—that is, spending on items intended to display wealth or status.

Looking at specific categories, the effect of FFD on clothing expenditure is negative and significant, with a coefficient of -0.04 and a t-statistic of -2.59, indicating that households reduce their spending on clothes after receiving FFD. Similarly, FFD has a negative and highly significant effect on iPhone expenditure (coefficient = -0.03, t = -3.75), suggesting a substantial reduction in spending on iPhones—items considered luxury or status symbols—after

borrowing from family and friends.

In contrast, the effect of FFD on non-conspicuous consumption is positive but not statistically significant (coefficient = 0.05, t = 0.34), implying no significant change in spending on items not intended to display wealth or status as a result of borrowing FFD.

Alternatively, as a robustness check, we also use a two-stage least square instrumental variable regression as in Miguel, Satyanath and Sergenti (2004) (TWFE-IV) combined with two-way fixed effects.

$$C_{c,it} = \beta \widehat{\text{FFD}}_{iT} \; + \; \lambda' HV_{iT} \; + \; \varepsilon_{iT},$$
$$\widehat{\text{FFD}}_{iT} = \gamma \, \text{CFR}_{iT} \; + \; \pi' HV_{iT} \; + \; u_{iT}.$$

This identification strategy also aims to identify the average treatment effect, specifically for borrowers whose borrowing decisions depend on the availability of FFD, albeit through a slightly different approach. Table 7 shows that, in the first stage of the regression, CFR has a significant positive impact on the likelihood of receiving FFD, with a coefficient of 1883 and a t-statistic of 4.79. This indicates that households with a higher number of close friends and relatives are substantially more likely to borrow debt from family and friends (One more CFR leads to 1880 RMB or 240 USD FFD). The F-test value for the instrument strength is 23.50, which is significant at the 1% level, confirming that CFR is a robust predictor of FFD.

The second stage of the regression examines the effect of FFD on various types of consumption: conspicuous consumption, expenditure on clothes, expenditure on iPhones, and non-conspicuous consumption. The coefficient for FFD on conspicuous consumption is -0.17, significant at the 1% level with a t-statistic of -3.72. This result suggests that borrowing debt from family and friends is associated with a reduction in overall conspicuous consumption, which includes spending on items that are likely intended to display wealth or status.

Focusing on specific categories within conspicuous consumption, the effect of FFD on expenditure on clothes is negative and significant, with a coefficient of -0.05 and a t-statistic of -2.71. This indicates that households decrease their spending on clothes after borrowing debt from family and friends. Similarly, the impact of FFD on expenditure on iPhones is also negative and highly significant, with a coefficient of -0.04 and a t-statistic of -3.27. This result suggests that households significantly reduce their spending on iPhones, which are also considered luxury or status items, following the taking of FFD.[23]

On the other hand, the effect of FFD on non-conspicuous consumption is positive but not statistically significant, with a coefficient of 0.01 and a t-statistic of 0.16. This implies that there is no significant change in non-conspicuous consumption, which includes spending on items that are not intended to display wealth or status, as a result of borrowing debt from family and friends.

Overall, the results suggest that borrowing debt from family and friends leads to a significant reduction in conspicuous consumption, including specific categories such as clothes and iPhones, while having no significant impact on non-conspicuous consumption. The economic magnitude of these estimates are consistent with the ones from our difference-in-differences regression specifications.

4 FFD and fiscal policy passthrough

We also hypothesize that FFD on the household balance sheet reduces the fiscal stimulus passthrough rate for conspicuous goods. We use the shopping coupon distribution during the COVID-19 pandemic to test whether FFD affect fiscal stimulus. According to our estimation, among 100 billion RMB were distributed during the time of Covid-19 in order to counter the recession brought by the COVID. Specifically, we categorize the vouchers into two categories, the ones that are related to conspicuous good, and the ones that are not re-

[23]In Column (6), we also present results using social media posting as the dependent variable. In this specification, both the predicted FFD and social media posting variables are transformed using the natural logarithm. The results are also similar that FFD reduces social media postings.

lated to conspicuous good. Next we consider the effect of the household balance sheet on the take-up rate of the shopping voucher program. In the regression, we include the interaction effects with the $Voucher_{iT}$.

Table 8 presents the estimates of coefficients and their t-statistics (in parentheses) from alternative panel regressions from 2019 to 2022. The dependent variable in the regressions, $Consumption_{iT}$ is the RMB amount of consumption in quarter T. The regression specification is given by:

$$Consumption_{iT} = \alpha_T + \beta_T FFD_{iT} + \delta_T FFD_{iT} * Voucher_{iT} + \lambda_T * Voucher_{iT} + \gamma_T^{HV} HV_{iT} + \epsilon_{iT} \ ,$$

Voucher equals per household RMB amount of government voucher offered during a quarter. If no voucher is offered in a given quarter, Voucher equals zero. When the independent variable is a non-conspicuous consumption voucher, the dependent variable is non-conspicuous consumption, denoted as $Others$. When the independent variable is a conspicuous consumption voucher, the dependent variable is conspicuous consumption.

The coefficient of Voucher is positive and significant across all columns, suggesting that an increase in the government voucher amount leads to an increase in conspicuous consumption for all households. For instance, a coefficient of 0.008 for Voucher in column (a) suggests that for every additional RMB in government vouchers, conspicuous consumption increases by 0.008 RMB. The t-statistic of 2.97 indicates that this relationship is statistically significant at the 1% level. The interaction term FFD*Voucher has a negative relationship with conspicuous consumption. This suggests that the positive effectiveness of the government voucher in increasing conspicuous consumption is reduced for households with FFD compared to those without FFD. For example, a coefficient of -0.003 for FFD*Voucher in column (a) indicates that for every additional RMB in government vouchers, the increase in conspicuous consumption is less for households with FFD than for those without FFD. The

t-statistic of -2.75 indicates that this relationship is statistically significant at the 1% level.

For non-conspicuous vouchers and non-conspicuous consumption, columns (c) and (d) show drastically different results. While the main effect of the voucher is similar across both specifications, the interaction term between the voucher and FFD shows no significant effect. This suggests that FFD only influences the fiscal passthrough for conspicuous consumption, but not for other types of consumption.

Overall, the results from Table 8 suggest that the fiscal stimulus take-up rate, as measured by government vouchers, has a positive per-dollar effect on conspicuous consumption for all households. However, the positive effectiveness of the government voucher in increasing conspicuous consumption is reduced for households with FFD compared to those without FFD.

5 Theoretical Motivation

Setup and players. We present a parsimonious framework with a borrower and informal lenders (family/friends). The borrower chooses conspicuous consumption C_c and non-conspicuous consumption C_n within the period; the outstanding informal debt D_{FFD} is taken as given (exogenous). Lenders impose sanctions $S(C_c)$ based on observed C_c relative to what they infer about the borrower's income and debt.

5.0.1 Borrower's Problem

Preferences combine standard consumption utility, status from signaling, and social (non-pecuniary) disutility from sanctions. Let

$$U(C_c, C_n) = \left[\alpha C_c^{\rho} + \beta C_n^{\rho}\right]^{1/\rho}, \qquad \sigma = \frac{1}{1-\rho} \text{ the CES elasticity.}$$

Status is tied to the income that lenders *infer* from the borrower's conspicuous consumption:

$$s(C_c) \equiv \hat{y}(C_c) = E[y \mid C_c], \qquad \hat{y}'(C_c) > 0.$$

Here, $\hat{y}(C_c)$ represents the *perceived income signal* formed by informal lenders based on observed conspicuous spending. It need not coincide with the borrower's true income or with a rational-expectations belief; we later show conditions under which the equilibrium inference $\hat{y} = y$ is consistent with lenders' expectations.

Sanctions generate both a *pecuniary* resource cost (entering the budget) and a *non-pecuniary* disutility (entering utility). The borrower solves

$$\max_{C_c, C_n} \; U(C_c, C_n) \; + \; \lambda\, \hat{y}(C_c) \; - \; S(C_c) \quad \text{s.t.} \quad C_c + C_n = y + D_{\text{FFD}} - S(C_c). \tag{2}$$

5.0.2 Lenders' Sanction Rule

Informal lenders penalize conspicuous consumption that exceeds a belief- and debt-based threshold:

$$S(C_c) = \gamma \, \max\Big\{ C_c - \kappa(D_{\text{FFD}}, \hat{y}(C_c)),\, 0 \Big\}, \tag{3}$$

$$\kappa(D_{\text{FFD}}, \hat{y}) = \phi\, \hat{y} + (1 - \phi)\, D_{\text{FFD}}, \qquad \phi \in [0, 1],\ \gamma > 0. \tag{4}$$

For $C_c > \kappa$, the marginal sanction accounts for the belief channel:

$$S'(C_c) = \gamma\big(1 - \phi\, \hat{y}'(C_c)\big), \quad \text{and} \quad S'(C_c) = 0 \text{ if } C_c \le \kappa. \tag{5}$$

This rule creates a dynamic trade-off: borrowers face heightened sanctions when visible conspicuous consumption is inconsistent with lenders' inference of income and debt (i.e., when $C_c > \kappa$), disciplining C_c toward expectations.

5.0.3 Equilibrium Conditions

We study static best responses under a given belief map $\hat{y}(C_c)$ and sanction rule. Write the Lagrangian

$$\mathcal{L} = U(C_c, C_n) + \lambda\, \hat{y}(C_c) - S(C_c) + \lambda_c\big(y + D_{\text{FFD}} - S(C_c) - C_c - C_n\big),$$

with multiplier λ_c. First-order conditions (interior) are

$$\frac{\partial \mathcal{L}}{\partial C_c} = \alpha C_c^{\rho-1} U^{1-\rho} + \lambda\, \hat{y}'(C_c) - S'(C_c) - \lambda_c\big(1 + S'(C_c)\big) = 0, \tag{6}$$

$$\frac{\partial \mathcal{L}}{\partial C_n} = \beta C_n^{\rho-1} U^{1-\rho} - \lambda_c = 0, \tag{7}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_c}: \quad C_c + C_n = y + D_{\text{FFD}} - S(C_c). \tag{8}$$

When $C_c \le \kappa$, set $S'(C_c) = 0$ in (6). When $C_c > \kappa$, use (5).

Separating benchmark. Assume $\hat{y}'(C_c) > 0$ and a single-crossing property that induces monotone best responses in C_c. Then a separating benchmark obtains in which higher y selects higher $C_c^*(y)$ and lenders' inference is correct, $\hat{y} = y$. Partial pooling may arise absent these conditions.

5.0.4 Key Results

- **FFD effect on conspicuous consumption.** From (4), $\partial\kappa/\partial D_{\text{FFD}} = 1 - \phi$. For $C_c > \kappa$,

$$\frac{\partial S}{\partial D_{\text{FFD}}} = \gamma(1-\phi)\,\mathbb{I}_{\{C_c > \kappa\}} \quad \Rightarrow \quad \frac{\partial C_c}{\partial D_{\text{FFD}}} < 0,$$

  i.e., higher informal debt tightens sanctions and suppresses C_c.

- **Imperfect substitution.** With $\sigma < 1$, tightening sanctions (larger γ) reduces C_c more than C_n, so the ratio C_n/C_c increases. Imperfect substitution prevents a one-for-one reallocation from C_c to C_n.

- **Comparative statics in belief weight.** A larger ϕ (more weight on inferred income relative to debt in κ) weakens the $D_{\text{FFD}} \to S$ channel, implying

$$\frac{\partial^2 C_c}{\partial D_{\text{FFD}} \partial \phi} > 0.$$

5.1 Extensions

5.1.1 Social Media Self-Censorship

Let $M \in [0,1]$ denote conspicuous consumption posting intensity. Beliefs and sanctions become

$$\hat{y}(C_c, M) = (1-\theta)\,\bar{y} + \theta\, g(C_c)\, M, \qquad \theta \in [0,1],\ g'(C_c) > 0, \tag{9}$$

$$S(C_c, M) = \gamma\, \max\{C_c - \kappa(D_{\text{FFD}}, \hat{y}(C_c, M)), 0\}\,\big(1 + \omega M\big), \qquad \omega > 0. \tag{10}$$

For given (C_c, D_{FFD}), the optimal M equates marginal status gain $\lambda\, \partial \hat{y}/\partial M$ with marginal sanction cost $\partial S/\partial M$. A sufficient condition for M^* to *decrease* in D_{FFD} is

$$\omega > \frac{\theta\, \lambda}{\gamma},$$

since higher D_{FFD} tightens κ and raises the posting penalty through the amplifier $(1 + \omega M)$.

