"QUICK RESPONSE" ECONOMIC STIMULUS:
THE EFFECT OF SMALL-VALUE DIGITAL COUPONS ON SPENDING

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ABSTRACT

We study a new consumption stimulus model that leverages mobile payment platforms to dispense massive amounts of small-value, use-it-this-week-or-lose-it digital coupons. We evaluate the effects of one such program in a large Chinese city using novel data of mobile platform transactions of 1 million program participants. Exploiting participants' rush to the first-come, first-served digital portal, we compare spending among those who won coupons to those who lost because of minor differences in the timing of their arrival at the portal. We find that coupons generate an immediate increase in weekly consumption among winners by $3 additional out-of-pocket spending for every $1 in government subsidy. Analysis of business customer flows suggests that coupons distort consumption toward more expensive options, leading the program to disproportionately favor big firms that sell pricier goods and services. Relaxing coupons' minimum spending requirements would alleviate such distributional concern without sacrificing consumer welfare. We conclude that the coupon model can be a useful addition to policy makers' stimulus toolbox.

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1. Introduction

Fiscal stimulus of consumer demand is a key to curbing recession and accelerating recovery. Economists and policy makers largely agree that a successful stimulus program should have three general features. A first component is timeliness: the program should be quickly implementable, with its stimulus effect emerging swiftly. A second feature involves targeting: the program should put stimulus in the hands of those who are most likely to spend, and the revenues should reach businesses most in need. The third important characteristic involves limiting the duration of the stimulus: the program should not be prolonged and create a long-run fiscal burden.[2] In practice, it is challenging for a fiscal program to incorporate all these features. For example, consider a direct cash stimulus payment, which is a frequently used tool by policy makers during economic recessions. While a cash stimulus increases consumer spending, its effect often takes weeks or months to fully emerge; it cannot be precisely targeted to help specific business sectors; and the fiscal burden of such a stimulus measure is often substantial because cash payments are generally sizable; yet, only a fraction of such payments goes toward consumption.[3]

In this paper, we analyze a new demand stimulus tool: using electronic, conditional discount coupons for purchase of goods and services (e.g., a coupon that offers $10 off a purchase of more than $30 in any restaurant). A ubiquitous marketing tool used by businesses to boost sales in a short time horizon, coupons provide consumers a salient incentive to spend. Though coupons have traditionally been administered by individual firms, recent innovations in mobile payment technology enable the application of coupons to larger-scale, multi-business settings – and, thus, enable their use as a government stimulus tool. We evaluate an innovative, digital coupon-based stimulus model in China that exploited a fast-growing mobile payment network to generate swift and pronounced spending responses in the wake of coronavirus lockdown measures that took a toll on the local economy. We estimate the stimulus impact of one such pioneering program, which was implemented in a large city over a period of six weeks. We analyze the pros and cons of the mechanism underlying coupons' stimulus effect, and we discuss the policy implications of our findings.

The focal city of our study is Shaoxing, a prefecture of China with a population of 5 million. In the aftermath of a COVID lockdown in January 2020, Shaoxing deployed a digital coupon stimulus program in an attempt to boost consumer spending, and it was the first time such a city-wide program was

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[2] See, for example, Summers (2007); Elmendorf and Furman (2008), Summers (2008), Yellen (2009).

[3] For example, historical U.S. tax rebate programs often provide cash amounts that exceed 1% of average annual household income. The marginal propensity to consume those rebates is estimated to range between 0.2 and 0.8 (Shapiro and Slemrod, 2003; Johnson, Parker, and Souleles, 2006; Agarwal, Liu, and Souleles, 2007; Shapiro and Slemrod, 2009; Parker et al., 2013; Broda and Parker, 2014; Kaplan and Violante, 2014).

implemented in Shaoxing's history. Shaoxing had very few COVID-19 cases, but due to stringent and prolonged stay-at-home orders, the city experienced a sharp and sudden economic downturn, including a 27% plunge in consumer spending in 2020Q1. To stimulate consumer spending, the city dispensed massive amounts of small-value digital coupons through a widely used mobile payment platform (Alipay), the world's largest mobile payment platform, which has 2.7 million users in Shaoxing and captures 72% of total consumption of the city. Based on Quick Response (QR) code technology, these coupons automatically apply a discount when Alipay users make offline purchases that exceed a minimum amount at eligible merchants. The program operated weekly for six consecutive weeks. Each Friday, Alipay users competed for free coupons through a digital portal on a first-come, first-served basis; once won, the coupons appeared in the user's e-wallet, and were valid for seven days until the following Friday, when another coupon rush began. During its six weeks of operation, the program dispensed coupons worth roughly 240 million-yuan (about 34 million USD), and over 1 million Alipay users in the city participated in the program.

