"No-Interest" Advertising in High-Interest Loan Markets

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February 28, 2025

Abstract

This paper studies how false advertising of borrowing cost influences consumer participation in the high-interest short-term loan market. We construct a unique and comprehensive dataset in the online cash advance app market that contains detailed advertising content, mobile app download and usage, and apps' actual borrowing costs. We first show that a sizable fraction of advertising makes "no interest" claims, that these claims are all false, and that apps with higher actual costs tend to make more such claims. Next, we demonstrate that "no interest" claims makes advertising seven to eleven times more effective in driving consumers' participation in this market, even when the actual fees are high and salient. Our results suggest a regulation that enforces genuine and transparent advertising would save consumers tens of millions of dollars in financial charges.

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1 Introduction

Advertising is a major channel through which firms communicate product information to consumers. When advertising contains misleading or false information, it can significantly distort consumer choices and cause harm. Whereas recent empirical works have demonstrated the prevalence of false advertising across various markets (e.g., Avery et al., 2013; Zinman and Zitzewitz, 2016; Chiou and Tucker, 2018), understanding of its impact on consumer decisions remains limited.

Financial products, such as consumer loans, may be particularly susceptible to false advertising. Loan terms are complex and multifaceted, and many consumers are unaware of their true borrowing costs (e.g., Bertrand and Morse, 2011), making them vulnerable to lenders' incentives to misrepresent these costs. Whereas the Truth in Lending Act (TILA) broadly mandates that lenders provide truthful borrowing cost information in their advertisements (ads), its enforcement varies significantly across different financial markets and often lags in emerging ones. In this paper, we study the impact of false borrowing cost information on consumer participation in a new high-interest loan market—the cash advance app market—where false advertising is prevalent due to the lack of regulation.

The cash advance app market has grown significantly in recent years, reaching millions of Americans with a total transaction of 32 billion dollars by 2022 (Consumer Financial Protection Bureau, 2024a). However, anecdotal evidence suggests that advertising may mislead consumers, causing them to underestimate their borrowing costs.[1] We demonstrate that false advertising of borrowing costs has a significant and potentially long-lasting impact on consumer decisions.

To examine false advertising's impact, we assemble a unique dataset that combines daily data on cash advance apps' new downloads and active users, their true fee structures, ad

[1]For instance, one user reported: "I hadn't fully realized that when converted to an annual percentage interest rate, it was actually equivalent to a 130 percent APR... They just portray it as being so simple and so easy." From https://www.nbcnews.com/tech/internet/millions-use-earnin-get-cash-payday-critics-say-app-taking-n1034071

impressions (the number of times ads are displayed to viewers), and the original advertising materials in images and videos. We identify common financial claims in these ads, such as "no interest" and "no hidden fee," and use machine learning methods to extract these claims alongside other ad content. Using these data and measures, we assess the authenticity of the advertised claims and measure the impact of false advertising.

We first examine whether the advertised claims reflect the true costs of the cash advance apps, focusing on the prevalent "no interest" claim. A typical app charges close to \$10 for a \$100 cash advance for a term of two weeks, suggesting an implied APR well above 200%. However, 36% apps claim "no interest," and those making such claims all have an implied APR above 200%, suggesting that cash advance apps do advertise false information about their borrowing costs. Further, apps' tendency to advertise "no interest" sharply rises over time, as the share of such claims increases by 23 percentage points in 4.5 years. The prevalence of false advertising increases over time, suggesting that firms not only have strong incentives to misrepresent their borrowing costs, but they may have discovered such strategy is effective.

We next study how advertising exposure to false information influences consumers' app adoption and usage. We focus on how advertising effects vary with the advertised and actual fees of the apps while controlling for other ad features. To do so, we use generalized random forests (Athey, Tibshirani and Wager, 2019) to non-parametrically estimate the heterogeneity of advertising effects by ad and app features. Our identification strategy leverages institutional features of the mobile advertising market and the cash advance app market to isolate quasi-random variation in advertising, in a similar spirit of Shapiro, Hitsch and Tuchman (2021).

On average, we find significant advertising effects in driving downloads and increasing active users of cash advance apps. These effects primarily come from people who would not have used cash advance apps otherwise. Examining the heterogeneity of the advertising effects, we find that the fraction of ads with "no interest" claims is the predominant factor in

explaining the heterogeneous effects on both app downloads and usage. In comparison, other advertised claims and ad features do not explain much of the advertising effect—including claims such as "no hidden fee," the true borrowing costs, features such as the gender, age, ethnicity, and facial expressions of the human actor, and the advertising format. Consumers seem to primarily respond to "no interest" claims in cash advance app ads.

We show that the false "no interest" claims are associated with a seven-to-eleven times increase in advertising effects, holding all other characteristics constant. A 1,000 increase in advertising impressions *without* "no interest" claims leads to a 0.11 increase in new downloads and 0.80 increase in active users. In contrast, the same increase in advertising impressions *with* "no interest" claims would lead to 0.79 more downloads and 8.67 more active users. This evidence suggests that the false "no interest" claims reduce consumer perceived borrowing costs, significantly increase their participation in this market, and particularly affect existing users.

We further examine whether the advertising effects of the "no interest" claims depend on the actual borrowing costs and the salience of the cost components. Consumers, especially existing users, may realize that the "no interest" claims are false when actual borrowing costs are high and salient, potentially reducing the impact of these claims. However, we find that the advertising effect of "no interest" claims remains consistent regardless of the actual borrowing costs and their salience. Additionally, suggestive evidence indicates that these claims do not lead to a lower app retention rate. These findings suggest that even after using the app, consumers may not recognize that the claims are false.

Lastly, we present a back-of-the-envelope calculation to simulate the effect of a regulation that bans false advertising. If TILA is enforced in this market, cash advance apps will not be able to advertise "no interest." Based on our estimates, this regulation would lead to a four-million reduction in active users in 2021, thereby saving consumers tens of millions of dollars in total expenses. This calculation highlights the importance and urgency in detecting and banning false advertising in high-interest consumer loan markets.

Our paper contributes to several streams of the literature. First, it contributes to the recent literature on consumers' responses to false advertised information. In the vast informative advertising literature (Nelson, 1974; Grossman and Shapiro, 1984), to our knowledge, only a handful of recent works study false advertised information. Closest to our paper, Fong, Guo and Rao (2024) design an online lab experiment to estimate the effect of misinformation and its debunking on consumers' stated choices. In contrast, we assemble new field data on advertising material and consumer choices to estimate the effect of advertised false information.[2]

Second, this paper is broadly related to the literature on how advertising affects financial decisions, including choices of mortgages (Gurun, Matvos and Seru, 2016; Kim, Jiang and Thomadsen, 2023), loans (Bertrand, Karlan, Mullainathan, Shafir and Zinman, 2010), and funds (Jain and Wu, 2000; Mullainathan and Shleifer, 2005; Reuter and Zitzewitz, 2006). Grullon, Kanatas and Weston (2004), Gurun and Butler (2012), and Lou (2014) study how product market advertising affects stock valuation and returns.

Third, we contribute to the literature on short-term high-interest consumer loans. A number of papers show the negative impact of such loans (Melzer, 2011; Carrell and Zinman, 2014; Gathergood, Guttman-Kenney and Hunt, 2019) and consumers making suboptimal borrowing decisions (Agarwal, Skiba and Tobacman, 2009). In particular, Bertrand and Morse (2011) show that a simple reminder of the loans' high APR can significantly reduce consumer borrowing of payday loans, suggesting that consumers are not fully aware of their true borrowing costs. Our paper studies the online cash advance app market and demonstrates that false advertising of borrowing costs has a substantial and seemingly long-lasting impact on consumers' participation in this market, offering direct support for regulatory discussions against lenders' misrepresentation of borrowing costs (Consumer Financial Protection Bureau, 2024b).

[2]Rao and Wang (2017) estimate the impact of FTC's banning of false claims on products' market shares. Avery, Cawley, Eisenberg and Cantor (2013) and Chiou and Tucker (2018) study the effect of policies that discourage misinformation on the volume of misinformation. Rhodes and Wilson (2018) develop a theoretical framework where false advertising arises in equilibrium and influences rational consumers.

The rest of the paper is organized in the following way. Section 2 discusses the institutional background and the data used in the paper. Section 3 compares the advertised costs and actual fees charged by cash advance apps. Section 4 discusses the empirical design and identification strategy. Section 5 presents the results and Section 6 concludes.

2 Institutional Background and Data

2.1 Institutional Background

Cash advance apps. Online cash advance apps allow users to borrow a small amount of money from their next paychecks before the paychecks arrive. The typical loans have a maturity of two to four weeks, and the average loan duration is 10 days (California Department of Financial Protection and Innovation, 2023). The maximum borrowing amounts generally fall between $100 to $500, though users often receive less, with an average loan amount of $106 (Consumer Financial Protection Bureau, 2024b). The apps typically do not require a credit check from users, but they may require users to authorize access to their bank accounts or provide payroll history, allowing the apps to withdraw repayments directly once paychecks arrive. Unlike traditional payday lenders, which operate with physical store fronts, cash advance apps operate online and often entirely through the smartphone app. Due to their convenience, these apps have seen a multiple-fold increase in downloads and active users in recent years (see Figure 1), establishing themselves as important players in the consumer loan market.

Fee structure. Cash advance apps typically charge users high fees, and these fees can take several forms. The first form is an upfront cost, typically charged as a flat monthly subscription fee to gain access to loans, such as Albert ($14.99 per month), Brigit ($9.99), and Empower ($8.00). A few apps charge fees as a fixed percentage to the loan amount, such as Varo (see Appendix Figure B1).

The second form is an "instant fee,"[3] a fee per advance that reduces wait time for funds. Without instant fees, the borrowed money typically arrives in 2 to 3 business days, while it arrives on the same day with instant fees. Many customers pay for the instant fee as 2 to 3 business days is a relatively long time, considering that the average cash advance duration is only 10 days.

The third form is tips, which some apps encourage users to pay in addition to other costs. From an investigation in 2023, cash advance apps receive tips 73 percent of the time when the option is available (California Department of Financial Protection and Innovation, 2023).

Combined, these fees suggest that borrowing from cash advance apps is costly. In fact, our analysis later shows that these fees can amount to an APR of several hundred percent. However, no cash advance app frames its costs as an APR.

Regulations. The Truth in Lending Act (TILA, or Regulation Z, 12 CFR Part 1026) makes specific transparency requirements about how lenders can advertise their credit terms. Section § 1026.16 (Advertising) requires lenders to "clearly and conspicuously" present all cost information if they were to make a "negative or affirmative reference" about their loan terms. The section gives specific examples including when the lender advertises "no interest" (an instance when it makes a negative reference), it must transparently present all fee components, including all fixed and variable fees that are required to access the loan. According to Section § 1026.4 (Finance charge) and CFPB's new interpretive rule issued in July 2024 (Consumer Financial Protection Bureau, 2024b), monthly subscription fees, instant fees, and tips are all considered as finance charges for cash advance apps.

Whereas CFPB has taken enforcement actions against false advertising in similar markets,[4] it has not enforced TILA in the cash advance app market.

[3]Some apps refer to this fee as an "express fee," "fast fee" or "lightning fee."

[4]For example, in 2016 CFPB took enforcement actions against LendUp, an online payday loan company that falsely advertises lower future interest rates if consumers were to repeatedly borrow.

The mobile advertising ecosystem. In the mobile advertising ecosystem, there are three main groups of players: advertisers (the app that pays for an ad), publishers (the app that shows an ad to its users and gets paid), and advertising exchange platforms ("ad exchange," platforms that intermediate the transaction). Advertisers organize advertising activities in "ad campaigns," which are clusters of marketing efforts that utilize a specific set of ad material within a set period of time. Publishers sell "ad impressions" to advertisers, allowing advertisers to show ads to the publishers' users. Most of the ad impressions are sold through guaranteed selling, which means that these impressions are negotiated *in advance* and sold for a fixed quantity at a fixed price for a fixed time. The rest of the ad impressions are sold as non-guaranteed selling — that is, they are sold on the spot market through online ad auctions. Choi, Mela, Balseiro and Leary (2020) estimate that guaranteed sales contribute to about 65% of all online advertising revenue.

2.2 Data

We assemble a new dataset from three separate sources: (1) a panel dataset on the number of active users, new downloads, and total advertising impressions, all measured at the daily frequency for each app, (2) all advertising material in the form of pictures or videos (referred to by the industry as "ad creatives") and their ad impressions, and (3) manually collected data about the fee structure of each app. Below, we discuss each of our data sources. We conclude this subsection by presenting sample screening.

Daily data on active users and new downloads. The primary data on mobile applications is from Sensor Tower, a leading provider of global mobile applications data and key metrics in the mobile industry. The Sensor Tower database contains a comprehensive collection of information on millions of mobile apps across more than 100 countries.

In this paper, we use mobile app data for cash advance apps on iOS from July 2017 to February 2022. For a given cash advance app in the sample, we obtain its daily num-

bers of downloads and active users. Sensor Tower combines actual data provided by their corporate partners (app developers and publishers), as well as app rankings and metadata information from the App Store to estimate each app's downloads and active users. Downloads are recorded at the account level, and importantly, re-downloads by the same account (even across devices) are not counted in this measure. Thus, app downloads capture new downloads.