5.1.2 Formalization of FFD Contracts

Following Lee and Persson (2016), let $F \in [0,1]$ index contract formalization (from pure informal $F = 0$ to written terms with schedule $F = 1$). Formalization reduces reliance on social enforcement and shifts the threshold toward verifiable repayment capacity (such as

collateral):

$$\gamma(F) = \gamma_0(1 - F), \tag{11}$$

$$\phi(F) = \phi_0 + F(1 - \phi_0), \tag{12}$$

$$\kappa(F) = F \cdot R(y, \text{collateral}, \text{verifiable income}) \; + \; (1 - F)\Big[\phi(F)\,\hat{y} + (1 - \phi(F))\,D_{\text{FFD}}\Big]. \tag{13}$$

Both the intensity channel ($\gamma \downarrow$) and the threshold mix (greater weight on $R(\cdot)$ and on income) attenuate the pass-through from debt to sanctions, yielding

$$\frac{\partial^2 C_c}{\partial D_{\text{FFD}}\,\partial F} > 0 \quad \text{(formalization mitigates the suppressing effect of FFD on } C_c\text{)}.$$

Assumptions: $\alpha, \beta > 0$; $\rho < 1$; $\sigma = \frac{1}{1-\rho}$; $\hat{y}'(C_c) > 0$; $\gamma > 0$; $\phi \in [0, 1]$; $g'(\cdot) > 0$; $\theta, \omega \in [0, 1]$. Sanctions enter both utility (non-pecuniary) and the budget (pecuniary), as in (2).

5.2 Testable Implications: Economic Interpretation

5.2.1 Three Testable Implications

- **Implication 1 (Income–vs–Debt Weighting).**

$$\frac{\partial^2 C_c}{\partial D_{\text{FFD}}\,\partial \phi} \; > \; 0.$$

  Mechanism: From $\kappa = \phi\,\hat{y} + (1 - \phi)D_{\text{FFD}}$, a larger ϕ shifts the threshold toward inferred income and away from debt. This weakens the $D_{\text{FFD}} \to S \to C_c$ channel, so the suppressing effect of informal debt on C_c is smaller when ϕ is higher.

- **Implication 2 (Social Media Amplification).** Let $\hat{y}(C_c, M) = (1-\theta)\bar{y} + \theta\, g(C_c)\, M$ and

$$S(C_c, M) = \gamma \, \max\{C_c - \kappa(D_{\text{FFD}}, \hat{y}(C_c, M)), 0\}\,(1 + \omega M).$$

A sufficient condition for posting to fall with debt is

$$\frac{\partial M^*}{\partial D_{\text{FFD}}} \;<\; 0 \quad \text{whenever} \quad \omega \;>\; \frac{\theta\,\lambda}{\gamma}.$$

Mechanism: Higher D_{FFD} raises κ's debt component, tightening the sanction trigger; with an amplifier $(1+\omega M)$, the marginal cost of visibility rises relative to status gains, so borrowers optimally reduce M.

- **Implication 3 (Formalization Mitigates FFD Suppression).** With $\gamma(F) = \gamma_0(1-F)$, $\phi(F) = \phi_0 + F(1-\phi_0)$, and

$$\kappa(F) = F \cdot R(y, \text{collateral}, \text{verifiable income}) + (1-F)\Big[\phi(F)\,\hat{y} + (1-\phi(F))\,D_{\text{FFD}}\Big],$$

we obtain

$$\frac{\partial^2 C_c}{\partial D_{\text{FFD}}\,\partial F} \;>\; 0.$$

Mechanism: Formalization lowers sanction intensity (via $\gamma \downarrow$) and shifts the threshold toward verifiable repayment capacity (and income weight), attenuating the pass-through from debt into sanctions and thus relaxing the suppression of C_c.

6 Additional Tests

6.1 Stronger Income Signaling Reduces the FFD Effect

Based on the Implication 1 of the model, we test whether the suppressing effect of informal debt on conspicuous consumption is weaker when lenders place more weight on (verifiable) income. Empirically, we proxy *lower* verifiability with *job instability*. Specifically, we construct two instability measures: (i) *income volatility*, defined as normalized income fluctuations over the past five years, and (ii) *job turnover*, the number of job changes a household experienced in the past three years.

We incorporate job instability as an interaction with FFD exposure. In our panel specification, the coefficient on $D_{\text{FFD}} \times \text{Instability}$ captures how the FFD effect varies with verifiability. Since higher instability indicates *lower* verifiability, the model predicts a *more negative* response of conspicuous consumption to FFD when instability is high; that is, we expect the interaction coefficient to be < 0.

Table 9 confirms this prediction. The interaction terms are negative and statistically significant for both proxies, indicating that borrowers with *less* verifiable incomes face *stronger* consumption restrictions from informal debt. Results are robust to the inclusion of borrower and time fixed effects, controls for income level, and alternative definitions of conspicuous consumption.

6.2 Social Media Amplification

Our theoretical setup also implies that when $\omega > \theta\lambda/\gamma$, FFD is more likely to negatively affect social media posting. This relationship is theoretically expected to hold when the income signaling channel is weaker or when the sanction intensity from social media posting is stronger. Empirically, we test the hypothesis that when social media posting inevitably leads to sanctions (being more observable or visible to family and friends), households tend to post less. We measure the ease with which households can conceal their conspicuous consumption, even when posting, by using the degree of overlap among family and friends. When the degree of overlap among friends is high, social media postings are more likely to be known by family and friends. We define several indicator variables to assess the overlap of household social circles from the Wechat social media dataset. The indicator variable $\mathbf{1}_{\text{SocialCircleOverlap}}$ represents the degree of overlap in social circles. Specifically, $\mathbf{1}_{\text{HighOverlap}}$ indicates that a household's social circles are highly overlapped, while $\mathbf{1}_{\text{LowOverlap}}$ signifies that the household's social circles have little or no overlap. The middle category, which is not explicitly represented by an indicator variable, serves as the omitted variable in our

analysis.[24] Table 10 shows that the interaction term for households with highly overlapping friend circles is indeed negative, and positive for households with low overlap.[25]

6.3 Formal Contractual Features and the FFD Effect

To provide additional evidence on the nature of the FFD effect, we test the hypothesis that having formal features such as a written contract, a positive interest rate, or a pre-determined repayment date can mitigate the negative FFD interaction effect according to theoretical

[24]This proxy is derived from our Tencent WeChat social media data, enabling us to objectively measure the degree of overlap in household social circles. Specifically, for each household, we identify all family members and all friends within a user's contact list. We then examine every possible pair among family members, among friends, and between every family member and every friend to determine whether each pair is directly connected on WeChat.

Formally, let $Fam = \{f_1, f_2, \ldots, f_m\}$ denote the set of family members and $Friends = \{g_1, g_2, \ldots, g_n\}$ denote the set of friends for a given user. We consider three types of pairs:

- **Family–Family pairs:** For each pair (f_i, f_j) where $1 \le i < j \le m$, check if f_i and f_j are WeChat contacts.
- **Friend–Friend pairs:** For each pair (g_i, g_j) where $1 \le i < j \le n$, check if g_i and g_j are WeChat contacts.
- **Family–Friend pairs:** For each pair (f_i, g_j) where $1 \le i \le m$, $1 \le j \le n$, check if f_i and g_j are WeChat contacts.

Let N_{overlap} denote the total number of connected pairs among all possible pairs:

$$\begin{aligned} N_{\text{overlap}} = & \sum_{1 \le i < j \le m} \mathbf{1}\{f_i \text{ and } f_j \text{ are WeChat friends}\} \\ & + \sum_{1 \le i < j \le n} \mathbf{1}\{g_i \text{ and } g_j \text{ are WeChat friends}\} \\ & + \sum_{i=1}^{m} \sum_{j=1}^{n} \mathbf{1}\{f_i \text{ and } g_j \text{ are WeChat friends}\} \end{aligned}$$

The total number of possible pairs is: $N_{\text{total}} = \binom{m}{2} + \binom{n}{2} + m \times n$

We define the overlap measure as: $\text{Overlap} = \frac{N_{\text{overlap}}}{N_{\text{total}}}$

To operationalize this measure, we sort households into terciles based on their overlap values. Households in the top tercile are classified as having *high overlap* ($\mathbf{1}_{\text{HighOverlap}}$), those in the bottom tercile as having *low overlap* ($\mathbf{1}_{\text{LowOverlap}}$), and those in the middle tercile serve as the omitted category. This approach provides a granular and objective assessment of how interconnected a household's family and friend social circles are on WeChat.

[25]Alternatively, we also use the Wechat social media dataset's "like per post" number as an another proxy for the cost of sanction. The results are similar. For brevity, the result is not reported but available upon request.

implication three. We test this additional hypothesis with the following regression:

$$Conspicuous_Consumption_{iT} = \alpha_T + \beta_T FFD_{iT} + \delta_T FFD_{iT} * \mathbb{1}_{iT}^{CT} + \gamma_{iT}^{HV} HV_{iT} + \epsilon_{iT} \ , \tag{14}$$

Here, $\mathbb{1}_{iT}^{CT}$ indicates whether the FFD has a written contract, a positive interest rate, or a pre-determined repayment date in alternative specifications. The coefficient δ_T quantifies the relation between the contractual feature and the effect of the FFD on the conspicuous good consumption.

Table 11 again confirms that FFD is negatively associated with conspicuous consumption and social media. For example, a coefficient of -0.20 for FFD in column (a) suggests that households with one more RMB of FFD outstanding consume 20 cents less compared to households without FFD. The t-statistic of -2.84 indicates that this relationship is statistically significant at the 1% level.

The rows labeled Maturity, Interest, Contract, and Any contain estimates of δ_T. These coefficients capture the interaction between FFD and the presence of formal contractual features. For instance, a coefficient of 0.08 for Maturity in column (a) implies that households with FFD that has a pre-determined repayment date consume 8 cents more compared to households with FFD without a pre-determined repayment date. The t-statistic of 2.25 indicates that this relationship is statistically significant at the 5% level. Similar interpretations can be made for the coefficients in columns (b) to (e), which capture the effects of FFD with interest rates, written contracts, or any of the three contractual features on conspicuous consumption and social media posts.

Our results align with the theoretical implications proposed by Lee and Persson (2016), which serve as the foundation for our theoretical motivation. Lee and Persson (2016) show theoretically that "formalizing" the informal finance can decrease many of its shadow costs. Most of the time, friend-and-family borrowers and lenders seal the debt contract with just a "handshake" because of the social collateral borrowers post. However, a more formally

complete debt contract implicitly specifies a richer set of contingencies in which the borrowers are exempt from pecuniary and non-pecuniary sanctions, thus relaxing the implicit covenant.

In summary, on the one hand, FFD carries with it an implicit covenant that restricts conspicuous good purchase. On the other hand, the results in Table 11 suggest that for FFD with one or more formal contractual features, the implicit covenant is weakened. Taken together, these results suggest that developing more formal channels for household borrowing can lead to increased levels of conspicuous good consumption.[26]

6.4 Open-ended Survey

A central question in exploring the mechanism behind our results is whether the economic mechanisms identified through "revealed preference" are indeed what is driving these results. To further support our hypothesis, we complement our main analysis with results from an open-ended survey that was conducted in addition to the main survey in 2018 and 2019 for a total of one thousand household. As Parker and Souleles (2019), Stantcheva (2023), and Haaland, Roth, Stantcheva and Wohlfart (2024) suggest, open-ended surveys can sometimes reveal the mechanisms behind economic agents' behavior better than the "revealed preference" approach, as the latter is often limited.

The survey questions are listed in Appendix I.1 and the response rates are shown in Appendix Table A.11. The survey included questions such as, "Have you ever experienced any form of pressure, criticism, or sanction from your bank/P2P/Fintech/FFD lender after you borrowed? If so, can you describe what happened?" (Q9) and "Do you ever hide or avoid sharing certain purchases on social media because you have borrowed from family or friends? Why or why not?" (Q15)

We use LLMs to assist our analysis. Specifically we use ChatGPT 4 coupled with China-

[26]Our parsimonious model also predicts that the presence of both collateral (such as housing assets) and a formalized debt contract will further strengthen the formalization effect. We indeed find evidence consistent with this prediction. However, due to the small sample size of individuals with formal debt contracts in our dataset, the results, while economically meaningful, are not highly statistically significant. These supplementary results are available upon request.

based LLMs, such as DeepSeek to help us conduct textual analysis with the coding scheme listed in Appendix I.1. We also manually check around 15% of the sample ourselves to make sure that the LLM model categorization can consistent with human perception before we fully adopt the analysis.

We report results that are most relevant to our main analysis. For question 9, we find that FFD lenders mainly impose sanctions through criticism or verbal abuse, with 23% of FFD borrowers (conditional on answering this question) reporting such experiences. In contrast, other debts, such as fintech or P2P loans, primarily result in harassment or intimidation (31%), while banks are more likely to impose sanctions through legal or formal actions (12%).[27] Moreover, 41% of the respondents reported experiencing future credit denial and early recall after conspicuous consumption when borrowing from FFD lenders. Less than 3% of respondents using other types of credit expressed similar concerns. These findings indicate that social sanctions for FFD take the form of both pecuniary penalties, such as early recall and future credit denial, and non-pecuniary penalties, such as verbal abuse and criticism, which can result in utility loss. Households also report feeling much more comfortable making luxury purchases after repaying FFD loans (42%), as expressed in question 12. In question 13, 38% of households indicate that if they fail to repay FFD, they anticipate relationship deterioration, loss of trust, anger, or sanctions from their friends or family members. Again, this suggests the presence of potential non-pecuniary costs associated with FFD.

