# Willingness to Pay for Liquidity: Evidence from an Interest-Free, Tip-Based Cash Advance Platform

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**Abstract**

Payday loans, characterized by very high APRs, are widely criticized as exploitative, yet evidence on borrowers' willingness to pay (WTP) for short-term liquidity remains limited. At the same time, a growing class of FinTechs offers "interest-free" tip-based cash advances that regulators increasingly view as payday lending in disguise. We study proprietary data from a FinTech that provides interest-free, voluntary tip-based cash advances, with repayment via pre-authorized debit on the borrower's next payday. Using over 6.8 million applications from approximately 289,000 borrowers, we recover a direct revealed-preference measure of WTP for liquidity in the absence of coercive or obligatory pricing terms. Strikingly, many borrowers voluntarily pay implicit interest rates comparable to those in traditional high-cost credit markets. WTP displays substantial heterogeneity across cognitive ability, demographics, financial constraints, local credit conditions, and macroeconomic factors. A stylized model helps reconcile these patterns. Our study informs ongoing debates over whether tip-based cash advances should be regulated as high-cost credit.

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# 1 Introduction

The challenge of providing affordable credit while protecting vulnerable households is a central and unresolved issue in finance. This tension is particularly acute in markets for short-term, small-dollar credit, where liquidity needs are immediate, borrowers are often financially constrained, and traditional banks have historically had a limited presence. At a global level, the scale of small-ticket retail credit is substantial, with small-dollar loans serving over 170 million borrowers worldwide and supporting an outstanding credit portfolio of roughly $ 180 billion (Impact Finance Barometer, 2023). At the same time, products such as payday loans, with Annual Percentage Rates (APRs) often exceeding 300% (Consumer Financial Protection Bureau, 2013), attract increasing regulatory scrutiny, fueling a central policy debate: are such rates a necessary consequence of high risk and operational costs, or evidence of predatory lending that exploits vulnerable consumers?

Over the past decade, the small-dollar credit market in the United States has been reshaped by a new class of FinTechs offering "cash advances" or "earned wage access" products. These providers market themselves as interest-free alternatives to payday loans: borrowers can access funds instantly and are asked, at most, to pay an optional "tip" or a small fee. Recently, however, regulators and state attorneys general have increasingly argued that these products amount to payday lending by another name, with tips and fees functioning as de facto interest charges that evade usury caps and consumer lending laws. Ongoing enforcement actions and policy consultations reflect a sharp disagreement about whether cash-advance FinTechs are genuinely expanding affordable access to liquidity or simply repackaging high-cost credit behind a veneer of voluntary payments.[1] At the federal level, the Consumer Financial Protection Bureau has proposed an interpretive rule clarifying that many paycheck-advance and earned wage access products are consumer loans, bringing explicit scrutiny to tip-based pricing models.[2]

This regulatory controversy is the latest manifestation of a long-standing debate over high-cost small-dollar credit. Payday loans, characterized by very high annual percentage rates (APRs) on short-term advances, have long been criticized as exploitative. In response, many U.S. states have adopted stringent payday regulations, including interest-rate caps, loan-size limits, rollover restrictions, and outright bans.[3] While these policies are designed to protect consumers, the empirical literature paints a more nuanced picture: restricting payday lending can reduce access to formal short-term credit, push borrowers toward overdrafts and late fees, and produce heterogeneous welfare effects across households (Morse, 2011). This regulatory impasse stems

[1] Recent enforcement actions illustrate the stakes. In 2024, the Attorney General of the District of Columbia sued EarnIn, an app-based "pay advance" provider, alleging that its ostensibly fee- and interest-free wage advances were in fact illegal high-interest loans marketed deceptively and offered without a lending license. California, Connecticut, and the District of Columbia have issued orders against cash-advance platforms such as SoLo, finding that once nominally "voluntary" tips and donations are treated as charges, effective APRs breach state usury caps. See https://www.nclc.org/ca-ct-dc-issue-orders-against-fintech-payday-loans-that-solicit-tips and https://oag.dc.gov/release/attorney-general-schwalb-sues-pay-advance-company

[2] See https://www.consumerfinance.gov/about-us/newsroom/cfpb-proposes-interpretive-rule-to-ensure-workers-know-the-costs-and-fees-of-paycheck-advance-products for the rule change.

[3] More recently, a bill was tabled in the US Congress to cap credit card interest rates at 10%.

from a critical gap in our understanding: while the supply-side dynamics of high-cost credit are well-studied, we lack a direct measure of what borrowers themselves are willing to pay for liquidity. Without a clear demand-side metric, it is nearly impossible to distinguish between exploitative pricing and rates that reflect a genuinely high marginal utility of immediate funds. If the marginal utility of a small, fast loan is high for a liquidity-constrained individual, they may rationally choose to incur substantial costs.

This paper confronts this measurement challenge by leveraging a unique empirical setting: a FinTech lender that provides small, short-term, interest-free cash advances. The firm's revenue model relies not on mandatory fees but on voluntary tips. The cash-advance product shares many institutional features with payday loans—small advances, rapid disbursement, and repayment timed to the borrower's next paycheck, but differs along several critical dimensions. Borrowers face no explicit interest or mandatory fee, there is no approval or underwriting process, and the platform allows users to choose any tip amount, including zero. Importantly, tipping does not affect a customer's eligibility for a cash advance. At the same time, borrowers must pre-authorize the platform to debit their bank account on payday, and default rates are extremely low, so in practice the advance is repaid in full on the next payday much like a traditional payday loan. This novel setting provides a clean environment to observe the revealed Willingness to Pay (WTP) for credit, free from the coercion of traditional loan contracts. Drawing on proprietary data covering 6.8 million applications from 289,000 borrowers, we ask: when interest is not required, how much do borrowers choose to pay for credit?

Our study makes four contributions. First, we document that borrowers voluntarily pay an effective APR averaging 270%, providing the first direct evidence that high prices in small-dollar credit markets reflect substantial demand-side willingness to pay, not solely supply-side market power. This finding fundamentally reframes the policy debate: if borrowers replicate high borrowing costs even when payments are voluntary, the problem may not be primarily one of predatory supply-side pricing. Second, we identify economic and behavioral drivers of this WTP, showing systematic variation across income, financial stress, cognitive ability (AFQT scores), and macroeconomic conditions. Third, through randomized field experiments, we provide causal evidence that targeted changes in choice architecture can balance lender viability (increasing the tipper base) with consumer welfare (reducing average borrowing costs). Finally, we develop a stylized theoretical framework in which a "warm-glow" reciprocity parameter is inversely related to net liquidity. Notably, our framework admits two behaviorally distinct but mathematically equivalent interpretations: borrowers may tip out of genuine gratitude for interest-free credit, or out of fear that failing to tip will jeopardize future access to this valuable liquidity source. Both mechanisms generate identical predictions but carry starkly different welfare implications—a distinction that speaks directly to whether tip-based pricing represents informed consumer choice or exploitation of behavioral vulnerabilities.

We use a unique and proprietary dataset obtained from a financial technology platform in the United States that has over eight million customers. The platform offers a full suite of

mobile banking services, including interest-free cash advances, debit accounts, fully managed investment accounts, interest-bearing loans, and rewards programs. The data covers cash advances given between September 2018 and December 2020 and includes detailed information on tipping behavior (both promised and paid amounts), loan characteristics, repayment outcomes, and borrower demographics, such as age, gender, income, and geographic location. The dataset also captures granular financial transactions, offering insights into borrowers' broader economic circumstances. This rich combination of observational and experimental data, including platform-initiated variations in tipping defaults and user interfaces, enables us to identify relationships between borrower characteristics, behavioral nudges, and the borrower's willingness to pay for credit.

The average loan amount is $44.79 with a duration of 14 days. 54% of the loan applicants promise a tip, but 37% eventually pay. The average promised tip is $1.73, while the actual tip amount is $1.15. This translates into an annualized implicit tip-based APR of 77% across borrowers. Conditioning on the sample of tippers, the average inferred APR is 208%. Further, 79% of the applications opt to expedite the cash disbursement (i.e., within hours after application), which incurs a fee of up to $4.99, rather than waiting for between 24 hours and 5 business days. This results in an average implicit annualized APR of 270% or 10.4% over the 14 days. This substantial willingness to pay highlights borrowers' valuation of credit access, even in the absence of mandatory interest charges. Notably, the implicit APR aligns with rates observed in traditional payday lending.

Guided by prior work on path-dependent financial choices (Agarwal et al., 2009; Beshears et al., 2018), we first document substantial path dependence in voluntary fee payments. We find that a borrower who tipped in the previous loan application is 64.50 percentage points more likely to tip again, while a one standard deviation increase in the lagged tip-based APR raises the current tip-based APR by 28.99 percentage points. These findings highlight strong intertemporal correlations: once borrowers commit to higher-cost strategies (e.g., tips), they tend to stay on these trajectories. This pattern resonates with research on payday lending, where users repeatedly accept high-cost loans despite cheaper alternatives (Agarwal et al., 2009), and underscores the role of liquidity constraints and anchoring (Morse, 2011; D'Astous and Shore, 2017; Tversky and Kahneman, 1974).

We next show that tipping incidence and effective borrowing costs vary systematically across observable traits. Female borrowers tip more frequently but at lower overall APRs, consistent with a blend of prosocial tendencies and more conservative financial management (Bertrand and Morse, 2011a; Croson and Gneezy, 2009). Older borrowers are more likely to tip, but conditional on tipping, they do not pay higher tip-based APRs, a gradient that aligns with documented differences in financial sophistication and product use (Carlin et al., 2017; Lusardi and Mitchell, 2014). We also observe meaningful racial and ethnic variation in both the propensity to tip and the implied APRs; these patterns likely reflect a combination of factors including differential access to alternative credit sources, historical exclusion from mainstream financial

services, and socioeconomic disparities (Morse, 2011; Lusardi and Mitchell, 2014; Hasler et al., 2023). Additionally, married individuals exhibit lower tipping and APRs, possibly due to shared household financial decision-making (Marks and Lambert, 1998; Koball et al., 2010), while urban borrowers are less likely to tip, consistent with readier access to alternative short-term credit. Finally, users who activate the platform's Automatic Investment Service (AIS) are more likely to tip, suggesting that broader engagement with the ecosystem correlates with a higher tipping tendency (Carlin et al., 2017). We view these gradients as descriptive; a confluence of demographic and behavioral predispositions determines the effective price of credit, even when that price is discretionary.

Turning to borrower finances, higher monthly paycheck levels are associated with both a lower propensity to tip and lower tip-based APRs, consistent with greater contemporaneous slack reducing the shadow value of immediacy (Friedman, 1957; Agarwal et al., 2018). In contrast, indicators of financial strain, proxied by higher interest paid on other loans, predict higher tipping on the extensive margin, suggesting a strategic motive to preserve goodwill for future credit access (Bertrand and Morse, 2011a). Finally, portfolio gains and higher investment balances correlate with a greater likelihood of tipping yet lower APRs conditional on tipping, a pattern consistent with wealth effects operating primarily on the extensive margin (Poterba, 2000; Carlin et al., 2017).

Next, we analyze whether and how the borrowers' voluntary cost-sharing behavior is shaped by their local financial environment. Across three complementary settings—the cost of local credit, payday lending regulation, and bank competition—we find a consistent pattern: when outside credit is scarcer or more expensive, borrowers are more likely to tip, but they do so more frugally, resulting in lower inferred tip-based APRs. These findings indicate that tipping is not merely an act of generosity but reflects the relative value and scarcity of credit.

We next investigate the sensitivity of voluntary borrowing costs to external macroeconomic conditions. Periods of elevated macroeconomic uncertainty are associated with lower tip-based APRs, consistent with households reducing discretionary outlays when uncertainty rises (Bloom, 2009; Guiso et al., 2018). Similarly, higher short-term policy rates (Federal Funds Rate) coincide with lower tip-implied borrowing costs: as posted interest rates in the economy increase, borrowers appear more cost-conscious in discretionary payments (Bernanke, 1983). Taken together, these results suggest that borrowers are not passively incurring add-on costs; rather, they adjust their voluntary payments to external macroeconomic conditions.

Finally, we explore how dynamic learning and cognitive abilities influence the incidence of voluntary borrowing costs. Repeated platform interactions generate significant "learning by doing" in managing these discretionary fees (Agarwal et al., 2008). Specifically, each additional standard deviation increase in the number of cash advances reduces tipping probability by 1.12 percentage points and the tip-based APR by 15.43 percentage points, suggesting that users learn over time to avoid or minimize these non-mandatory payments. We further observe that cognitive ability, measured via AFQT scores, shapes how users manage tip-based costs: while general scores do not drive the likelihood of tipping, higher numeracy leads to lower APRs (as proxied

by specific AFQT subcomponents) for those who do tip (Stango and Zinman, 2009; Lusardi and Mitchell, 2014). This evidence reinforces the notion that individual financial decision-making is complex, governed by both accumulated experience and cognitive capital.

The final, and causal, component of our analysis leverages randomized control trials (RCTs) to examine the role of choice architecture in shaping WTP. We find that minor interface tweaks, specifically, introducing and recommending a low, nominal default tip (e.g., $1) significantly influence user behavior. This intervention generates a larger uptick in tipping participation along the extensive margin (more users choose to tip), which is consistent with the potency of default options as behavioral nudges (Thaler and Sunstein, 2009; Thaler and Benartzi, 2004). Simultaneously, the nudge leads to a reduction in average tip-based APRs along the intensive margin, as the low default anchor steers users toward smaller, lower-cost contributions. Strikingly, users frequently deviate from the recommended tip, indicating they retain autonomy even when nudged.

Collectively, these experiments causally demonstrate that targeted design interventions can guide sustainable lending practices by enabling lenders to recover their costs by expanding the base of voluntary tippers while simultaneously reducing the costs incurred by each borrower. From a policy perspective, behavioral design offers a compelling alternative to top-down regulation relying on blunt policy instruments like price caps and outright bans.

Motivated by these findings, we develop a highly stylized conceptual framework in which borrowers face liquidity constraints and derive "warm-glow" (reciprocity) utility from tipping to help reconcile these empirical findings. We endogenize the effective reciprocity parameter to depend on net liquidity—the funds available after covering a basic consumption floor. We then analyze comparative statics to understand the effects of income and loan size increases. The optimal tip balances two effects: a higher tip reduces consumption while increasing the warm-glow utility. The effect of an increase in income or relaxation in liquidity constraints is thus ambiguous and reflects the balance between the income effect (higher-income individuals can afford higher tips) and the perceived value of credit (higher liquidity results in a lower propensity to reciprocate). We examine and show that macroeconomic uncertainty reduces tip-based APRs. Finally, we extend the model dynamically to incorporate reputation building and learning, which help explain the persistence in tip behavior.

Our framework is highly stylized and treats many potentially endogenous parameters as given. Nonetheless, the simple exercise provides a useful framework for interpreting our empirical findings and anchoring our reasoning. Specifically, the voluntary tipping model explains a substantial portion of the observed behavior: high implicit APRs can be rationalized as the cost borrowers are willing to pay for liquidity when they face severe income constraints, and a low-income borrower (with higher effective reciprocity) will tip more and thus incur a higher implicit cost of credit. It suggests that while high APRs may appear predatory, they are partly the equilibrium outcome reflecting the borrower's perceived value of credit. The observed cost of credit reflects not only immediate liquidity constraints but also dynamic considerations of

reputation and learning and adjustments to macroeconomic conditions.

Our research lies at the intersection of two major streams in household finance: the economics of high-cost credit and the role of behavioral factors in financial decision-making. We add to these streams of literature by leveraging a novel setting—voluntary, tip-based credit pricing—to re-examine long-standing questions about consumer welfare and market regulation.

A vast literature grapples with the welfare implications of high-cost credit, such as payday loans. One perspective argues these products are predatory, exacerbating financial fragility and leading to debt traps (Skiba and Tobacman, 2019; Carrell and Zinman, 2014). An alternative view posits that they provide essential liquidity to constrained households, preventing outcomes like foreclosure or crime (Morse, 2011). This entire debate, however, is predicated on a crucial assumption: that high interest rates are a supply-side phenomenon, imposed by lenders due to risk, operational costs, or market power.

Regulatory interventions, such as interest rate caps, operate on this same assumption. Yet, evidence shows these top-down measures often have unintended consequences, either by restricting credit access for the most vulnerable or by pushing borrowers to other high-cost alternatives (Dobbie and Skiba, 2017; Bhutta et al., 2015). This regulatory impasse suggests that a purely supply-side view is incomplete.

Our study challenges this paradigm by shifting the focus from the price lenders charge to the price borrowers voluntarily choose to pay. By analyzing a setting where interest is optional, we provide a clean measure of the demand-side WTP for liquidity. The finding that borrowers willingly self-impose effective APRs comparable to the payday market (270%) suggests that high prices are not solely a product of lender behavior but are also sustained by borrowers' own valuation of immediate credit. This reframes the policy problem: if borrowers replicate high costs even when they are not mandatory, supply-side price caps may be addressing a symptom rather than the root cause of the behavior.