Advertising impressions and creatives. We collect advertising data for each cash advance mobile app from Sensor Tower. The raw data comes in the format of daily impression shares across different advertising campaigns for overlapping short time windows. An impression share represents the percentage of times an ad appears on a user's screen relative to all other ads. We assemble the impression shares across all advertising campaigns and dates and normalize them by a proxy of the total number of impressions among iOS users, which gives us the daily impressions for each advertising campaign. Appendix A details the construction process of the ad impression data.

Importantly, we obtain information on the advertising creatives for each campaign. These ad creatives include videos and images, which we obtain in their native formats (e.g., mp4 and png). To illustrate the typical content featured in these ad creatives, we present two examples of video ads and two examples of image ads in Figure 2. Panel (a) shows four screenshots that show key moments in a video ad by the app Albert. The ad starts with the main character sitting in the car in need of cash, and the text prompt shows "Download Albert. They can spot you up to $250." Then the video turns to large-font text that repeats the previous message and highlights "0% interest. No late fees. No credit check." The video ad ends with the main character holding cash in his hand. Similar to other mobile ads, cash advance apps' ad creatives often use text prompts to highlight the main messages in the ads, including financial claims such as the maximum borrow amount ($250) and claims of "no interest," "no late/hidden/overdraft fees," and "no credit checks," which can also be seen

in panel (c) (an image ad by Brigit). Panel (b) shows a similar video ad as panel (a) by Earnin, which features human actors that show facial expressions of distress as they need money, and expressions of excitement after they receive money from the app. Different from Albert's ad in panel (a), Earnin's ad in panel (b) highlights the instant speed but does not make the "no interest" claim. Finally, panel (d) shows an image ad by MoneyLion which emphasizes "early" and, other than hinting the maximum borrow amount, does not make other claims about its cost structures and features. To use the rich information contained in these creatives, we extract advertising features using various machine-learning methods, which we discuss later.

Upfront costs, instant fees, tips, and implied APRs. We manually collect the fee structures of each cash advance app. As introduced earlier, these fees can be categorized into three broad types: (1) upfront costs, (2) instant fees, and (3) tips. This information is collected from the financial information aggregator *finder.com*, which reviews most large cash advance apps, and various other information websites. To standardize each fee component and make it comparable across apps, we assume each consumer takes two advances per month, each amounting to $100. So the upfront cost per advance includes half of the monthly subscription fee and percentage borrowing costs, if any. We also assume that the consumer requires same-day money delivery and leaves the average $5 tips if the app encourages tips. We consider upfront costs as more salient than instant fees and tips, as consumers need to pay the former fees before starting the borrowing process. Further, based on these fees, we also compute an implied APR for each app and use it as an alternative measure of apps' fees.

Sample screening. To define cash advance apps in the sample, we start with the universe of apps classified as finance apps. Then, we construct a preliminary list of cash advance apps that consists of the list under the "payday loan" categorization from Sensor Tower and the list of ChatGPT-identified cash advance apps. Taking the union of the two sets, we

arrive at a list of 92 apps. Then, we remove small apps of which we do not have complete data. Of the 92 apps, 63 are too small for Sensor Tower to collect active user data reliably, leaving us a sample of 29 apps. Further, we manually check all apps and remove three that are mis-categorized by either Sensor Tower or ChatGPT. Lastly, we remove four apps that never advertised in our sample and 20% app-year level observations with zero advertising, because we can only measure advertising content for apps that advertise. We thus arrive at the final sample of 22 apps and 25,791 app-day level observations.

2.3 Extracting Advertising Features

The primary focus of this paper is an ad's communication about the app's financial features, such as its effective interest rate. We extract such information from the advertising creatives. We also extract emotional features that could affect the effectiveness of communication, such as the facial expression of the actor and the tone in the speech.

We start from a set of 27,529 ad creatives in our sample, which include 15,605 images and 11,924 videos. For each video, we capture one frame per second to convert the video into a set of images. We then extract text and human faces from each image and analyze the soundtracks of the videos, which we detail below.

In mobile app advertising, text is critical as it precisely conveys the message the app wants to communicate to users. Even for videos, since users often use their phones in silent mode, apps rely on highlighted text to display the video scripts. Thus, text contains essential information for each ad creative. We extract text from each image using *pytesseract*, a state-of-the-art optical character recognition tool. Next, we use regular expressions to identify keywords, including phrases like "no interest," "no fee," "no overdraft," "quick," "FDIC insured," "no credit check" and mentions of whole dollar amounts (e.g., "$250").

Human faces and emotions are also crucial in cash advance app advertising. As we have seen in Figure 2, a common theme in these ads features a short story where a person in need of cash gets an advance through the app and displays a happy face. Previous research has

demonstrated that character demographics (Kim, Jiang and Thomadsen, 2023) and emotions (Small and Verrochi, 2009) can play a role in advertising effectiveness. Thus, we recognize human faces in each image using *DeepFace*, which extracts gender, age, race, and facial emotions from each face. Users may identify with the demographics of the characters and be influenced by the emotions. We then use the characteristics of the largest face in each ad creative as the representative human characteristics and emotions of the creative.

Additionally, we extract the soundtrack from each video-format creative. Using *moviepy*, we isolate the soundtrack in mp3 format from the videos and then separate the foreground from the background sound using *librosa*. We identify blank audio and classify the soundtracks into different audio types using VADNet and YAMNet. We also convert the soundtracks into a 180-dimensional embedding using *librosa*, following Gorodnichenko, Pham and Talavera (2023). We then use principal component analysis (PCA) to reduce the soundtrack features to two principal dimensions for each video.

In total, we extract seven advertised features from the text on image, seven face and emotion features from image, two sound features from soundtracks, and three other features capturing the ad format. The text features cover advertising claims of: high borrow limit, no hidden fee, no interest, no overdraft fees, quick to get funds, FDIC insured, and no credit check. The image features are: ad features human actor(s), young actor, female actor, African American actor, actor with a happy face, with a sad face, and with a fearful face. The two soundtrack features are the first two principal components of the classification and the embedding. The ad format features are indicators of the ad being a full screen ad, a video ad, and an ad showing a clickable button.

After extracting textual, facial, soundtrack, and format features from each ad creative, we aggregate these creative-level features up to the app-month level using their impression shares. We aggregate ad features to the monthly level because this level roughly corresponds to the duration of a long advertising campaign, given the interquartile range of an ad campaign at [1, 30] days. This construction allows us to mostly use the variation in advertising

impressions within a month to identify advertising effects, and to relegate app-month level ad-creative features as shifters of these advertising effects.

2.4 Summary Statistics

Table 1 presents summary statistics for the major variables across the 22 cash advance apps. On average, these apps have about 56,000 active users on an average day and about 127,000 active users on their most popular days. The number of active users differs significantly across apps, as the 10th to 90th percentile of daily active users is between 1,000 and 202,000. Over the 4.7-year sample period, the average total downloads per app is 3.2 million, reaching nearly 8 million at the 90th percentile. About 5% of downloads convert to regular users who persistently use these apps, as measured by the 90-day retention rate.[5] These apps have also heavily advertised, with an average of 784 million total impressions during this period.

In terms of the fee structure, the average upfront cost per paycheck cycle (two weeks) is $3, the instant fee is $3, and, assuming $5 tip if the app encourages tips, the average tips is $2. Fees vary significantly across apps, with some apps charging high fees for one type (e.g., $9 for instant fee) and zero for others. The typical APR, derived from these fees, averages 270%, reaching 455% at the 90th percentile.

3 Advertised Costs and Actual Fees

Typical cash advance apps charge high fees for each cash advance. Figure 3 presents the fees for borrowing $100 in one advance for each app in our sample. As we can see, 21 out of the 22 apps charge a fee for their cash advance services, varying between $2 to $17.5 across different apps. Remarkably, Albert, the app that advertises "no interest" in our first example in Figure 2, charges $17.5 per advance. There is also a large variation in the type

[5]The retention rate is an estimate of the fraction of users who, after 90 days since their initial download of the app, continue to use it.

of fees charged across apps. In the graph, the blue bar represents upfront costs, the green bar represents instant fees, and the red bar represents tips. Most apps charge upfront costs for borrowing, with some charging as high as $10 for a two-week advance. About half of them charge an instant fee, with some more than $10. Several apps "encourage" tipping to the apps for borrowing. Overall, the total fees charged by the online cash advance apps are of the same order of magnitude compared to the traditional payday lenders (Melzer, 2011).

Next, we compare the advertised claims made by these apps versus their actual fees. As we discussed in section 2, in markets such as credit cards and mortgages, provisions in Regulation Z mandate that lenders present all components of borrowing costs in a transparently manner in their advertising material if they were to advertise some components of costs. However, these regulations currently do not apply to online cash advance apps. In Figure 4, we plot the average fraction of ads with "no interest" claims against the implied APR and each of the upfront costs, instant fees, and tips. As we can see, 8 out of the 22 apps advertise "no interest," but these apps all have an implied APR of more than 200%. Thus, despite the high fees, a sizeable fraction of their ads advertise no interest, implying a 0% APR. These claims are false and violate the typical advertising disclosure requirements for financial products. In addition, the "no interest" claims only become more prevalent over years, as shown in Appendix Table B2.

In Figure 4, we also show that apps with higher fees tend to make more "no interest" claims. The relationships between the fraction of ads that claim "no interest" and the actual fees are either positively significant (instant fees and tips, panels (c) and (d), t-statistic = 3.66 and 3.05) or statistically insignificant (implied APR and upfront costs, panels (a) and (b), t-statistic = 1.17 and -0.53). These results complement the findings in Gurun, Matvos and Seru (2016) that more expensive lenders advertise more.

This advertised false cost information can mislead consumers into using the apps and making suboptimal borrowing decisions when they do not know the true borrowing costs. However, if consumers are fully aware of the actual fees, these false claims might have little

impact on their choices or could even backfire. To determine which is the case, in the following sections, we examine how advertising influences consumers' usage and downloads of cash advance apps, and how these advertising effects are shaped by the presence of "no interest" claims.

4 Measuring Advertising Effects

In this section, we examine how advertising effects of cash advance apps vary by advertised claims and app characteristics, especially the false "no interest" claims. We start by outlining our empirical framework to estimate the heterogeneous advertising effects. We then discuss identification and estimation.

4.1 Framework

We specify a model where the log number of daily active users of app j on date t is a function of j's ad stock and fixed effects:

$$\log(\text{users}_{jt}) = \beta(x_{j,m(t)}) \log(\text{ad stock}_{jt} + 1) + \alpha_{j,m(t)} + \lambda_t + \epsilon_{jt}, \tag{1}$$

where $\text{ad stock}_{jt} = \sum_{\tau \leq t} \delta^{t-\tau} \times \text{ad impressions}_{j\tau}$ captures geometric decay of ad effects, $\alpha_{j,m(t)}$ is app-month fixed effects, and λ_t is date fixed effects. The coefficient $\beta(x_{j,m(t)})$ captures the advertising effect for cash advance apps, which might be heterogeneous depending on app and ad features $x_{j,m(t)}$ at the app-month level. We also estimate the advertising effects on app download using the same specification and the log number of downloads $\log(\text{download}_{jt})$ as the outcome variable. This log-log specification is widely-used in the advertising literature (e.g., Shapiro, Hitsch and Tuchman (2021)) to capture the diminishing returns of advertising impressions. The estimate of $\beta(x_{j,m(t)})$ represents advertising elasticity, which captures the percentage change in users for a percentage change in ad stock.

We interpret the heterogeneous advertising effects $\beta(x_{j,m(t)})$ as a conditional average

treatment effect on the treated (CATT). In the mobile advertising market, ad delivery algorithms may expose ads with different features, such as "no interest" claims, to different target audiences. Our identification strategy for $\beta(x_{j,m(t)})$ thus primarily relies on variation in ad exposure (ad stock$_{jt}$) for a given set of features $x_{j,m(t)}$, as opposed to comparing users with different $x_{j,m(t)}$. That is, the identification primarily relies on variation across days within an app-month in ad stock$_{jt}$, as opposed to comparing app-months with different $x_{j,m(t)}$. Hence, $\beta(x_{j,m(t)})$ represents the average advertising effect among individuals who are exposed to ads with specific app and ad features $x_{j,m(t)}$. We explain our detailed identification strategy in Section 4.2.

4.2 Identification

As recognized in the economics and marketing literature, firms often spend more on advertising when demand is higher (e.g., during holiday seasons). This targeting poses an identification challenge for estimating advertising effectiveness in observational studies. In our empirical setting, demand for cash advance apps may fluctuate with paycheck cycles and may peak at the end of the cycle, before the next paycheck arrives. The apps' advertising strategies might target these fluctuations. In addition, apps that perform better over time might gradually increase their advertising spending, introducing a correlation that confounds the true effectiveness of advertising.