In question 10, 62% of households indicate that if their FFD had a written agreement, their spending behavior would be freer and clearer, allowing them to plan their expenditures more effectively. In question 15, households report that they often avoid sharing such purchases on social media due to fear of sanctions or feelings of guilt (39%). The responses to these two questions further support our empirical findings. Overall, the open-ended survey responses enrich and corroborate our main analysis by demonstrating that most concerns associated with FFD take the form of non-pecuniary penalties, such as verbal abuse, and

[27]When we report a certain percentage, the remainder typically report "prefer not to answer".

pecuniary penalties, such as future credit denial and demands for immediate repayment.

7 Robustness Checks

7.1 Cross-Validation with Tencent Dataset

We cross-validate our main findings on conspicuous consumption using Tencent's WeChat Pay consumption data. Table A.9 presents the summary statistics for different subcategories of consumption. The overall magnitude of each consumption type is about one-third to one-half of the level found in the survey data. This reflects the fact that Tencent's WeChat Pay accounts for slightly less than half of the total mobile payment market share in China, and that households may also use credit cards or cash for payments. The correlation between the Tencent dataset and the survey is around 60%, validating the results in our survey summary statistics.

Table A.10 shows that for the consumption categories we can identify in the Tencent dataset, the coefficients for conspicuous consumption are negative and mostly statistically significant. The economic magnitude is, on average, one-third of the result obtained from the survey data. This supports our finding that FFD debt deters conspicuous consumption but not other types of consumption. Overall, these results serve to cross-validate the reliability of the survey dataset.

7.2 Conspicuous consumption in reference group

How to verify that the consumption category that we characterize as conspicuous consumption are indeed conspicuous consumption? Charles, Hurst and Roussanov (2009) shows that conspicuous consumption has the feature that the consumption increases as the reference group's income decreases. In the context of China, a similar analogy can be drawn: the reference group is often defined as households originating from the same province but residing in a different, typically more affluent, province. For example, this dynamic is observed

among individuals from the Northeastern region of China who have migrated to cities like Shanghai or Beijing. Therefore, we use the same specification as in Charles, Hurst and Roussanov (2009).

$$\begin{aligned}\ln(\text{ visible }_{ik}) =& \beta_0 + \delta_1(\mu_k^y) + \delta_2(D_k^y) \\ &+ \varphi \text{ Expenditure }_i + \theta X_i + \eta_i,\end{aligned}$$

Where μ_k^y is the reference group mean consumption, D_k^y is the reference group consumption standard deviation. We indeed find that δ_1 is negative for consumption categories such as clothing and luxury goods, including jewelry, handbags, watches, and vehicles, as documented in Charles et al. (2009). This suggests that these categories in China exhibit similar conspicuous consumption patterns as those observed in the U.S.[28] Moreover, we also find that other consumption categories, such as iPhones, travel, sports, entertainment, and restaurant spending, display a similar pattern, with δ_1 turning negative after 2015. Notably, these categories have also become more correlated with clothing and jewelry after 2015, coinciding with the rise of social media (Appendix Table A.7). Therefore, our results support the broader definition of conspicuous consumption proposed in this paper.

In contrast, consumption categories such as rent, transportation, utilities, pet expenses, education, health, alcohol/tobacco, food (excluding restaurants), and home appliances, which are typically considered non-conspicuous in Charles et al. (2009), remain non-conspicuous in our analysis, as indicated by δ_1 values that are close to zero and statistically insignificant.

7.3 Other Checks

As an alternative robustness test, we redefine the dependent variable using core conspicuous consumption as in Charles, Hurst and Roussanov (2009) (or the narrowly defined conspicuous consumption used in the previous table) and re-estimate the main specifications in Table 7 (instrumental variable analysis), Table 8 (fiscal stimulus analysis), Table 9 (income

[28]These results are available upon request.

verifiability analysis, as predicted by the theoretical model), and Table 11 (formalization of FFD analysis). The results remain statistically significant, albeit smaller in magnitude, and the overall economic intuition of our baseline findings remains unchanged.[29]

Moreover, Table A.8 panel A presents the results of robustness checks for the relationship between FFD and conspicuous consumption in subsamples. Parker, Souleles, Johnson and McClelland (2013) and Baker and Yannelis (2017) show there is wide range of heterogeneity when household response to cash stimulus or financial shocks in general due to demography. Therefore, we also similarly test heterogeneity in terms of demography.

Table A.8 Panel A presents estimates of the coefficients and their t-statistics (in parentheses) from panel regressions. The regression specification (1) in Panel A is:

$$Conspicuous_Consumption_{iT} = \alpha_T + \beta_T FFD_{iT} + \gamma_{iT}^{HV} HV_{iT} + \epsilon_{iT} \ ,$$

The FFD coefficients in Panel A are negative and significant for different subgroups of the population, such as Female Head, Male Head, Below 30, and 30 to 60. This suggests that households with FFD have a decrease in conspicuous consumption compared to households without FFD, and this result is consistent across various demographic groups.

For example, a coefficient of -0.09 for FFD in the Female Head column suggests that households with a female head and FFD have a 0.09 unit decrease in conspicuous consumption compared to households without FFD. The t-statistic of -3.96 indicates that this relationship is statistically significant at the 1% level.

We proceed to check another concern: that households with FFD and without FFD might be differentially affected by fiscal stimulus due to varying levels of program awareness. Financially distressed households might be more aware of such programs. Table A.8 panel B presents results from a logistic regression where the dependent variable is an indicator that a household is aware of a shopping coupon from the government. The coefficient of FFD in Panel B is negative and not statistically significant, suggesting that there is no

[29]We don't report these results in the Main Table for brevity but they are availabe upon request.

significant association between FFD and households' awareness of shopping coupons from the government.

The other coefficients in Panel B, such as Income, Liquid Wealth (LW), Mortgage, and Fintech Debt, show varying degrees of association with the awareness of shopping coupons from the government. For instance, the coefficient of Income is -0.85 and statistically significant at the 1% level, suggesting that higher-income households are less likely to be aware of shopping coupons from the government.

In conclusion, the results from Table A.8 provide robust evidence that households with FFD have a decrease in conspicuous consumption compared to households without FFD. Additionally, the logistic regression results in Panel B show no significant association between FFD and households' awareness of shopping coupons from the government.

8 Conclusion

In this paper, we show that the presence of debt owed to family and friends (FFD) on the household balance sheet significantly reduces conspicuous consumption. This reduction is not offset by an increase in non-conspicuous consumption, suggesting an overall decrease in total consumption. Moreover, FFD also reduces social-status signaling by households through social media. Social media can potentially transform non-conspicuous consumption into conspicuous consumption, amplifying the effect. This influence is especially pronounced among households whose FFD lacks a fixed repayment schedule, written contract, or positive interest rate. Furthermore, FFD offsets the stimulus effect of shopping coupons, indicating that arm's-length finance can be superior to relationship lending for households. Relationship lending may discourage households from consuming conspicuous and durable goods due to the risk of social sanctions or early debt recall.

Our open-ended survey provides valuable insights that support our main analysis by highlighting the distinct mechanisms of sanction associated with different lenders. FFD

lenders predominantly impose non-pecuniary penalties such as criticism and verbal abuse, distinguishing FFD from other forms of debt. The survey further reveals that households feel greater freedom in their spending behavior after repaying FFD loans, yet often avoid sharing luxury purchases on social media due to concerns about sanctions or guilt. These findings underscore the unique social and psychological dimensions of FFD, which may not be fully captured by traditional revealed preference approaches.

Finally, our paper contributes to the broader debate on the importance of formal versus informal finance for economic growth by documenting a previously under-recognized cost of informal finance. Our results may also have implications for conspicuous consumption induced by other forms of fiscal stimulus, such as cash distributions or tax rebates, since social media enriches the definition of conspicuous goods. Notably, our research is the first to establish a causal relationship between debt and social media behavior. Evidence from China's consumption-oriented fiscal stimulus shows that FFD reduces participation in such programs. Overall, these findings suggest that formalizing household financing channels can boost consumption and, consequently, economic growth: an outcome especially vital for countries with low consumption rates.

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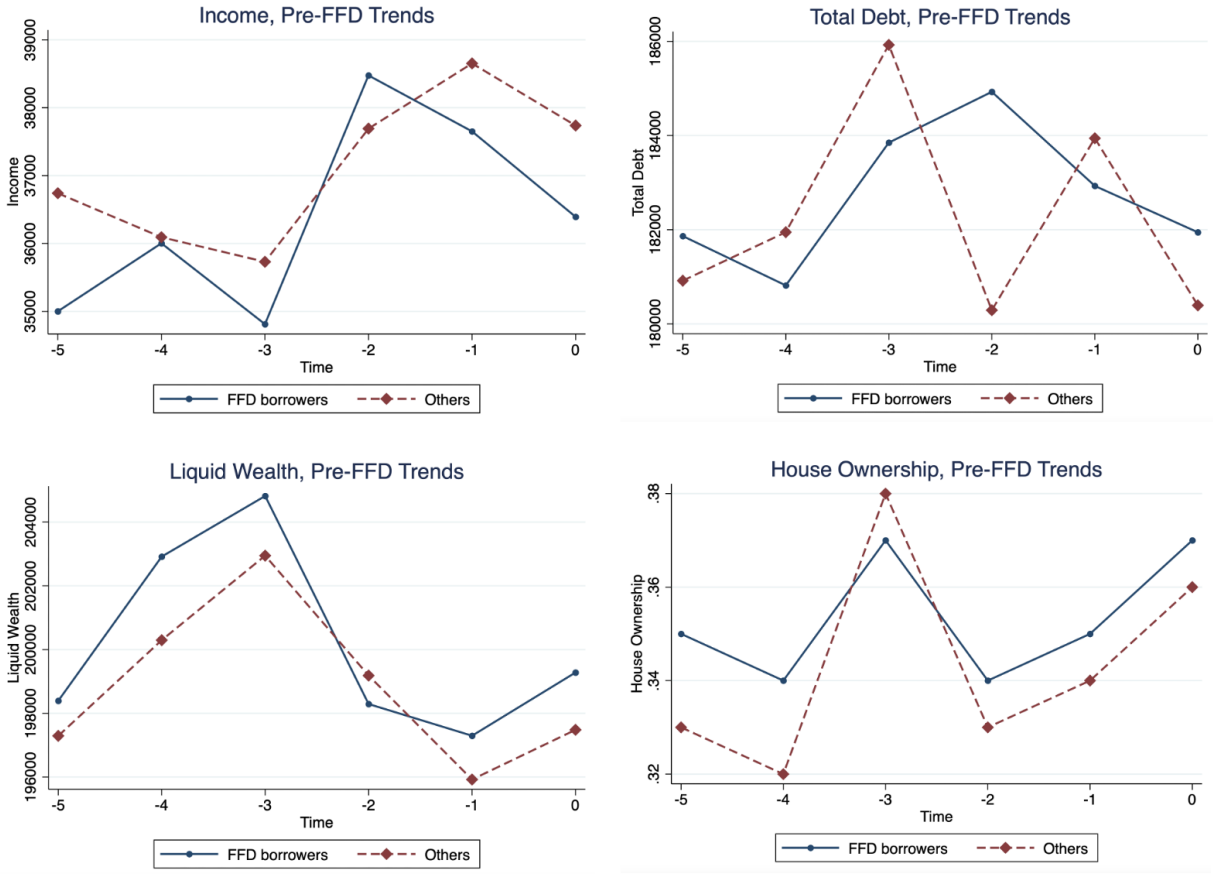
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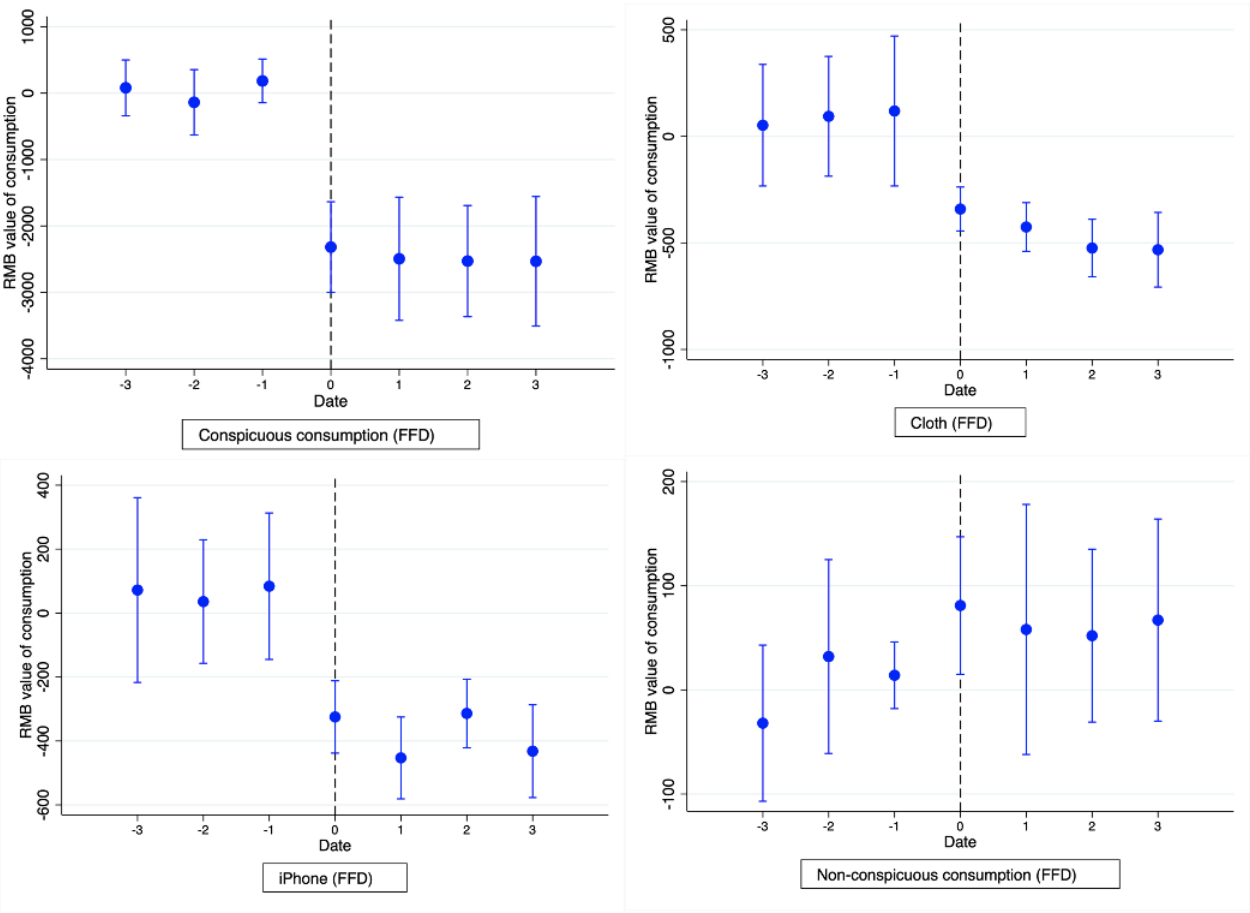
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Figure 1: Pre-FFD Trends