We estimate the causal effect of the coupon program on spending using Alipay's administrative data on transactions from users who participated in the program. We exploit the fact that, in each round of coupon claiming, a large number of users competed for a limited number of coupons, generating a "rush" to the coupon program portal. We focus on users who logged onto the portal within a narrow time window around the moment that the last coupon was claimed, and compare subsequent spending among users who barely won coupons versus users who barely lost. Due to privacy constraint, we cannot access minute-by-minute information on user log-on time to implement a regression discontinuity design. Instead, our primary specification compares users who logged onto the coupon program portal five minutes before and five minutes after the moment the last coupon was claimed. We then explore a series of tests to address potential confounds due to selection into winner and non-winner groups: we show that observable characteristics – such as age, gender, and previous-year account cash inflows (i.e., a proxy for income) – differ little between winner and non-winner groups, that the two groups exhibit parallel trends in spending prior to the program, and that the coupon stimulus effect estimates are similar across repeated cross-sectional estimation (comparing winners vs. non-winners in different rounds) and panel data specifications with user fixed effects (comparing the same users across winning vs. non-winning weeks). Together, these evidence lend confidence to the identification assumption that users' minor difference in log-on time can serve as a valid source of exogeneous shocks for the purpose of our study.

Four sets of results emerge. First, the coupon program was popular among Alipay users. During the six weeks of its implementation, 1.57 million users participated in the Coupon Rush events, and over 70% of these users won coupons in at least one round. The process of coupon claiming was highly

competitive. In each round, all coupons were claimed in mere minutes.[4] Redemption rates are high. Among the coupon winners, over 85% made at least one coupon-eligible purchase in the following week. Roughly 61% of the total subsidy values were redeemed during the six weeks. This evidence suggests that the rush mechanism reached people who wanted to use the coupons. We find that redemption rates were highest for shopping and dining coupons – the two hardest-hit sectors during the economic downturn – suggesting that small-value subsidies are effective in stimulating consumption in these sectors.

Second, winning a coupon led users to significantly increase out-of-pocket spending over the next seven days (i.e., before coupon's expiration) by 225 yuan (or "¥"). This effect size translates into "returns" from the government subsidy of over 300%: for every ¥1 of government subsidy, out-of-pocket spending increased by ¥3.07. This effect size reflects the fact that most coupons have a design of *X-yuan off purchase 3X-yuan or more*. Consistent with this evidence, we show that most subsidized transactions (i.e., the transactions involving coupon redemption) have values that "bunch" at the coupons' minimum spending requirements. The coupon program's effects were slightly larger among certain users: females, those between the ages of 20 and 40, and those who had higher levels of e-wallet account cash inflows (a proxy for wealth) in 2019. Overall, we do not find evidence that the stimulus effect concentrated in particular subgroups. In total, the coupon program has generated 850 million yuan (121 million USD) spending in six weeks, which corresponds to a recovery of 13% of the Alipay platform-wide spending loss and 8% of the city-wide consumption loss in 2020Q1.

Third, we ask whether the coupon program generates *net* increase in consumption by testing if the stimulus effect is offset by reduction in purchases "elsewhere". We examine three potential types of spending substitution. First, we find no evidence that coupon winners reduce unsubsidized spending (i.e., transactions that do not involve coupon redemption). Quite the opposite, winning a coupon *increases* unsubsidized spending by a mild margin (50 yuan out of a weekly average spending of 1,000 yuan), suggesting that, if anything, the coupons' stimulus impact spilled over to unsubsidized purchases. Next, we assess intertemporal spending patterns, examining whether initial increases in subsidized spending due to coupons are offset by subsequent spending reductions in later weeks. We estimate that over 85% of the initial stimulus effect persists through the end of the third week, and over 75% of the effect persists through the end of six weeks. Finally, we explore variation in user's historical spending intensity on Alipay to shed light on potential cross-platform substitution: winning a coupon induces users to make transactions with Alipay which would otherwise have been made through different venues such as WeChatpay or cash payment. We find that winning a coupon has a similar stimulus effect for heavy users who were already