We draw on the literature on behavioral and social drivers of financial decisions to understand why borrowers would choose to voluntarily incur such high costs of credit. Prior research shows that reciprocity and fairness influence economic choices like charitable giving (DellaVigna, 2009) and "pay-what-you-want" pricing (Gneezy et al., 2010), these concepts have rarely been applied to financial markets. Our tip-based setting provides the first direct test, demonstrating that social norms or a desire to maintain goodwill with the lender can motivate payments substantial enough to mirror high-cost interest rates, extending evidence regarding the social-preference narrative from prosocial contexts to household finance.

Our work also builds on findings that financial sophistication and experience shape borrowing outcomes (Lusardi and Mitchell (2014); Agarwal et al. (2008); Agarwal et al. (2024)). We contribute by showing how these factors operate in a discretionary cost environment. We find that users "learn" to minimize voluntary costs over time, and those with higher numeracy select lower effective APRs. This aligns with prior work documenting seemingly irrational behavior, such as payday borrowers ignoring cheaper, available credit (Agarwal et al., 2009), by highlighting the

roles of inertia, learning, and cognitive bandwidth in shaping choices.

Finally, we provide clean, causal evidence that speaks to the power of "nudges" in financial settings (Thaler and Sunstein, 2009; Madrian and Shea, 2001). Within fintech, Carroll et al. (2009) and Madrian and Shea (2001) underscore how default options and nudge-based interventions alter user decisions, whereas Thaler and Benartzi (2004) show that simplified or lower-cost default options can improve consumer outcomes.[4] Through randomized experiments, we show that simple changes to the tipping interface—such as introducing a low default can significantly lower average borrowing costs while increasing the base of voluntary payers. This offers a practical alternative to blunt price regulations, demonstrating how platform design can be harnessed to improve consumer welfare, without explicit restrictions on lenders.

Taken together, our findings speak directly to ongoing debates about high-cost lending, regulation, behavioral biases, and the design of fintech platforms. By demonstrating that borrowers voluntarily impose elevated APRs on themselves, we challenge conventional narratives attributing all high rates to lender exploitation or uncompetitive market structures. Instead, our evidence suggests that social preferences, perceived credit constraints, and interface-driven nudges may be just as decisive in explaining persistently high borrowing costs even when borrowers retain the option of paying zero interest.

At the same time, from a policy perspective, these insights underscore the limits of regulation in consumer protection. If user behaviors and biases remain unaddressed, borrowers may still end up paying high effective rates. This tension between financial access and protection takes on renewed importance in fintech ecosystems, where swift innovation can empower users while also risking further exploitation of biases.

## 2 Data and summary statistics

We use a unique, proprietary dataset from a U.S.-based financial technology platform that serves over eight million customers. The platform provides a full suite of mobile banking services, including interest-free cash advances, debit accounts, managed investment accounts, interest-bearing loans, and a rewards program. By aggregating transaction data from both the platform and external bank accounts shared voluntarily by customers to access the platform's services, the dataset offers a comprehensive view of each individual's financial activities.[5]

The platform introduced its interest-free cash advance product in 2018. While the cash advance itself is interest-free, customers choose whether and how much to tip; tipping does not affect their eligibility for future cash advances. The preset tipping options are 0%, 4%, 6%, 10%, and 16% of the cash advance, with 10% as the recommended choice. Funds are typically disbursed within 24 hours to five business days, although users can pay a nominal fee for immediate access.

[4] Agarwal et al. (2024) show that credit limit hikes may act as cues that stimulate consumption for behavioral reasons.

[5] Customers have incentives to share financial transaction histories from other bank accounts, particularly their salary-crediting accounts, to qualify for the complete range of services.

The principal, any expedite fee, and any promised tips are due two weeks after application[6]. Repayment is automatically deducted from a linked salary-crediting account, minimizing default risk. If a customer defaults, the platform blacklists the individual from future cash advances and initiates its debt recovery process. The default risk is low, and in our sample, there are no unpaid cash advances.

Our sample begins with one million randomly selected platform users, 288,793 of whom subscribed to the cash advance product. Over 27 months (September 24, 2018, to December 31, 2020), they collectively submitted 7,090,456 cash advance applications, 6,871,885 (97.1%) of which were successful. The geographic distribution of these users by state closely aligns with each state's population (see Figure 3), indicating that the sample is broadly representative of the USA customer base. The dataset also contains demographic information, including age, gender, income, occupation, ethnicity, address, and area type (city, suburb, or rural). Figures 3A and 3B, respectively, present the distribution of gender and area type across different age groups.

Table 1 provides summary statistics. The average cash advance amount is \$44.79. Of all applications, 54% include a promised tip, but only 37% actually pay one. The mean tip pledged is \$1.73, whereas the mean tip paid is \$1.15, indicating a shortfall of \$0.58. On average, customers select tipping options two steps (approximately 4 percentage points) below the recommended 10%. Although the product advertises a zero annual percentage rate (APR) for 14 days, 79% of users pay an expedite fee of up to \$4.99 to receive their funds within hours, rather than waiting 24 hours to five business days. These fees, together with the short repayment period, yield an annualized implicit APR of roughly 310% for promised tips and 270% for paid tips—about 11.9% and 10.4%, respectively, over 14 days. Overall, 71% of cash advances, along with any fees and pledged tips, are repaid on time.

**APR Terminology.** Throughout this paper, we distinguish between two measures of effective borrowing costs. First, the *tip-only APR* captures the annualized cost from voluntary tips alone: averaging 77% across all borrowers and 208% among those who actually tip. Second, the *total APR* includes both tips and expedite fees, yielding an average of 270% for paid amounts. Unless otherwise noted, references to "APR" in our empirical analysis refer to the tip-only measure, as this isolates the purely voluntary component of borrowing costs.

On average, each customer takes out 28 cash advances (standard deviation of 30). Within a customer's first 150 applications[7], the percentage of users pledging tips (Figure 4) and the average tip amount both decline, while the average cash advance amount increases. These patterns collectively lower the implicit promised APR. This evolution likely reflects learning through repeated interactions on the platform.

In addition, we observe transaction-level data on inflows and outflows across e-wallets, credit

[6]Repaying the principal and expedite fee is mandatory, whereas tips are voluntary and may differ from what was initially pledged.

[7]This is within four standard deviations of the mean; beyond 150 applications, sample sizes become too small for meaningful analysis.

cards, and debit cards, both on and off the platform. Each record includes the transaction date, amount, category (e.g., paycheck, unemployment benefit, loan payment, interbank transfer), merchant name, and merchant type. We aggregate earnings (e.g., salaries, unemployment benefits) at the individual-month level. To focus on active users, we limit the sample to those with at least one year of transaction data who have signed up for at least one of the platform's financial services.

**Experiments**

We conducted a series of randomized experiments on the platform to investigate the behavioral determinants of tipping. Each experiment modified the default tipping interface—specifically, the recommended tip amount and the ordering of available tipping options—to assess how interface design influences tipping behavior. Table 7 and Table 8 describe the experimental conditions in detail.

To ensure uniformity across experimental groups, we required participants to be active and eligible for cash advances, have at least four prior cash advance applications, and have never previously paid any tip (i.e., they were "non-tippers"). A total of 2,166 customers meeting these criteria were randomly assigned to each of three groups: the counterfactual (control) group and two treatment groups (1 and 2). These users eventually made 33,020 cash advance applications during the study period. We tracked user-level cash advance activity from December 22, 2020, to February 22, 2021, with the experimental treatments implemented on January 22, 2021. This design allowed for a one-month pre-treatment window (December 22, 2020–January 21, 2021) and a one-month post-treatment window (January 22, 2021–February 22, 2021), enabling a clear comparison of user behavior before and after the intervention.

The control group experienced the platform's standard tipping scheme: a recommended tip of 10% and tipping options of 0%, 4%, 6%, 10%, and 16%. In *treatment Group 1*, we introduced a $1 tip choice and lowered the recommended tip to 6% while retaining the remaining options from the control group. This setup generated 32,300 applications from 1,973 unique users. Treatment Group 2 likewise included a $1 tip choice but made it the recommended option and comprises 32,602 applications by 1,973 unique users.

These experiments facilitate a comprehensive investigation into how interface elements and default settings shape borrowers' willingness to tip for credit. Comparing user responses to varying tip anchors and user interface designs allows us to gain insight into the behavioral determinants of tipping behavior.

# 3 Results

## 3.1 Behavioral Persistence

In panel A of Table 2, we report OLS estimates examining the determinants of borrowers' tipping behavior on the fintech platform. Building on prior work that emphasizes path-dependent financial choices (Agarwal et al., 2009; Beshears et al., 2018; Debo and Snitkovsky, 2025), we focus on two lagged variables to capture persistence. Specifically, we include Promised $\text{Tips}_{t-1}$ (an indicator variable) and Inferred tip-based $\text{APR}_{t-1}$. The coefficient on Promised $\text{Tips}_{t-1}$ is 0.6450 (significant at the 1% level), indicating that borrowers who tipped on their previous loan application are 64.50 percentage points more likely to tip again. Moreover, a one standard deviation increase in the lagged Inferred tip-based APR is associated with a 28.99 percentage points rise in the current Inferred tip-based APR, suggesting a strong intertemporal persistence in borrowers' voluntary cost choices. Together, these results provide empirical support for theories of habit formation and path dependence in consumer finance (Beshears et al., 2018; Agarwal et al., 2009).

The persistence in both tipping behavior and effective APRs implies that once borrowers initiate costlier lending strategies by paying voluntary tips, they continue along these higher-cost trajectories. Several explanations are consistent with this pattern. First, liquidity constraints, especially among financially constrained borrowers, may limit their access to lower-cost credit and thus funnel them into repeatedly choosing higher-cost options (Morse, 2011; D'Astous and Shore, 2017). Second, behavioral biases such as the status quo bias or anchoring (Tversky and Kahneman, 1974) could lead borrowers to reinforce existing tipping or fee-paying habits, even when presented with ostensibly cost-free alternatives. In this sense, tipping and fee payments may become internalized as "normal," particularly if borrowers perceive such actions as necessary to maintain access to immediate liquidity.

Importantly, the repeated choice to pay elevated APRs through tipping highlights potential inconsistencies with standard models of rational decision-making. In particular, our findings parallel those of Agarwal et al. (2009), who document that many payday borrowers incur high fees despite having unused credit lines at much lower APRs. Here, we show that even in a setting without a mandated interest rate, many individuals still select a de facto high-interest arrangement through tips. This behavioral pattern underscores the role of perceived credit cost, which appears to be significantly larger for low-income and liquidity-constrained users.

## 3.2 Demographic and regional heterogeneity

We next examine whether tipping incidence and effective borrowing costs vary systematically across observable traits. Panel B of Table 2 reports these results.

**Gender.** Along the intensive margin, we find that female borrowers are, on average, 0.44 percentage points more likely to tip than their male counterparts. This is consistent with research suggesting that women often exhibit more prosocial or cooperative tendencies in financial contexts

(Bertrand and Morse, 2011a). Interestingly, along the intensive margin, being female is also associated with a 4.04 percentage points lower tip-based APR. One plausible interpretation is that while women are more inclined to tip, they do so in a way that curbs overall borrowing costs—perhaps indicating a combination of pro-social and financial prudent behavior. This finding aligns with prior literature documenting that women frequently display more cautious and methodical financial behavior (Croson and Gneezy, 2009).

**Age.** Borrower age also appears to influence financing decisions. A one-standard-deviation increase in age corresponds to a 2.75 percentage-point higher probability of tipping. This finding is consistent with prior research highlighting a lack of financial sophistication among older individuals, especially on fintech platforms (Carlin et al., 2017; Lusardi and Mitchell, 2014).

**Race and Ethnicity.** We observe variation across racial and ethnic groups in tipping behavior, though we interpret these patterns with caution given the many confounding factors that correlate with race and ethnicity in the United States. Non-Hispanic Black borrowers are 0.62 percentage points less likely to tip but incur higher inferred tip-based APRs conditional on tipping, while Non-Hispanic AAPI borrowers are 2.55 percentage points less likely to tip and incur lower APRs. Hispanic borrowers show no difference in tipping propensity but tip lower amounts on average. These patterns likely reflect a combination of structural factors—including differential access to alternative credit sources, historical exclusion from mainstream financial services, variation in local banking competition, and socioeconomic disparities—rather than intrinsic group differences (Morse, 2011; Lusardi and Mitchell, 2014; Hasler et al., 2023). We view these results as descriptive correlations that warrant further investigation into underlying mechanisms.

**Marital Status.** Being married is associated with a 0.45 percentage points lower propensity to tip and a 7.84 percentage points lower tip-based APR. These results align with research showing that married individuals often adopt more prudent financial strategies (Marks and Lambert, 1998; Koball et al., 2010). In our context, a married borrower's behavior may also reflect the greater financial security conferred by dual incomes and, consequently, a smaller perceived value of liquidity.

**Geographic Location.** Living in an urban area is correlated with a 0.67 percentage point lower probability of tipping. One possible explanation is that urban borrowers face higher living costs and thus allocate fewer funds to voluntary fees. Additionally, urban residents may have greater access to alternative sources of liquidity and thus place a lower value on access to liquidity, thereby reducing the likelihood of tipping for credit

**Automatic Investment Service (AIS) Usage.** From panel C of Table 2, borrowers who activate the Automatic Investment Service (AIS) show a 1.91 percentage points higher probability of tipping.

It is not straightforward to interpret these findings. First, AIS users may represent individuals with persistence in financial behavior. Second, these are likely individuals with a high perceived value of the financial services offered by the platform; that is, their willingness to pay higher tips could be motivated by reciprocity for perceived higher-value services (Carlin et al., 2017).

Overall, these results indicate that individual financial decision-making is far more complex than what standard models of household behaviors predict. A confluence of demographic factors (e.g., gender, age, race, marital status, and geographic residence) influences financial behavior and effective borrowing costs.

### 3.3 Borrowers' financial situation

A borrower's financial standing (e.g., regular income, indebtedness, and employment status) can affect both their immediate liquidity needs and their willingness to pay for liquidity. Our next set of tests examines how borrowers' finances affect their tipping behavior and effective borrowing costs. Panel C of Table 2 reports the results.

**Paychecks.** We begin by examining how borrowers' regular income influences tipping and overall borrowing costs. A one standard deviation increase in *Paychecks Received During the Last Calendar Month* is associated with a 0.13 percentage points decrease in the probability of tipping and a 4.44 percentage points decrease in the *Inferred tip-based APR*. These findings align with the permanent income hypothesis (Friedman, 1957), suggesting that individuals with higher or more stable incomes perceive lower liquidity needs and thus are less likely to incur high borrowing costs in the form of voluntary tips. Consequently, they reduce both the frequency of tipping and their effective borrowing costs. These results are in line with prior evidence that income level mediates credit usage (Agarwal et al., 2018). Another possibility is that unemployed or low-income borrowers are likely under duress and consequently exhibit costly financial mistakes (Sergeyev et al., 2025).

**Financial Stress and Liquidity constraints.** Turning to financial stress and liquidity indicators, we find that a one standard deviation increase in *Loan Interest Paid During the Last Calendar Month* corresponds to a 0.68 percentage points higher probability of tipping along the extensive margin. Although financial strain typically motivates conservative spending, our results suggest that liquidity-constrained borrowers may tip because they believe it can help preserve goodwill with the platform—perhaps to secure future credit access (Zinman, 2010). Further, liquidity-constrained borrowers may have past experience of taking high-cost loans from payday lenders; they may have internalized that accessing liquidity warrants a high price. The observed behavior aligns with prior research showing that financially strained individuals may engage in actions they believe will protect or enhance lender relationships (Bertrand and Morse, 2011a).

At the same time, along the intensive margins. Borrowers with existing interest payments appear to tip lower amounts, reducing their overall borrowing costs proxied using the *tip-based APR*. This finding indicates a delicate balance: while they tip due to non-pecuniary motivation, they simultaneously minimize borrowing costs, conditional on tipping.

**Investment Portfolio Performance.** Finally, we examine the influence of asset holdings. Changes in portfolio value can alter the borrower's liquidity constraints and willingness to make discretionary payments. A one standard deviation rise in the *Total Equity Portfolio Value ($)* corresponds to a 0.12 percentage points increase in tipping and lower tip-based APR. These patterns align with wealth effect theories (Poterba, 2000), wherein perceived gains in portfolio value prompt more discretionary spending—including tipping. At the same time, wealthier borrowers incur lower voluntary APRs overall, suggesting they selectively tip for behavioral reasons such as reciprocity while minimizing the annualized cost of borrowing conditional on tipping.