The figure illustrates the trends of covariates for up to five years prior to the FFD (Family and Friends Debt) event. The blue line represents the treatment group, comprising households that begin borrowing from family and friends in year zero. In contrast, the orange line represents the control group, which consists of households randomly selected from the pool of controls and assigned a pseudo event year. The median values of each covariate are reported at the quarterly level.

Figure 2: Consumption response to FFD

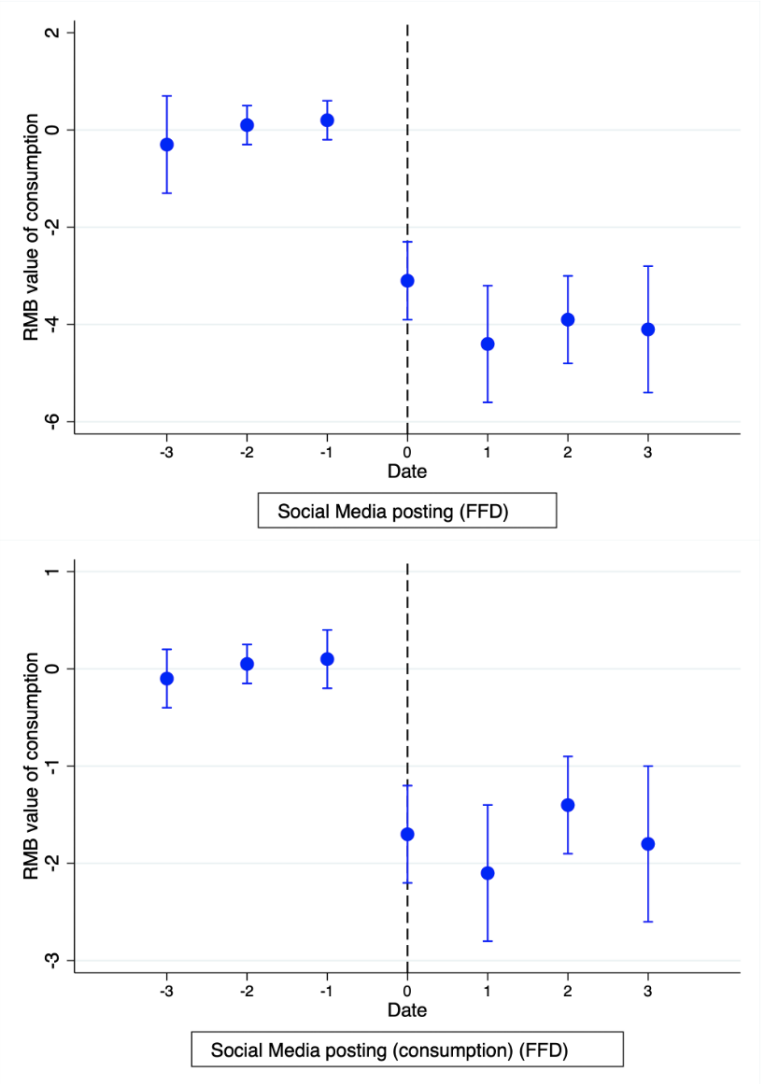


We estimate the following specification:

$$Consumption_{iT} = \alpha_T + \sum_{\tau=-3}^{+3} \beta_\tau \, \mathbb{1}(FFD\text{-}EventTime_{iT} = \tau) + \lambda_T \, HV_{iT} + \epsilon_{iT},$$

where $Consumption_{iT}$ denotes household i's consumption in quarter T. $\mathbb{1}(FFD\text{-}EventTime_{iT} = \tau)$ is an indicator for event time τ relative to the onset of borrowing from family and friends (FFD), with $\tau = -1$ representing the last quarter without any FFD and $\tau = 0$ the first quarter with FFD. The vector HV_{iT} includes household balance-sheet and income/wealth controls. All β_τ coefficients are estimated relative to a control group of households that have not yet experienced an FFD event by quarter T. The figure plots the time series of $\{\beta_\tau\}_{\tau=-3}^{+3}$ and their one–standard–error confidence bands, showing how consumption evolves before and after the FFD event.

Figure 3: Social media posting responses to FFD



We estimate:

$$SocialMedia_{iT} = \alpha_T + \sum_{\tau=-3}^{+3} \beta_\tau \, \mathbb{1}(FFD\text{-}EventTime_{iT} = \tau) + \lambda_T \, HV_{iT} + \epsilon_{iT},$$

where $SocialMedia_{iT}$ is household i's number of social-media posts in quarter T. $\mathbb{1}(FFD\text{-}EventTime_{iT} = \tau)$ indicates event time τ relative to the onset of borrowing from family and friends (FFD), with $\tau = -1$ the last quarter without any FFD and $\tau = 0$ the first quarter with FFD. The vector HV_{iT} includes household balance-sheet (debt) and income/wealth controls. All β_τ are estimated relative to a control group of households that have not yet experienced an FFD event by quarter T. The figure plots $\{\beta_\tau\}_{\tau=-3}^{+3}$ (with one–standard–error bands), showing how social-media posting evolves before and after the FFD event.

Table 1: Summary Statistics for Household Balance Sheet Variable

Conspicuous consumption (Narrow) is the quarterly RMB amount of consumption for consumption categories that are considered conspicuous as in Charles, Hurst and Roussanov (2009), which includes clothes and jewellery. Conspicuous consumption (Broad) is the quarterly RMB amount of consumption of those in Conspicuous consumption (Narrow) but also include iphone, sport/ sports equipment, travel, entertainment, and restaurants (excluding food expenditure of cooking at home). All consumption is defined as the total quarterly RMB expenditure across all categories, with the exception of vehicle expenses. Vehicle includes car purchase as well as car maintenance cost. FFD is the RMB amount of debt from family and friends in quarter t. Conditional on FFD equal to one, Contract indicates whether the FFD has a written contract; Interest indicates whether the FFD has a positive interest rate; Maturity indicates whether the FFD has a pre-determined repayment date; and Any indicates whether the FFD has any of these three features. The mean values of Contract, Interest, Maturity, and Any are conditional on FFD equal to one. Home mortgage debt balance is the debt balance in RMB measured at a quarterly level. Fintech lender debt balance is the debt balance in RMB measured at a quarterly level. Fintech lenders are one such as P2P lenders, Ant Financial, or JingDong BaiTiao, or debt borrowed from an online lender that is other than a bank. Other is the debt balance of household other than home mortgage, FFD, and fintech lenders. Liquid wealth measures household wealth in cash or a checking account in RMB. Income is for the survey responder's income in RMB per quarter. The number of social media posts per quarter is obtained from Tencent's WeChat dataset, and each post is categorized as related to consumption or sentiment using Tencent's textual analysis algorithm.

	Mean	SD	5%	50%	95%
Consumption descriptors					
Conspicuous (Narrow)	3,194	12,487	492	2,784	12,394
Conspicuous (Broad)	8,672	30,584	1,643	6,011	35,965
All	28,171	44,281	9,490	18,295	50,296
Vehicle	2,449	32,160	0	0	40,432
Clothing	1,165	5,832	638	882	6,261
Jewellry	2,029	11,217	0	783	10,180
Iphone	874	4,075	0	0	5,085
Travel	748	15,382	0	0	6,382
Sports	637	2,394	0	487	3,391
Entertainment	1,075	9,642	0	984	9,075
Restaurants	1,644	8,160	0	862	10,093
Food (exclude Restaurants)	4,041	8,382	2,492	3,819	7,628
Rent	8,315	19,859	0	6,984	23,974
Transportation	1,443	3,864	642	1131	4,075
Utilities	1,576	3,295	529	1,481	3,204
Pet	395	2,853	0	0	2,075
Education	1,352	8,532	0	1,086	6,783
Health	864	5,248	0	348	4,965
Alcohol/Tabacoo	976	6,073	0	527	4,852
Home Appliance	768	5,935	0	0	7,472
Miscellaneous	274	562	0	193	1,043

Table 1: Summary Statistics for Household Balance Sheet Variable (Continued)

Conspicuous consumption (Narrow) is the quarterly RMB amount of consumption for consumption categories that are considered conspicuous as in Charles, Hurst and Roussanov (2009), which includes clothes and jewellery. Conspicuous consumption (Broad) is the quarterly RMB amount of consumption of those in Conspicuous consumption (Narrow) but also include iphone, sport/ sports equipment, travel, entertainment, and restaurants (excluding food expenditure of cooking at home). All consumption is defined as the total quarterly RMB expenditure across all categories, with the exception of vehicle expenses. Vehicle includes car purchase as well as car maintenance cost. FFD is the RMB amount of debt from family and friends in quarter t. Conditional on FFD equal to one, Contract indicates whether the FFD has a written contract; Interest indicates whether the FFD has a positive interest rate; Maturity indicates whether the FFD has a pre-determined repayment date; and Any indicates whether the FFD has any of these three features. The mean values of Contract, Interest, Maturity, and Any are conditional on FFD equal to one. Home mortgage debt balance is the debt balance in RMB measured at a quarterly level. Fintech lender debt balance is the debt balance in RMB measured at a quarterly level. Fintech lenders are one such as P2P lenders, Ant Financial, or JingDong BaiTiao, or debt borrowed from an online lender that is other than a bank. Other is the debt balance of household other than home mortgage, FFD, and fintech lenders. Liquid wealth measures household wealth in cash or a checking account in RMB. Income is for the survey responder's income in RMB per quarter. The number of social media posts per quarter is obtained from Tencent's WeChat dataset, and each post is categorized as related to consumption or sentiment using Tencent's textual analysis algorithm.