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[4] For example, over 0.4 million users participated in the final Coupon Rush, competing for over 0.28 million sets of coupons. All coupons had been claimed within 128 seconds.

making many transactions (e.g., over 10,000 yuan per month) through Alipay prior to the coupon program – a group that is less likely to exhibit cross-platform substitution for a small-value subsidy. Together, the evidence suggests that coupons generate *net* increases in out-of-pocket spending that are not subject to substantial displacement across subsidized and unsubsidized goods, time periods, or different payment venues.

Fourth, we examine mechanisms underlying coupons' stimulus effect. We combine transaction data with merchant information to construct measures of customer flows for all merchants. We then analyze how consumers, depending on their treatment status, flowed to merchants with different characteristics. Our analysis reveals that coupon winners disproportionally favored large firms (as measured by total revenue in 2019), and, in particular, firms selling more expensive goods and services (as measured by revenue per transaction in 2019), *when they ended up redeeming coupons*. We find no such pattern for non-winners, or for *winners* when they make unsubsidized transactions. This finding has two implications. First, the coupon program likely distorted consumption towards pricier options that the consumers would not have chosen in the absence of the coupon's minimum spending requirements. Second, because large and pricier firms take up the vast majority of the market share, most of the government subsidy of the coupon program necessarily lands in the hands of those firms. Our analysis, however, reveals that the coupon program disproportionately favors large and pricier firms – that is, these firms receive more business from coupon winners even on a *percentage* basis. In fact, in both the shopping and dining sectors, firms in the bottom price decile received almost no benefits from the coupon program. This unequal allocation of the program's benefits might not be optimal, for example, from an employment recovery perspective if firms with lower-priced goods and services account for substantial shares in the labor market. To provide further perspectives on policy solutions to the distributional concerns, we build a conceptual model that captures consumer spending with coupon treatment. We show that relaxing the minimum spending requirements on coupons – such as issuing larger quantities of smaller-value coupons, or allowing consumers to spread a coupon's spending requirement across multiple transactions – alleviates distributional inequality, while at the same time preserving, or even increasing, total consumer surplus.

What can we learn from Shaoxing's experience? Our analysis illustrates how digital innovations that are already playing an increasing role in day-to-day business (e.g., Philippon, 2016) can spur innovative solutions to broader social and economic problems. Discount coupons are widely used in marketing and retailing (e.g., Leone and Srinivasan, 1996; DelVecchio, Henard, and Freling, 2006), but their usage as a large-scale fiscal stimulus tool is limited due to coupons' traditional reliance on physical dispensing venues (e.g., newspapers, magazines, booklets), which may cause various administrative and security complications. Shaoxing's fully-digitized, Quick Response (QR) code-based approach features a host of

advantages, including low (marginal) cost of administration, arguably fair coupon assignment, impossibility of coupon forgery, automated coupon redemption, and, importantly, quick consumption stimulus response. In many ways, these advantages echo those in prior studies on financial technology ("FinTech") applications in banking and personal finance settings (Goldstein, Jiang, and Karolyi, 2019; Agarwal and Chua, 2020), including payment services (Rysman and Schuh, 2017; Agarwal et al., 2020), mortgage screening (Berg et al., 2019; Fuster et al., 2019), and wealth management (D'Acunto, Prabhala, and Rossi, 2019). Our paper is the first to study the value of digital payment technology in a fiscal stimulus context through a quasi-experimental application (Nakamura and Steinsson, 2018).