## 3.4 Role of Local Credit Market Conditions

The broader financial environment plays a critical role in shaping voluntary cost-sharing behavior on the platform. By linking users' tipping behavior to external credit market conditions, we provide evidence that borrowers interpret and respond to the platform's voluntary tipping model through the lens of their local financial constraints. We consider three distinct but complementary dimensions of the local credit ecosystem: (i) the prevailing cost of credit, (ii) the availability of payday lending, and (iii) the degree of bank competition. Across all three analyses, a consistent behavioral pattern emerges: when outside credit options are scarce or costly, borrowers are more likely to tip, but they do so more frugally—resulting in lower inferred tip-based APRs. This pattern underscores the strategic nature of voluntary tipping, reflecting a balance between reciprocity and cost minimization that depends on borrowers' external financial environments.

### 3.4.1 Local Credit Costs

We begin by examining whether borrowers' tipping behavior responds to differences in prevailing local credit costs. Using the median annual loan yield of community banks within each state as a proxy for the local price of credit, we find that borrowers in high-cost credit environments are significantly more likely to tip, yet they do so at a lower inferred tip-based APR (Table 3). A one standard deviation increase in the median local loan yield raises the likelihood of tipping by 0.22 percentage points while reducing the tip-based APR by 0.48 percentage points.

This seemingly paradoxical pattern can be understood through a two-margin framework. On the extensive margin, higher credit costs increase the platform's relative value, prompting more users to reciprocate through tipping to preserve future access to this cheaper form of liquidity. On the intensive margin, the same borrowers exhibit greater cost-consciousness, offering smaller tips that minimize their effective borrowing cost. In other words, borrowers in expensive credit markets

engage in strategic reciprocity—they acknowledge the platform's value and signal goodwill, but do so in a disciplined, economically rational manner.

### 3.4.2 Payday Lending Regulation

We next leverage quasi-exogenous variation in state-level payday lending regulation to further isolate this mechanism. Payday lending restrictions, by constraining access to a key form of high-cost credit, alter borrowers' outside options and allow us to examine how voluntary tipping adjusts when alternative liquidity sources shrink. Table 3 presents the results. When payday lending laws are in force, the likelihood to tip increases by 0.47 percentage points, but the effective borrowing cost drops by 1.78 percentage points.

These results reveal two complementary forces. First, the increased tipping propensity reflects the platform's heightened value when high-cost credit is curtailed. As regulatory constraints remove payday loans—a key source of liquidity for many households—borrowers increasingly rely on the platform as a financial safety net, motivating greater reciprocity. Second, the simultaneous decline in tip-based APR points to heightened cost sensitivity. Thus, the response to payday lending restrictions mirrors the behavior seen under high credit costs—increased participation, lower effective cost, and disciplined reciprocity.

### 3.4.3 Local Bank Competition

Finally, we examine how the structure of local banking markets affects tipping. Using the Herfindahl-Hirschman Index (HHI) of bank assets as a measure of concentration, we find that borrowers in less competitive markets (higher HHI) are again more likely to tip, but at lower implied borrowing costs (Table 3). A one standard deviation increase in HHI raises the probability of tipping by 0.28 percentage points and lowers the tip-based APR by 0.37 percentage points.

This pattern parallels our earlier findings. In concentrated credit markets, limited access to traditional financial institutions elevates the value of the platform's liquidity service, increasing users' incentive to maintain a positive relationship through tipping. Yet, borrowers in such markets are also acutely cost-sensitive—perhaps because scarce and expensive credit fosters financial prudence. As a result, they engage in calibrated reciprocity: they participate more frequently in the tipping norm, but with smaller amounts that preserve affordability.

Taken together, these findings show that voluntary tipping on the platform is systematically influenced by the structure and cost of borrowers' external credit options. Borrowers in high-cost, restricted, or concentrated credit markets are more likely to engage in the act of tipping, but they do so in a measured and strategic manner. This evidence underscores that voluntary cost-sharing in fintech ecosystems is dependent on the local credit context and shaped by borrowers' learned financial behavior (Agarwal et al., 2008).

### 3.5 Role of macroeconomic conditions

We next investigate whether broader economic conditions affect these voluntary tipping decisions. As shown in Table 4, *Economic Policy Uncertainty* is negatively associated with the Inferred tip-based APR. A one standard deviation increase in *Economic Policy Uncertainty* coincides with a 0.83 percentage points decrease in Inferred tip-based APR. This result is economically meaningful and consistent with prior work that suggests that heightened uncertainty induces precautionary behavior (Bloom, 2009). Specifically, in periods of elevated uncertainty, borrowers appear to adopt more conservative financing choices, forgoing nonessential expenditures such as tips. The observed behavior is also consistent with Guiso et al. (2018), who also document that heightened uncertainty can induce precautionary motives and heightened risk aversion, fundamentally altering an individual's utility and financial decision-making.

An important implication is that borrowers seem to be at least partially aware of these costs, adjusting their behavior in response to changing economic conditions. Specifically, the fact that tipping propensity declines in "bad" macroeconomic states indicates that individuals do not passively incur add-on costs; rather, they reduce or omit these charges when faced with heightened uncertainty or tighter liquidity constraints.

The impact of *Federal Rate* on voluntary tipping decisions is more nuanced. A one standard deviation increase in the Federal Rate is linked to a 27.20 percentage points decrease in the propensity to tip, but a 26.23 percentage points increase in inferred tip-based APR. The divergence stems from a behavioral split where inflation drives the decision to *participate*, while credit scarcity drives the decision of *how much to pay*. As the cost of living rises, cash-strapped users view voluntary tips as a discretionary expense to cut, causing a drop in overall tipping propensity (the extensive margin). However, for the users who continue to tip, the tightening credit market increases the marginal value of liquidity. These users increase their tip size.

Taken together, these macroeconomic results highlight the dynamic nature of borrowers' willingness to pay for credit. On the one hand, the very presence of tipping in a cash advance contract raises the possibility that borrowers incorporate reciprocity or altruism into their utility functions, likely because they perceive the platform as providing helpful services or want to maintain good standing for repeated borrowing. Nonetheless, rather than reflecting purely altruistic or reciprocal motives, borrowers' decisions to pay extra fees appear sensitive to shifts in uncertainty, interest rates, and personal liquidity needs, suggesting that credit-cost awareness is highly context-dependent, with "bad times" prompting more cautious strategies.

### 3.6 State Characteristics

We next examine how state-level factors such as social safety nets and wage regulations shape borrowers' discretionary tipping behavior to capture the broader policy and economic context in which lending occurs. Prior studies show that macro-level policies, such as unemployment insurance, can both stabilize household consumption and affect debt usage (Ganong and Noel,

2019). By linking state characteristics to tipping and APR outcomes, we assess whether region-specific conditions affect borrowers' willingness to pay for credit.

**Unemployment Insurance.** We find that a one standard deviation increase in the *State-Level Average Weekly Unemployment Insurance Paid* corresponds to a 0.19 percentage points higher probability of tipping (significant at the 1% level). This suggests that more generous social safety nets free up resources for discretionary spending even among those relying on short-term loans, mirroring the consumption-stabilizing effect of unemployment benefits documented by Ganong and Noel (2019). Concurrently, higher state-level unemployment insurance is associated with a 0.84 percentage points decrease in the tip-based APR. This dual effect underscores how improved short-term financial support can boost borrowers' ability to cover optional costs like tips, yet also reduce their overall reliance on high-cost forms of credit (Kroft and Notowidigdo, 2016).

**Minimum Tipped Wage.** Likewise, an increase in the *State-Level Minimum Tipped Wage* by one standard deviation is associated with a 0.47 percentage point decrease in the tip-based APR. In states mandating higher baseline earnings for tipped workers, borrowers appear to face less financial vulnerability and thus are less willing to incur additional fees. This result parallels broader evidence that wage policies can influence consumer behavior and financial well-being (Allegretto and Reich, 2018).

## 3.7 Learning and cognitive abilities

### 3.7.1 Do individuals learn through repeat interactions?

Repeated interactions may teach borrowers how to minimize costs (Agarwal et al., 2008). Panel A of Table 2 reports the results. Consistent with prior work that shows that individual households learn to avoid add-on fees in the credit card market through experience, one standard deviation increase in the *Number of Cash Advance Applications to Date* is associated with a 1.12 percentage points lower likelihood of tipping and a 15.43 percentage points decrease in the tip-based APR. These findings are consistent with the thesis that repeat usage can foster learning in financial markets (Agarwal et al., 2008; Carlin and Manso, 2011). For instance, consumers may learn that tipping does not affect the likelihood of loan approval. Further, insofar as borrowers are able to take multiple cash advances, their perceived liquidity constraints may go down, reducing their assessment of credit value.

### 3.7.2 Cognitive Ability, Tipping Behavior, and Inferred Borrowing Costs

A growing body of literature highlights the importance of cognitive skills in financial decision-making (Stango and Zinman, 2009; Lusardi and Mitchell, 2014), yet less is known about how these skills influence voluntary, non-mandatory transactions such as tipping on fintech platforms. A subsample of borrowers in our sample served in the armed forces. We obtain data on their

AFQT (Armed Forces Qualification Test) scores as a proxy of their cognitive ability and investigate whether general cognitive ability, as captured by AFQT scores, shapes borrowers' decisions to tip and their resulting borrowing costs.

Column 1 of Table 5 reports a marginally significant relationship between AFQT scores and the likelihood of tipping, implying that overall cognitive ability is negatively correlated with the propensity to tip. This finding is consistent with the view that tipping is often guided by social norms, platform design, and default settings rather than by complex cognitive deliberation (Lynn and McCall, 2000; Thaler and Sunstein, 2009).

Interestingly, Column 2 shows that AFQT scores are negatively and significantly associated with the *Inferred tip-based APR*. One standard deviation increase in AFQT is associated with a 5.77 percentage point decrease in the *Inferred tip-based APR*. This suggests that while cognitive ability does not alter the likelihood of tipping, it does affect *how* borrowing costs, conditional on tipping. Users with higher cognitive scores incur lower tip-based APRs and are less likely to tip.

Table 6 delves deeper into the subcomponents of the Armed Forces Qualification Test (AFQT) to investigate how distinct facets of cognitive ability, such as numerical operations, verbal comprehension, and processing speed, shape tipping decisions. Prior research indicates that numeracy is particularly crucial for avoiding financial errors (Agarwal and Mazumder, 2013; Lusardi and Mitchell, 2014), but less is known about how specific skills interact with discretionary financial behaviors like tipping.

Columns 3 and 4 reveal that higher scores in *Numerical Operations*, *Math Knowledge*, and *Arithmetic* Reasoning are each negatively correlated with the probability of tipping. This suggests that individuals adept at numerical reasoning may see tipping as a cost with no mandatory obligation and opt to minimize it, reinforcing existing evidence that numeracy promotes cost-conscious behavior (Stango and Zinman, 2009; Lusardi and Mitchell, 2014). In contrast, verbal skills, such as *Word Knowledge* (Column 1) and *Paragraph Comprehension* (Column 2), do not significantly predict tipping. This discrepancy underscores the primary importance of quantitative aptitude, rather than verbal comprehension, in shaping voluntary financial outlays. This pattern parallels research by Stango and Zinman (2009), who find that individuals with stronger numerical skills are better able to navigate complex credit markets.

Other specialized aptitudes, such as *Mechanical Components*, *General Science*, and *Electronic Information* (Columns 5, 6, and 7, respectively), also show no notable relationship with tipping. These findings indicate that domain-specific technical knowledge exerts minimal influence on whether borrowers opt to incur discretionary costs.

Of particular interest, Column 8 demonstrates a negative relationship between *Coding Speed* and tipping. Higher processing speed often correlates with more optimal financial choices; however, here it appears associated with a lower propensity to tip. One possible explanation is that individuals who process information rapidly rely on cognitive shortcuts or heuristics (Gigerenzer and Gaissmaier, 2011), choosing to bypass optional decisions like tipping in favor of efficiency—despite potentially missing out on other subjective benefits (e.g., improved lender

goodwill).

These insights extend the literature on financial literacy and cognitive skills by illustrating that the decision to incur additional voluntary costs is closely tied to experience-based learning and quantitative aptitudes. Quantitative aptitude and coding speed negatively correlate with tipping incidence. Intriguingly, earlier results in our analysis (Section 3.5 and 3.7.1) suggest that users learn over time to minimize costs and avoid extra fees. Cognitive ability likely magnifies or accelerates this learning effect: users with higher numerical or processing skills may adapt more quickly to the platform's cost structures, thereby achieving systematically lower voluntary APRs **(See Figure 7)**. Collectively, these findings underscore that both "learning by doing" and innate cognitive capacity shape how borrowers engage in discretionary financial decisions.

The findings thus far highlight the complex interplay between financial stress, economic conditions, cognitive ability, and behavioral factors in shaping borrower decisions. Our results reveal that borrowers' financial status, state-level economic conditions, and engagement with the platform all shape their tipping and borrowing behaviors. Stable or rising incomes reduce the likelihood of tipping and lower effective APRs, while financial stress can paradoxically increase tipping for relationship-building purposes even as borrowers try to manage overall costs. Generous state-level safety nets appear to encourage discretionary fees while lowering borrowing costs in APR terms.

Finally, repeated interactions and numerical ability reduce the borrower's propensity to incur voluntary costs. Overall, both learning and liquidity constraints affect the voluntary incurred cost of credit. Our findings underscore the importance of considering both macro-level economic factors and micro-level behavioral influences in designing policies governing borrower welfare and decision-making in credit markets.

## 3.8 Randomized Experiments

To isolate the causal impact of choice architecture on borrower WTP, we leverage two randomized experiments. These controlled interventions allow us to move beyond correlation and understand how platform design directly shapes the voluntary price borrowers pay for credit. Our findings reveal a powerful insight: minor interface "nudges" can influence behavior, creating a "win-win" outcome that benefits both borrowers and the lender. Figure 8 shows the default User Interface (UI) flow, and Figure 9 shows changes to the tipping interface and recommended tip levels under the experiments that we ran.[8]

### 3.8.1 Experiment 1: A Nudge Towards Lower Costs

In our first experiment, we tested the effect of introducing a low, recommended default tip of \$1 (illustrated in Figure 9B). The results are presented in Table 7. Focusing on the *Post* $\times$ *Treated* coefficient, the intervention successfully expands the base of voluntary tippers. Recommending a

[8]The design of the user interface has been adjusted to keep the identity of the platform confidential.

$1 tip increases the likelihood of a borrower tipping by 5.8 percentage points, consistent with a nudge effect on the extensive margin (Thaler and Sunstein, 2009). By making the default tip lower cost, the platform can encourage broader participation in its revenue model.

Importantly, treated users also faced lower implied borrowing costs, as reflected in a negative and significant effect on the tip-based APR. Thus, the platform successfully nudged users toward participation while reducing the financial cost per borrower, a combination that enhances both platform sustainability and consumer welfare. The likelihood of deviating from the default rose as well, suggesting that while more users began tipping, they retained discretion over how much to contribute. Overall, Experiment 1 demonstrates that a low-cost, salient default can expand participation on the extensive margin and simultaneously lower costs along the intensive margin.

#### 3.8.2 Experiment 2: Reinforcing the Nudge with Salience

Our second experiment tests a slightly different interface, which places the $1 tip option in the most prominent position while also presenting a recommended 6% tip (Figure 9C). This design tests whether the salience of a simple, low-cost option can steer behavior even when a higher, percentage-based anchor is present.

Table 8 reports the results. The *Post* × *Treated* coefficient of 0.0204 again shows that the intervention increased tipping participation. Consistent with Experiment 1, treated users incurred lower tip-implied APRs, indicating that the new interface successfully promoted tipping at a lower overall cost.

At the same time, users were more likely to deviate from the recommended default, implying that the design fostered participation without inducing mechanical compliance. This highlights a key feature of effective choice architecture—it guides behavior while preserving autonomy. Transparent, low-friction interfaces can both encourage prosocial engagement and leave room for user discretion (Carroll et al., 2009).

Taken together, Experiments 1 and 2 demonstrate the potential of choice architecture to resolve the apparent trade-off between lender viability and consumer welfare by shaping voluntary financial behavior. Defaults and visual prominence steer users toward participation but also toward more cost-efficient outcomes, even in the absence of external incentives or regulation. For fintechs, a key insight is that low-cost interface modifications can simultaneously enhance platform sustainability and borrower welfare, providing fintechs with a scalable path toward inclusive and efficient credit design. From a policy perspective, behavioral design offers a compelling alternative to top-down regulation relying on blunt policy instruments like price caps and outright bans.