	Mean	SD	5%	50%	95%
FFD descriptors					
FFD	20,538	40,372	0	1,585	30,963
Contract	7.60%	18.14%	0	0	1
Interest	11.03%	22.20%	0	0	1
Maturity	8.36%	20.51%	0	0	1
Any	18.19%	31.35%	0	0	1
Other Debt descriptors					
Home mortgage balance	217,102	638,167	0	173,826	743,121
Fintech lender	7,481	30,391	0	5,184	28,738
Others	2,729	5,376	0	1,934	52,195
Wealth descriptors					
Liquid wealth	251,284	424,294	65,113	212,019	572,193
Income	37,391	107,827	10,827	29,295	92,291
Social Media descriptors					
All	12.7	15.3	1	8	27
Consumption	6.2	6.4	0	5	10
Sentiment	6.5	8.3	0	5	12

Table 2: Debt Owed to Family and Friend and Conspicuous Consumption

Estimates of the coefficient β_T and their t-statistics (in parentheses) are reported for the following consumption regression.

$$Consumption_{iT} = \alpha_T + \beta_T FFD_{iT} + \gamma_T^{HV} HV_{iT} + \epsilon_{iT} \ ,$$

For dependent variables, $Conspicuous_Consumption_{iT}$ indicates the conspicuous consumption in quarter T. Specifically, Conspicuous consumption (Narrow) is the quarterly RMB amount of consumption for consumption categories that are considered conspicuous as in Charles, Hurst and Roussanov (2009), which includes clothes and jewellery. Conspicuous consumption (Broad) is the quarterly RMB amount of consumption of those in Conspicuous consumption (Narrow) but also include iphone, sport/ sports equipment, and travel. Other consumption is the consumption category that is in not in conspicuous consumption category (broad). For independent variables, FFD is the RMB amount of debt owed to family and friends in a given quarter T. HV is a vector of household balance sheet debt variables as well as income/wealth variables. T-statistics are in the parenthesis. Standard errors are two-way clustered at the household and quarter levels. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Consumption type:	Conspicuous (Broad) (a)	Conspicuous (Broad) (b)	Conspicuous (Broad) (c)	Conspicuous (Narrow) (d)	Conspicuous (Narrow) (e)	Conspicuous (Narrow) (f)	Others (g)	Others (h)	Others (i)
FFD	-0.15^{***}	-0.17^{***}	-0.12^{***}	-0.10^{***}	-0.09^{***}	-0.06^{***}	0.05	0.03	0.01
	(-5.53)	(-4.29)	(-2.92)	(-4.19)	(-4.33)	(-3.81)	(0.69)	(0.44)	(0.31)
Liquid wealth		0.01^{***}	0.01		0.02^{***}	0.02^{***}		0.01^{***}	0.01^{***}
		(4.24)	(1.05)		(3.19)	(2.83)		(3.97)	(3.17)
Income		0.04^{***}	0.02^{*}		0.20^{***}	0.12^{**}		0.03^{***}	0.02^{**}
		(3.95)	(1.78)		(3.40)	(2.34)		(2.86)	(2.15)
Mortgage		0.01	0.01		0.05	0.03		-0.01	-0.01
		(1.24)	(0.64)		(0.94)	(0.77)		(-0.94)	(-0.79)
Fintech Debt		0.03^{**}	0.02^{*}		0.10^{*}	0.04		-0.02^{**}	-0.01
		(2.32)	(1.80)		(1.90)	(0.93)		(-2.12)	(-1.19)
Other Debt		0.24	-0.11		-0.42	-0.35		0.10	0.06
		(1.03)	(-0.47)		(-0.74)	(-0.51)		(0.64)	(0.42)
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
City FE	Y	Y		Y	Y		Y	Y	
Household FE			Y			Y			Y
R^2	16%	21%	47%	14%	16%	41%	10%	12%	35%
No. Observations	82749	82749	82749	82749	82749	82749	82749	82749	82749

Table 3: FFD Consumption by category

Estimates of the coefficient β_T, along with their t-statistics (in parentheses), are presented for each consumption category using the following regression specification:

$$Consumption_{iT} = \alpha_T + \beta_T FFD_{iT} + \gamma_T^{HV} HV_{iT} + \epsilon_{iT} \ ,$$

$Consumption_{iT}$ indicates the RMB amount spent on a specific category of consumption in quarter T. HV is a vector of household balance sheet debt variables as well as income/wealth variables. Quarter Fixed effects and City Fixed effects are included. T-statistics are in the parenthesis. Standard errors are two-way clustered at the household and quarter levels. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A								
Conspicuous Consumption:	Clothing Shoe	Jewelry/Handbag /Watch	Car	Iphone	Travel/Vacation	Sports	Entertainment (Movie/KTV)	Restaurants
	(1a)	(1b)	(1c)	(1d)	(1e)	(1f)	(1g)	(1h)
FFD	-0.02^{**}	-0.06^{***}	-0.09^{*}	-0.02^{***}	-0.02^{**}	-0.03^{*}	-0.02*	-0.01^{**}
	(-2.13)	(-4.81)	(-1.85)	(-3.20)	(-2.49)	(-1.76)	(-1.85)	(-2.29)
Panel B:								
Other Consumption	Rent	Transportation	Utilities	Pet	Education	Health	Alcohol/Tabacoo	Food (Exclude Restaurants)
	(2a)	(2b)	(2c)	(2d)	(2e)	(2f)	(2g)	(2h)
FFD	0.03	0.01	0.02	0.02	0.02	0.01	0.01	0.02
	(0.42)	(0.37)	(0.80)	(1.29)	(0.79)	(0.85)	(0.49)	(0.31)
Other Consumption	Home Appliance	Miscellaneous						
	(2i)	(2j)						
FFD	0.02	0.01						
	(0.36)	(0.29)						
No. Observations	58851	58851	58851	58851	58851	58851	58851	58851

Table 4: Debt Owed to Family and Friend and Social Media Presence

Estimates of the coefficient β_T are reported, with their corresponding t-statistics in parentheses, for the following regression specification. The dependent variable is the natural logarithm of the number of social media posts:

$$Ln(Social_Media_{iT}) = \alpha_T + \beta_T Ln(FFD_{iT}) + \gamma_T^{HV} HV_{iT} + \epsilon_{iT} \ ,$$

$Social_Media_{iT}$ indicates the number of social media posts in quarter T. $Consumption_Post_{iT}$ indicates the number of social media posts in quarter T related to any forms of consumption. $Sentiment_Post_{iT}$ indicates the number of social media posts in quarter T unrelated to any forms of consumption. HV is a vector of household balance sheet debt variables as well as income/wealth variables. All the independent variable and dependent variable are taken natural logarithm in this regression. T-statistics are in the parenthesis. Standard errors are two-way clustered at the household and quarter levels. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Social_Media	Social_Media	Social_Media	Social_Media	Consumption_Post	Sentiment_Post
	(a)	(b)	(c)	(d)	(e)	(f)
FFD	-0.18^{***}	-0.12^{***}	-0.09^{***}	-0.08^{**}	-0.10^{***}	0.02
	(-9.19)	(-5.53)	(-3.10)	(-2.40)	(-2.85)	(0.96)
Liquid wealth			0.01	0.01	0.01	0.00
			(1.10)	(0.97)	(0.93)	(0.85)
Income			0.04	0.04	0.03	0.02
			(1.14)	(0.90)	(0.84)	(1.30)
Mortgage			0.03	0.03	0.03	-0.01
			(0.91)	(0.86)	(0.92)	(-0.79)
Fintech Debt			0.02	0.01	0.01	-0.02
			(0.98)	(0.39)	(0.20)	(-0.90)
Other Debt			0.15	0.11	0.05	0.03
			(1.32)	(0.83)	(0.61)	(0.47)
Quarter FE		Y	Y	Y	Y	Y
City FE		Y	Y			
Household FE				Y	Y	Y
R^2	2%	10%	12%	30%	35%	20%
N	30217	30217	30217	30217	30217	30217

Table 5: Exclusion Restriction Tests

Estimates of coefficients and their t-statistics (in parentheses) from a panel regression. The independent variable is the number of close family and friends a household has. The dependent variables are household characteristics such as age, salary, liquid wealth, mortgage, and fintech debt. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	No. Friends&Family	No. Friends&Family	No. Friends&Family
	(a)	(b)	(c)
Age	-0.01	0.01	0.01
	(-0.17)	(0.22)	(0.14)
Car ownership	0.48	0.29	0.33
	(0.42)	(0.21)	(0.29)
House ownership	-0.73	0.62	0.69
	(-0.51)	(0.48)	(0.50)
Salary	0.00	0.00	0.00
	(0.44)	(0.63)	(0.38)
Liquid wealth	-0.00	-0.00	-0.00
	(-0.49)	(-0.44)	(-0.48)
Mortgage	-0.00	0.00	0.00
	(-0.43)	(0.40)	(0.38)
Fintech debt	-0.00	-0.00	-0.00
	(-0.29)	(-0.15)	(-0.80)
Quarter FE	X		X
City FE	X		
Household FE		X	X
No. of Observations	34213	34213	34213

Table 6: Instrumental Variables (Long-Difference)

We report point estimates from a long-difference regression that compares changes in a household's outcomes from half a year after FFD uptake to half a year before FFD uptake, similar to the approach in Dinerstein, Koustas, Yannelis and Earnest (2024). We estimate this specification using two-stage least squares regression.

$$C_i = \beta \text{ FFD }_i + \lambda X_i + \epsilon_i$$
$$\text{FFD }_i = \gamma \text{ CFR }_i + \pi X_i + \mu_i$$

CFR is the average number of close relatives or friends that the household has. For the control group, we also randomly assign a placebo FFD date. This identification strategy estimates the local average treatment effect for borrowers whose borrowing decisions depend on the availability of FFD. T-statistics are reported in parentheses. For the results presented in column (6) only, both the dependent variables (number of social media postings) and FFD have been transformed using the natural logarithm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Results for instrumental variable: Number of close friends and relatives

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	FFD	Conspicuous	Clothes	Iphone	Non-Conspicuous	Social Media
CFR	2539.41***					
	(5.38)					
FFD		-0.19***	-0.04***	-0.03***	0.05	-0.13**
		(-2.61)	(-2.59)	(-3.75)	(0.34)	(-2.48)
F-test	25.17***					
N	26,596	26,596	26,596	26,596	26,596	12,194
Adj. R^2	0.068	0.114	0.073	0.081	0.031	0.124
Controls	No	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Instrumental Variables (IV-2SLS)

We present the point estimates from an instrumental variable regression analyzing the effect of FFD. This estimation is conducted using a two-stage least squares regression approach.

$$C_{c,it} = \beta \widehat{\text{FFD}}_{iT} \; + \; \lambda' HV_{iT} \; + \; \varepsilon_{iT},$$
$$\widehat{\text{FFD}}_{iT} = \gamma \, \text{CFR}_{iT} \; + \; \pi' HV_{iT} \; + \; u_{iT}.$$

CFR is the average number of close relatives or friends the household has. We utilize the WeChat social media dataset to identify, for each household, the number of individuals with whom they have interacted on at least 10 days within a given month, provided that the WeChat algorithm classifies these conversations as non-work-related. *Conspicuous* is the RMB value of conspicuous consumption in a given quarter T according to the broad definition. We use the two way fixed effect instrumental variable approach. For the results presented in column (6) only, both the dependent variables (number of social media postings) and FFD have been transformed using the natural logarithm. T-statistics are in parenthesis. Standard errors are two-way clustered at the household and quarter levels. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Results for instrumental variable: Number of close friends and relatives

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	FFD	Conspicuous	Clothes	Iphone	Non-Conspicuous	Social Media
CFR	1883.42***					
	(4.79)					
FFD		-0.17***	-0.05***	-0.04***	0.01	-0.17***
		(-3.72)	(-2.71)	(-3.27)	(0.16)	(-3.86)
F-test	23.50***					
N	26,596	26,596	26,596	26,596	26,596	12,194
Adj. R^2	0.318	0.289	0.384	0.402	0.205	0.272
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Household FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: FFD and Other Balance Sheet Variables on the Fiscal Stimulus Take-Up Rate

Estimates of coefficients and their t-statistics (in parentheses) are reported from the following regression. Voucher equals per household RMB amount of government voucher that is offered during a quarter. If no voucher is offered in a given quarter, Voucher equals zero. When the independent variable is a non-conspicuous consumption voucher, the dependent variable is non-conspicuous consumption, denoted as *Others*. When the independent variable is a conspicuous consumption voucher, the dependent variable is conspicuous consumption. The regression specification is

$$Consumption_{iT} = \alpha_T + \beta_T FFD_{iT} + \delta_T FFD_{iT} * Voucher_{iT} + \lambda_T * Voucher_{iT} + \gamma_T^{HV} HV_{iT} + \epsilon_{iT} \ ,$$

For dependent variables, *Conspicuous* is the RMB value of conspicuous consumption in a given quarter T according to the broad definition. *Others* is the RMB value of non-conspicuous consumption. T-statistics are in the parenthesis. Standard errors are two-way clustered at the household and quarter levels. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(a)	(b)	(c)	(d)
	Conspicuous	Conspicuous	Others	Others
FFD*Voucher	-0.003^{***}	-0.003^{**}	0.000	0.000
	(-2.75)	(-2.47)	(0.03)	(0.02)
FFD	-0.131^{***}	-0.151^{***}	0.036	0.062
	(-3.50)	(-2.84)	(0.25)	(0.48)
Voucher	0.008^{***}	0.008^{***}	0.009^{***}	0.009^{***}
	(2.97)	(2.80)	(4.04)	(3.01)
Liquid wealth*Voucher		0.002		-0.002
		(0.86)		(-0.84)
Liquid wealth		0.002^{***}		0.002^{***}
		(2.85)		(2.71)
Income*Voucher		0.003		0.003
		(1.12)		(0.94)
Income		0.009^{***}		0.008^{**}
		(2.74)		(2.31)
Mortgage*Voucher		-0.002		-0.002
		(-1.02)		(-0.49)
Mortgage		0.003		0.002
		(0.74)		(0.63)
Fintech Debt*Voucher		0.001		-0.001
		(0.86)		(-0.39)
Fintech Debt		0.001		0.002
		(0.39)		(0.40)
City FE	Y	Y	Y	Y
R^2	24%	27%	17%	19%
No. of Observations	18851	18851	18851	18851