Our identification strategy leverages institutional details of online advertising market and uses fixed effects to address the above endogeneity concerns. Specifically, the date fixed effects λ_t absorb any market-level time-specific shocks, including the demand fluctuation along the paycheck cycle and cash need for holiday seasons. These time-specific shocks commonly apply to every cash advance app as they provide similar functions. Further, the app-month fixed effects $\alpha_{j,m(t)}$ sweep out any persistent difference across apps and capture app-specific trends over time. As noted in Choi, Mela, Balseiro and Leary (2020), about 65% of online display ads are sold through guaranteed channels that involve advance sales. As

such, most ad spots are likely sold months in advance, and the app-month fixed effects $\alpha_{j,m(t)}$ can control for month-level app-specific trends targetable at the time of ad purchase. Many practitioners also acknowledge the time and effort it takes to design new ad creatives (Altstiel, Grow and Jennings, 2019), suggesting that ad creative features (captured by $x_{j,m(t)}$) cannot respond to demand shocks ϵ_{jt} after controlling for the app-month fixed effects. Further, we find that the "no interest" claims do not correlate with major app updates and appear in publisher apps with similar user demographics, suggesting that the "no interest" claims may not be targeted at a specific time or to a specific audience (see Appendix B1). Together, given institutional details of the online mobile ad market, our fixed effects isolate the exogenous variation in cash advance app advertising. This strategy shares a similar spirit as Shapiro, Hitsch and Tuchman (2021), which isolate quasi-random variation in TV advertising using institutional details of the TV ad buying market.

Our identifying variation mainly comes from within-month variation in campaign timing and the level of advertising impressions, given the fixed effects. To illustrate this exogenous variation, we present a set of graphs in Figure 5 to show how an app's number of users and download vary with its advertising campaign net of fixed effects. We focus on the first day within an app-year that has positive ad impressions for an app and define it as the start of a campaign. For illustrative purposes, we focus on campaigns that begin at least 20 days after the start of the year and at least two months before the end of the year. As shown in Figure 5, campaigns typically begin with a high volume of impressions on day 1 and then gradually die out over the next two months. In response, the number of users and downloads spike on the first day of the campaign. Their subsequent peaks occur after one week, two weeks, and a month, aligning with typical paycheck cycles when users either take the next advance or repay a previous one. Overall, there is some carryover in advertising effects on the number of users and downloads, but this impact is not long-lasting. These graphs also suggest that our fixed effects are able to control for the long-term trend in this category.

4.3 Estimation

Our goal is to estimate the heterogeneous advertising effect function $\beta(x_{j,m(t)})$. We characterize this function as a random forest and estimate it using the generalized random forests estimator (Athey, Tibshirani and Wager, 2019). The estimation is implemented in the R package "grf," developed by Athey, Tibshirani and Wager (2019). Because the package does not permit fixed effects and δ, the persistence parameter embedded in ad stocks, to be estimated simultaneously with the heterogeneous advertising effect function, our estimation strategy follows four steps.

First, we conduct a grid search to find the best-fitting persistence parameters δ, assuming constant advertising effect $\beta(x_{j,m(t)}) = \beta_0$. We identify the optimal δ's by minimizing the mean squared errors. Using the best-fitting δ's, we construct ad stocks for subsequent analyses and obtain the average ad elasticity β_0.

Second, we leverage Frisch-Waugh-Lovell theorem to partial out fixed effects $\alpha_{j,m(t)}$ and λ_t in equation (1). Specifically, we run separate linear regressions of the outcome variables and the log ad stocks on these fixed effects. We then use the residuals from these regressions in the following steps.[6]

Third, we determine which $x_{j,m(t)}$ enter the advertising effect function $\beta(\cdot)$, because not all advertising features are important. We start by assuming that $x_{j,m(t)}$ contains the three fee components—upfront costs, instant fees, and tips—and a subset of the advertising creative features. To select which advertising creative features enter x, we estimate $\beta(\cdot)$ with the full set of 22 app and ad creative features using the generalized random forests estimator. We then select the ad creative feature variables based on their variable importance, following Athey and Wager (2019). We select the top seven variables that explain the heterogeneous advertising effects on either download and users. These variables include two advertised claims (claimed borrow limit and claimed no interest) and four additional ad features (have

[6]The application of Frisch-Waugh-Lovell theorem leverages the specific model structure that $\beta(x_{j,m(t)})$ does not vary within the fixed effects $\alpha_{j,m(t)}$, which implies that we can partial out fixed effects from log ad stocks directly.

human actors, have young actors, the first sound principal component, and video ad), beyond the three fee components. Together, these selected ad creative features and the three fee components form the set of variables $x_{j,m(t)}$. We show the robustness of our results to this selection approach in Section 5.4.

Finally, we estimate $\beta(\cdot)$ with the selected set of app and advertising features using the generalized random forests estimator. We compute bootstrap standard errors clustered at the app-week level, which allows for error correlation within a time window comparable to the median duration of an advertising campaign.

4.4 Discussion

Does Rival Advertising Play an Important Role? A key question is whether advertising primarily attracts people who would otherwise borrow from competing cash advance apps or those who would not borrow from these apps at all (the outside option). This distinction is crucial for policy implications. If advertising mainly attracts people who would not otherwise borrow from cash advance apps, regulations on how these apps can advertise could meaningfully reduce the total amount of high-interest loans. However, if advertising mainly shifts users between competing apps, such regulations would have little effect on total app usage and total loans.

To examine this question, we estimate a specification that incorporates both own and rival advertising stocks, assuming homogeneous advertising effects:

$$\log(\text{users}_{jt}) = \beta_0 \log(\text{own ad stock}_{jt} + 1) + \beta_1 \log(\text{rival ad stock}_{jt} + 1) + \alpha_{j,m(t)} + \epsilon_{jt}, \quad (2)$$

where $\text{rival ad stock}_{jt} = \sum_{j' \neq j} \sum_{\tau \leq t} \delta^{t-\tau} \times \text{ad impressions}_{j'\tau}$ is the sum of rival advertising impressions with the same geometric decaying effect over time. For each day t, the sum of own and rival advertising is constant across all apps, making the two variables co-linear with date fixed effects. For this reason, we do not include date fixed effects in this specification,

but we have checked that including date fixed effects or not does not have a meaningful impact on the baseline advertising effect estimate.

Do "No Interest" Claims Associate with Lower Retention Rates? To assess whether users attracted by "no interest" claims continue using the app, we examine whether apps that advertise such claims have lower retention rates—the proportion of existing adopters continue using the app. Our data directly measure the retention rate for each app in each quarter, defined as the share of users still using the app 90 days after their initial download. Because this measure is quarterly, we cannot apply our main identification strategy to analyze its response to daily variation in advertising impressions. Instead, we provide suggestive, correlational evidence on the relationship between advertising claims and app retention. Specifically, we regress

$$\text{retention}_{jq} = \beta_0 + \beta_1 \text{ share "no interest" claims}_{jq} + \alpha_j + \lambda_q + \epsilon_{jq}, \tag{3}$$

where retention_{jq} and share "no interest" claims_{jq} are retention rates and the fraction of impressions with "no interest" claims at the app j, quarter q level, and α_j and λ_q are app and quarter fixed effects. We interpret β_1 as the changes in retention rate explained by quarterly variation in an app's tendency to advertise "no interest" claims, controlling for the fixed effects. We also estimate a similar specification at the app level, where we leverage across-app variation in advertising content and control for observed characteristics.

5 Empirical Results

In this section, we first present estimates of the average advertising effects and their persistence. Then, we turn our attention to the estimates of heterogeneous advertising effects, examining the importance of various app and ad features and demonstrating that false advertising is effective in this market. Next, we show that the false advertising effect is

significant even when the true costs are high and salient. Finally, we conclude by presenting robustness checks and discussing policy implications of our results.

5.1 Baseline Advertising Effects and Distribution

Average ad effects and their persistence. Table 2 presents the baseline results for outcome variables download (columns (1)-(2)) and users (columns (4)-(5)). These results are obtained by estimating equation (1) without allowing for heterogeneity over $x_{j,m(t)}$. We use zero persistence in columns (1) and (4), which capture the daily effect of advertising, and the best-fitting persistence in columns (2) and (5), which are our preferred specifications.

On average, we find an advertising elasticity of 0.038 for downloads and 0.012 for active users. These estimates imply that, if an app increases 10% of discounted sum of impressions (ad stock), it should have on average a 0.38% increase in new downloads and a 0.12% increase in active users. At the sample averages of new downloads and active users, these estimates imply that every 1,000 advertising impressions convert to a 0.16 increase in new downloads and a 1.22 increase in active users. These estimated advertising elasticities are similar to the general findings in the advertising literature, such as studies on consumer packaged goods (Shapiro, Hitsch and Tuchman, 2021).

We also find that the ad effects on downloads and active users are short-lived, as they decay to 2% of their initial values in three days. These short-lived effects are expected, as most ads are clickable, allowing viewers to directly access the app store to download the focal app if they have not installed it, or open the app if they have. As a result, one should expect that most of the ad responses occur immediately after the viewers have seen the ad.

Further, through estimating equation (2) and its related persistent parameter, we find that rival advertising effects are negligible in this market (columns (3) and (6) in Table 2). The average advertising elasticity of rival ad stocks is -0.003 for new downloads and 0.001 for active users, with both effects statistically insignificant. Importantly, the own ad stock elasticities remain virtually unchanged controlling for rival ads. These findings suggest that

rival advertising effects are negligible, thus implying that the primary advertising effect is to drive app usage and downloads for people who would otherwise not use cash advance apps.

The distribution of ad elasticities Figure 6 presents the distribution of the heterogeneous advertising effects from (1), estimated by the generalized random forests and projected onto the observed covariates $x_{j,m(t)}$. We find that the average ad elasticities across app-months are 0.036 for downloads and 0.011 for users, closely aligning with the baseline estimates reported in Table 2.

On top of these averages, we find significant heterogeneity in ad elasticities across apps and over time. The inter-quartile range for ad elasticities is [0.002, 0.056] for downloads and [0.000, 0.020] for users. This large discrepancy suggests that some ad creatives or app characteristics are more effective than others in driving downloads and usage. We will next investigate the extent to which these features explain the discrepancies in the ad treatment effects.

5.2 Advertising Effects Explained by False "No Interest" Claims

To understand what drives the heterogeneous advertising effects, we first present the variable importance for all dimensions of $x_{j,m(t)}$, separately for the download and user models. Variable importance is measured as the share of tree splits that occur on a specific variable's node among all tree splits in the random forests. A variable is considered highly important if a large part of the variation in $\beta(x)$ comes from the forest splitting on that variable. Thus, this importance metric reflects how much a variable explains the heterogeneity in $\beta(x)$.

We show in Figure 7 that the fraction of ad impressions with a "no interest" claim consistently takes high importance of 0.50 for both downloads and users. Other than "no interest" claims, the advertised borrow limit and the app's upfront cost are also important explanatory variables. On the other hand, factors such as the use of human actors and their characteristics, soundtrack, video format, clickable buttons, and the app's less salient fees

(instant fee and tips) do not explain much of the variation in $\beta(x)$. In Appendix Figure B3, we also present the variable importance for all ad and app features estimated in the feature selection stage. We show that other advertising claims do not explain advertising effects. In particular, the message "no hidden fees" explains little advertising effects, which highlights the importance of "no interest" claims to consumers.

Next, we show how "no interest" claims drive the advertising effect. Ad effects $\beta(x)$ is a function of multiple ad and app features, most of which could be correlated with "no interest" claims. To isolate out the marginal effect of "no interest" claims, we need to hold other features constant when predicting $\beta(x)$. To this end, we vary the fraction of impressions with the "no interest" claims using the 2.5–97.5 percentile sample support range of [0, 0.54] but use the same distribution of other features, sampled from their empirical joint distribution. We then predict $\beta(\cdot)$ for each such vector x, integrate out other features, and present the average $\hat{\beta}$("no interest") for each specific fraction of "no interest" claims. We also present confidence intervals and statistical tests of these results based on bootstrap standard errors clustered at the app-week level.

Figure 8 shows that advertising effects increase in the fraction of impressions exposed to the "no interest" claim, with a sharp increase when about 30% of ad impressions go to creatives that claim "no interest." Holding other features constant at their empirical distribution, ad campaigns without "no interest" claims have advertising elasticities 0.035 for downloads and 0.011 for users. These effects imply that 1,000 ad impressions would convert to 0.11 new downloads and 0.80 active users. In contrast, if half of the ads communicate "no interest," the elasticities are much higher, at 0.261 for downloads and 0.114 for users, implying that the same 1,000 ad impressions will convert to 0.79 new downloads and 8.67 active users.

We examine the statistical significance of these findings by testing against a series of null hypotheses $H_0 : \beta(\text{"no interest"} = 0) = \beta(\text{"no interest"} = x)$ for $x \in (0, 0.54]$. As shown in Appendix Figure B4, we find that the advertising effects are statistically significantly higher

when the share of "no interest" claims exceeds 0.3.