Our paper also sheds light on the pros and cons of digital coupons as a policy option that can supplement conventional stimulus tools, such as cash-based stimulus (Shapiro and Slemrod, 2003; Johnson, Parker, and Souleles, 2006; Agarwal, Liu, and Souleles, 2007; Shapiro and Slemrod, 2009; Parker et al., 2013; Agarwal and Qian, 2014; Broda and Parker, 2014; Kaplan and Violante, 2014). Several unique advantages of the coupon-based stimulus model have become apparent during Shaoxing's economic recovery from the COVID-19 episode. The "use-it-this-week-or-lose-it" design of coupon expiration schedule generates immediate increases in spending, which could be critical for businesses that need immediate liquidity to survive the sudden economic downturn. The coupon program achieves a large spending stimulus response of ¥2.4 to ¥3 for every ¥1 of government subsidy. Such a rate of return is higher than most cash payment-based stimulus programs, where estimated consumer spending per dollar of government subsidy ranges between 0.2 to 0.8.[5] Coupons can be sector specific, and thus can help businesses that are hit hardest in a recession. Shaoxing's experience also indicates the coupon program can be tractably administered by the *local* government, and thus can be tailored to better fit local economic recovery needs. Finally, there is no need for the government to provide subsidy for coupons that are not redeemed, which could be an attractive feature for governments with relatively small budgets. A caveat that we emphasize is that the mechanism underlying coupons' stimulus impact may lead to distributional inequalities that disproportionally favor large and expensive businesses, which should be taken account into when designing coupons' minimum spending requirements.[6]

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[5] Evaluations of other stimulus programs, such as the Food Stamp Program and the Supplemental Nutrition Assistance Program, show corresponding MPC estimates of similar orders of magnitude (e.g., Hoynes and Schanzenbach, 2016; Hastings and Shapiro; 2018).

[6] Coupon program's promotion of small-value, repetitive treatment echoes prior literature on delivery methods for food stamp benefits (Shapiro, 2005; Hastings and Washington, 2010). Our paper is also related to a broader literature on stimulus programs that helped spur demand in other contexts such as the First Time Homebuyer Tax Credit (Berger, Turner, and Zwick, 2020), the Cash-For-Clunkers program (Mian and Sufi, 2012; Green, Melzer, Parker, and Rojas, 2020), and the U.K. Stamp Duty Land Tax holiday (Best and Kleven, 2017).

Our paper is among the first evaluations on the efficacy of the digital coupon-based stimulus model. A concurrent research project (Liu et al., 2020) evaluates a similar digital coupon program in Hangzhou.[7] Reassuringly, a part of their analysis also finds large marginal propensity to consume in response to coupon subsidy. Shaoxing and Hangzhou are among the first cities that pioneered the digital coupon programs, and in the wake of these initiatives, many cities in China intend to adopt similar programs. More broadly, consumption stimulus will likely become a first-order policy task – on both consumer and firm dimensions – facing many economies affected by the COVID-19 pandemic (see, for example, Acharya and Steffen, 2020; Baker et al., 2020; Chen, Qian, and Wen, 2020; Chetty et al., 2020; Cox et al., 2020; Eichenbaum, Rebelo, and Trabandt, 2020; Guerrieri et al., 2020). We hope that our evidence may inspire new policy approaches for countries (or local economies) with similar mobile payment infrastructure.

The rest of the paper is organized as follows. Section 2 provides background and a description of the data. Section 3 explains our research strategy. Section 4 reports our main results on the stimulus impact. Section 5 explores mechanisms underlying the stimulus impact. Section 6 concludes the paper.

2. Background and Data

2.1. The City of Shaoxing and the Spending Decline during the COVID-19 Pandemic

Shaoxing, the focal city of our study, is a prefecture-level city located on the eastern coast of China (Appendix Figure B.1). Data from 2019 show that the city is home to about 5 million people, and it ranks around 30 in both total GDP and per capita GDP among the 333 prefecture cities in China. In many aspects, Shaoxing represents a vibrant "second-tier" city on a good growth track. In 2019, it had a per capita GDP (dispensable income) of 114,317 yuan (53,839 yuan), compared to a national average of 71,932 yuan (30,733 yuan).[8] Shaoxing's real GDP grew by about 7% in 2019, compared to a national growth rate of 6.1%. The city adopts a typical Zhejiang (the province in which Shaoxing is located) growth model that encourages small businesses, and the bulk production of low-cost, small-value commodities. Shaoxing has a large textile manufacturing sector; the city is also widely known for its specialty food such as poultry, traditional wine, tofu, and tea. Shaoxing also emphasizes the role of research and development in growth, especially in high-tech sectors such as artificial intelligence and next-generation communication

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[7] Our project is a part of the dual partnership between Alipay and two separate research teams to provide independent analysis of coupon programs in two pioneering cities.