Table 9: Debt Owed to Family and Friend and Income Stability

Estimates of the coefficient β_T are reported and t-statistics are shown in parentheses. The results are obtained from the following regression:

$$ConspicuousConsumption = \alpha_T + \beta_1 FFD_{iT} + \beta_2 FFD_{iT} * Job_Instability_{iT} + \beta_3 Job_Instability_{iT} + \gamma_T^{HV} HV_{iT} + \epsilon_{iT} ,$$

Job Instability is measured by two variables, Income volatility and Job turnover. Income volatility is the normalized income volatility in the past five years. Job turnover is the number of job turnover the household has in the past three years. HV is a vector of indicators for household balance sheet debt variables as well as income/wealth variables. *Conspicuous* is the RMB value of conspicuous consumption in a given quarter T according to the broad definition. Standard errors are two-way clustered at the household and quarter levels. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Conspicuous (a)	Conspicuous (b)	Conspicuous (c)	Conspicuous (d)
FFD*Income volatility	−0.01**	−0.01**		
	(-2.27)	(-1.99)		
Income volatility	0.01	0.01		
	(0.95)	(0.79)		
FFD*Job Turnover			−0.01**	-0.01**
			(-2.41)	(-2.03)
Job Turnover			0.01	0.01
			(0.36)	(0.25)
FFD	−0.06***	−0.05**	−0.06***	−0.05***
	(-2.78)	(-2.30)	(-2.91)	(-2.41)
Quarter FE	Y	Y	Y	Y
City FE	Y		Y	
Household FE		Y		Y
R^2	17%	31%	18%	32%
N	29827	29827	23214	23214

Table 10: Debt Owed to Family and Friend and Social Media Presence, Social Circle Overlap

Estimates of the coefficient β_T are reported and t-statistics are shown in parentheses. The results are obtained from the following regression:

$$\ln(Social_Media_{iT}) = \alpha_T + \beta_1 \ln(FFD_{iT}) + \beta_2 \ln(FFD_{iT}) \times \mathbf{1}_{SocialCircleOverlap} + \beta_3 \mathbf{1}_{SocialCircleOverlap} + \gamma_T^{HV} HV_{iT} + \epsilon_{iT}.$$

We define several indicator variables to assess the overlap of household social circles. The overlap measure is calculated from the Tencent social media dataset by counting the number of actual connections between all of a user's friends and dividing it by the total number of possible connections among them. The indicator variable **1**SocialCircleOverlap measures the degree of overlap among a household's social circles. Specifically, **1**HighOverlap equals one if the household's social circle overlap is in the top tercile of the distribution, indicating that the household's social circles are highly interconnected. Conversely, $\mathbf{1}_{\text{LowOverlap}}$ equals one if the overlap value falls in the lowest tercile, representing little or no overlap among the household's social circles. The middle tercile, which is not explicitly represented by an indicator variable, serves as the omitted reference category in our analysis. $Social_Media_{iT}$ indicates the number of social media posts in quarter T. $Consumption_Post_{iT}$ indicates the number of social media posts in quarter T related to any forms of consumption. $Sentiment_Post_{iT}$ indicates the number of social media posts in quarter T unrelated to any forms of consumption. HV is a vector of household balance sheet debt variables as well as income/wealth variables. All the independent variable (indicator variables excluded) and dependent variable are taken natural logarithm in this regression. T-statistics are in the parenthesis. Standard errors are two-way clustered at the household and quarter levels. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Social_Media	Social_Media	Consumption_Post	Sentiment_Post
	(a)	(b)	(c)	(d)
FFD* $\mathbf{1}_{HighOverlap}$	-0.05^{***}	-0.04^{**}	-0.04^{**}	0.00
	(-2.71)	(-2.25)	(-2.39)	(0.04)
FFD* $\mathbf{1}_{LowOverlap}$	0.04^{***}	0.02^{**}	0.03^{**}	0.00
	(2.63)	(2.12)	(2.35)	(0.08)
$\mathbf{1}_{HighOverlap}$	0.01	-0.01	-0.01	-0.01
	(0.23)	(-0.37)	(-0.20)	-(0.52)
$\mathbf{1}_{LowOverlap}$	0.01	0.01	0.01	0.01
	(0.19)	(0.28)	(0.32)	(0.16)
FFD	-0.07^{**}	-0.06^{**}	-0.08^{**}	0.02
	(-2.36)	(-2.25)	(-2.39)	(0.63)
Quarter FE	Y	Y	Y	Y
City FE	Y			
Household FE		Y	Y	Y
R^2	29%	33%	37%	18%
N	24217	24217	24217	24217

Table 11: The FFD Effect and Formal Contractual Features

Estimates of the coefficients and their t-statistics (in parentheses) from interaction regressions with FFD contract terms are reported using the following regression specification:

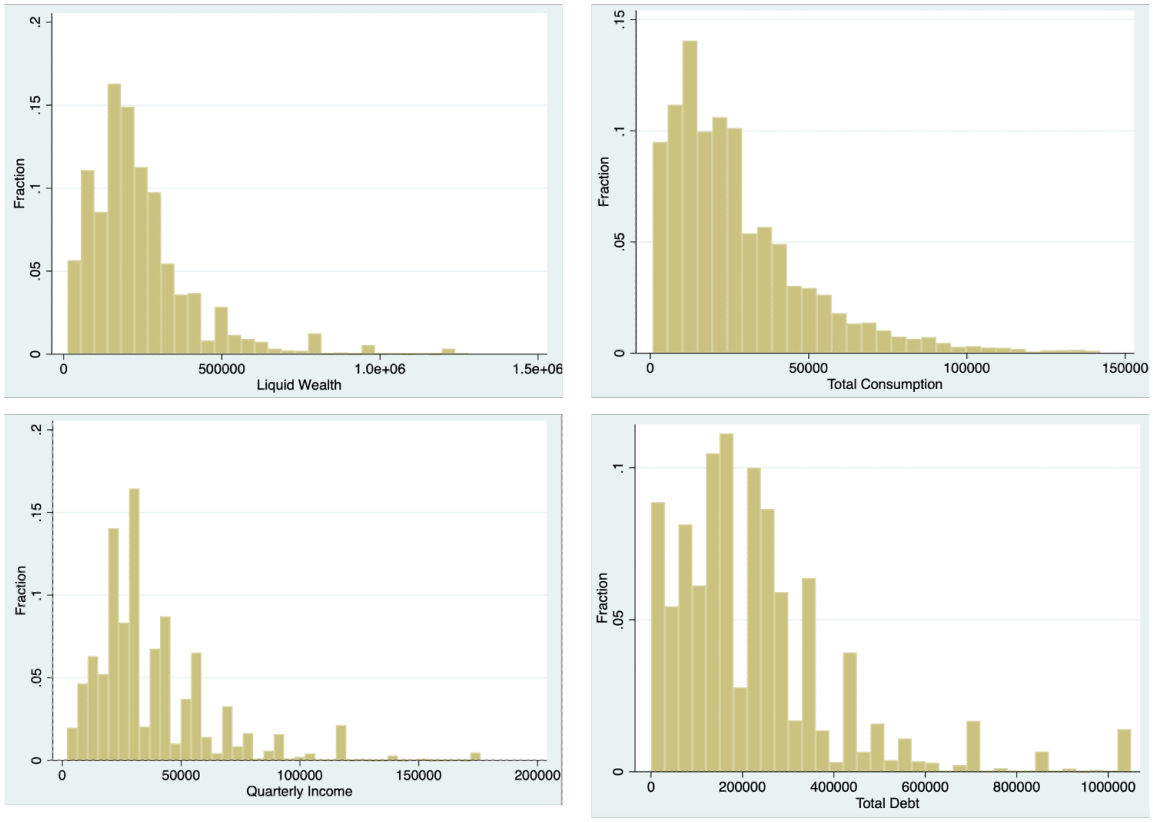
$$Conspicuous_Consumption_{iT} = \alpha_T + \beta_T FFD_{iT} + \delta_T FFD_{iT} * \mathbb{1}_{iT}^{CT} + \gamma_T^{HV} HV_{iT} + \epsilon_{iT} \ ,$$

The dependent variable in the regressions, $Conspicuous_Consumption_{iT}$ indicates the conspicuous consumption in quarter T, according to the broad definition. $\mathbb{1}_{iT}^{CT}$ is a FFD contract indicator variable that alternately equals Maturity, which indicates whether the FFD has a pre-determined repayment date; Interest, which indicates whether the FFD has a positive interest rate; Contract, which indicates whether the FFD has a written contract; or Any, which indicates whether the FFD has any of these three features. The rows labeled Maturity, Interest, Contract, and Any contain estimates of δ_T. For the results presented in column (e) only, both the dependent variables (number of social media postings) and FFD have been transformed using the natural logarithm. HV is a vector of indicators for household balance sheet debt variables as well as income/wealth variables. T-statistics are in the parenthesis. Standard errors are two-way clustered at the household and quarter levels. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent:	Conspicuous (a)	Conspicuous (b)	Conspicuous (c)	Conspicuous (d)	Social Media (e)
FFD	-0.20^{***}	-0.22^{***}	-0.24^{***}	-0.29^{***}	-0.12^{***}
	(-2.84)	(-2.99)	(-3.10)	(-3.80)	(-2.66)
Maturity	0.08^{**}				
	(2.25)				
Interest		0.12^{**}			
		(2.30)			
Contract			0.17^{**}		
			(2.41)		
Any				0.25^{***}	0.05^{**}
				(3.41)	(2.09)
No. of Observations	36271	36271	36271	36271	36271

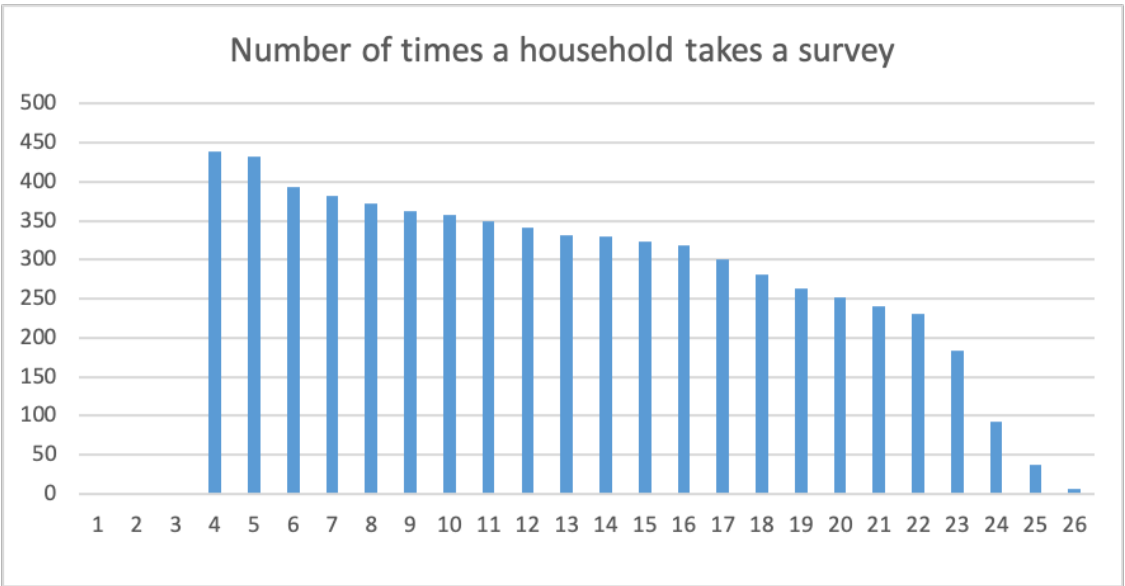
9 Online Appendix

Figure A.1: Histogram of household balance sheet variables



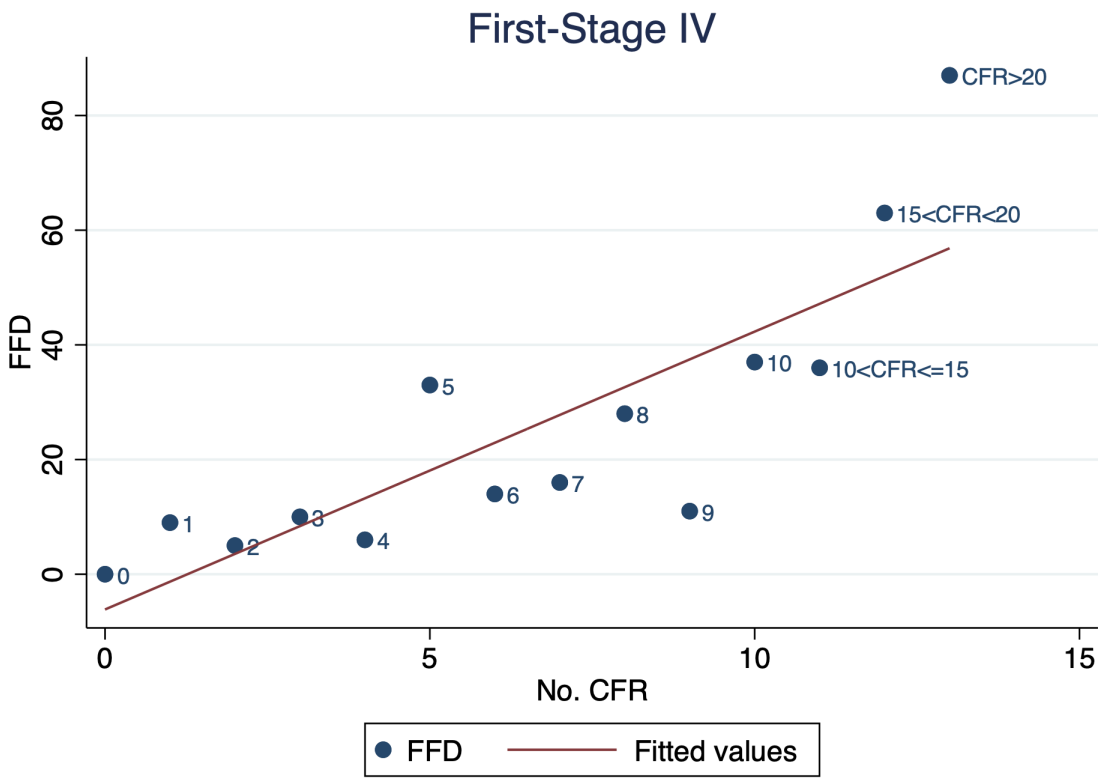
This Figure shows the histogram of key household balance sheet variables.