## 4 A conceptual framework of Borrower Tipping

Our findings and those of other studies on high-cost credit markets have documented that borrowers in payday lending and similar settings incur very high effective annual percentage rates (APRs) (e.g., Agarwal et al. (2009); Morse (2011)). In our setting, even though the lender

does not impose a formal interest rate, borrowers often pay a voluntary "tip" that serves as a self-selected price for credit. Moreover, our empirical work reveals striking patterns: only a fraction of borrowers tip, tip behavior is highly persistent,[9] and borrowing costs vary systematically with income, financial stress, and macroeconomic conditions. Behavioral insights from the literature on warm-glow giving (Andreoni, 1989, 1990) and on heuristics and anchoring (Tversky and Kahneman, 1974) suggest that reciprocity and learning play a role in these decisions.

Motivated by these findings, we develop a stylized conceptual framework in which borrowers face liquidity constraints and derive "warm-glow" (reciprocity) utility from tipping. A key feature of our model is that the warm-glow parameter is purely driven by liquidity constraints, that is, on the funds available after covering a basic consumption floor. This parsimonious specification generates monotonically declining APRs with income, matching the empirical patterns in the data. While our framework is highly stylized and treats many potentially endogenous parameters as given, the simple exercise provides a useful framework to interpret and reconcile many of our empirical findings.

A key feature of our model is that the warm-glow parameter is purely driven by liquidity constraints—there is no baseline reciprocity motive. This parsimonious specification generates monotonically declining APRs with income, matching the empirical pattern in Figure 2.

### 4.1 The Basic Static Model

**Setup.** There is a lender who provides the loan without charging interest and relies on voluntary tips for revenue. The borrower receives noncredit income $y$ and obtains a loan $L$. She chooses a voluntary tip $\tau \geq 0$, leaving consumption $C = y + L - \tau$. Her utility combines consumption and a warm-glow benefit from tipping:

$$U(C, \tau) = \ln(y + L - \tau) + \theta(y) \ln(1 + \tau), \tag{1}$$

where the warm-glow parameter depends solely on discretionary income, that is the funds available after meeting a minimum consumption requirement:

$$\theta(y) = \frac{\theta_1}{y - c}. \tag{2}$$

Here $\theta_1 > 0$ reflects sensitivity to income constraints and $c \geq 0$ is a consumption floor representing subsistence needs. When discretionary income $(y - c)$ is small, the borrower places a higher weight on the warm-glow benefit. Crucially, as income rises, the warm-glow weight falls to zero: $\theta(y) \to 0$ as $y \to \infty$.

[9] See, e.g., Agarwal et al. (2009) and Beshears et al. (2018) for examples of persistence in consumer financial behavior.

**Optimal Tip.** The borrower maximizes (1) subject to $\tau \geq 0$. The first-order condition yields:

$$\tau^* = \frac{\theta(y)(y+L)-1}{1+\theta(y)} = \frac{\theta_1(y+L)-(y-c)}{y-c+\theta_1}. \tag{3}$$

Simplifying and rearranging, we get:

$$\tau^* = \frac{(\theta_1-1)y+\theta_1 L+c}{y-c+\theta_1} \tag{4}$$

The feasibility condition for an interior solution ($\tau^* > 0$) is $\theta_1(y+L) > (y-c)$, or equivalently $\theta(y)(y+L) > 1$.[10] The condition $\theta(y) > \frac{1}{y+L}$ implies that borrowers tip when the marginal warm-glow benefit exceeds the marginal consumption cost at the corner ($\tau^* = 0$). The feasibility condition captures this trade-off: borrowers with tight liquidity constraints value the loan highly and feel compelled to reciprocate, while wealthier borrowers, for whom the loan is less consequential, experience little warm-glow and optimally choose not to tip. This explains partial participation: non-tippers are those for whom the loan simply isn't valuable enough to warrant a gesture of gratitude.

**Asymptotic Behavior.** As income grows large:

$$\lim_{y\to\infty} \tau^* = \lim_{y\to\infty} \frac{(\theta_1-1)y+\theta_1 L+c}{y-c+\theta_1} = \theta_1 - 1$$

Tips converge to a finite constant $(\theta_1 - 1)$ rather than growing unboundedly. This implies that APR declines monotonically with income and flattens at higher income levels, consistent with the empirical pattern documented in Figure 2.

### 4.2 Comparative Statics: Income

Income $y$ and loan size $L$ affect the optimal tip through different channels:

- **Direct effect (both $y$ and $L$)**: Higher $(y+L)$ increases available resources, tending to raise $\tau^*$.
- **Indirect effect (only $y$)**: Higher $y$ increases discretionary income $(y-c)$, which lowers $\theta(y)$ and reduces the warm-glow incentive, tending to decrease $\tau^*$.

**Effect of Loan Size.** Since $\theta(y)$ does not depend on $L$:

$$\frac{\partial \tau^*}{\partial L} = \frac{\theta(y)}{1+\theta(y)} = \frac{\theta_1}{y-c+\theta_1} > 0. \tag{5}$$

An increase in loan size unambiguously increases the optimal tip.

[10] The second-order condition is verified in Appendix IA2.

**Effect of Income.** We show in Appendix IA1 that:

$$\frac{d\tau^*}{dy} = \frac{\theta_1(\theta_1 - 1 - L - c)}{(y - c + \theta_1)^2}. \tag{6}$$

The sign depends on whether $\theta_1 \gtrless 1 + L + c$. With typical values ($L \approx 45$, $c \geq 0$), we have $1 + L + c > 46$, so for any reasonable $\theta_1$ (say, $\theta_1 < 10$):

$$\frac{d\tau^*}{dy} < 0 \quad \text{(monotonically declining tips)}$$

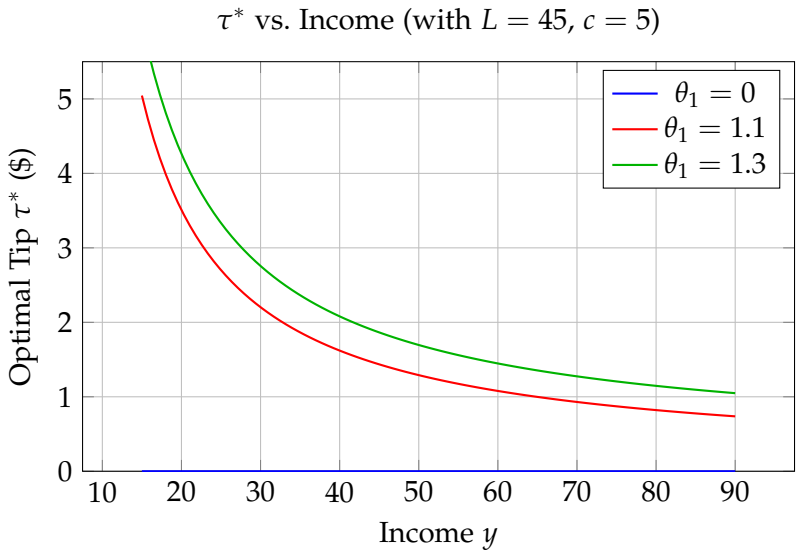
**APR Behavior.** The implied APR is proportional to $\tau^*/L$. Since $L$ is fixed across borrowers in our setting:

$$\frac{d(\tau^*/L)}{dy} = \frac{1}{L} \cdot \frac{d\tau^*}{dy} < 0$$

APR is **monotonically declining in income**—matching the empirical pattern documented in Figure 2.

Figure 1 illustrates how the optimal tip $\tau^*$ varies with income for different values of the liquidity sensitivity parameter $\theta_1$. For all parameter values, tips decline monotonically with income, reflecting the dominance of the indirect effect (falling $\theta$) over the direct effect (more resources).

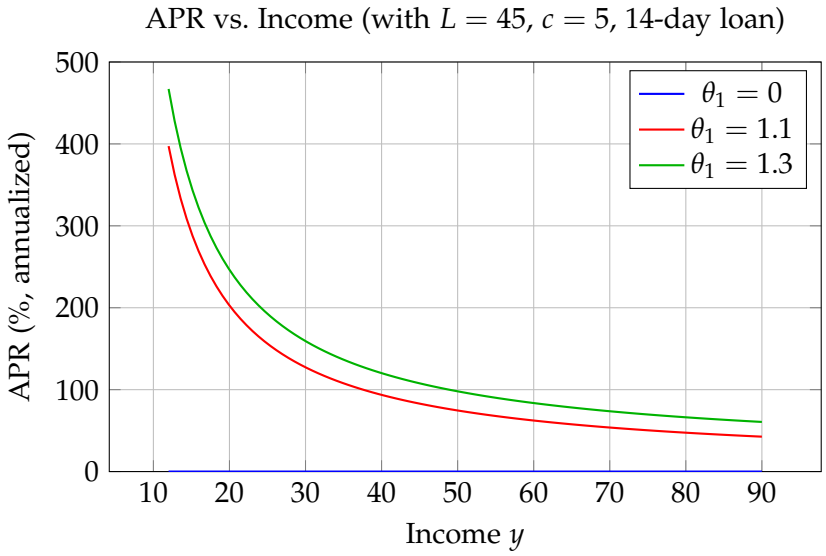
**Figure 1**
**Optimal Tip $\tau^*$ as a Function of Income $y$**




*Note: The optimal tip declines monotonically with income for $\theta_1 > 0$. When $\theta_1 = 0$, there is no warm-glow motive and the borrower optimally tips nothing. At low income, the high warm-glow weight $\theta(y) = \theta_1/(y - c)$ generates high tips. As income rises, $\theta(y) \to 0$ and tips converge to $\theta_1 - 1$.*

Figure 2 shows the corresponding APR (annualized $\tau^*/L$) as a function of income. The monotonically declining pattern matches the empirical evidence in Figure 2 of the paper.

**Figure 2**
**APR $(\tau^*/L)$ as a Function of Income $y$**




*Note: APR declines monotonically with income for $\theta_1 > 0$, ranging from approximately 350–450% at low income levels to 40–60% at high income. When $\theta_1 = 0$, the borrower never tips and APR is zero. Higher $\theta_1$ implies higher APRs at all income levels.*

### 4.3 Uncertainty and Precautionary Savings

When income is uncertain, $y = \bar{y} + \epsilon$ with $E[\epsilon] = 0$ and $\text{Var}(\epsilon) = \sigma^2$, two effects emerge:

1. **Precautionary savings effect**: Income volatility increases the marginal utility cost of reducing consumption. This pushes the optimal tip downward.
2. **Jensen's inequality effect on $\theta$**: Since $\theta(y) = \theta_1/(y - c)$ and $1/(y - c)$ is convex in $y$, uncertainty raises $E[\theta(y)]$, which tends to increase tips.

We show in Appendix IA4 that the precautionary savings effect dominates:

$$\frac{d\tau^*}{d\sigma^2} < 0. \tag{7}$$

Higher uncertainty **unambiguously reduces** the optimal tip. This is consistent with the empirical finding that macroeconomic uncertainty is associated with lower tip-based APRs.[11]

### 4.4 Dual Interpretation: Warm-Glow Reciprocity versus Fear of Losing Access

Before proceeding to the dynamic extension, we note that our framework admits two behaviorally distinct, but mathematically equivalent interpretations of the parameter $\theta(y)$.

[11]The CRRA extension in Appendix IA5 shows that higher risk aversion ($\gamma$) also reduces tips, providing an alternative channel through which uncertainty affects tipping behavior.

**Interpretation 1: Warm-Glow Reciprocity.** Under this view, $\theta(y)$ captures the borrower's intrinsic utility from reciprocating the lender's provision of interest-free credit. This interpretation aligns with the classic warm-glow literature (Andreoni, 1989, 1990): borrowers derive satisfaction from "doing the right thing" or maintaining a fair exchange relationship. The inverse dependence on net liquidity ($y - c$) reflects that reciprocity motives intensify when borrowers feel grateful for access to credit during times of financial strain. Recent evidence from credit card markets suggests that non-economic factors, including moral considerations, play a significant role in debt repayment decisions, even when strategic default would be financially optimal (Antoniou et al., 2025).

**Interpretation 2: Fear of Losing Access.** An alternative interpretation views $\theta(y)$ as capturing the borrower's anxiety about jeopardizing future credit availability. Under this lens, tipping is not driven by prosocial warmth but by loss aversion (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991): borrowers fear that failing to tip may signal low quality or ingratitude, potentially resulting in reduced access to future loans. This interpretation connects to the behavioral literature on scarcity mindsets (Mullainathan and Shafir, 2013b), where resource-constrained individuals exhibit heightened sensitivity to threats against their limited safety nets. The inverse relationship with net liquidity now reflects that borrowers with fewer outside options (lower $y - c$) face greater perceived costs from losing platform access.

**Mathematical Equivalence, Distinct Policy Implications.** Crucially, both interpretations generate identical mathematical predictions: $\theta(y)$ rises as net liquidity falls, optimal tips increase with financial constraints, and persistence emerges through the dynamic reputation channel. However, the welfare and policy implications diverge substantially. Under the warm-glow interpretation, high tip-based APRs represent genuine revealed preferences for liquidity access, suggesting that borrowers rationally value the product at its implicit price. Under the fear-of-losing-access interpretation, the same APRs may reflect behavioral exploitation of loss aversion and credit anxiety—borrowers pay not because they want to, but because they fear the consequences of not paying. This distinction speaks directly to ongoing regulatory debates: if tipping is primarily fear-driven, the voluntary nature of tips provides a weaker justification against consumer protection interventions.

Our empirical findings are consistent with both mechanisms operating simultaneously, though the balance of evidence may favor warm-glow reciprocity. The strong persistence in tipping (64.50 percentage points) aligns naturally with warm-glow motivation: if borrowers derive stable utility from reciprocating, this preference does not evaporate across transactions. By contrast, if persistence were primarily fear-driven, we would expect borrowers to learn over repeated interactions that their fear is unfounded, since tipping does not actually affect future credit eligibility. Indeed, the decline in tipping with experience and higher cognitive ability is consistent with this learning channel: some borrowers who initially tip out of fear eventually discover

that tips do not affect access and adjust accordingly. Meanwhile, demographic patterns such as higher tipping among financially engaged users who activate automatic investment services suggest genuine reciprocity among users who value the platform ecosystem. [12] We leave the formal decomposition of these channels to future research, but note that the persistence evidence tentatively favors the warm-glow interpretation.

### 4.5 Dynamic Extension: Persistence in Tipping

Empirical evidence shows that borrowers who tip once are about 64.5 percentage points more likely to tip in subsequent periods (panel A of Table 2). These findings provide empirical support for theories of habit formation and path dependence in consumer finance and echo similar findings in other settings (Beshears et al., 2018; Agarwal et al., 2009). For instance, tipping and fee payments may become internalized as "normal," particularly if borrowers perceive such actions as necessary to maintain access to immediate liquidity. The fact that most borrowers are able to receive multiple cash advances reinforces such beliefs.

To capture this persistence, we extend the model dynamically.

**Setup.** In each period $t$, the borrower receives income $y_t$, obtains loan $L$, and chooses tip $\tau_t$. The period utility is:

$$U_t = \ln(y_t + L - \tau_t) + \tilde{\theta}_t \ln(1 + \tau_t), \tag{8}$$

where the effective warm-glow parameter incorporates a reputation state:

$$\tilde{\theta}_t = \theta(y_t) + \kappa R_t, \qquad R_{t+1} = \lambda R_t + \mu \tau_t. \tag{9}$$

Here $\kappa > 0$ measures the benefit of reputation, $\lambda \in [0, 1)$ captures persistence (forgetting), and $\mu > 0$ captures the impact of tips on reputation.

**Steady State.** In steady state, $R^* = \frac{\mu}{1-\lambda}\tau^*$, and the effective parameter becomes:

$$\tilde{\theta}^* = \theta(y) + \frac{\kappa\mu}{1-\lambda}\tau^*. \tag{10}$$

This creates a feedback loop: higher tips increase reputation, which raises the effective warm-glow parameter, which further increases the propensity to tip.[13]

**Comparative Statics.** Higher reputation sensitivity ($\kappa$), stronger tip impact ($\mu$), or greater persistence ($\lambda$ closer to 1) all increase the steady-state tip. These effects amplify the warm-glow benefit through the reputation channel.

[12] Interestingly, Antoniou et al. (2025) find that credit card holders do *not* borrow opportunistically before default, suggesting that non-economic factors mitigate purely strategic behavior—a pattern consistent with our observation that borrowers voluntarily pay substantial tips even when economically unnecessary.

[13] The steady-state tip solves a fixed-point problem characterized in Appendix IA6.

### 4.6 Interpreting Empirical Findings

Our framework provides a unified interpretation of the key empirical findings:

**High Implicit APRs.** The voluntary tip, when annualized over the loan duration, serves as an implicit "price" for credit that borrowers set for themselves. In our framework, borrowers face a trade-off: sacrificing current consumption by paying a tip maintains access to liquidity that is especially valuable when income is low. The empirical findings—an average inferred APR of 77% overall (208% among tippers) and even higher APRs for expedited disbursement—reflect borrowers with high effective $\theta(y)$.