[8] Shaoxing has a gross (net) savings rate of 50.8% (23.4%) in 2019, compared to a national level of 44.9% (22.5%).

technologies. The city's annual R&D budget exceeds 2.4% of its GDP. In 2018, Forbes China rated Shaoxing as one of the 30 most innovative cities based on its high rate of generating new patents, and on local government investment in science and technology.[9]

Shaoxing formulated its stimulus plan against the backdrop of a decline in consumption activities following Zhejiang's provincial shutdown at the onset of concerns about the spread of COVID-19. Although Shaoxing had few cases at the outset (one active case and no deaths at the time of Wuhan's lockdown on January 23, 2020), it followed Zhejiang's order to implement a stay-at-home order. All non-essential businesses shut down; all schools closed; and authorities strictly limited use of all inter-city highway entries and exits. On February 8, the city government issued a plan for re-opening. The city lifted its inter-city highway restrictions on February 18. Shaoxing's active case dropped to zero on March 16, with a reported total of 42 cumulative cases and zero deaths. By March 25, virtually all businesses were allowed to re-open.

Shaoxing's shutdown led to a sharp reduction in consumer spending. The city reported a 26.7% reduction in sales revenues from consumption goods in 2020Q1 from levels in 2019Q4.[10] Figure 1 plots trends in weekly spending made through the Alipay platform among all coupon program participants, revealing a similar, 21% drop of spending over the same time frame.[11] We do not have official data on other economic impacts of the COVID-19 shutdown, such as employment tolls. However, due to the short duration of businesses shutdowns both at the city and the provincial levels, we expect the immediate economic impact to come largely through spending reductions (e.g., Chetty et al., 2020; Cox et al., 2020).

2.2. The Coupon Program

On March 25, 2020, the city government of Shaoxing announced the six-week coupon program.[12] Below we provide relevant details about the program.

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[9] https://www.forbeschina.com/lists/15
[10] http://www.shaoxing.com.cn/caijing/p/2812095.html
[11] We report separate trends for shopping, dining, and other categories in Appendix Figure B.2. The decline in spending is pronounced in all categories.
[12] http://www.sx.gov.cn/art/2020/3/25/art_1228998371_42390812.html This is the first city-wide coupon program ever implemented in Shaoxing's history.

Alipay Platform. The Alipay platform administered the coupon program. As of 2019, Alipay was the largest mobile payment platform in the world with over 1.2 billion users worldwide and about 1 billion users in China. Alipay accounts for 54.3% of third-party payment market in China.[13]

Payment functions on Alipay are based on Quick Response (QR) codes, a type of matrix barcode that most smartphone cameras can scan. Merchants may charge consumers by simply scanning the QR code associated with the consumer's Alipay e-wallet; alternatively, the merchant could display *its* QR code on the cashier register screen, and have consumers scan the code and make transfers. To preserve security, an Alipay user's QR code is auto-regenerated every minute without the need of Internet connection.

Alipay was used as the platform for the coupon program largely due to its high market penetration on both the consumer and the firm sides. We are not able to display detailed market share statistics in the city of Shaoxing due to business confidentiality, but we can say that during our study period there were at least 2.7 million Alipay users in Shaoxing (among the population of 5 million city residents), and over 0.6 million registered merchants. On average, an Alipay user spent 41,292 yuan in 2019 (the year before the pandemic). Shaoxing government's official statistics indicate that annual per capita consumption was 31,109 yuan in 2019. We can thus infer that transactions made through the Alipay platform comprised 72% of all spending. Each Alipay account is linked to the user's government-issued ID, and, thus, each Alipay user account represents a unique individual. This feature ensures that each person may obtain at most one coupon treatment per round.

Eligibility. All Alipay users could participate in the coupon program. Our data show that 94.2 % of all participants were Shaoxing residents. All offline merchants (in sectors associated with the coupons targeted categories such as dining and shopping, etc.) were eligible for coupon redemption as long as they are registered with the Shaoxing city government. Coupons could not be used for online transactions and could not be transferred across users. Participation and coupon redemption were free for both individuals and merchants.[14]

Coupon Rush. Coupons were dispensed using a "rush" process in which all participants competed for a limited number of coupons based on a first-come, first-served basis. Six rounds of Coupon Rush events occurred on six consecutive Fridays: April 3, April 10, April 17, April 24, May 1, and May 8. On each of these Fridays, users could log onto a digital portal for coupon claiming. The portal was activated at 10:00 a.m., and all users logged onto the portal after that time to obtain coupons, until all coupons were claimed.