Figure A.2: Distribution of the number of times a household takes the survey



This figure shows the number of times a household takes the survey. Our sample only includes household has taken a survey for at least four years, or at least a year.

Figure A.3: First-stage Instrument



The regression shows the OLS relationship between the No. CFR and FFD (in thousand RMBs).

Table A.1: Shopping Coupon by Province and Quarter

Shopping Coupon by Province and Quarter

	Below 10 mil	10 mil to 100 mil	100 mil to 1 bil	Above 1 bil
Jiangsu	15	6	2	0
Guangdong	3	12	4	0
HeBei	13	3	0	0
Shanghai	1	1	6	6
Zhejiang	5	5	4	0
Sichuang	4	8	1	0
Shandong	7	5	0	0
Beijing	2	6	2	0
Fujian	7	2	0	0
Jiangxi	3	4	1	0
Liaoning	3	3	0	0
Anhui	2	2	1	0
Henan	2	2	1	0
Tianjing	3	2	0	0
Guizhou	1	3	0	0
HuBei	1	1	0	0
Hunan	2	0	0	0
Jilin	1	1	0	0
Yunan	1	1	0	0
Hainan	0	1	0	0
Neimeng	0	1	0	0
Shanxi	0	1	0	0
Chongqing	1	0	0	0
2020Q1	3	0	0	0
2020Q2	22	27	13	3
2020Q3	10	14	2	1
2020Q4	3	2	1	0
2021Q1	10	7	0	0
2021Q2	2	0	1	2
2021Q3	11	5	0	0
2021Q4	5	3	0	0
2022Q1	12	10	5	0

Table A.2: Debt Owed to Family and Friend and Conspicuous Consumption (FFD dummy variable)

Estimates of the coefficient β_T in percent and their t-statistics (in parentheses) are reported for the following consumption regression.

$$Consumption_{iT} = \alpha_T + \beta_T \mathbb{1}FFD_{iT} + \gamma_T^{HV} \mathbb{1}HV_{iT} + \epsilon_{iT} \ ,$$

For dependent variables, $Conspicuous_Consumption_{iT}$ indicates the conspicuous consumption in quarter T. Specifically, Conspicuous consumption (Narrow) is the quarterly RMB amount of consumption for consumption categories that are considered conspicuous as in Charles, Hurst and Roussanov (2009), which includes clothes and jewellery. Conspicuous consumption (Broad) is the quarterly RMB amount of consumption of those in Conspicuous consumption (Narrow) but also include iphone, sport/ sports equipment, and travel. Other consumption is the consumption category that is in not in conspicuous consumption category (broad). For independent variables, $\mathbb{1}FFD$ is an indicator of whether household i has borrowed from family and friends in that quarter. $\mathbb{1}HV$ is a vector of indicators for household balance sheet debt variables as well as income/wealth variables. T-statistics are in the parenthesis. Standard errors are two-way clustered at the household and quarter levels. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Consumption type:	Conspicuous (Broad) (a)	Conspicuous (Broad) (b)	Conspicuous (Broad) (c)	Conspicuous (Narrow) (d)	Conspicuous (Narrow) (e)	Conspicuous (Narrow) (f)	Others (g)	Others (h)	Others (i)
FFD	-2713^{***}	-2418^{***}	-2213^{***}	-928^{***}	-882^{***}	-871^{***}	391	294	194
	(-4.27)	(-4.29)	(-3.02)	(-3.29)	(-2.87)	(-2.64)	(0.69)	(0.44)	(0.31)
Mortgage		831	628		1029	895		759	573
		(0.84)	(0.58)		(0.62)	(0.53)		(0.74)	(0.58)
Fintech Debt		1039^{**}	818^{*}		928^{*}	721		-381	-295
		(2.18)	(1.85)		(1.85)	(1.48)		(-0.48)	(-0.27)
Other Debt		128	-102		-85	-74		101	81
		(0.33)	(-0.47)		(-0.21)	(-0.19)		(0.27)	(0.19)
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
City FE	Y	Y		Y	Y		Y	Y	
Household FE			Y			Y			Y
R^2	16%	21%	47%	14%	16%	41%	10%	12%	35%
No. Observations	82749	82749	82749	82749	82749	82749	82749	82749	82749

Table A.3: FFD Consumption by category (FFD dummy variable)

Estimates of the coefficient β_T, along with their t-statistics (in parentheses), are presented for each consumption category using the following regression specification:

$$Consumption_{iT} = \alpha_T + \beta_1 \mathbb{1}FFD_{iT} + \gamma_T^{HV} \mathbb{1}HV_{iT} + \epsilon_{iT} \ ,$$

$Consumption_{iT}$ indicates the specific RMB amount of consumption in quarter T. $\mathbb{1}HV$ is a vector of indicators for household balance sheet debt variables as well as income/wealth variables. Quarter Fixed effects and City Fixed effects are included. T-statistics are in the parenthesis. Standard errors are two-way clustered at the household and quarter levels. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A								
Conspicuous	Clothing	Jewelry/Handbag	Car	Iphone	Travel/Vacation	Sports	Entertainment	Restaurants
Consumption:	Shoe	/Watch					(Movie/KTV)	
	(1a)	(1b)	(1c)	(1d)	(1e)	(1f)	(1g)	(1h)
FFD	-517^{***}	-592^{***}	-1925^{*}	-381^{***}	-291^{***}	-182	-482^{***}	-395^{***}
	(-2.62)	(-3.72)	(-1.91)	(-4.25)	(-2.59)	(-1.27)	(-3.49)	(-3.15)
Panel B:								
Other Consumption	Rent	Transportation	Utilities	Pet	Education	Health	Alcohol/Tabacoo	Food
	(2a)	(2b)	(2c)	(2d)	(2e)	(2f)	(2g)	(2h)
FFD	385	184	95	105	-52	42	105	94
	(0.49)	(0.31)	(0.83)	(0.49)	(-0.32)	(0.35)	(0.74)	(0.92)
Other Consumption	Home Appliance	Miscellaneous						
	(2i)	(2j)						
FFD	164	214						
	(0.37)	(0.25)						
No. Observations	58851	58851	58851	58851	58851	58851	58851	58851

Table A.4: Debt Owed to Family and Friend and Social Media Presence (FFD dummy variable)

Estimates of the coefficient β_T and their t-statistics (in parentheses) are reported using the following regression specification:

$$Social_Media_{iT} = \alpha_T + \beta_T \mathbb{1}FFD_{iT} + \gamma_T^{HV} \mathbb{1}HV_{iT} + \epsilon_{iT} \ ,$$

$Social_Media_{iT}$ indicates the number of social media posts in quarter T. $Consumption_Post_{iT}$ indicates the number of social media posts in quarter T related to any forms of consumption. $Sentiment_Post_{iT}$ indicates the number of social media posts in quarter T unrelated to any forms of consumption. $\mathbb{1}FFD$ is an indicator of whether household i has borrowed from family and friends in that quarter. $\mathbb{1}HV$ is a vector of indicators for household balance sheet debt variables as well as income/wealth variables. T-statistics are in the parenthesis. Standard errors are two-way clustered at the household and quarter levels. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Social_Media	Social_Media	Social_Media	Social_Media	Consumption_Post	Sentiment_Post
	(a)	(b)	(c)	(d)	(e)	(f)
FFD	-3.39^{***}	-3.18^{***}	-3.02^{***}	-2.28^{**}	-2.42^{***}	0.48
	(-8.24)	(-4.19)	(-3.10)	(-2.31)	(-2.92)	(1.19)
Quarter FE		Y	Y	Y	Y	Y
City FE			Y			
Household FE				Y	Y	Y
R^2	2%	10%	17%	30%	35%	20%
N	30217	30217	30217	30217	30217	30217

Table A.5: Debt Owed to Family and Friend and Conspicuous Consumption (Excluding Never-Treated Households)

Estimates of the coefficient β_T and their t-statistics (in parentheses) are reported for the following consumption regression.

$$Consumption_{iT} = \alpha_T + \beta_T FFD_{iT} + \gamma_T^{HV} HV_{iT} + \epsilon_{iT} \ ,$$

For dependent variables, $Conspicuous_Consumption_{iT}$ indicates the conspicuous consumption in quarter T. Specifically, Conspicuous consumption (Narrow) is the quarterly RMB amount of consumption for consumption categories that are considered conspicuous as in Charles, Hurst and Roussanov (2009), which includes clothes and jewellery. Conspicuous consumption (Broad) is the quarterly RMB amount of consumption of those in Conspicuous consumption (Narrow) but also include iphone, sport/ sports equipment, and travel. Other consumption is the consumption category that is in not in conspicuous consumption category (broad). For independent variables, FFD is the RMB amount of debt owed to family and friends in a given quarter T. HV is a vector of household balance sheet debt variables as well as income/wealth variables. In this robustness check, we also exclude households that have never taken FFD from the sample. T-statistics are in the parenthesis. Standard errors are two-way clustered at the household and quarter levels. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Consumption type:	Conspicuous (Broad) (a)	Conspicuous (Broad) (b)	Conspicuous (Broad) (c)	Conspicuous (Narrow) (d)	Conspicuous (Narrow) (e)	Conspicuous (Narrow) (f)	Others (g)	Others (h)	Others (i)
FFD	-0.17^{***}	-0.15^{***}	-0.06^{**}	-0.13^{***}	-0.07^{***}	-0.05^{**}	0.03	0.02	0.01
	(-3.18)	(-2.87)	(-2.02)	(-3.49)	(-3.09)	(-2.37)	(0.46)	(0.29)	(0.10)
Liquid wealth		0.01^{***}	0.00		0.02^{***}	0.01^{**}		0.01^{***}	0.01^{**}
		(3.10)	(0.62)		(2.84)	(2.11)		(2.70)	(2.41)
Income		0.03^{***}	0.01^{*}		0.06^{**}	0.05^{**}		0.02^{**}	0.02^{**}
		(3.09)	(1.86)		(3.02)	(2.01)		(2.31)	(2.09)
Mortgage		0.01	0.01		0.02	0.01		-0.01	-0.01
		(0.42)	(0.39)		(0.51)	(0.42)		(-0.72)	(-0.57)
Fintech Debt		0.02^{**}	0.02^{*}		0.09^{*}	0.02		-0.02^{**}	-0.01
		(2.03)	(1.82)		(1.85)	(0.63)		(-1.99)	(-0.87)
Other Debt		0.19	-0.08		-0.29	-0.30		0.08	0.05
		(0.82)	(-0.64)		(-0.57)	(-0.39)		(0.39)	(0.31)
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
City FE	Y	Y		Y	Y		Y	Y	
Household FE			Y			Y			Y
R^2	17%	19%	45%	13%	17%	40%	9%	11%	37%
No. Observations	10482	10482	10482	10482	10482	10482	10482	10482	10482

Table A.6: Debt Owed to Family and Friend and Social Media Presence (Excluding Never-Treated Households)

Estimates of the coefficient β_T are reported, with their corresponding t-statistics in parentheses, for the following regression specification. The dependent variable is the natural logarithm of the number of social media posts:

$$Ln(Social_Media_{iT}) = \alpha_T + \beta_T Ln(FFD_{iT}) + \gamma_T^{HV} HV_{iT} + \epsilon_{iT} \ ,$$