In summary, our findings demonstrate that, all else equal, "no interest" claims substantially increase the advertising effect by seven-to-eleven-times, greatly enhancing cash advance apps' ability to use advertising to attract new and returning users. These findings suggest that the "no interest" claims influence users' belief about the apps' true borrowing costs, leading to their suboptimal borrowing decisions.

5.3 "No Interest" Claims Are Effective Even When Costs Are High and Salient

We have shown that "no interest" claims increase advertising effectiveness in influencing consumer behavior. Our next question is: how does the effectiveness of these "no interest" claims depend on the actual fees charged by the apps and the salience of those fees? Consumers may or may not be more likely to recognize these claims are false when there is a large difference between the actual and advertised claims, and when such a difference is made salient by upfront fees.[7]

In Figure 9, we present three sets of graphs to show how the effectiveness of "no interest" claims depends on the level and type of app costs. Each graph plots the "no interest" effects for different level of costs for a single cost component, while setting the other two components to zero. For upfront costs and instant fees, we divide the sample into four quartiles. For tips, we distinguish between whether or not the app encourages tips. We hold other features constant by integrating over other features using their empirical distributions, similar to Section 5.2. These figures can be viewed as slices from the overall contour plots shown in Appendix Figures B5 and B6, which show the predicted advertising effect $\beta(x)$ as a function of the share with "no interest" claims and app cost.

We find that the effectiveness of the "no interest" claims does not depend much on the

[7] A recent literature emphasize the role of salience on consumer behavior, see Bordalo et al. (2013); Frydman and Wang (2020); Blake et al. (2021); Bordalo et al. (2022).

level and type of the actual costs. The advertising effects are always higher with the "no interest" claims than without these claims. Compared to campaigns that do not advertise "no interest," those with 54% of ads containing this claim have higher advertising elasticities for both download (higher by about 0.20) and active users (by about 0.09), regardless of the actual fees charged by the app and their type. The finding that "no interest" claims are effective even with high actual costs is consistent with the observations that so many apps falsely advertise "no interest," masking their true costs from consumers.

The above finding raises a conjecture, that consumers may not realize the true borrowing costs even after initially adopting the app because of the "no interest" advertising claim. We indirectly examine the plausibility of this conjecture in two ways. First, we examine how the effectiveness of "no interest" claims depends on the salience of the fees. We conjecture that upfront costs are the most salient fee component, while instant fees are less salient until users are about to finalize the loans. If consumers realize the app's true borrowing costs are much higher than claimed, they might not respond to the "no interest" claims, leading to a lower advertising effect when the app's fees are high and salient. Appendix Figure B7 shows how the advertising effects change with the fraction of total fees in upfront costs, while keeping the total fee amount at \$8 and holding all other features fixed. We find that the advertising effects of "no interest" claims vary little with the fee salience, suggesting that consumers may not realize these claims are false, even when the actual fees are salient. Second, we directly examine the correlation between an app's user retention rate and the fraction of its advertising that claims "no interest." As we document in Appendix Table B4, there is no correlation between the retention rate and these false advertising claims, both when we compare between apps (controlling for actual fees) and between quarters within the same app. These findings suggest that even when some users are drawn to the app because of the falsely advertised borrowing costs, they do not display a higher tendency to leave the app after adoption, further supporting the conjecture that users who are affected by false advertised information never learn about the actual borrowing costs.

5.4 Robustness Checks

We conduct two robustness checks throughout our analysis. First, we investigate whether our main results are sensitive to our choice of fixed effects. In our main analysis, we include app-month and date fixed effects to capture demand shocks that may be predictable ex ante when apps decide how many ad slots to purchase and what ad creative to design. We alternatively include app-specific quadratic time trends on top of the app-month and date fixed effects, as another specification of the predictable demand shocks. As shown in Appendix Table B3, the estimated advertising effect is 0.037 for downloads and 0.012 for active users, very close to the estimates reported in Table 2.

Second, we examine whether our main results are sensitive to the choice of app features. In our main specification, we include the three fee components: upfront costs, instant fees, and tips. As an alternative specification, we use the implied APR by our calculation (see Section 2.2) as a summary of the three aspects. As we show in Appendix Figures B8 and B9, we find that our main findings are robust. In particular, "no interest" claims continue to have high importance in explaining the advertising effects for driving download and active users. In addition, advertising effects are eight-to-eleven times higher with the "no interest" claims than without the "no interest" claims.

5.5 Policy Implications

Our findings have important implications for regulating the cash advance app industry. The results suggest that false advertising of "no interest" claims significantly influences consumer beliefs, leading to substantially higher advertising effects. These false ads drive many new users to adopt the apps and encourage recurring users to return, despite the apps often charging high fees that amount to triple-digit APRs.

If regulations in the cash advance app market were to follow TILA's advertising standards, which mandate that lenders either transparently report all costs or not mention costs at all,[8]

[8]See 12 CFR § 1026.16 and 12 CFR § 1026.24

"no interest" claims would likely be deemed illegal unless the app transparently reveals all cost components and the high APR. Under such regulations, apps would likely choose to not mention costs or fees at all in their advertising.

To quantify the potential impact of such a regulatory change, we conduct the following counterfactual analysis. We simulate a scenario where all "no interest" ads are replaced with ads that do not make such claims. Using our estimated $\beta(x)$, we compute the counterfactual advertising effect and the resulting total number of active user-days in this market. Our calculations show that removing "no interest" claims reduces the number of user-days by 39.9 million in 2021, which is 50.3% smaller compared to all user-days currently driven by advertising.

We further estimate the potential impact of this policy on loan volumes. Whereas we cannot directly estimate the effect of advertising on loan counts, we can present a back-of-the-envelope calculation using industry statistics. We project that the total number of active user-days is 774 million in 2022. According to Consumer Financial Protection Bureau (2024a), the total number of loans in 2022 is 86 million, implying that one loan is taken every nine user-day occasions on average. If one were to assume that the marginal user who adopt the app would borrow the same amount as the average user, we project that a ban on "no interest" ads would likely translate into a 4.4 million reduction in the number of loans in 2021. This decrease could potentially save users 44 million dollars in total expenses. These numbers could only become bigger since 2021 due to the increasing trend in both the consumer usage of cash advance apps and the advertiser's use of "no interest" claims. These calculations highlight the substantial impact that regulating false advertising in the cash advance app industry could have on consumer behavior and financial outcomes. They support the CFPB's broader and ongoing efforts on regulating fee transparency in this market.

6 Conclusion

This paper examines the authenticity of information in cash advance app advertising and studies the impact of such information on consumers' adoption and usage of the apps. To achieve this, we compile a unique dataset that combines mobile app utilization data, detailed advertising content, and the actual fee structures of online cash advance apps.

We first show that cash advance apps make false "no interest" claims about their services in the advertising while their actual fees amount to more than 200% APR. We then demonstrate that these "no interest" claims significantly increase advertising effects by seven-to-eleven times, bringing in new downloads and increasing the daily number of active users. In addition, false "no interest" claims increase advertising effects even when the actual borrowing costs are high and salient.

Our findings suggest that false information of borrowing costs affects consumer beliefs about these costs, highlighting the importance of regulations on the transparent presentation of borrowing costs, such as those mandated by TILA in regular credit markets. Our back-of-the-envelope calculation suggests that such regulation would have saved consumers tens of millions of dollars every year in borrowing costs that they might not be aware of. As such, our findings provide direct evidence in support of the CFPB's ongoing discussions on mandating fee transparency in the cash advance app market (Consumer Financial Protection Bureau, 2024b).

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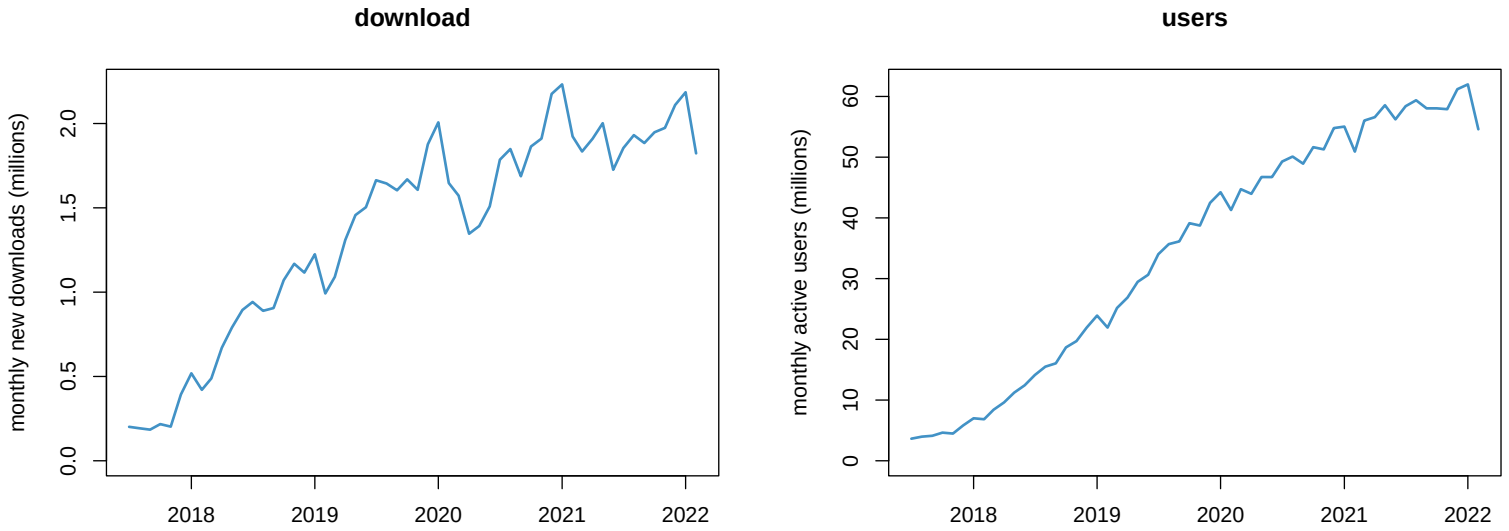
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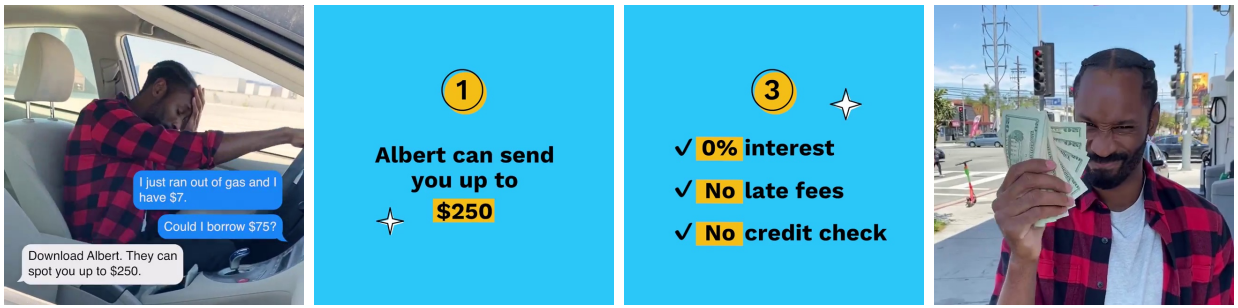
Graphs and Tables

Figure 1: Downloads and Active Users over Time

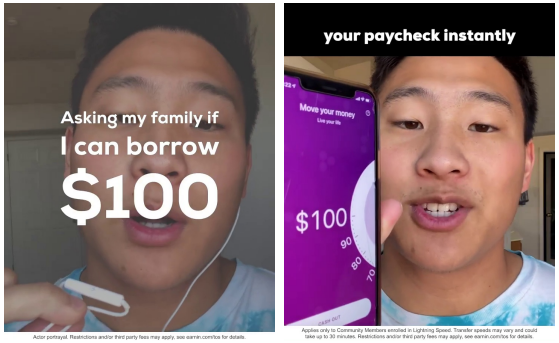


This figure shows the monthly total number of active users and downloads for the cash advance apps in our sample.