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[13] The next biggest player in the market is WeChatpay (39.9% nationally). Other platforms account for very small shares of the market.

[14] Alipay charges merchants a transaction fee of 0.6% of the transaction value. There are no additional fees charged for coupon redemption.

Technically, users rushed for coupon "packets," the contents of which varied depending on the log-on time. For example, in the first round (April 3), the total stock consisted of 80,000 dining coupons, 200,000 shopping coupons, 50,000 gym coupons, 50,000 lodging coupons, 20,000 book coupons, and 20,000 cellphone coupons. The first coupon winner (i.e., the first user that logged onto the Coupon Rush portal after 10:00 a.m.) obtained a packet with 11 coupons in all 6 categories: 2 dining ([¥30 off ¥90+][15] and [¥70 off ¥210+]), 2 shopping ([¥20 off ¥60+] and [¥30 off ¥90+]), 2 gym ([¥10 off ¥25+] and [¥30 off ¥75+]), 2 lodging ([¥30 off ¥90+] and [¥70 off ¥210+]), 2 book (both [¥25 off ¥50+]), and 1 cellphone (both [¥200 off ¥2,000+]). By the time the 10,001[st] user logged onto the system, book and cellphone coupons would have been taken, and his or her packet would thus have contained 8 coupons: 2 dining, 2 shopping, 2 gym, and 2 lodging. Our primary analysis studies the causal effect of winning a coupon packet, regardless of the particular coupon composition of a given packet. In the Appendix, we exploit variations in coupon packet compositions to estimate the marginal effect of different types of coupons.

To access the Coupon Rush portal, users first entered the "Yue-niu" mobile app, a widely used local news aggregator in Shaoxing, that contained a link to the Alipay Coupon Rush portal. After logging onto the portal, the user would have seen a button that contained one of three messages: "Opens at 10" (not clickable) if the Rush had yet to begin, "Claim at no cost" if the event was ongoing and coupons remained, and "Out of stock" (not clickable) if all coupons have been taken. Appendix Figure B.3 provides example screenshots of the three stages of the portal. It is important to note that our data record the time at which the user logged onto the Alipay portal (the time of the first log-on attempt, if the user tried multiple attempts), not the time the coupon-claiming button was clicked (which is only clickable at the "Claim at no cost" stage). Our data show that time of first log-on attempt is a near-perfect measure of whether a user won any coupon. We find only 11 cases in which the user did not win any coupons even though his or her first log-in occurred before the coupon supply was exhausted; we find no case in which a user won a coupon when his or her first log-on time occurred after the supply of coupons ran out.

We abstract away from two facts that we believe are unlikely to interfere with our analysis. First, on each Coupon Rush day, there was a separate, 11:00 a.m. Rush for small-value taxi coupons (¥5 off any transaction) and ride-sharing coupons (¥2 off ¥10+, ¥3 off ¥15+, and ¥4 off ¥20+). These rush events were administered on a different mobile platform for ride-sharing (DiDi). Second, Shaoxing implemented a Coupon Rush "comeback" in the week of May 22, two weeks after the end of our study period. We do not have enough data to look at these comeback events. Both the transportation coupons and comeback events

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[15] That is, 30 yuans off a purchase of 90 yuans or more.

are separate from the main coupon program, so we do not expect them to have an impact on our empirical findings.

Coupon Redemption Rules. Once claimed on a Friday Coupon Rush event, each coupon was valid for use until the midnight of the following Thursday. The coupon automatically applied to the next eligible consumption (Appendix Figure B.4 shows an example screenshot). Each coupon could be redeemed only once, and could only be applied to one transaction. Coupons could only be used for transactions made through the Alipay platform. Thus, although our data do not capture all spending of the consumer because transactions can be made through other payment platforms or through cash, our estimates do capture the total effect of winning coupons.