$Social_Media_{iT}$ indicates the number of social media posts in quarter T. $Consumption_Post_{iT}$ indicates the number of social media posts in quarter T related to any forms of consumption. $Sentiment_Post_{iT}$ indicates the number of social media posts in quarter T unrelated to any forms of consumption. HV is a vector of household balance sheet debt variables as well as income/wealth variables. All the independent variable and dependent variable are taken natural logarithm in this regression. In this robustness check, we also exclude households that have never taken FFD from the sample. T-statistics are in the parenthesis. Standard errors are two-way clustered at the household and quarter levels. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Social_Media	Social_Media	Social_Media	Social_Media	Consumption_Post	Sentiment_Post
	(a)	(b)	(c)	(d)	(e)	(f)
FFD	-0.16^{***}	-0.11^{***}	-0.07^{***}	-0.07^{**}	-0.08^{***}	0.01
	(-5.29)	(-3.72)	(-2.98)	(-2.19)	(-2.69)	(0.79)
Liquid wealth			0.01	0.01	0.01	0.00
			(0.86)	(0.73)	(0.61)	(0.57)
Income			0.02	0.02	0.03	-0.01
			(1.14)	(0.90)	(0.84)	(-0.73)
Mortgage			0.02	0.02	0.04	-0.01
			(1.28)	(0.61)	(1.19)	(-0.79)
Fintech Debt			0.00	0.00	0.01	-0.02
			(0.31)	(0.74)	(0.80)	(-0.42)
Other Debt			0.10	0.07	0.06	0.04
			(0.80)	(0.62)	(0.75)	(0.51)
Quarter FE		Y	Y	Y	Y	Y
City FE		Y	Y			
Household FE				Y	Y	Y
R^2	1%	9%	13%	31%	37%	22%
N	4728	4728	4728	4728	4728	4728

Table A.7: Conspicuous Consumption Linkage: Restaurant, Entertainment, Sports, and Travel

This table examines whether spending on restaurants, entertainment, sports, and travel behaves increasingly like narrowly defined conspicuous consumption (jewelry and clothing) after the rise of social media. The following specification is estimated:

$$Consumption_{iT}^{k} = \alpha_i + \delta_T + \beta_T Conspicuous_{iT}^{core} + \theta_T(Conspicuous_{iT}^{core} \times Post_T) + \gamma_T^{HV} HV_{iT} + \varepsilon_{iT},$$

where $Consumption_{iT}^{k}$ is total household spending in category k (in levels, e.g., quarterly RMB); $Conspicuous_{iT}^{core}$ is total spending on narrowly defined conspicuous goods (jewelry and clothing); and $Post_T$ equals one for observations after 2015, when social media posting became widespread on WeChat and other platforms. HV_{iT} is a vector of household balance sheet and income/wealth controls. Household and quarter fixed effects are included. T-statistics are in parentheses. Standard errors are clustered at the household level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Restaurant	Entertainment	Travel	Sports
	(a)	(b)	(c)	(d)
θ_T	0.12***	0.08***	0.15**	0.09***
	(2.82)	(3.83)	(3.72)	(2.90)
Household FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
R^2	0.17	0.16	0.20	0.19
Observations	13,922	13,922	13,922	13,922
	Utilities	Education	Transportation	Alcohol/Tobacco
	(e)	(f)	(g)	(h)
θ_T	-0.04	-0.03	-0.15	-0.09
	(-0.24)	(-0.25)	(-0.72)	(-0.84)
Household FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
R^2	0.17	0.16	0.20	0.19
Observations	13,922	13,922	13,922	13,922

Table A.8: Robustness Checks

Panel A presents estimates of the coefficients and their t-statistics (in parentheses) from panel regressions. The dependent variable in the regressions, $Conspicuous_Consumption_{iT}$ indicates the conspicuous consumption in quarter T, according to the broad definition. The Panel A regression specification is

$$Conspicuous_Consumption_{iT} = \alpha_T + \beta_T FFD_{iT} + \gamma_T^{HV} HV_{iT} + \epsilon_{iT} \ ,$$

For the results in Panel A, T-statistics are in the parenthesis. Standard errors are clustered at the household level. Panel B presents results from a logistic regression where the dependent variable is an indicator that household is aware of a shopping coupon from the government. Z-statistics are in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A:					
	Female Head	Male Head	Below 30	30 to 60	Above 60
FFD	-0.09^{***}	-0.11^{***}	-0.17^{***}	-0.14^{***}	-0.03
	(-3.96)	(-4.75)	(-3.97)	(-3.12)	(-0.87)
Panel B:					
	FFD	Income	Liquid Wealth	Mortgage	Fintech
Coupon	-0.98	-0.85^{***}	-0.88^{***}	0.73	1.15^{**}
	(-0.18)	(-2.94)	(-3.10)	(0.91)	(2.21)

Table A.9: Summary Statistics (Tencent/Wechat Pay)

This table presents summary statistics for the consumption categories that can be reliably matched to specific categories in the Tencent dataset. "Correlation" refers to the average time series correlation across households between our survey dataset and the proprietary Tencent dataset.

	Mean	SD	5%	50%	95%	Correlation
Consumption descriptors						
Clothing	518	2,529	301	428	2,618	0.635
Travel	271	3,038	0	0	2,018	0.781
Sports	319	1,038	0	219	1,837	0.651
Entertainment	318	2,381	0	319	3,928	0.473
Restaurants	819	4,018	0	418	4,362	0.751
Transportation	1,443	3,864	642	1131	4,075	0.481
Pet	395	2,853	0	0	2,075	0.769
Alcohol/Tabacoo	976	6,073	0	527	4,852	0.551

Table A.10: FFD Consumption by category (Tencent/Wechat Pay)

Estimates of the coefficient β_T are reported, with their t-statistics in parentheses, for each consumption category using the following regression specification with the Tencent dataset.

$$Consumption_{iT} = \alpha_T + \beta_T FFD_{iT} + \gamma_T^{HV} HV_{iT} + \epsilon_{iT} \ ,$$

For consumption categories that cannot be mapped to the Tencent dataset, we indicate them with "N/A." $Consumption_{iT}$ indicates the RMB amount spent on a specific category of consumption in quarter T. HV is a vector of household balance sheet debt variables as well as income/wealth variables. Quarter Fixed effects and City Fixed effects are included. T-statistics are in the parenthesis. Standard errors are two-way clustered at the household and quarter levels. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A								
Conspicuous	Clothing	Jewelry/Handbag	Car	Iphone	Travel/Vacation	Sports	Entertainment	Restaurants
Consumption:	Shoe	/Watch					(Movie/KTV)	
	(1a)	(1b)	(1c)	(1d)	(1e)	(1f)	(1g)	(1h)
FFD	-0.011^{**}	-0.034^{***}	N/A	N/A	-0.007^{*}	-0.006	-0.012^{**}	-0.023^{**}
	(-2.13)	(-3.09)			(-1.85)	(-0.57)	(-2.01)	(-2.42)
Panel B:								
Other Consumption	Rent	Transportation	Utilities	Pet	Education	Health	Alcohol/Tabacoo	Food
								(Exclude Restaurants)
	(2a)	(2b)	(2c)	(2d)	(2e)	(2f)	(2g)	(2h)
FFD	N/A	0.007	N/A	0.003	N/A	N/A	0.002	N/A
		(0.62)		(0.18)			(0.49)	
Other Consumption	Home Appliance	Miscellaneous						
	(2i)	(2j)						
FFD	0.002	0.005						
	(0.49)	(0.80)						
No. Observations	12327	12327	12327	12327	12327	12327	12327	12327

I.1 Open-ended Survey

Question lists:

1. Why do you borrow?
2. What emotions do you feel when you borrow?
3. What is your preferred way of borrowing?
4. Does borrowing increase or decrease your consumption?
5. What kind of borrowing increases your consumption, and what kind decreases it?
6. Why does borrowing increase/decrease your consumption?
7. For FFD, what specific types of consumption do you increase or decrease?
8. Can you recall how you feel when you have difficulties repaying your debt?
9. Have you ever experienced any form of pressure, criticism, or sanction from your bank/P2P/Fintech/FFD lender after you borrowed? If so, can you describe what happened?
10. If your borrowing from family or friends had a written agreement or a fixed repayment schedule, would your spending behavior change? How?
11. When you borrow from family and friends, how specific are the rules or agreements about how you should use the money?
12. After you repay your family or friends, do you feel your consumption behavior changes? Please explain.
13. How do you think your relationship with the lender (family or friends) would change if you used borrowed money for purposes they did not expect? Please describe.
14. Does your borrowing affect your social media behavior?
15. Do you ever hide or avoid sharing certain purchases on social media because you have borrowed from family or friends? Why or why not?

I.1.1 LLM coding scheme

Q9 Sample Responses:

1. No Negative Experience:

- No experience of pressure, criticism, or sanction.

2. Pressure to Repay:
    - Frequent reminders or phone calls about repayment
    - Threats of legal action if payment is late
    - Urgent or aggressive demands to pay back the loan
3. Criticism or Verbal Abuse:
    - Criticism for late payments or borrowing
    - Negative comments about financial management
    - Feelings of shame or humiliation resulting from lender communication
4. Financial Sanctions or Penalties:
    - Extra fees or penalties charged for late payment
    - Access to further credit denied or restricted
    - Collateral seized or threatened with seizure
5. Harassment or Intimidation:
    - Repeated, unwanted contact through calls, messages, or visits
    - Harassment of family members or guarantors
    - Threats to report to employer, community, or authorities
6. Legal or Formal Actions:
    - Receiving legal notices or being taken to court
    - Blacklisting or negative credit reporting
7. Other:
    - Any other forms of negative treatment not covered above (with description)
8. Not Sure / Prefer Not to Say:
    - Uncertainty about whether the experience counts as pressure, criticism, or sanction

- Prefer not to answer

Q10 Sample Responses:

1. Yes, I'd be more cautious or constrained with my spending:
    - I'd be more careful about what I buy so I don't break the agreement.
    - A formal contract would make me take the loan more seriously.
    - I would avoid spending on things not allowed by the agreement.
2. Yes, I'd feel more pressure or stress:
    - Having a fixed schedule would make me feel anxious about repayment, so I'd cut back on unnecessary expenses.
    - I'd probably restrict my spending to make sure I can pay on time.
3. No, my spending wouldn't change:
    - I'd spend the same whether or not there's a formal agreement.
    - My behavior doesn't depend on paperwork; I'm responsible anyway.
4. Yes, I'd feel more freedom or clarity:
    - A written agreement would clarify expectations, so I'd feel more comfortable making purchases within those limits.
    - With clear rules, I'd know what's acceptable and could plan my spending better.
5. Conditional or Contextual:
    - It depends on how strict the agreement is.
    - Maybe if the repayment schedule was tight, I'd spend less, but otherwise not.
6. Unclear or Unsure:
    - I'm not sure, I've never had a written agreement.
    - I haven't thought about it.

Q12 Sample Responses:

1. Increased Consumption (Rebound Effect):
    - Yes, I feel free to spend more on myself after I finish repaying.
    - Once I'm out of debt, I buy things I had postponed, like new clothes or eating out.
    - I definitely feel more comfortable making big or luxury purchases.
2. No Change in Consumption:
    - No, my spending habits stay the same before and after repayment.
    - Repaying the loan doesn't affect how I consume.
    - I don't really change my consumption just because the debt is gone.
3. More Responsible or Cautious Consumption:
    - After repaying, I am more careful with money so I don't have to borrow again.
    - I learned to budget better, so I keep spending conservatively.
    - The experience made me value saving, so I still avoid unnecessary purchases.
4. Conditional or Contextual Change:
    - It depends—if the loan was big, I might celebrate, otherwise no change.
    - If I feel financially secure after repaying, I might spend more, but if not, I continue being careful.
5. Unclear or Unsure:
    - I'm not sure, I haven't thought about it.
    - I haven't finished repaying yet, so I don't know.

Q13 Sample Responses:

1. Negative Change: Responses indicating relationship deterioration, loss of trust, anger, or sanctions.
2. No Change: Responses indicating the relationship would remain unaffected.

3. Conditional: Responses indicating it depends on the context, amount, or nature of the purchase.
4. Justification/Explanation: Responses focused on communication, explanation, or apology to mitigate effects.
5. Unclear/Unsure: Responses expressing uncertainty or lack of experience.

Q15 Sample Responses:

1. Hides/Avoids Sharing

   Respondent hides or avoids sharing information about certain purchases with the lender. Reasons may include:

   - Fear of sanction or punishment
   - Feelings of guilt or embarrassment
   - Desire for privacy or autonomy
   - Worry about damaging the relationship

2. Does Not Hide/Avoid

   Respondent does not hide or avoid sharing purchases with the lender. Reasons may include:

   - Trust in the lender
   - Indifference to lender's opinion
   - Open or strong relationship with the lender
   - Belief that purchases are justified

3. Conditional/Contextual

   Respondent's behavior depends on specific situations, such as:

   - Nature or size of the purchase
   - The lender's personality or expectations
   - Cultural or familial norms
   - The type of relationship with the lender

4. Unclear/Other

   Responses that are ambiguous, indicate uncertainty, or do not fit the categories above.

Table A.11: Open-ended Survey Response Rate

This Table presents the open-ended survey question response rate conditional on the question applies to the responder. For example, if a household has never borrowed, then question one, "Why do you borrow money" does not apply. These questions are recorded in Appendix I.1. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Question No.					
	(1)	(2)	(3)	(4)	(5)
Response Rate:	47%	11%	47%	42%	19%
	(6)	(7)	(8)	(9)	(10)
Response Rate:	15%	32%	36%	11%	8%
	(11)	(12)	(13)	(14)	(15)
Response Rate:	27%	19%	18%	35%	32%