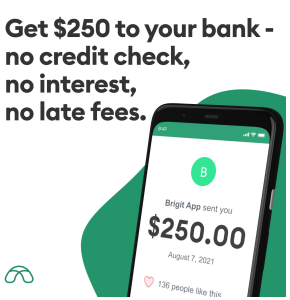
Figure 2: Advertising Examples



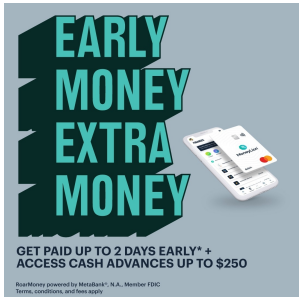
(a) Albert



(b) Earnin



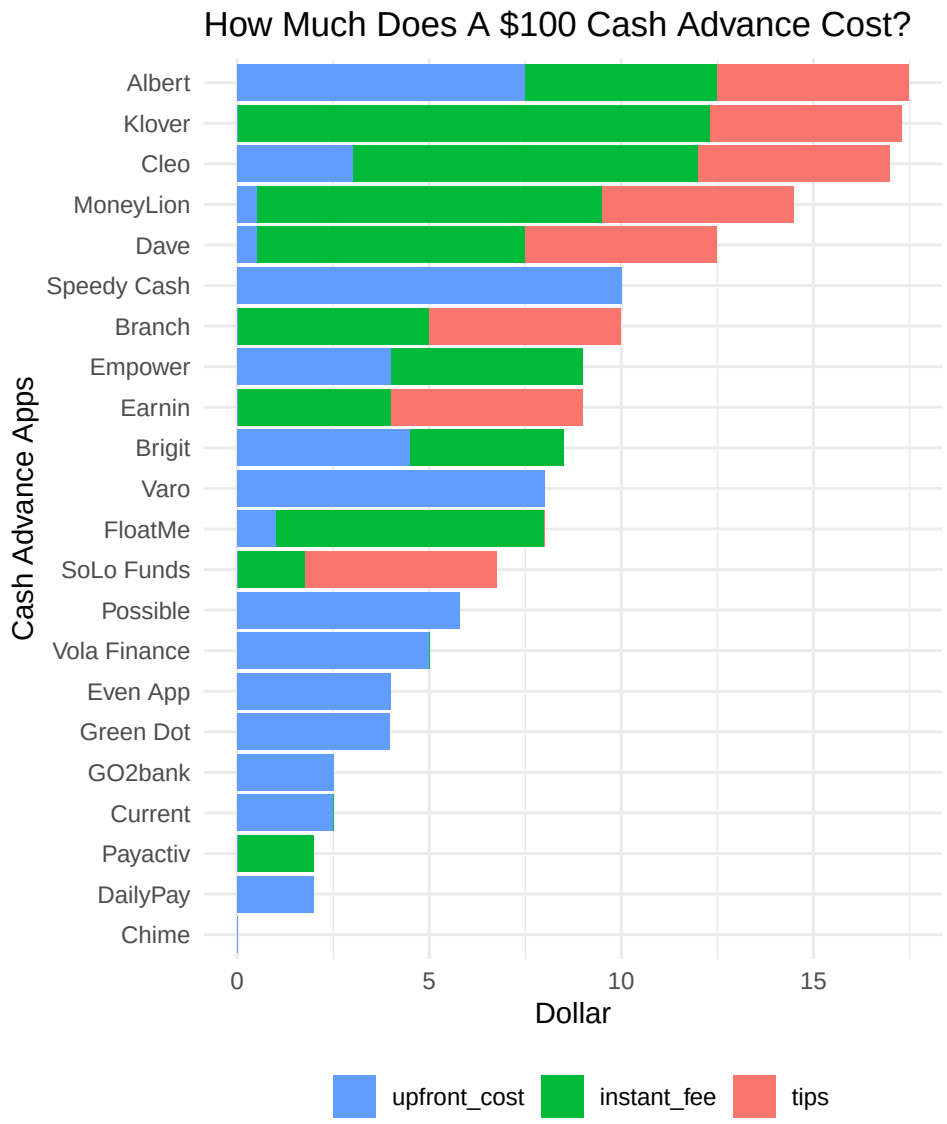
(c) Brigit



(d) MoneyLion

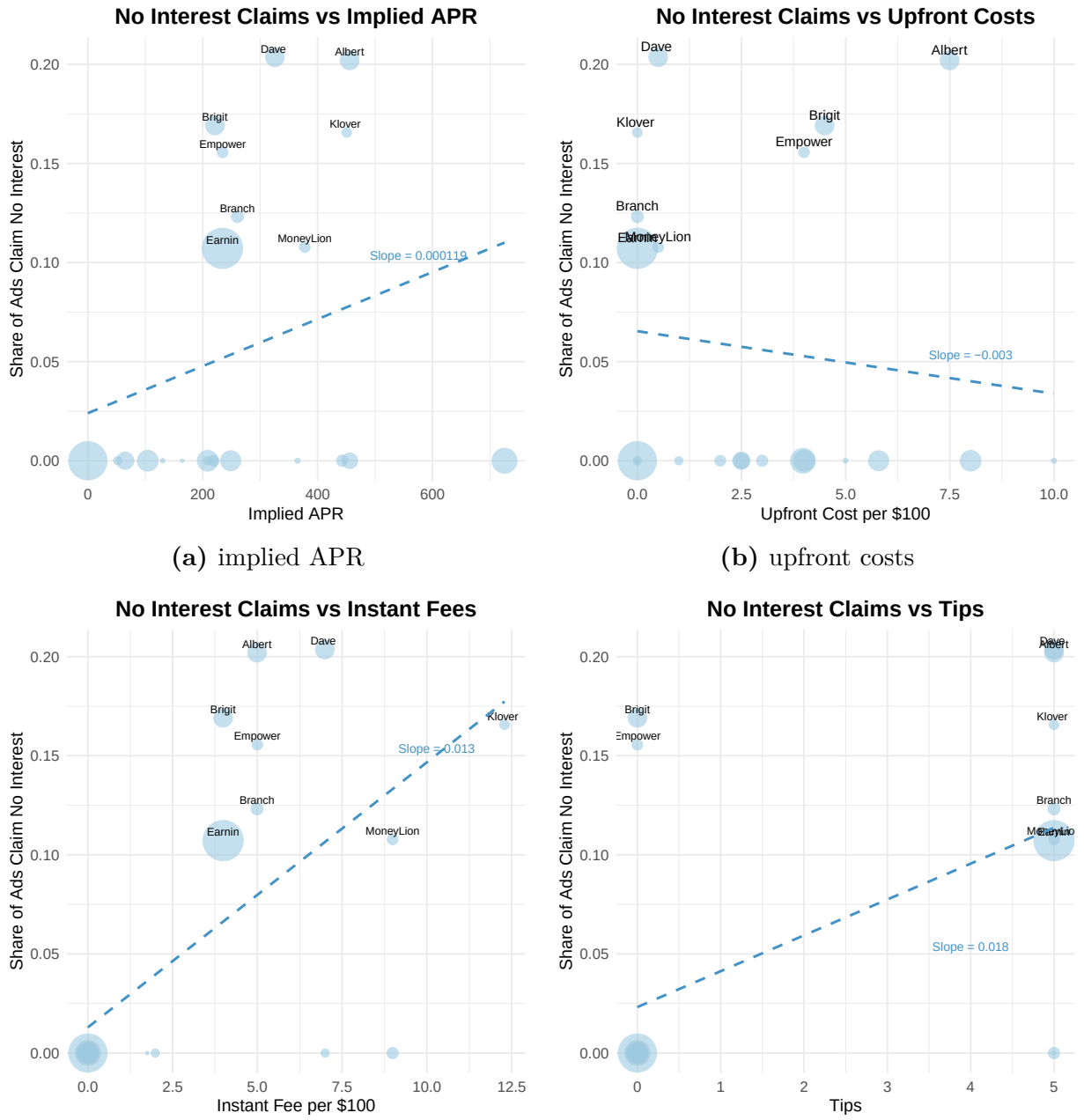
This figure gives examples of typical ads in the sample. Panel (a) is extracted from an Albert's video ad, panel (b) is extracted from an Earnin's video ad, panel (c) is a Brigit's image ad, and panel (d) is a MoneyLion's image ad.

Figure 3: Cash Advance Costs



This figure shows the implied costs of borrowing $100 for once from each cash advance app in the sample. The cash advanced apps are sorted from high to low by the implied costs. The blue, green, and red colors represent upfront costs, instant fees, and tips. The upfront cost includes half of the monthly subscription fee (assuming two advances per month) and cost per advance, if any.

Figure 4: Relationship Between Ad and App Features



(a) implied APR

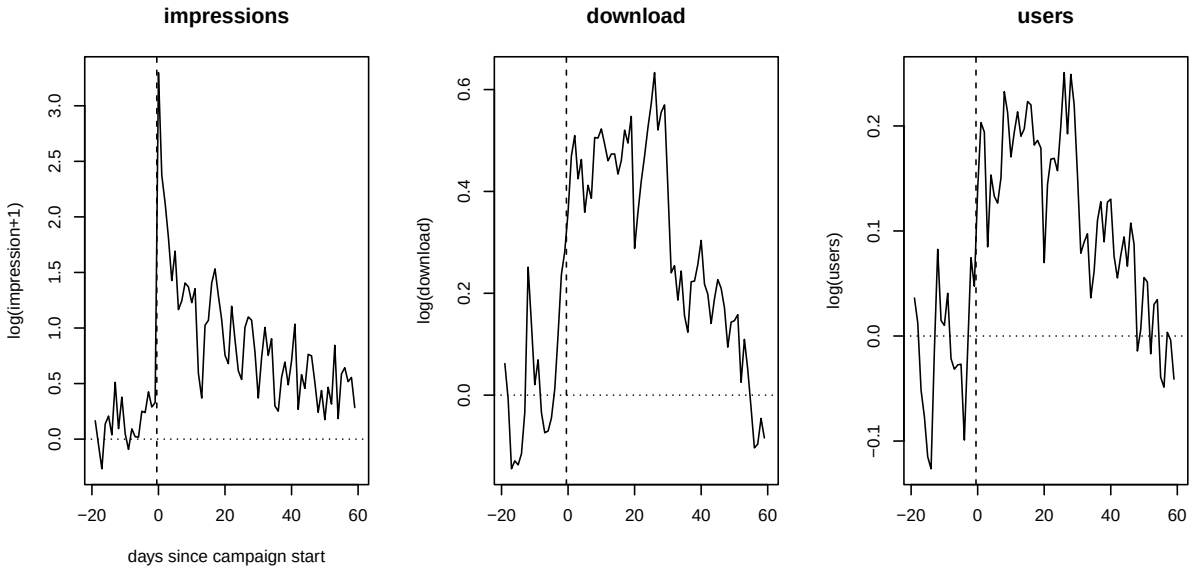
(b) upfront costs

(c) instant fees

(d) tips

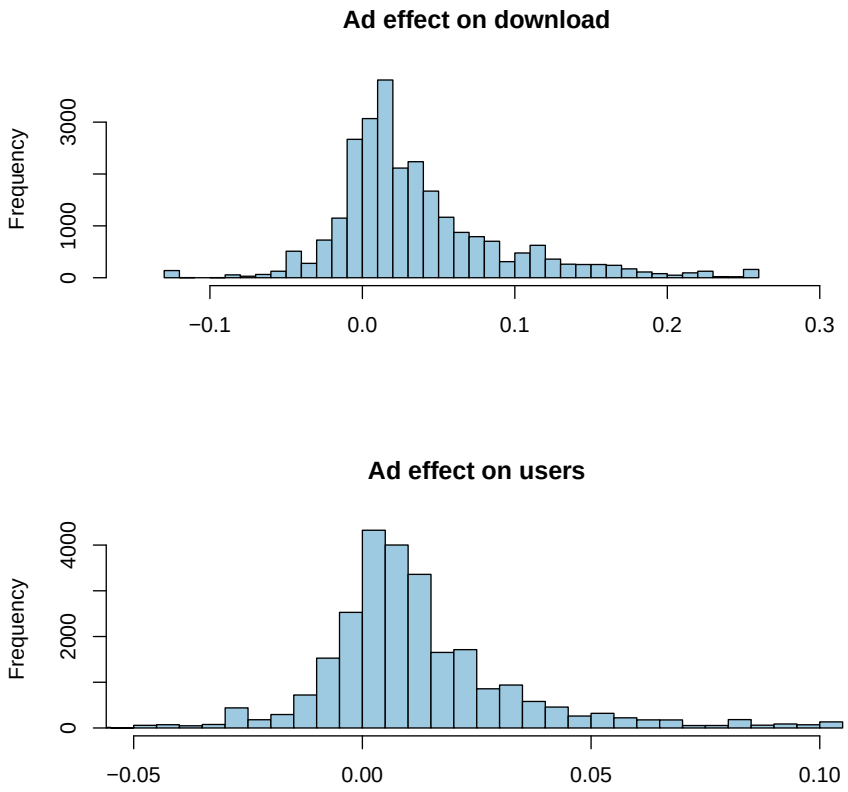
This figure shows the relationship between the average fraction of no interest by apps and the different app features. The app features include the implied APR per $100, upfront cost per $100, instant fee per $100, and tips. The size of the circles represents the size of the apps and the dashed lines are the OLS fitted lines.