A key insight from our model is that high $\theta(y)$ arises endogenously when liquidity constraints are severe. With $\theta(y) = \theta_1/(y-c)$, a low-income borrower (with small $y-c$) has a high $\theta(y)$, leading to a higher optimal tip and thus a higher implicit APR. This is not evidence of exploitation; rather, it reflects the borrower's high valuation of liquidity access when constraints are binding. That is, even without mandatory interest charges, borrowers are willing to pay a substantial "price" for liquidity access. The observed tipping behavior in principle is consistent with both warm-glow reciprocity (borrowers internalize tipping as normatively appropriate) and fear of losing access (borrowers are reluctant to jeopardize their standing as "good" customers).

**Monotonically Declining APR with Income.** **Figure 6** shows that APR declines from approximately 80% in the lowest income decile to approximately 70% in the highest. Our model with $\theta(y) = \theta_1/(y-c)$ generates this pattern:

- At low income, $\theta(y)$ is high $\Rightarrow$ high tips $\Rightarrow$ high APR
- At high income, $\theta(y)$ fall $\Rightarrow$ tips converge to $\theta_1 - 1 \Rightarrow$ APR flattens

The indirect effect (falling $\theta$, given a lower value of liquidity) dominates the direct effect (more resources) throughout the income distribution, yielding a monotonic decline.

**Partial Tipping Participation.** Empirically, 54% of applicants promise a tip and only 37% eventually pay one. Our model explains this through the feasibility condition: when $\theta(y)(y+L) \leq 1$, the optimal tip is zero. Borrowers with higher income have lower $\theta(y)$, making the condition less likely to hold. This generates a natural selection mechanism: tippers are disproportionately those facing tighter liquidity constraints.

The relatively flat participation rate (53–58%) across income deciles, with a slight dip at the lowest decile, suggests heterogeneity in $\theta_1$ across borrowers. Some borrowers have high liquidity sensitivity (always tip), others have low sensitivity (never tip), and at very low income, even high-sensitivity borrowers may hit binding constraints.

**Persistence in Tipping.** Borrowers who tip once are 64.5 percentage points more likely to tip again. Our dynamic extension explains this through reputation accumulation: each tip raises the borrower's reputation state $R_t$, which increases the effective warm-glow parameter $\tilde{\theta}_t$, making future tipping more likely. This creates path dependence: early tipping decisions have lasting effects on borrowing costs. As discussed in Section 4.4, this persistence is more naturally consistent with warm-glow reciprocity, since a stable preference for reciprocating does not evaporate across transactions. If fear were the primary driver, we would expect persistence to erode as borrowers learn that tipping does not affect future eligibility.

**Macroeconomic Uncertainty.** Our model shows that uncertainty unambiguously reduces tips through the precautionary savings channel. When income is volatile, borrowers face a higher marginal utility cost of reducing consumption, leading them to conserve resources by tipping less. The empirical finding that macroeconomic uncertainty is associated with lower tip-based APRs is consistent with this prediction.

Importantly, this effect operates through the consumption channel rather than through changes in $\theta(y)$. While Jensen's inequality implies that uncertainty raises $E[\theta(y)]$ (which would tend to increase tips), this effect is dominated by the direct precautionary motive. The net result is lower tipping during uncertain times.

**Income.** Within-borrower increases in wealth correlate with higher tipping probability and lower APRs. On the one hand, higher income or wealth relaxes liquidity constraints: there is more "budget" from which to tip, capturing the income effect. On the other hand, higher discretionary income $(y - c)$ reduces $\theta(y)$ and the incentive to tip. Our findings of a negative correlation between receiving paychecks and both the propensity to tip and tip-based implicit APR suggest that the latter effect dominates (i.e., less liquidity constraint lowers the effective $\theta(y)$ and hence $\tau^*$).

**Learning and Cognitive Capacity.** Borrowers with higher cognitive ability (measured by AFQT scores) tip less and incur lower APRs. In our framework, more sophisticated borrowers may learn that tipping does not actually affect future credit access, effectively reducing their perceived $\theta_1$. The dynamic model's reputation mechanism captures this: if borrowers discover that $\kappa \approx 0$ (reputation doesn't matter), the feedback loop breaks down, and tipping converges to the static optimum.

**Welfare Implications.** Taken together, our framework suggests that high voluntary APRs are not prima facie evidence of exploitation, but neither are they unambiguous evidence of rational revealed preference. If warm-glow reciprocity dominates, borrowers are expressing genuine gratitude for a valued service, and regulatory intervention may reduce welfare by restricting mutually beneficial exchange. If fear of losing access dominates, the same tipping behavior reflects

exploitation of loss aversion and credit anxiety, strengthening the case for consumer protection. While the strong persistence in tipping tentatively favors the warm-glow interpretation, the decline in tipping with experience suggests that fear may also play a role for some borrowers. Disentangling these channels remains an important question for future research, particularly given its centrality to ongoing regulatory debates over tip-based and earned wage access products.

# 5 Conclusion

This paper sheds new light on borrowers' valuation of credit access in a novel lending framework where tipping serves as a voluntary mechanism for lender compensation. By analyzing detailed transaction-level data, we provide the first direct estimate of willingness to pay for liquidity absent contractual interest obligations. Our findings indicate that borrowers willingly contribute amounts leading to implicit APRs comparable to those in traditional payday lending, suggesting that demand-side factors, including liquidity constraints, behavioral biases, and social preferences, shape observed borrowing costs. These insights challenge prevailing narratives about interest rate regulation and financial exploitation, underscoring the need for a more nuanced approach to regulating credit markets. Importantly, our results highlight the potential of borrower-centric innovations to achieve financial inclusion while ensuring lender sustainability. Taken together, our findings speak directly to the emerging regulatory debate over tip-based cash-advance and earned wage access products. Future research should explore the long-term viability of voluntary contribution models and their broader implications for consumer welfare, and whether we need guardrails that prevent voluntary tips from becoming de facto, opaque interest charges.

A caveat to our findings is that they are based on small-ticket loans and may not generalize to larger credit settings where the cost of borrowing is more salient. Future research could extend this analysis to higher-value loans and other lending contexts, examining whether the same behavioral mechanisms hold and how they evolve over time.

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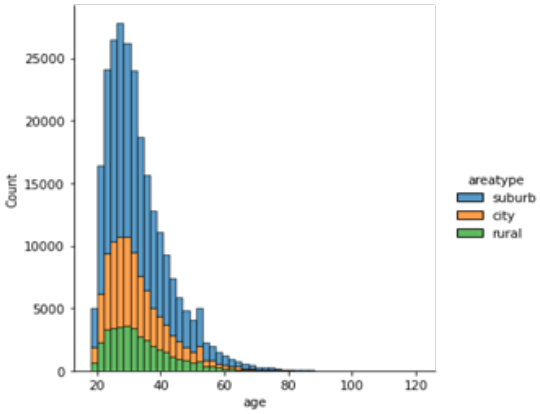
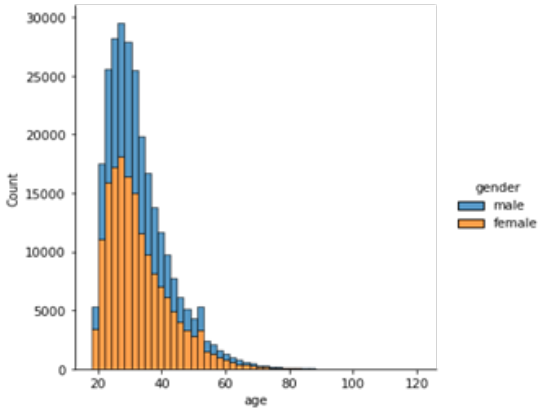
**Figure 3**

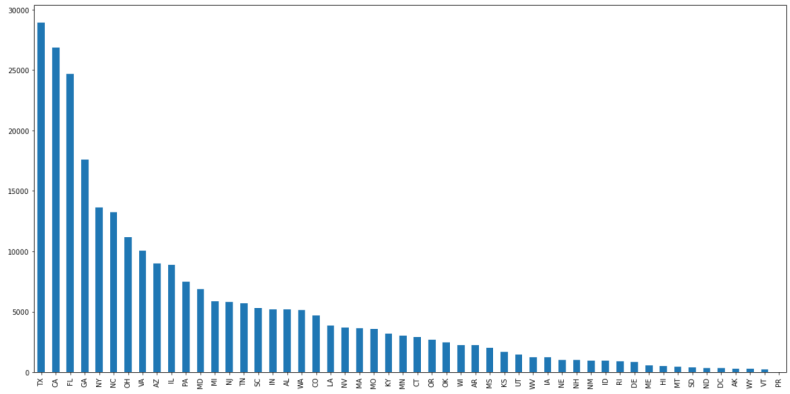
**Distribution of the population across different demographics: (A) by age and area type, (B) by age and gender, and (C) across states.**




**A. Distribution by age and area type**

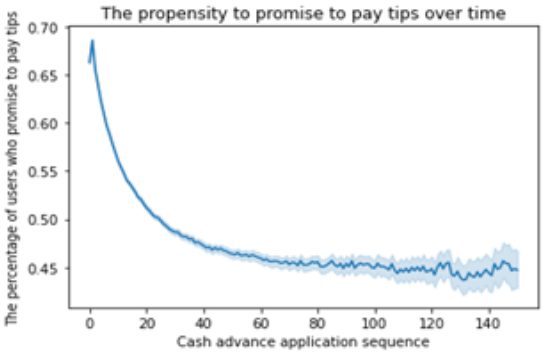



**B. Distribution by age and gender**

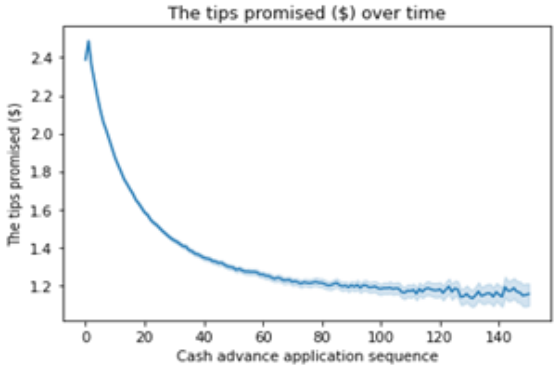


**C. Distribution across states**

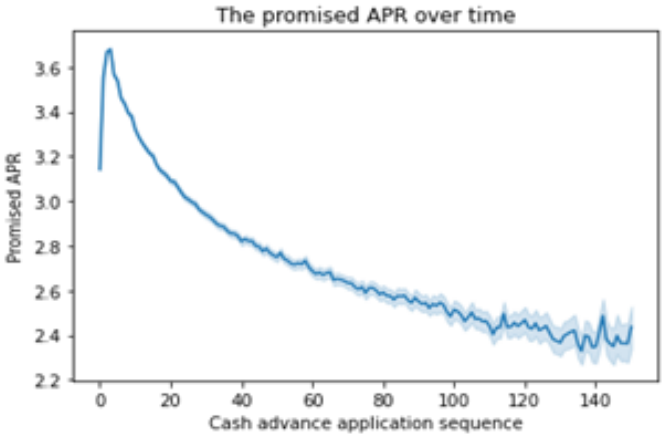
**Figure 4**
**Trends in tipping behavior over time: (A) propensity to promise to pay tips, (B) total tips promised ($), and (C) promised APR.**




**A. Propensity to promise to pay tips**



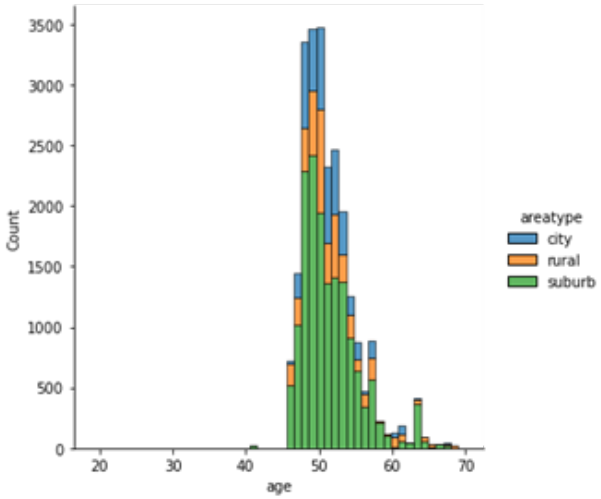

**B. Total tips promised ($)**



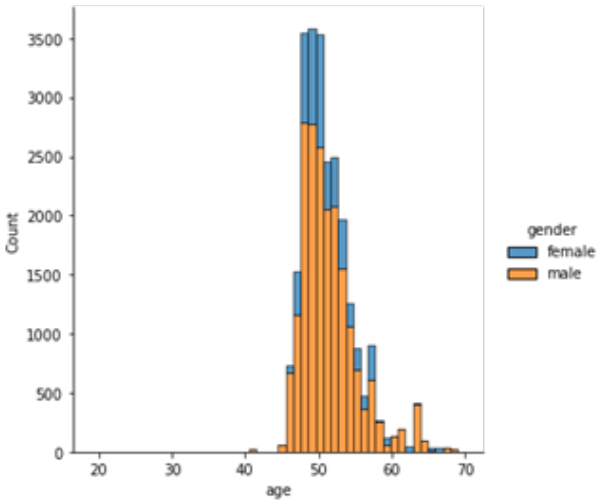

**C. Promised APR over time**

**Figure 5**

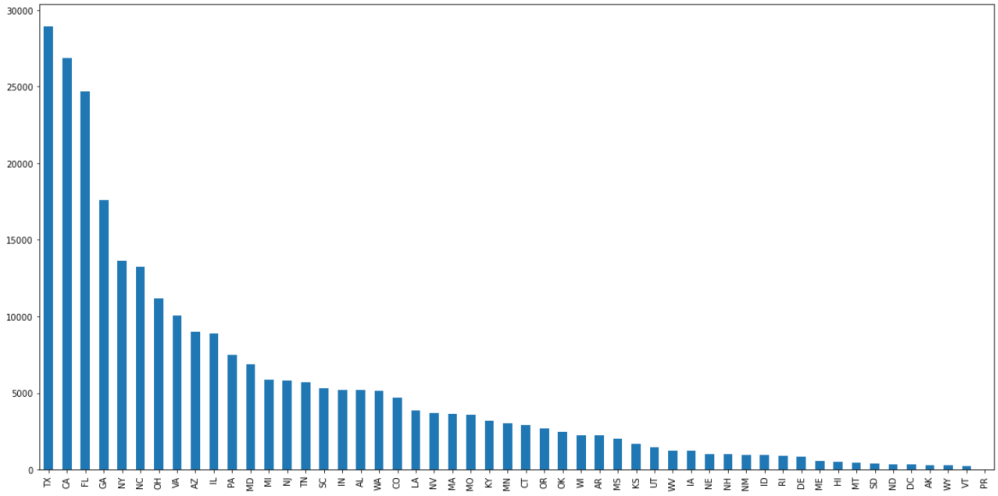
**Demographic distribution of the population: (A) by age and area type, (B) by age and gender, and (C) across states.**