Figure 5: Illustration of Identification



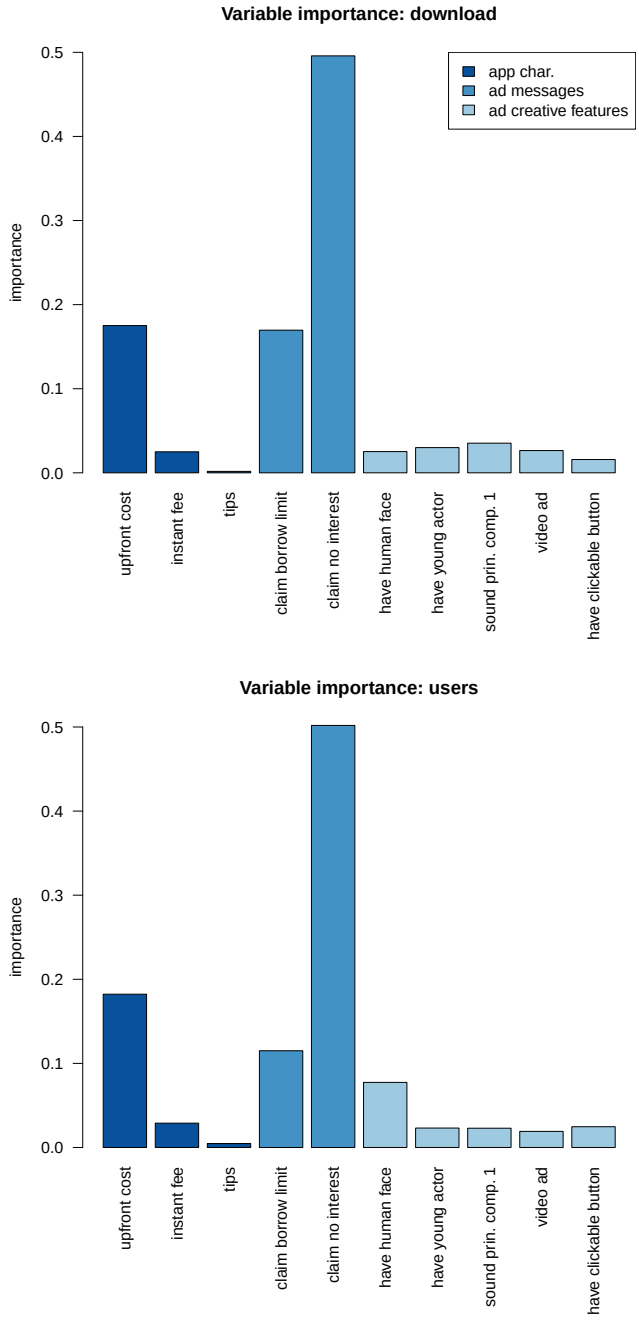
This figure shows the logged number of impressions, logged number of active users, and logged number of downloads around the start of a campaign.

Figure 6: Ad Elasticities at Observed Data Points



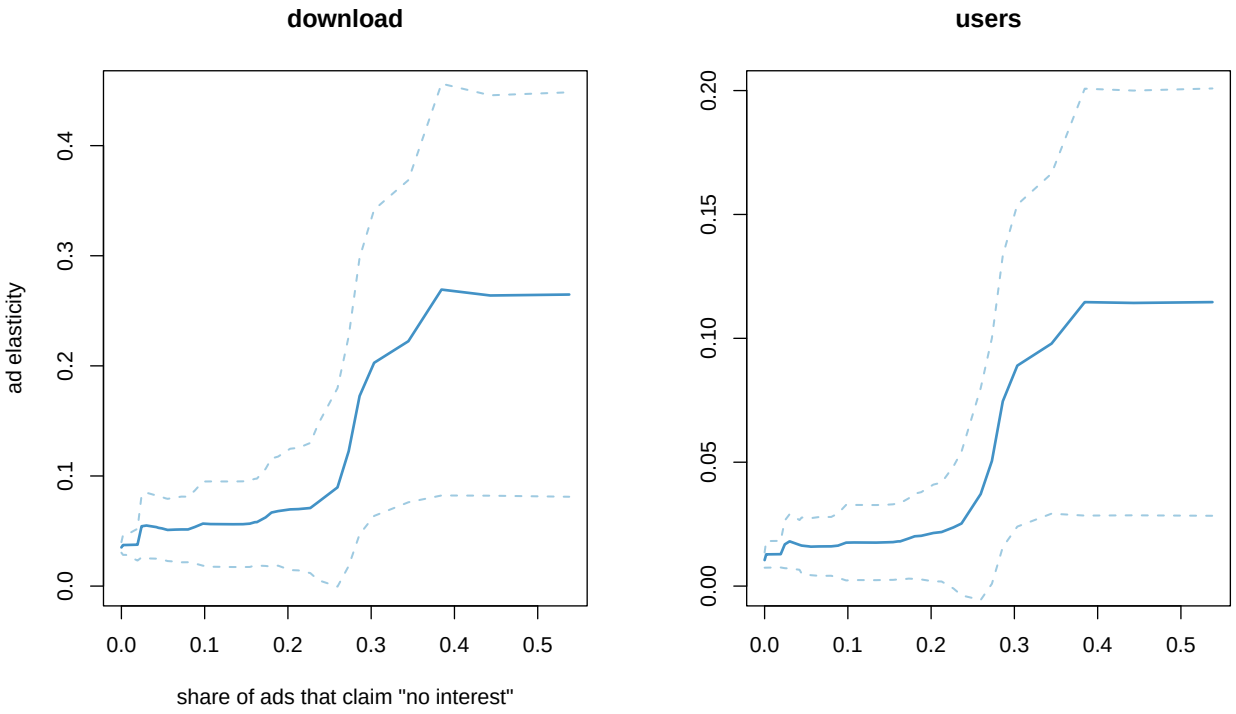
This figure shows the distribution of advertising elasticities estimated by the generalized random forests and projected onto the observed covariates.

Figure 7: Importance Weights of Different App and Ad Features



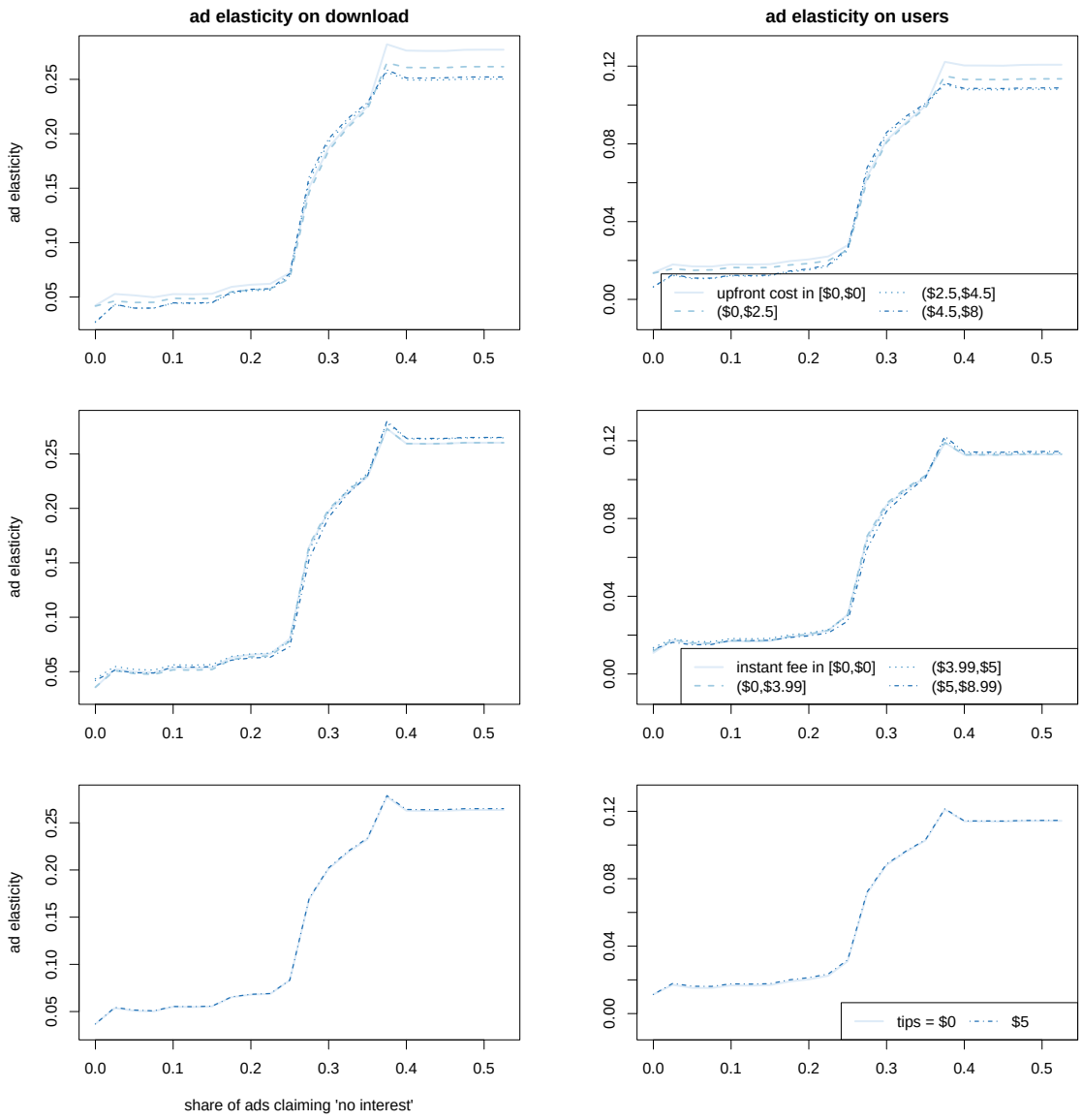
This figure shows the importance weights of different app and ad features in the generalized random forest estimation. The importance of a variable is calculated as the share of tree splits on that variable's node among all tree splits. A variable takes a high importance if much of the differences in $\beta(x)$ relies on the forest splitting on this variable.

Figure 8: Ad Elasticities as a Function of "No Interest" Claims



This figure shows the predicted advertising effects $\beta(x_{j,m(t)})$ for apps where the share of "no interest" claims in the campaign varies between 0 and 54%. At each value of "no interest" share, we integrate over all other characteristics from their joint empirical distribution. Dashed lines mark 95% confidence intervals.

Figure 9: Are Ad Elasticities Affected by the App's True Costs?



This figure shows the predicted advertising effects $\beta(x_{j,m(t)})$ for apps where the share of "no interest" claims in the campaign varies between 0 and 54%. In each panel, one specific fee component varies between four quartiles of its support whereas other components are held at zero.

Table 1: Summary Statistics

	mean	10%	50%	90%
average daily users (in thousands)	56	2	26	103
peak daily users (in thousands)	127	10	58	202
total download (in thousands)	3,233	387	2,227	7,896
90-day retention rate (%)	5	4	5	8
total impressions (in millions)	784	0	143	2,455
upfront cost (in dollar)	3	0	2	7
instant fee (in dollar)	3	0	2	9
tips (in dollar)	2	0	0	5
APR typical case (%)	270	69	235	455

This table shows the summary statistics of the major variables across the 22 cash advance apps.

Table 2: Average Advertising Elasticities

	log(download)			log(users)		
	delta=0	delta=0.27	delta=0.16	delta=0	delta=0.28	delta=0.11
log(impression stock+1)	0.028***	0.038***	0.036***	0.008***	0.012***	0.011***
	(0.003)	(0.004)	(0.003)	(0.001)	(0.002)	(0.001)
log(impression stock opponent+1)			-0.003			0.001
			(0.004)			(0.002)
App-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes		Yes	Yes	
Observations	25,791	25,791	25,791	25,791	25,791	25,791

Note: *p<0.1; **p<0.05; ***p<0.01

This table presents the average advertising elasticities estimated by fixed effects regressions. In columns (3) and (6), we do not include date fixed effects because the sum of own and rival advertising is constant across all apps for each day t, making the two variables co-linear with date fixed effects.

Appendix

A Assembling of ad impression data

The advertising impression data is from Sensor Tower, a leading data provider in the mobile industry. We collect daily impression share data from the company's API. The data comes in small chunks - each chunk records campaign-level normalized impression shares for 100 apps for a 29-day window. We then need to assemble the impression shares across all apps and dates and re-scale the normalization across chunks. We take the following steps to assemble this data:

1. Define each 100 apps as a batch. First, for each batch, we calculate inter-date ratios based on the overlapping date between chunks.

2. Using the ratios, we re-scale and combine data across dates for each batch.

3. To re-scale the impression shares across batches, we use a separate dataset of monthly advertising impression shares collected across batches.

4. We match the daily and monthly level data to calculate the inter-batch ratios. For cases that there is no advertising on the overlapping date for inter-date ratio calculation, we also match the daily and the monthly level data to calculate the inter-date ratios.

5. Using the inter-batch ratios, we re-scale and combine data across batches. We then save them as final files of impression shares.

6. We then multiple these shares by the total number of impressions among iOS users to gett the daily impressions for each advertising campaign.

B Additional figures and tables

Figure B1: Upfront Cost of Varo



Table B1: Publisher App Features

	Ads with 'no interest' claims	Other ads from apps that advertise 'no interest'	Other ads from other apps
Female (%)	49.5	48.9	48.5
Average age	31.8	32	33.3

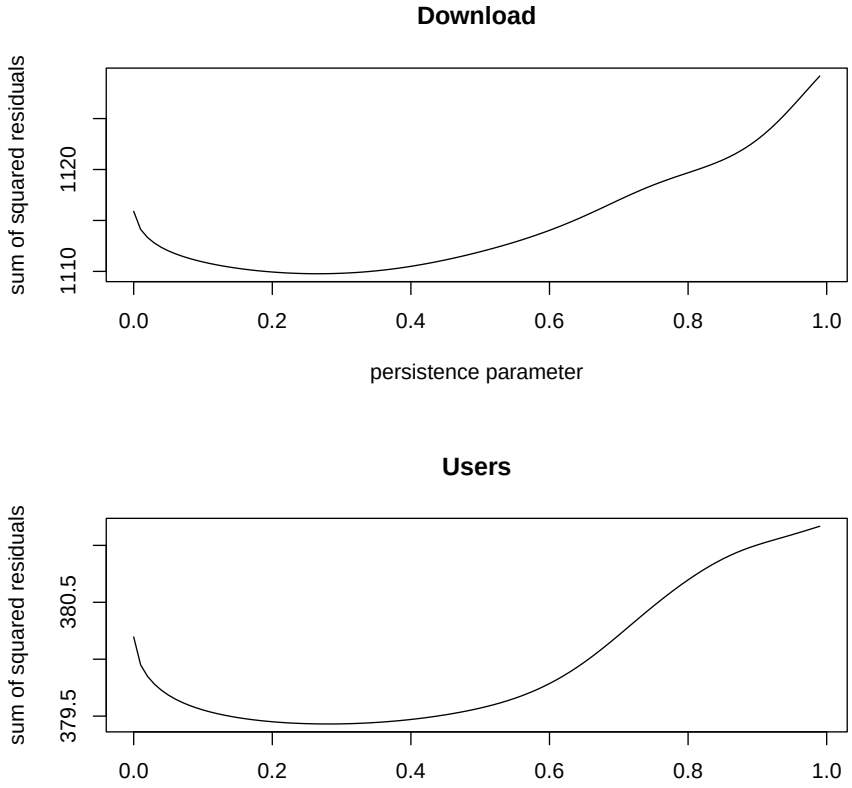
This table presents the characteristics of publisher apps for ads with "no interest" claims, other ads by advertisers that ever advertise "no interest" claims, and other ads by the other apps. Publisher apps are apps that show ads to users and get paid by ad exchanges.

Table B2: Fraction of "No Interest" Claims Over Time

	fraction of no interest claims	
time trend	0.186***	0.230***
	(0.006)	(0.005)
Constant	-0.028***	
	(0.003)	
App FE	No	Yes
Observations	13,634	13,634
R^2	0.077	0.278
Note:	*p<0.1; **p<0.05; ***p<0.01	

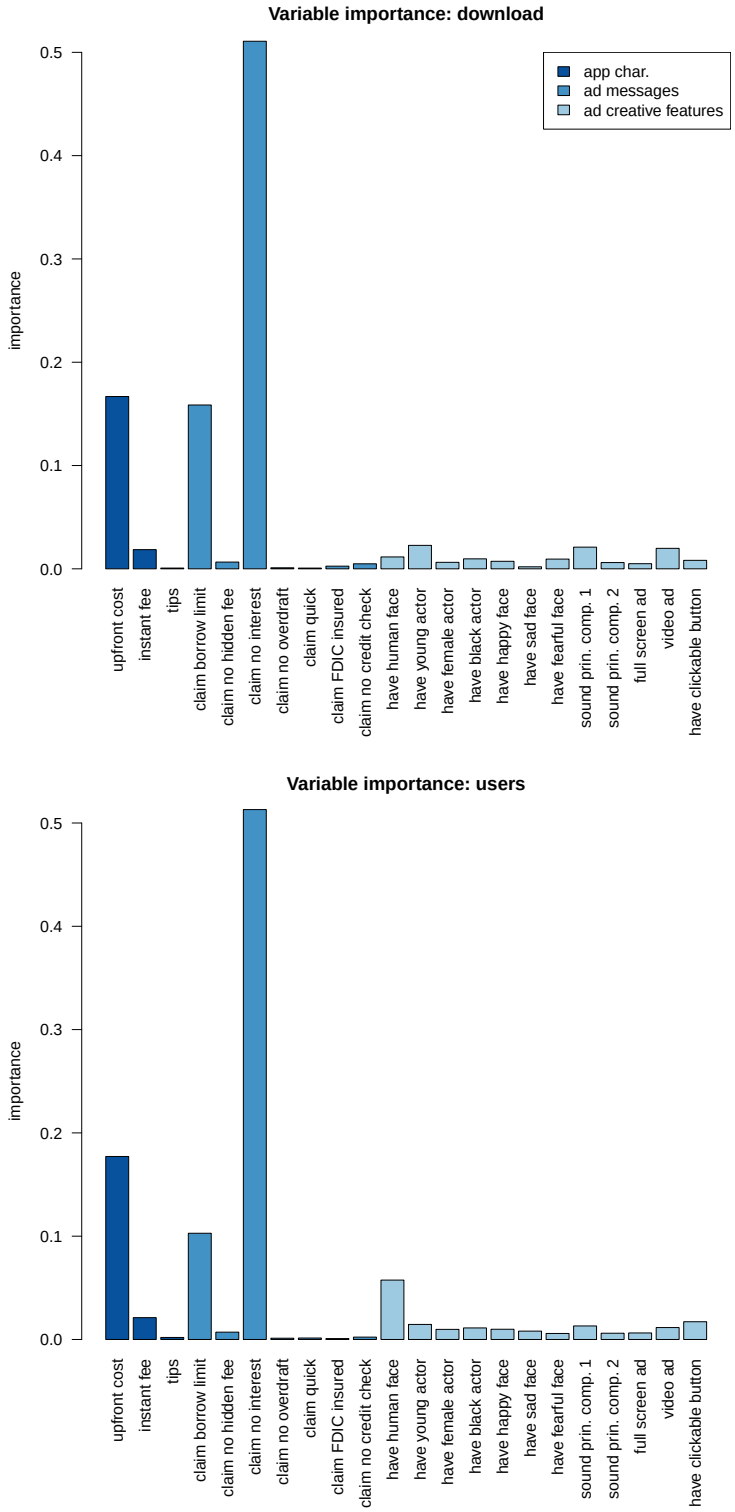
This table shows the positive time trend in the fraction of "no interest" claims in cash app advertising. The "time trend" variable is defined between 0 and 1.

Figure B2: Grid Search for the Best-Fitting Persistence Parameters



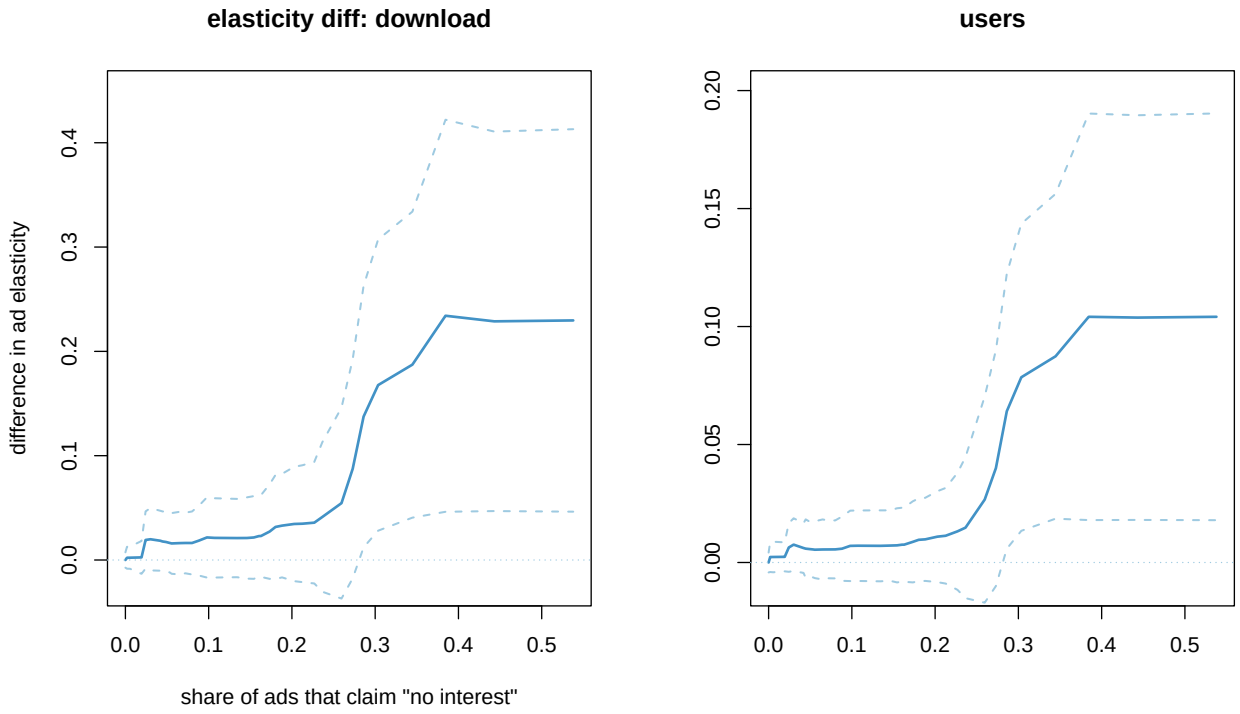
This figure shows the sum of squared residuals from estimations for different persistence parameters.

Figure B3: Importance Weights of All App and Ad Features



This figure shows the importance weights of different app and ad features in the generalized random forest estimation, where we include all 19 ad features in $x_{j,m(t)}$. See Figure 7 for detail.

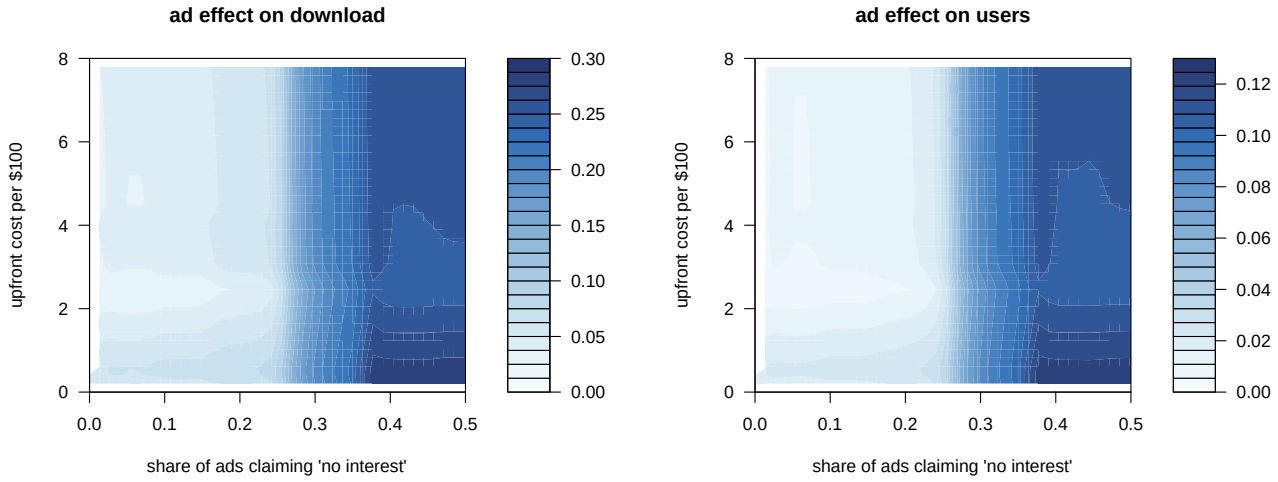
Figure B4: Statistical Tests of Null $\beta(x) = \beta(0)$



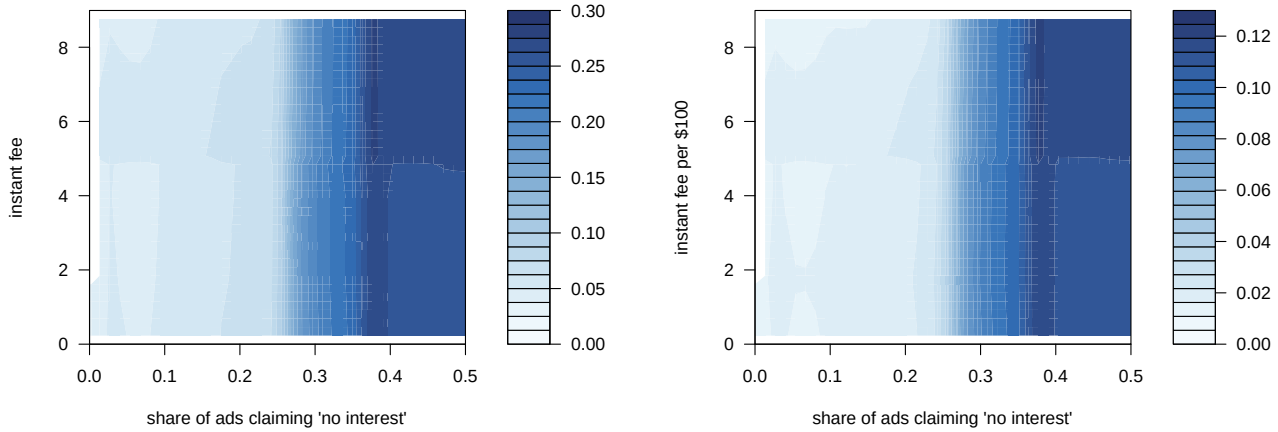
This figure shows the difference $\beta(x) - \beta(0)$ where $x \in (0, 0.5]$ is the share of "no interest" claims. The $\beta(x)$'s are averaged across the empirical distribution of other app and ad characteristics. Dashed lines present 95% confidence intervals. The dotted horizontal line is at 0, representing the null hypothesis that advertising effects under "no interest" claims are the same as those without such claims.