**A. Distribution by age and area type**




**B. Distribution by age and gender**



**C. Distribution across states**

**Figure 6**
**Tipping and APR by Income Decile**

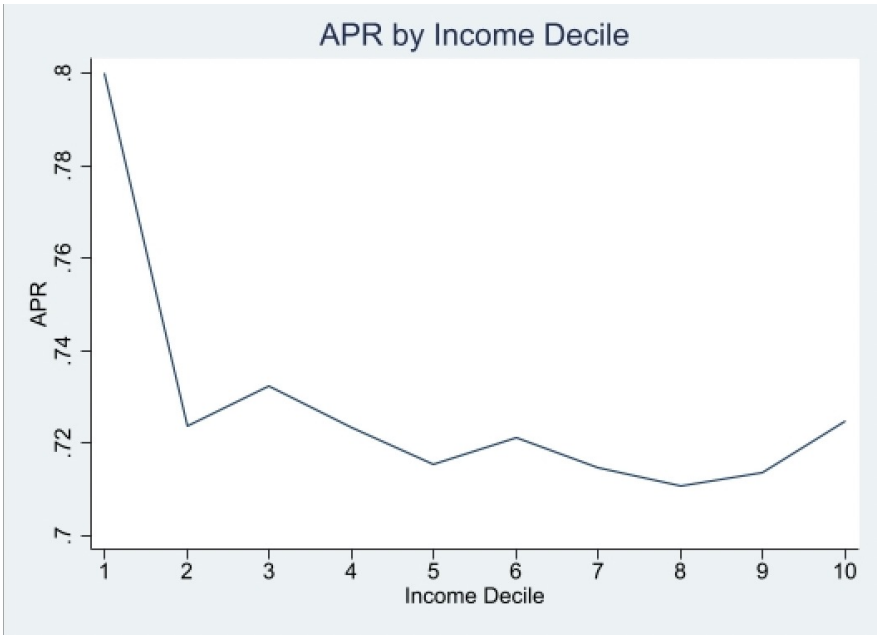
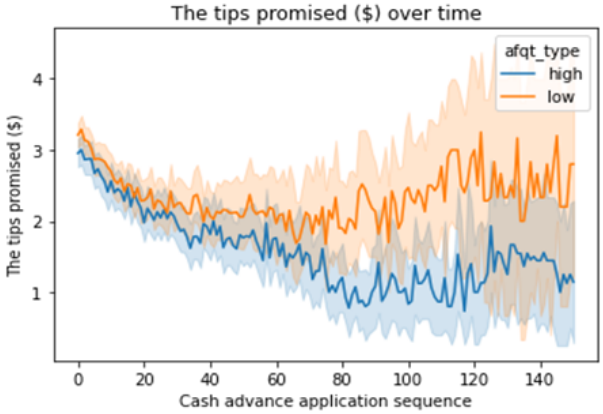
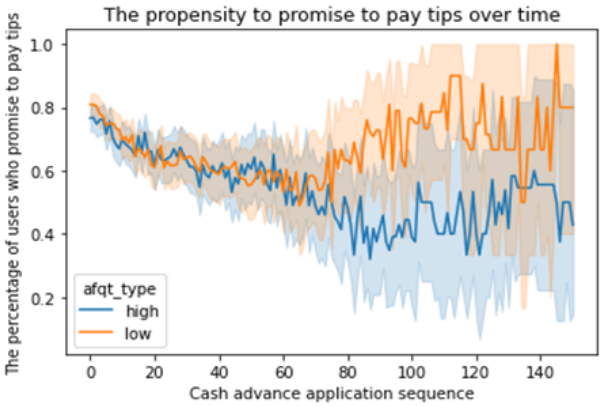


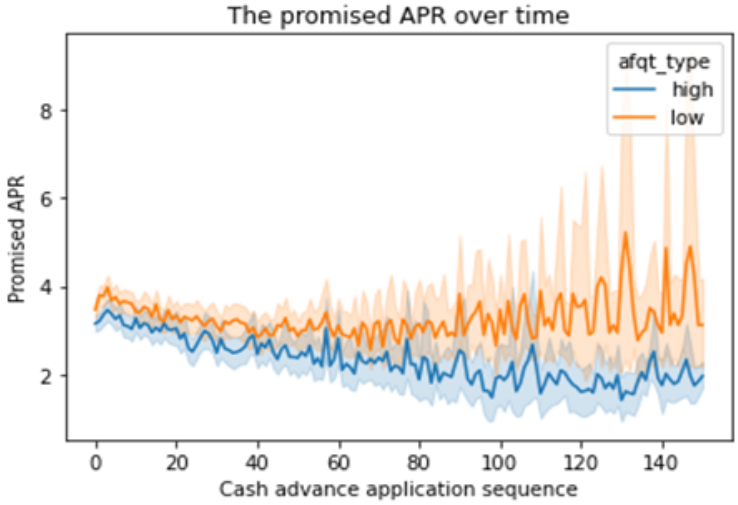
**Figure 7**
**Trends in tipping behavior over time by AFQT group: (A) total tips promised ($), (B) propensity to promise to pay tips, and (C) promised APR.**




**A. Total tips promised ($) by AFQT group**

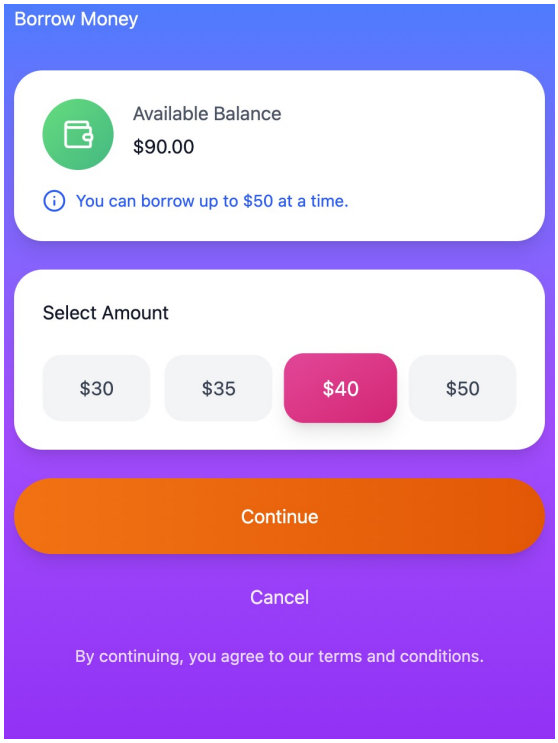



**B. Propensity to promise to pay tips by AFQT group**

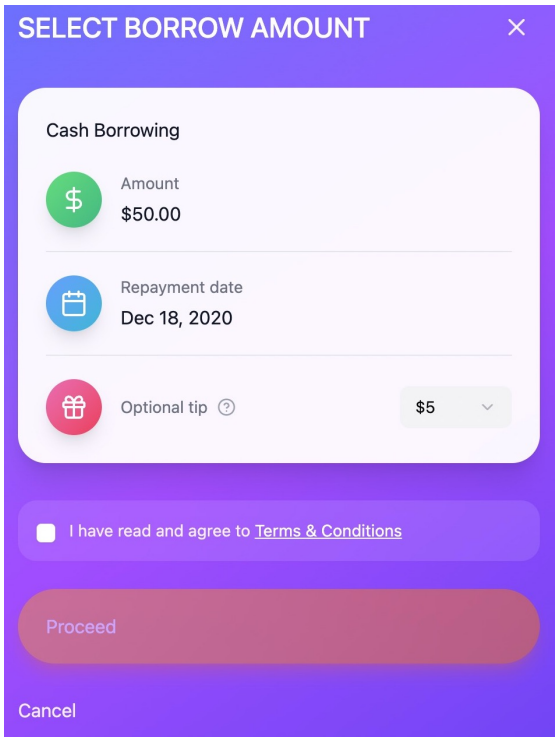



**C. Promised APR by AFQT group**

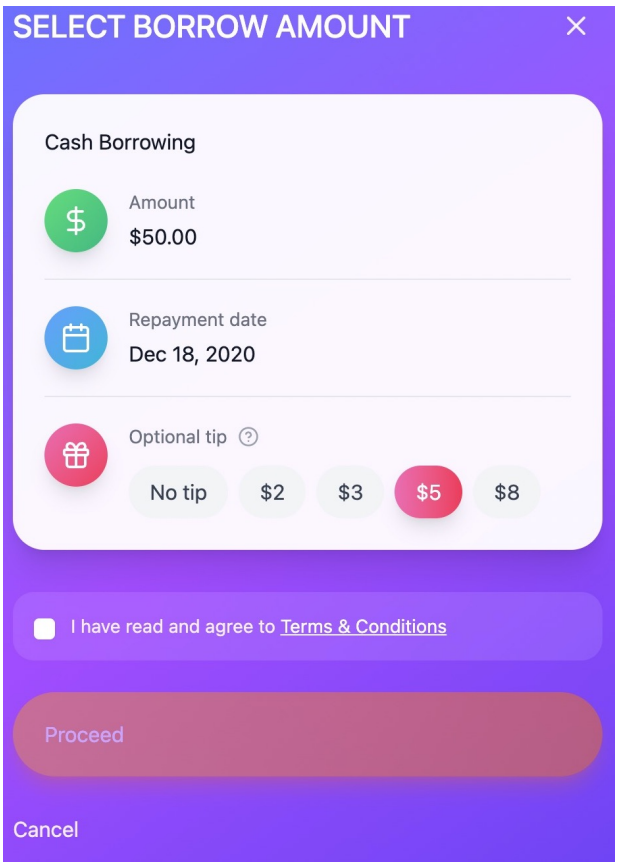
**Figure 8**
**User Interface (UI) Flow of the Fintech Lending Platform**




**A. The loan amount selection screen**

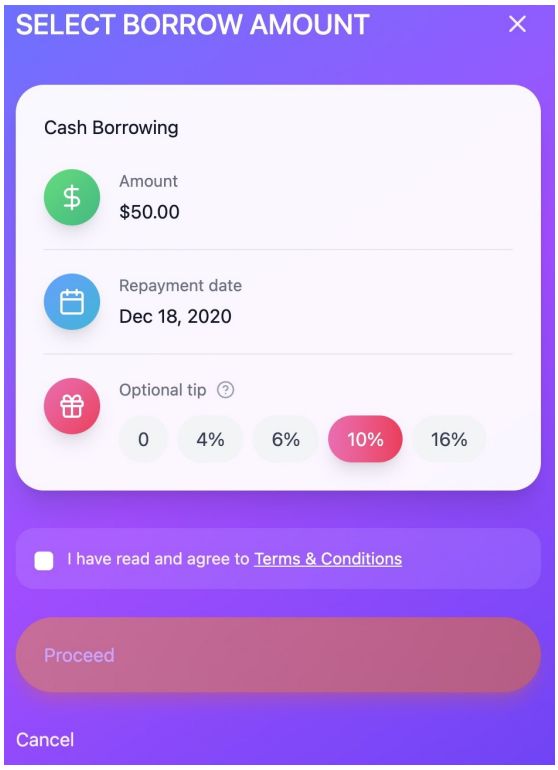



**B. The loan confirmation page with a default tip option**

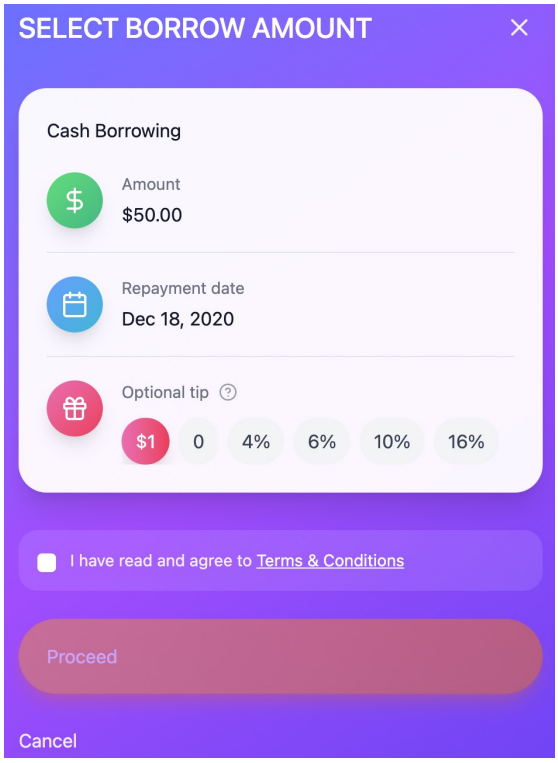



**C. Expands the tip selection into multiple alternatives**

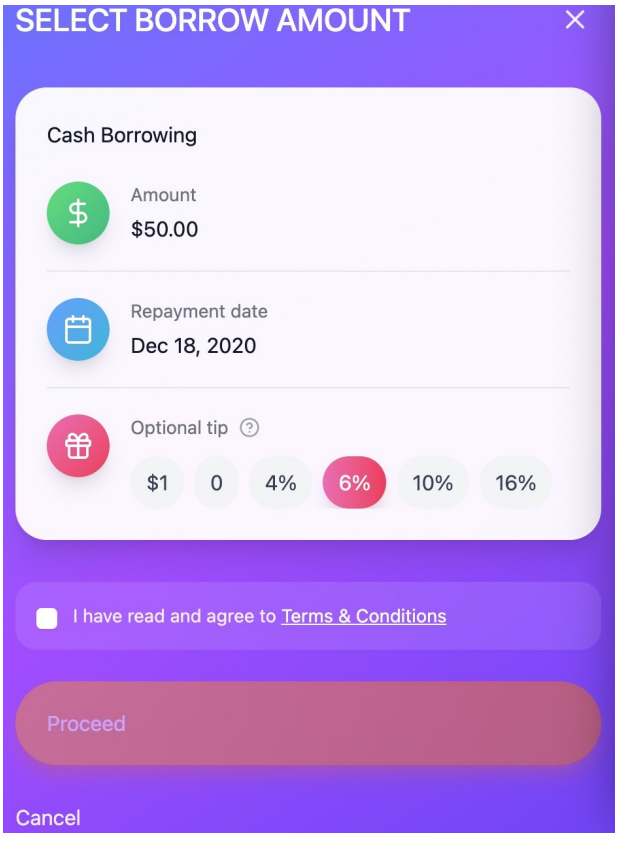
**Figure 9**
**User Interfaces (UI) shown to participants in the control and two treatment groups in the tipping experiment**




**A. Control group UI interface**




**B. Treatment group 1 UI interface**




**C. Treatment group 2 UI interface**

## Table 1
## Summary Statistics by Construct

This table reports summary statistics for the main variables used in the empirical analysis. Panel A presents persistence variables that capture users' prior tipping and borrowing behavior on the platform. Panel B summarizes demographic characteristics, including age, gender, and ethnicity. Panel C reports financial characteristics such as income, loan activity, investment behavior, and employment status. Panel D includes macroeconomic indicators such as the Federal Funds Rate and the Economic Policy Uncertainty Index, while Panel E presents state-level variables on unemployment insurance benefits and minimum tipped wages. All monetary variables are expressed in U.S. dollars. Statistics are computed using user-month observations, with reported values showing the mean and standard deviation (SD).

| Variable | Description | N | Mean | SD |
|---|---|---|---|---|
| **Panel A. Persistence Variables** | | | | |
| Promised Tips (0/1) | Indicator of whether the user promises any tips. Source: Platform. | 6,871,885 | 0.54 | 0.50 |
| Free coffee (0/1) | Indicator of whether a cash advance is preceded by a free coffee. Source: Platform. | 6,871,885 | 0.21 | 0.41 |
| Number of Cash Advance Applications To Date | Total number of cash advance applications to date. Source: Platform. | 6,871,885 | 27.67 | 29.93 |
| Tip-only Inferred APR (Paid) | Implicit APR based on tips paid (winsorized 1%/99%). Source: Platform. | 6,871,885 | 0.77 | 1.46 |
| Cash Advance Amount ($) | The cash advance amount (winsorized 1%/99%) Source: Platform. | 6,871,885 | 44.79 | 13.42 |
| Expedited Cash Disbursement (0/1) | Indicator of whether the user applies to expedite cash disbursement. Source: Platform. | 6,871,885 | 0.79 | 0.41 |
| Paid Tips (0/1) | Indicator of whether the user pays any tips. Source: Platform. | 6,871,885 | 0.37 | 0.48 |
| Paid Tips ($) | The tips paid. Source: Platform. | 6,871,885 | 1.15 | 1.72 |
| Overpromised ($) | The promised tips less paid tips (by due date) . Source: Platform. | 6,871,885 | 0.58 | 1.4 |
| Inferred APR (Paid) | The implicit annualized percentage rate based on tips and fees (to expedite the disbursement of a cash advance application) paid (winsorized 1%/99%). Source: Platform. | 6,871,885 | 2.7 | 2.35 |
| Spend the cash advance on the day of its disbursement (0/1) | Indicator of whether the user spends on the day when cash advance is disbursed. Source: Platform. | 6,871,885 | 0.66 | 0.47 |
| Pay for Loan on Cash Disbursement (0/1) | Indicator of whether the user pays for loans on the day when cash advance is disbursed. Source: Platform. | 6,871,885 | 0.26 | 0.44 |
| Pay for Shopping on Cash Disbursement (0/1) | Indicator of whether the user pays for shopping on the day when cash advance is disbursed. Source: Platform. | 6,871,885 | 0.13 | 0.34 |
| Pay for Subscription Services on Cash Disbursement (0/1) | Indicator of whether the user pays for subscription service on the day when cash advance is disbursed. Source: Platform. | 6,871,885 | 0.07 | 0.25 |
| Pay for Service, Food, Drink, and Travel on Cash Disbursement (0/1) | Indicator of whether the user pays for service, food, or travel on the day when cash advance is disbursed. Source: Platform. | 6,871,885 | 0.18 | 0.39 |
| **Panel B. Demographic Characteristics** | | | | |
| Age (Year) | User age on application day. Source: Platform. | 6,871,885 | 33.60 | 9.14 |
| Female (0/1) | Indicator of whether the user is a female. Source: Platform and US Census. | 6,871,885 | 0.37 | 0.48 |
| Non-Hispanic Black (0/1) | Indicator of whether the user is non-Hispanic Black. Source: Platform and US Census. | 6,871,885 | 0.04 | 0.20 |
| Non-Hispanic Asian and Pacific Islander (0/1) | Indicator of whether the user is non-Hispanic Asian/Pacific Islander. Source: Platform and US Census. | 6,871,885 | 0.01 | 0.11 |
| Hispanic (0/1) | Indicator of whether the user is Hispanic. Source: Platform and US Census. | 6,871,885 | 0.14 | 0.35 |
| Married (0/1) | Indicator of whether the user is married. Source: Platform. | 6,871,885 | 0.08 | 0.28 |
| City (0/1) | Indicator of whether the user lives in a city. Source: Platform. | 6,871,885 | 0.23 | 0.42 |