Figure B5: Are Ad Elasticities Affected by the App's True Costs?

(A) upfront cost



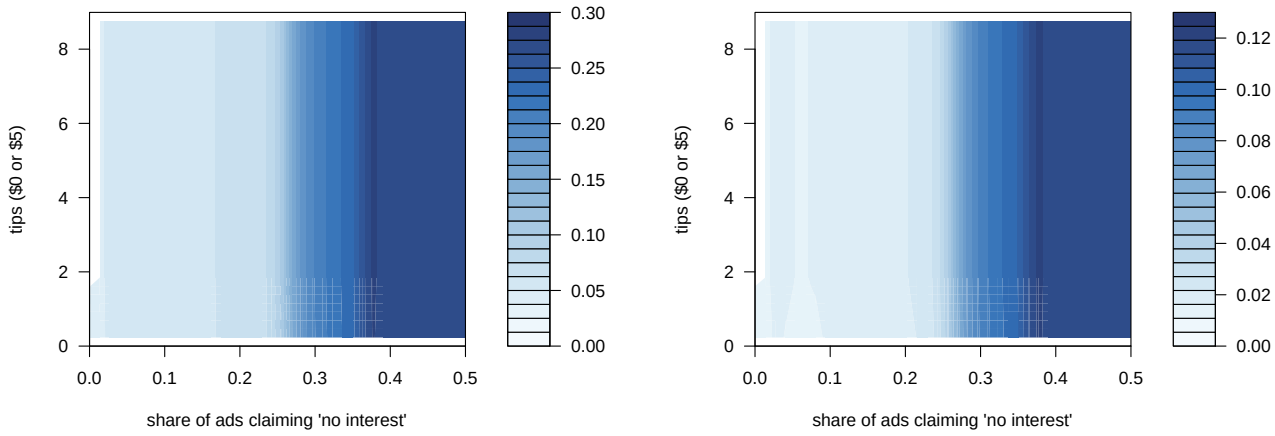
(B) Instant fee



This figure shows the predicted advertising effects $\beta(x_{j,m(t)})$ for apps where the share of "no interest" claims in the campaign varies between 0 and 54% (x-axis). In panel A, we also vary the upfront cost per $100 (y-axis). In panel B, we vary the instant fee (y-axis).

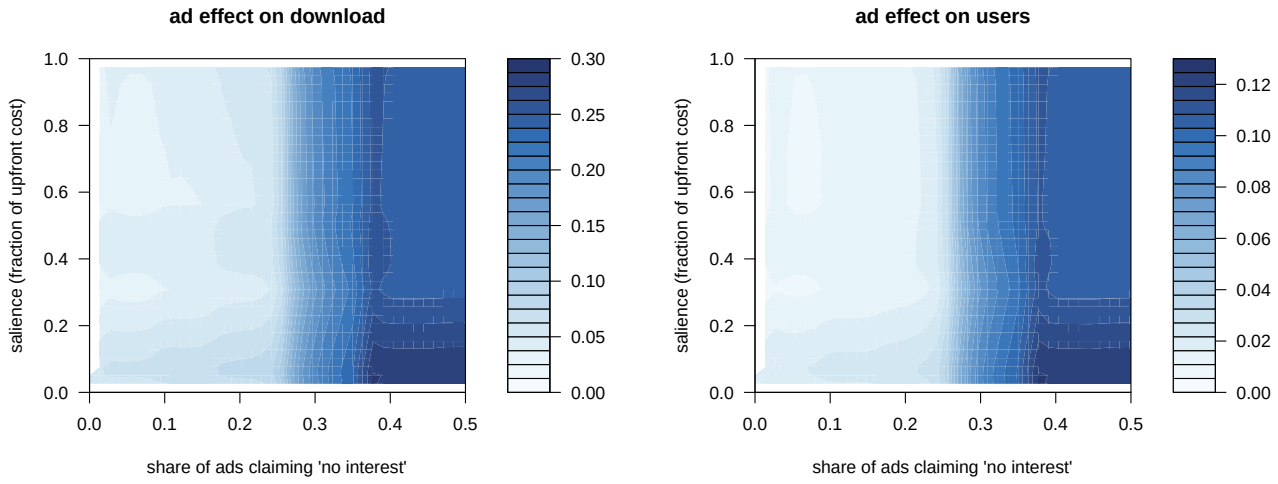
Figure B6: Are Ad Elasticities Affected by the App's True Costs? (Con'd)

(C) Tips



This figure shows the predicted advertising effects $\beta(x_{j,m(t)})$ for apps where the share of "no interest" claims in the campaign varies between 0 and 54% (x-axis). In panel C, we vary the tips (y-axis).

Figure B7: Do Ad Elasticities Depend on the Salience of Fees?



This figure shows the predicted advertising effects $\beta(x_{j,m(t)})$ for apps where the share of "no interest" claims in the campaign varies between 0 and 54%. For both panels, we hold the sum of upfront cost and instant fee at \$8 and we vary the composition of the two fees. We hold wait time at two days and assume the app does not encourage tips.

Robustness checks

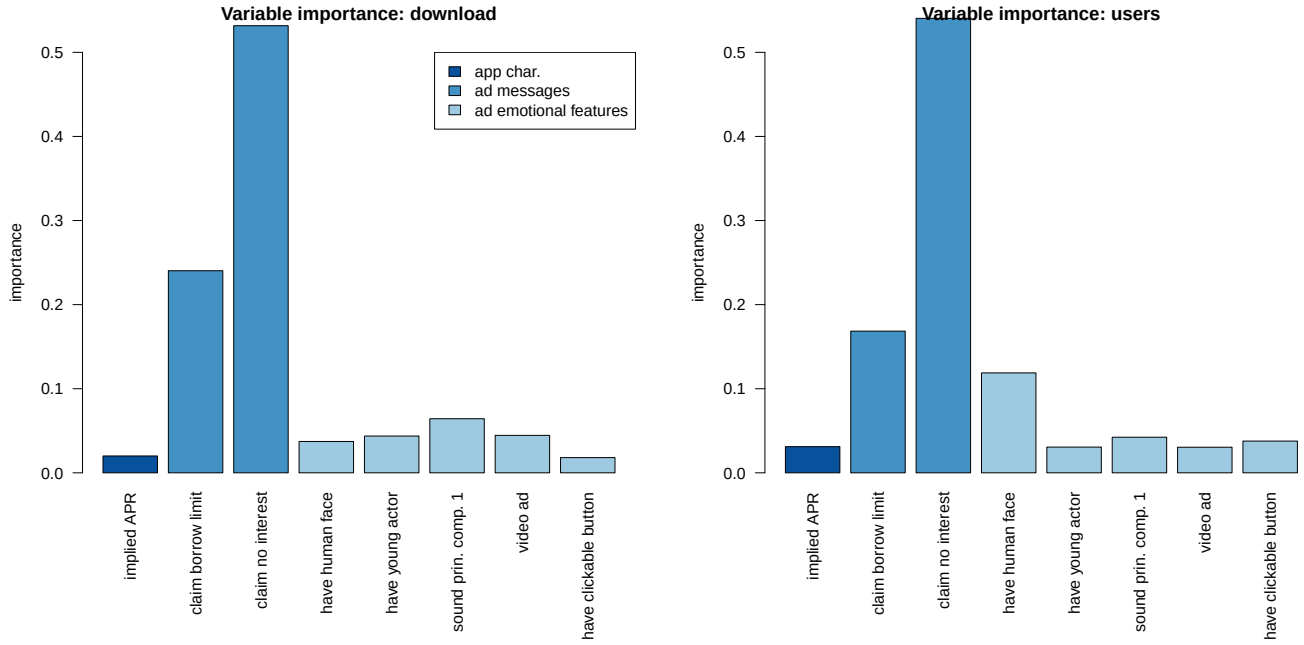
Table B3: Average Advertising Elasticities (Robustness 1)

	log(download)		log(users)	
	delta=0	delta=0.27	delta=0	delta=0.28
log(impression stock+1)	0.029***	0.037***	0.009***	0.012***
	(0.003)	(0.003)	(0.001)	(0.002)
App-month and Date FE	Yes	Yes	Yes	Yes
App-quadratic Trend	Yes	Yes	Yes	Yes
Observations	25,791	25,791	25,791	25,791

Note: *p<0.1; **p<0.05; ***p<0.01

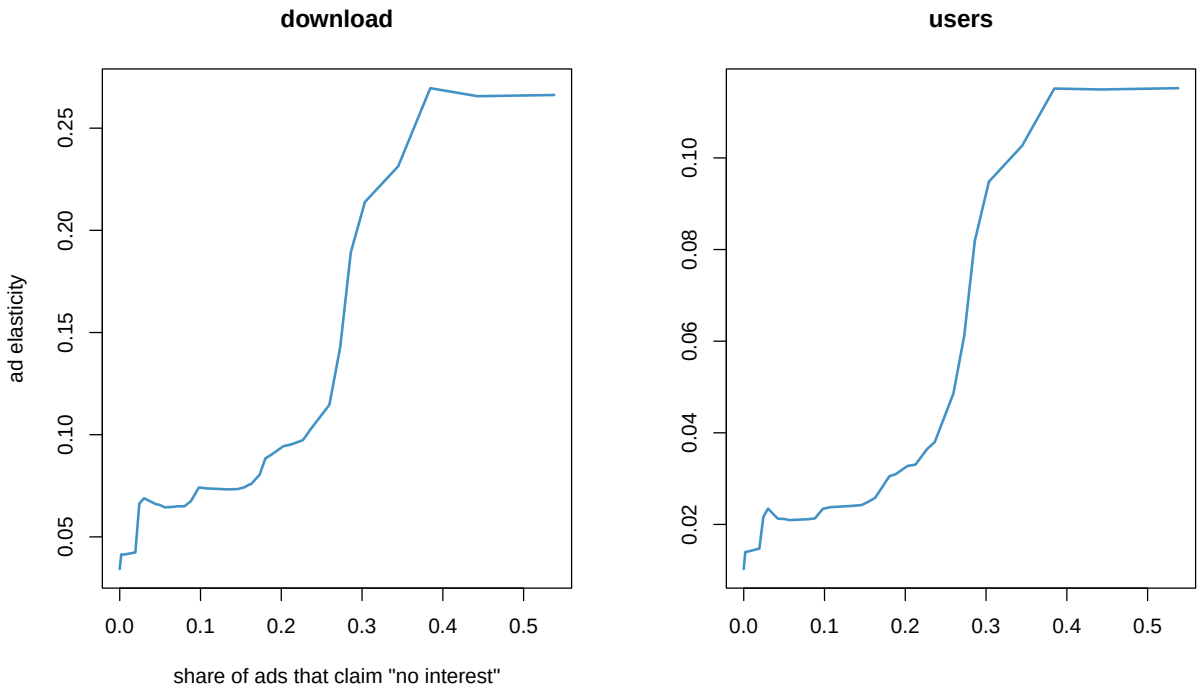
This table presents the average advertising elasticities estimated with app-month, app-specific quadratic trend, and date fixed effects.

Figure B8: Importance Weights of Different App Features (Robustness 2)



This figure shows the importance weights of different app and ad features in the generalized random forest estimation, when we measure an app's cost using an implied APR. See Figure 7 for detail.

Figure B9: Ad Elasticities as a Function of "No Interest" Claims (Robustness 2)



This figure shows the predicted advertising effects $\beta(x_{j,m(t)})$ for apps where the share of "no interest" claims in the campaign varies between 0 and 54%. All other characteristics are held at sample median. In this robustness test, we use the implied APR instead the three aspects of costs in our specification of $\beta(x_{j,m(t)})$.

Table B4: Retention Rates and the Fraction of "No Interest" Claims

	90-day retention rate		
	OLS		*felm*
frac no interest claims	-0.052	0.001	-0.006
	(0.048)	(0.067)	(0.014)
upfront cost		-0.002	
		(0.001)	
instant fee		-0.002	
		(0.002)	
tips		-0.001	
		(0.002)	
Constant	0.057***	0.066***	
	(0.005)	(0.008)	
App FE	No	No	Yes
Quarter FE	No	No	Yes
Observations	22	22	285
R^2	0.055	0.172	0.736
Note:	*p<0.1; **p<0.05; ***p<0.01		

This table shows regression coefficients between apps' retention rates and the fraction of ad impressions with "no interest" claims. Column 1 regresses the two variables using app-level averages without controls. Column 2 controls for the three fee measures. Column 3 estimates equation (3) using app-quarter level data and controlling for app and quarter fixed effects. All columns show that there is no relationship between retention rate and false advertising claims.