**Table 1 (continued)**

| Variable | Description | N | Mean | SD |
|---|---|---|---|---|
| **Panel C. Financial Characteristics** | | | | |
| Automatic Investment Service (0/1) | Indicator of whether the user opts for automatic investment. Source: Platform. | 6,871,885 | 0.10 | 0.30 |
| Paychecks received last month ($) | Total paycheck received in the last calendar month. Source: Platform. | 6,871,885 | 2,864.28 | 2,253.50 |
| Loan interest paid last month ($) | Total loan interest paid in the last calendar month. Source: Platform. | 6,871,885 | 838.77 | 867.70 |
| Unemployed last month (0/1) | Indicator of unemployment in the last calendar month. Source: Platform. | 6,871,885 | 0.15 | 0.36 |
| Percentage Change in Investment Equity Value | Percentage change in investment equity value (winsorized 1%/99%). Source: Platform. | 6,871,885 | -0.02 | 0.15 |
| Total equity portfolio value ($) | Total equity portfolio value (investment and cash balance). Source: Platform. | 6,871,885 | 0.00 | 1.00 |
| **Panel D. Macroeconomic Variables** | | | | |
| Economic Policy Uncertainty | Economic Policy Uncertainty Index by state. Source: PolicyUncertainty.com. | 6,871,885 | 312.94 | 215.06 |
| Federal Rate (%) | Effective federal funds rate. Source: Federal Reserve Bank of New York. | 6,871,885 | 0.00 | 0.01 |
| **Panel E. State-Level Variables** | | | | |
| State-Level Avg Weekly Unemployment Insurance ($) | State UI benefits. | 6,871,885 | 313.08 | 70.27 |
| State-Level Minimum Tipped Wage ($/h) | State tipped minimum wage. | 6,871,885 | 4.89 | 3.35 |

## Table 2
## Determinants of Tipping Behavior and Inferred Tip-Only APRs: Persistence, Demographics, and Financial Characteristics

*Notes:* This table presents OLS regression estimates analyzing user tipping behavior and inferred tip-only APRs on a fintech lending platform. Column (1) shows whether a user tipped (binary indicator), and Column (2) focuses on the inferred tip-only APR among paying tippers. Panel A examines persistence and selected financial variables. Panel B includes demographic characteristics (adding to variables from Panel A). Panel C includes financial characteristics. Robust standard errors are clustered at the user level and reported in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

| | Tipping (0/1) (1) | Inferred Tip-Only APR (2) |
|---|---|---|
| **Panel A. Persistence Variables** | | |
| Promised Tips (0/1) t–1 | 0.6450*** | |
| | (0.0010) | |
| Free coffee (0/1) | –0.0051*** | 0.0152*** |
| | (0.0010) | (0.0023) |
| Number of Cash Advance Applications To Date | –0.0112*** | –0.1543*** |
| | (0.0006) | (0.0032) |
| Inferred Tip-Only APR t–1 (Paid) | | 0.2899*** |
| | | (0.0017) |
| Constant | –0.6538*** | 2.4112*** |
| | (0.0009) | (0.1933) |
| Observations | 6,548,775 | 2,412,085 |
| R-squared | 0.425 | 0.1206 |
| Time FE | YES | YES |
| **Panel B. Demographic Characteristics** | | |
| Female (0/1) | 0.0044*** | –0.0404*** |
| | (0.0009) | (0.0042) |
| Non-Hispanic Black (0/1) | –0.0062*** | 0.0504*** |
| | (0.0020) | (0.0103) |
| Non-Hispanic Asian and Pacific Islander (0/1) | –0.0255*** | –0.1049*** |
| | (0.0038) | (0.0194) |
| Hispanic (0/1) | 0.0009 | –0.0834*** |
| | (0.0012) | (0.0058) |
| Married (0/1) | –0.0045*** | –0.0784*** |
| | (0.0017) | (0.0075) |
| City (0/1) | –0.0067*** | 0.0089* |
| | (0.0010) | (0.0049) |
| Age (Year) | 0.0275*** | 0.0029 |
| | (0.0004) | (0.0021) |
| Persistence variables | Included | Included |
| Constant | –0.6524*** | 2.5002*** |
| | (0.0014) | (0.0066) |
| Observations | 6,548,775 | 2,412,085 |
| R-squared | 0.428 | 0.122 |
| Time FE | YES | YES |
| **Panel C. Financial Characteristics** | | |
| Automatic Investment Service (0/1) | 0.0191*** | 0.0107 |
| | (0.0015) | (0.0070) |
| Paychecks received last month ($) | –0.0013*** | –0.0444*** |
| | (0.0004) | (0.0021) |
| Loan interest paid last month ($) | 0.0068*** | –0.0526*** |
| | (0.0004) | (0.0020) |
| % Percentage change of Investment Equity Value | 0.0006*** | 0.0042*** |
| | (0.0002) | (0.0009) |
| Total equity portfolio value ($) | 0.0012*** | –0.0038*** |
| | (0.0003) | (0.0014) |
| Persistence Variables | Included | Included |
| Demographic Characteristics | Included | Included |
| Constant | –0.6653*** | 2.6103*** |
| | (0.0027) | (0.0101) |
| Observations | 6,548,775 | 2,412,085 |
| R-squared | 0.4283 | 0.1272 |
| Time FE | YES | YES |

## Table 3
## Impact of Average Local Credit Cost, Regulatory Changes to Payday Loan Provision and State-Level Bank Competition on User Tipping Behavior

Panel A reports regression estimates examining the relationship between average local credit cost and user tipping behavior on the fintech platform. Average local credit cost is measured by *Median Annual Loan Yield (10b)*, the median annual loan yield for community banks within a given state and year (FDIC Call Report), computed as annualized interest income divided by loans outstanding. *Median Annual Loan Yield (1b)* represents the median annual loan yield for community banks with total assets below $1 billion.
Panel B examines quasi-exogenous regulatory changes that restrict payday-loan provision. *Law in Force* equals one when a state regulation (e.g., rate caps, anti-evasion rules, tighter licensing, or term limits) is active.
Panel C reports the relationship between local bank competition and user tipping. *HHI of Assets (10b)* measures competition as the Herfindahl–Hirschman Index of community banks with at least $10 billion in assets. *HHI of Assets (1b)* covers banks below $1 billion in assets. *HHI of Assets* (unbanded) comes from branch-level assets (FDIC Summary of Deposits).
Dependent variables: (i) tipping indicator and (ii) inferred tip-only APR. All regressions control for individual level characteristics including demographic, persistence financial characteristics, plus time fixed effects. Robust SEs in parentheses. *, **, *** denote significance at 10%, 5%, and 1%.

| | Tipping (0/1) | Inferred Tip-only APR | Tipping (0/1) | Inferred Tip-only APR |
|---|---|---|---|---|
| **Panel A. Average Local Credit Cost** | | | | |
| Median Annual Loan Yield (1b) | 0.0022*** | -0.0031 | | |
| | (-0.0004) | (-0.0022) | | |
| Median Annual Loan Yield (10b) | | | 0.0022*** | -0.0048** |
| | | | (-0.0005) | (-0.0023) |
| Constant | -0.6589*** | 2.6122*** | -0.6602*** | 2.6152*** |
| | (-0.0031) | ( -0.0102 ) | (-0.0031 ) | (-0.0106) |
| Time FE | YES | YES | YES | YES |
| Observations | 6,548,290 | 2,411,854 | 6,078,930 | 2,237,287 |
| R-squared | 0.4283 | 0.1272 | 0.428 | 0.1275 |
| **Panel B. Regulatory Changes to Payday Loan Provision** | | | | |
| Law in Force | 0.0047*** | -0.0178*** | | |
| | (-0.0011) | ( -0.0053 ) | | |
| Constant | -0.6652*** | 2.6098*** | | |
| | (-0.0028) | ( -0.0101 ) | | |
| Time FE | YES | YES | | |
| Observations | 66,548,775 | 2,412,085 | | |
| R-squared | 0.4283 | 0.1272 | | |
| **Panel C. State-Level Bank Competition** | | | | |
| HHI of Assets (1b) | 0.0018*** | -0.0012 | | |
| | (-0.0004) | (-0.002 ) | | |
| HHI of Assets (10b) | | | 0.0028*** | -0.0037* |
| | | | (-0.0004) | (-0.0021 ) |
| Constant | -0.6642*** | 2.6096*** | -0.6634*** | 2.6103*** |
| | (-0.0028) | (-0.0101) | (-0.0029 ) | (-0.0103) |
| Time FE | YES | YES | YES | YES |
| Observations | 6,548,290 | 2,411,854 | 6,078,930 | 2,237,287 |
| R-squared | 0.4283 | 0.1272 | 0.428 | 0.1275 |
| **Persistence Characteristics** | | Included | | Included |
| **Demographic Characteristics** | | Included | | Included |
| **Financial Characteristics** | | Included | | Included |

## Table 4
## Determinants of Tipping Behavior and Inferred Tip-Only APRs: Macroeconomic and State-Level Variables

*Notes:* This table presents OLS estimates examining the relationship between macroeconomic and state-level factors and user tipping behavior on a fintech lending platform. Columns (1)–(4) correspond to different model specifications. Columns (1) and (2) include Median Annual Loan Yield (1b) and HHI of Assets (1b); Columns (3) and (4) include Median Annual Loan Yield (10b) and HHI of Assets (10b). All regressions control for persistence, demographic, financial, macroeconomic, and regulatory-change variables, and include time fixed effects. Robust standard errors (with signs retained from the raw output) are shown in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

| | (1) Tipping | (2) Inferred Tip-only APR | (3) Tipping | (4) Inferred Tip-only APR |
|---|---|---|---|---|
| **Panel A. Macroeconomic Variables** | | | | |
| Economic Policy Uncertainty | 0.0001 | -0.0083*** | -0.0008* | -0.0068*** |
| | (-0.0005) | (-0.0022) | (-0.0005) | (-0.0024) |
| Federal Rate (%) | -0.2720*** | 0.2623*** | -0.2725*** | 0.2627*** |
| | (0.0010) | (0.0040) | (0.0012) | (0.0042) |
| *Median Annual Loan Yield (1b)* | | Included | | |
| *HHI of Assets (1b)* | | Included | | |
| *Median Annual Loan Yield (10b)* | | | | Included |
| *HHI of Assets (10b)* | | | | Included |
| *Persistence Variables* | | | Included | |
| *Demographic Characteristics* | | | Included | |
| *Financial Characteristics* | | | Included | |
| *Regulatory Changes to Payday Loan Provision* | | | Included | |
| Constant | 0.0538*** | 1.7941*** | 0.0530 | 1.7964*** |
| | (0.0017) | (0.0089) | (0.0018) | (0.0092) |
| Observations | 6,548,290 | 2,411,854 | 6,078,930 | 2,237,287 |
| $R^2$ | 0.4284 | 0.1272 | 0.4281 | 0.1275 |
| Time FE | YES | YES | YES | YES |
| **Panel B. State-Level Variables** | | | | |
| State-Level Average Weekly Unemployment Insurance Paid ($) | 0.0019*** | -0.0084*** | 0.0018*** | -0.0074*** |
| | (-0.0004) | (-0.0022) | (-0.0005) | (-0.0022) |
| State-Level Minimum Tipped Wage ($) | -0.0002 | -0.0047* | -0.0002 | -0.0062** |
| | (-0.0006) | (-0.0027) | (-0.0006) | (-0.0027) |
| *Median Annual Loan Yield (1b)* | | Included | | |
| *HHI of Assets (1b)* | | Included | | |
| *Median Annual Loan Yield (10b)* | | | | Included |
| *HHI of Assets (10b)* | | | | Included |
| *Persistence Variables* | | | Included | |
| *Demographic Characteristics* | | | Included | |
| *Financial Characteristics* | | | Included | |
| *Regulatory Changes to Payday Loan Provision* | | | Included | |
| *Macroeconomic Variables* | | | Included | |
| Constant | 0.0537*** | 1.7950*** | 0.0529*** | 1.7976*** |
| | (0.0017) | (0.0089) | (0.0018) | (0.0092) |
| Observations | 6,548,290 | 2,411,854 | 6,078,930 | 2,237,287 |
| $R^2$ | 0.4284 | 0.1272 | 0.4281 | 0.1275 |
| Time FE | YES | YES | YES | YES |

## Table 5
## Cognitive Ability, Tipping Behavior, and Inferred Borrowing Costs

This table presents the results of OLS regressions examining the relationship between cognitive ability, as measured by the Armed Forces Qualification Test (AFQT) scores, and two key outcomes: tipping behavior and inferred tip-only APR. Column (1) evaluates the likelihood of tipping (a binary variable), while Column (2) focuses on inferred tip-only APR among paying tippers. The regressions control for demographic characteristics, financial conditions, platform behavior, and both user and time fixed effects. All regressions control for individual level characteristics including demographic, persistence financial characteristics , macroeconomic, and state-level characteristics. All independent variables are standardized. Robust standard errors are clustered at the user level. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

| | Tipping (0/1) | Inferred Tip-only APR |
|---|---|---|
| **AFQT Score** | -0.0124* | -0.0577*** |
| | (0.0069) | (0.0163) |
| **Constant** | 0.2102*** | 0.9373*** |
| | (0.0171) | (0.0319) |
| *Other controls* | Included | |
| User fixed effects | YES | |
| Time fixed effects | YES | |
| Observations | 24,684 | 23,770 |
| $R^2$ | 0.4408 | 0.3512 |

## Table 6
## Components of Cognitive Abilities and Their Correlation with Tipping Behavior

This table presents the results of OLS regressions examining the relationship between individual components of the Armed Forces Qualification Test (AFQT) scores and the likelihood of tipping. Each regression evaluates one AFQT subcomponent, including Word Knowledge, Paragraph Comprehension, Numerical Operations, Math Knowledge, Mechanical Components, General Science, Electronic Information, Coding Speed, and Arithmetic Reasoning, as predictors of tipping behavior. The dependent variable is a binary indicator of whether the user tipped during a given cash advance transaction. The regressions control for key variables, including demographic characteristics, financial conditions, platform behavior, and time fixed effects.The inclusion of user fixed effects results in the exclusion of time-invariant user-specific variables, thereby isolating the effects of time-varying factors on user behavior.All regressions control for individual level characteristics including demographic, persistence financial characteristics , macroeconomic, and state-level characteristics. All the independent variables are standardized. Robust standard errors are clustered at the user level, with significance levels denoted by *, **, and *** at the 10%, 5%, and 1% thresholds, respectively

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | **Tipping (0/1)** | | | | |
| **Word Knowledge** | 0.0028 | | | | | | | | |
| | (0.0077) | | | | | | | | |
| **Paragraph Comprehension** | | -0.0061 | | | | | | | |
| | | (0.0072) | | | | | | | |
| **Numerical Operations** | | | -0.0200*** | | | | | | |
| | | | (0.0074) | | | | | | |
| **Math Knowledge** | | | | -0.0179** | | | | | |
| | | | | (0.0071) | | | | | |
| **Mechanical Components** | | | | | -0.0005 | | | | |
| | | | | | (0.0072) | | | | |
| **General Science** | | | | | | -0.0002 | | | |
| | | | | | | (0.0072) | | | |
| **Electronic Information** | | | | | | | -0.0099 | | |
| | | | | | | | (0.0081) | | |
| **Coding Speed** | | | | | | | | -0.0245** | |
| | | | | | | | | (0.0075) | |
| **Arithmetic Reasoning** | | | | | | | | | -0.0152** |
| | | | | | | | | | (0.0074) |
| **Constant** | 0.2072*** | 0.2084*** | 0.2095*** | 0.2115*** | 0.2079*** | 0.2078*** | 0.2093*** | 0.2121*** | 0.2153*** |
| | (0.0182) | (0.0181) | (0.0181) | (0.0183) | (0.0185) | (0.0182) | (0.0185) | (0.0181) | (0.0183) |
| *All other controls* | | | | | Included | | | | |
| User fixed effects | | | | | YES | | | | |
| Time fixed effects | | | | | YES | | | | |
| Observations | 22,327 | 22,327 | 22,327 | 22,327 | 22,327 | 22,327 | 22,327 | 22,327 | 22,327 |
| $R^2$ | 0.4369 | 0.4371 | 0.4386 | 0.4383 | 0.4369 | 0.4369 | 0.4370 | 0.4392 | 0.4378 |

## Table 7
## Effects of Modified Tipping Interface on Tipping Behavior, Inferred Tip-Only APR, and Deviation from Recommended Defaults (Experiment 1)

*Notes:* This table presents the results of Experiment 1, evaluating the effects of an alternative tipping interface on user behavior in a fintech platform. The experiment contrasts a treatment group exposed to an interface that introduces and recommends a $1 tip option with a counterfactual group using the platform's standard interface. The standard interface features tipping options ranging from 0% to 16%, with 10% as the recommended tip level. The analysis examines three primary outcomes: tipping behavior (whether users tipped), inferred tip-only APR (based solely on tipping among those who tipped), and deviation from the recommended tipping level. The regressions control for demographic characteristics, financial conditions, platform behavior, and user and time fixed effects. All regressions control for individual level characteristics including demographic, persistence financial characteristics , macroeconomic, and state-level characteristics. All independent variables are standardized. Robust standard errors are clustered at the user level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

| **OUTCOME** | Tipping (0/1) | Inferred Tip-only APR | Deviation from the Default | Tipping (0/1) | Inferred Tip-only APR | Deviation from the Default |
|---|---|---|---|---|---|---|
| **MODEL** | (1) | (2) | (3) | (4) | (5) | (6) |
| **TREATMENT** | Add $1 tip, recommend $1 tip | Add $1 tip, recommend $1 tip | Add $1 tip, recommend $1 tip | Add $1 tip, recommend $1 tip | Add $1 tip, recommend $1 tip | Add $1 tip, recommend $1 tip |
| **COUNTERFACTUAL** | Recommend 10% tip | Recommend 10% tip | Recommend 10% tip | Add $1 tip, recommend 10% tip | Add $1 tip, recommend 10% tip | Add $1 tip, recommend 10% tip |
| **Post × Treated** | 0.0582*** | -0.7938*** | 2.8572*** | 0.0455*** | -0.6245*** | 2.2497*** |
| | (0.0042) | (0.0871) | (0.2583) | (0.0046) | (0.1178) | (0.5139) |
| **Post** | 0.1650 | -0.2583 | 0.2511 | 0.1233 | -0.2850 | 0.6868 |
| | (0.3766) | (0.1931) | (0.4241) | (0.3738) | (0.2800) | (0.8690) |
| **Constant** | 0.2549 | 1.1483*** | -0.7155 | -0.1782 | 0.2526 | 4.7782 |
| | (0.3874) | (0.4382) | (0.8975) | (0.3758) | (1.1939) | (4.2408) |
| *All other controls* | | | | Included | | |
| User fixed effects | | | | YES | | |
| Time fixed effects | | | | YES | | |
| Observations | 61,667 | 2,023 | 2,023 | 61,015 | 2,217 | 2,217 |
| $R^2$ | 0.3015 | 0.9018 | 0.9197 | 0.2916 | 0.8897 | 0.8900 |

## Table 8
## Effects of Modified Tipping Interface on Tipping Behavior, Inferred Tip-Only APR, and Deviation from Recommended Defaults (Experiment 2)

*Notes:* This table presents the results of Experiment 2, which evaluates the effects of a modified tipping interface on user behavior in a fintech platform setting. The experiment contrasts a treatment group exposed to an interface with an added $1 tip option and a recommended 6% tip against a counterfactual group using the platform's standard interface, where tipping options range from 0% to 16%, with 10% as the recommended level. The analysis examines three key outcomes: tipping behavior (whether users tipped), inferred tip-only APR (based solely on tipping among those who tipped), and deviation from the recommended tipping level. The regressions control for key variables, including demographic characteristics, financial conditions, platform behavior, and time fixed effects.All regressions control for individual level characteristics including demographic, persistence financial characteristics , macroeconomic, and state-level characteristics. Robust standard errors are clustered at the user level, with significance levels denoted by *, **, and *** at the 10%, 5%, and 1% thresholds, respectively.

| **OUTCOME** | Tipping (0/1) | Inferred Tip-only APR | Deviation from the Default | Tipping (0/1) | Inferred Tip-only APR | Deviation from the Default |
|---|---|---|---|---|---|---|
| **MODEL** | (1) | (2) | (3) | (4) | (5) | (6) |
| **TREATMENT** | Add $1 tip, recommend 6% tip | Add $1 tip, recommend 6% tip | Add $1 tip, recommend 6% tip | Add $1 tip, recommend 6% tip | Add $1 tip, recommend 6% tip | Add $1 tip, recommend 6% tip |
| **COUNTERFACTUAL** | Recommend 10% tip | Recommend 10% tip | Recommend 10% tip | Add $1 tip, recommend 10% tip | Add $1 tip, recommend 10% tip | Add $1 tip, recommend 10% tip |
| **Post × Treated** | 0.0204*** | -0.4213*** | -0.0234 | 0.0074** | -0.3611*** | -0.8088 |
| | (0.0031) | (0.1096) | (0.6331) | (0.0035) | (0.1364) | (0.7589) |
| **Post** | 0.1801 | 2.3352 | 16.2021 | 0.1934 | -6.8582 | 14.9341 |
| | (0.3116) | (5.1327) | (20.5160) | (0.2963) | (5.8735) | (27.3983) |
| **Constant** | -0.1224 | -1.0685 | -17.7435 | -0.1082 | 9.2869 | -13.0256 |
| | (0.2919) | (4.8432) | (20.0803) | (0.2750) | (6.2377) | (31.5102) |
| *All other controls* | | | Included | | | |
| User fixed effects | | | YES | | | |
| Time fixed effects | | | YES | | | |
| Observations | 61,365 | 1,296 | 1,296 | 60,713 | 1,490 | 1,490 |
| $R^2$ | 0.1896 | 0.8986 | 0.8400 | 0.1883 | 0.8663 | 0.8146 |

# Appendix A

This appendix reports additional tests discussed in the manuscript.

# Internet Appendix

This appendix reports more details about the conceptual framework reported in Section 4.

## IA1 Derivation of Comparative Statics

With $\theta(y) = \frac{\theta_1}{y-c}$ and the optimal tip:

$$\tau^* = \frac{(\theta_1 - 1)y + \theta_1 L + c}{y - c + \theta_1}$$

### IA1.1 Effect of Loan Size $L$

Since $\theta(y)$ does not depend on $L$:

$$\frac{\partial \tau^*}{\partial L} = \frac{\theta_1 \cdot (y - c + \theta_1) - [(\theta_1 - 1)y + \theta_1 L + c] \cdot 0}{(y - c + \theta_1)^2} = \frac{\theta_1}{y - c + \theta_1} > 0$$

An increase in loan size unambiguously increases the optimal tip.

### IA1.2 Effect of Income $y$

Let $N = (\theta_1 - 1)y + \theta_1 L + c$ and $D = y - c + \theta_1$. Then:

$$\frac{dN}{dy} = \theta_1 - 1$$
$$\frac{dD}{dy} = 1$$

Using the quotient rule:

$$\begin{aligned}
\frac{d\tau^*}{dy} &= \frac{(\theta_1 - 1)(y - c + \theta_1) - [(\theta_1 - 1)y + \theta_1 L + c]}{(y - c + \theta_1)^2} \\
&= \frac{(\theta_1 - 1)(y - c + \theta_1) - (\theta_1 - 1)y - \theta_1 L - c}{(y - c + \theta_1)^2} \\
&= \frac{(\theta_1 - 1)(-c + \theta_1) - \theta_1 L - c}{(y - c + \theta_1)^2} \\
&= \frac{-c\theta_1 + c + \theta_1^2 - \theta_1 - \theta_1 L - c}{(y - c + \theta_1)^2} \\
&= \frac{\theta_1^2 - \theta_1 - \theta_1 L - c\theta_1}{(y - c + \theta_1)^2} \\
&= \frac{\theta_1(\theta_1 - 1 - L - c)}{(y - c + \theta_1)^2}
\end{aligned}$$

**Sign:** $\frac{d\tau^*}{dy} < 0$ if and only if $\theta_1 < 1 + L + c$.
With $L \approx 45$ and $c \geq 0$, this condition is satisfied for any $\theta_1 < 46$.

## IA2 Second-Order Conditions

**Static Model.** The SOC requires:

$$\frac{\partial^2 U}{\partial \tau^2} = -\frac{1}{(y + L - \tau)^2} - \frac{\theta(y)}{(1 + \tau)^2} < 0$$

Since $\theta(y) = \theta_1/(y - c) > 0$ for $y > c$, both terms are negative, so the SOC holds. ✓

**CRRA Model.** With utility $U = \frac{(y+L-\tau)^{1-\gamma}}{1-\gamma} + \theta(y)\frac{(1+\tau)^{1-\gamma}}{1-\gamma}$:

$$\frac{\partial^2 U}{\partial \tau^2} = -\gamma(y + L - \tau)^{-\gamma-1} - \gamma\theta(y)(1 + \tau)^{-\gamma-1} < 0 \quad \checkmark$$

**Dynamic Model (Steady State).** The period problem in steady state has the same structure as the static model with $\tilde{\theta}^*$ replacing $\theta(y)$. Since $\tilde{\theta}^* > 0$, the SOC holds.

## IA3 Second-Order Taylor Approximation for Uncertainty

Let $f(y) = \ln(y + L - \tau)$. The Taylor expansion around $\bar{y}$ is:

$$f(y) \approx f(\bar{y}) + f'(\bar{y})(y - \bar{y}) + \frac{1}{2}f''(\bar{y})(y - \bar{y})^2$$

With $f'(\bar{y}) = \frac{1}{\bar{y}+L-\tau}$ and $f''(\bar{y}) = -\frac{1}{(\bar{y}+L-\tau)^2}$, taking expectations:

$$E[f(y)] \approx \ln(\bar{y} + L - \tau) + 0 - \frac{\sigma^2}{2(\bar{y} + L - \tau)^2}$$

# IA4 Uncertainty Effects

## IA4.1 FOC Under Uncertainty

Define $A = \bar{y} + L$. The adjusted expected utility is:

$$\tilde{U}(\tau) \approx \ln(A - \tau) - \frac{\sigma^2}{2(A-\tau)^2} + \theta(\bar{y}) \ln(1 + \tau)$$

**Derivative.** Let $u = A - \tau$, so $\frac{du}{d\tau} = -1$. Then:

$$\frac{d}{d\tau} \ln(A - \tau) = -\frac{1}{A - \tau}$$

$$\frac{d}{d\tau}\left[-\frac{\sigma^2}{2(A-\tau)^2}\right] = -\frac{\sigma^2}{2} \cdot (-2)(A-\tau)^{-3} \cdot (-1) = -\frac{\sigma^2}{(A-\tau)^3}$$

The **FOC** is:

$$-\frac{1}{A-\tau} - \frac{\sigma^2}{(A-\tau)^3} + \frac{\theta(\bar{y})}{1+\tau} = 0$$

## IA4.2 Comparative Statics with Respect to $\sigma^2$

Define:

$$F(\tau, \sigma^2) \equiv -\frac{1}{A-\tau} - \frac{\sigma^2}{(A-\tau)^3} + \frac{\theta}{1+\tau} = 0$$

By the implicit function theorem:

$$\frac{d\tau^*}{d\sigma^2} = -\frac{\partial F / \partial \sigma^2}{\partial F / \partial \tau}$$

**Computing $\partial F / \partial \sigma^2$:**

$$\frac{\partial F}{\partial \sigma^2} = -\frac{1}{(A-\tau)^3} < 0$$

**Computing $\partial F / \partial \tau$:**

$$\frac{\partial F}{\partial \tau} = -\frac{1}{(A-\tau)^2} - \frac{3\sigma^2}{(A-\tau)^4} - \frac{\theta}{(1+\tau)^2} < 0$$

**Result:**

$$\frac{d\tau^*}{d\sigma^2} = -\frac{(-1/(A-\tau)^3)}{(-1/(A-\tau)^2 - 3\sigma^2/(A-\tau)^4 - \theta/(1+\tau)^2)} = \frac{-1/(A-\tau)^3}{\text{negative}} < 0$$

**Proposition 1.** *Uncertainty unambiguously reduces the optimal tip:* $\frac{d\tau^*}{d\sigma^2} < 0$.

# IA5 CRRA Extension

## IA5.1 Setup and Solution

With CRRA utility:

$$U(C,\tau) = \frac{(y+L-\tau)^{1-\gamma}}{1-\gamma} + \theta(y)\frac{(1+\tau)^{1-\gamma}}{1-\gamma}$$

The FOC is:

$$-(y+L-\tau)^{-\gamma} + \theta(y)(1+\tau)^{-\gamma} = 0$$

Solving:

$$\tau^* = \frac{\theta(y)^{1/\gamma}(y+L)-1}{1+\theta(y)^{1/\gamma}}$$

## IA5.2 Comparative Statics with Respect to $\gamma$

Let $X = \theta(y)^{1/\gamma}$ and $A = y + L$. Then $\tau^* = \frac{XA-1}{1+X}$.

$$\begin{aligned}\frac{d\tau^*}{d\gamma} &= \frac{d\tau^*}{dX}\cdot\frac{dX}{d\gamma} \\ &= \frac{A+1}{(1+X)^2}\cdot\left(-\frac{X\ln\theta(y)}{\gamma^2}\right) \\ &= -\frac{(A+1)X\ln\theta(y)}{\gamma^2(1+X)^2}\end{aligned}$$

If $\theta(y) > 1$ (typical case for liquidity-constrained borrowers), then $\ln\theta(y) > 0$, so $\frac{d\tau^*}{d\gamma} < 0$.

**Proposition 2.** *Under CRRA utility with* $\theta(y) > 1$*, higher risk aversion reduces the optimal tip.*

# IA6 Dynamic Model: Steady-State Analysis

## IA6.1 Steady-State Fixed-Point Problem

In steady state with $R^* = \frac{\mu}{1-\lambda}\tau^*$ and $\tilde{\theta}^* = \theta(y) + \frac{\kappa\mu}{1-\lambda}\tau^*$:

The optimal tip satisfies:

$$\tau^* = \frac{\tilde{\theta}^*(y+L)-1}{1+\tilde{\theta}^*}$$

Let $\phi = \frac{\kappa\mu}{1-\lambda}$ and $A = y + L$. Substituting:

$$\tau^* = \frac{(\theta(y)+\phi\tau^*)A-1}{1+\theta(y)+\phi\tau^*}$$

Cross-multiplying and rearranging:

$$\phi(\tau^*)^2 + (1+\theta(y)-\phi A)\tau^* - (\theta(y)A-1) = 0$$

### IA6.2 Existence and Uniqueness

This is a quadratic $a(\tau^*)^2 + b\tau^* + d = 0$ with:

$$\begin{aligned} a &= \phi > 0 \\ b &= 1 + \theta(y) - \phi A \\ d &= -(\theta(y)A - 1) \end{aligned}$$

**Case 1: Interior solution in static model** $(\theta(y)A > 1)$. Then $d < 0$. Since $a > 0$ and $d < 0$, the product of roots is negative, so exactly one positive root exists.

**Case 2: Corner solution in static model** $(\theta(y)A \leq 1)$. Then $d \geq 0$. The positive root exists if and only if $b < 0$ and the discriminant is positive. This requires sufficiently large reputation effects.

**Proposition 3.** *If $\theta(y)A > 1$, a unique positive steady-state tip exists. If $\theta(y)A \leq 1$, a positive steady state exists only with sufficiently strong reputation effects.*

### IA6.3 Comparative Statics

**Effect of $\kappa$:** Higher $\kappa$ increases $\phi$, raising $\tilde{\theta}^*$ and thus $\tau^*$.

**Effect of $\mu$:** Higher $\mu$ increases $\phi$ and $R^* = \frac{\mu}{1-\lambda}\tau^*$, raising $\tau^*$.

**Effect of $\lambda$:** Higher $\lambda$ (closer to 1) increases $\phi = \frac{\kappa\mu}{1-\lambda}$, raising $\tau^*$.

## IA7 Jensen's Inequality for $E[\theta(y)]$

With $\theta(y) = \frac{\theta_1}{y-c}$, the function $g(y) = \frac{1}{y-c}$ is convex since $g''(y) = \frac{2}{(y-c)^3} > 0$ for $y > c$.

By Jensen's inequality:

$$E[g(y)] > g(E[y]) \quad \Rightarrow \quad E\left[\frac{1}{y-c}\right] > \frac{1}{\bar{y}-c}$$

Using a second-order approximation:

$$E\left[\frac{1}{y-c}\right] \approx \frac{1}{\bar{y}-c} + \frac{\sigma^2}{(\bar{y}-c)^3}$$

Therefore:

$$E[\theta(y)] \approx \theta_1\left[\frac{1}{\bar{y}-c} + \frac{\sigma^2}{(\bar{y}-c)^3}\right] > \theta(\bar{y})$$

This effect tends to increase tips, but is dominated by the precautionary savings effect in the full model.