Fraudulent Cases. During the coupon program's implementation, there were occasional reports of merchants "cashing out" coupons by making dummy transactions by coordinating with coupon holders. Shaoxing's city government and the police department responded with anti-fraud actions, including a ramped-up use of Alipay's fraud detection algorithm, and unannounced audits. Violating merchants face severe punishments including removal from the coupon program, and possible prosecution for extensive fraudulent transactions. We believe the number of fraudulent transactions in our data is unlikely to be significant.[16]

Program Financing. The coupon program budget is about 240 million yuan, or about 0.37% of Shaoxing's 2019 fiscal budget. For each transaction, the cost is shared between the city government (20% of the cost) and the sub-city level government of the district where the transaction occurred (80% of the cost).

2.3. Data and Summary Statistics

We use administrative data from Ant Financial, the financial technology provider behind Alipay. A total of 1.57 million Alipay users (54% of all users in the city, 31% of the city population) participated in Coupon Rush events during the six weeks between April and May, 2020.[17] For each participant, we have data on all transactions made since January 2019. For each transaction, we observe the transaction time, value, whether a coupon (and what coupon) was redeemed, and information about the merchant associated with the transaction. We also observe the user's age, gender, and, as a proxy for wealth, his/her weekly

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[16] We are only aware of three cases of criminal charges on coupon-related fraudulence as of May 2020: http://www.shaoxing.com.cn/xinwen/p/2805040.html

[17] During the program, 66% of user participated in more than one rounds, and 3% of users participated in all six rounds.

Alipay account cash inflow in 2019.[18] For participants in each round of Coupon Rush events, we observe their log-on time in 5-minute intervals relative to the moment when the last coupon is claimed. We record the first successful log-on time if there were multiple attempts during a Rush event.[19] Due to privacy restrictions, we cannot use more granular time information. Our primary empirical strategy compares individuals who logged onto the Coupon Rush portal within the -5 to 5 minute window. Out of a total of 1.57 million participants, 958,920 fell within this time window. We establish that this 10-minute window is sufficiently narrow to capture users who "barely" won the coupons and users who "barely" did not (Section 4.1). Our analysis focuses on the six consecutive weeks (April 3 to May 14, 2020) during which the coupon program was in place. In several specifications in which we look at longer-term spending patterns, we add the two weeks of data after the last round of the Coupon Rush (the weeks of May 15 and May 22). When the data were extracted, we had the data for only the first five days of transactions during the week of May 22; as a result, we scale up spending in that week by a factor of 7/5.

While the ratio of Alipay users to city population (58%) and the ratio of coupon program participants to all Alipay users in Shaoxing (54%) are both fairly high, it is still important to consider potential selection into our estimation sample. Per city's yearbook data, Shaoxing's 2019 per capita consumption was 31,109 yuan, or about 600 yuan per week. In 2019, Alipay users conducted transactions worth on average 794-yuan per week on the platform. By contrast, the coupon program participants' spending through Alipay was 1,122 yuan per week. This difference suggests that the Coupon Rush process attracted users with higher-than-average capacity to spend. However, we cannot make precise statements on the incomes of participants and non-participants, or on consumption propensity differences because the observed difference in spending may also reflect differential propensities to make transactions through the Alipay platform. Table 1 shows that Coupon Rush participants are younger (average age of 36.6) than the city average age (39.1). Females account for a greater proportion of Coupon Rush participants (60.1 percent) than the proportion of female city residents (49.7).[20] We discuss the external validity of our results with these caveats in mind.

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[18] Cash inflows could be direct cash transfers from a personal bank account or cash transfers from other users. Alipay users' account balances are by default invested in a money market fund; users can use or withdraw money free of charge on demand.

[19] As previously detailed, each user can win at most one packet of coupons each round, and will win if his/her first attempt of logging onto the Coupon Rush portal happens before the last coupon is claimed. Repeated attempts thus do not increase the odds of winning, but they did occur in practice.

[20] In Appendix Figure B.5, we summarize age profile of the coupon program participants. We find that, relative to the city population, the population groups aged below 20 and over 60 are underrepresented in the program participants, while those ages 20 to 40 are overrepresented. This pattern is consistent with higher Alipay usage among the middle-age groups.

3. Research Strategy

Our empirical strategy is motivated by two unique features of the coupon program design. First, each round of coupon claiming exhibits a "rush" that spans only matter of several minutes, which helps us identify users who obtain coupons (or not) largely by chance. Figure 2 plots the Coupon Rush portal's click traffic in the hour before and the hour after the rush began on 10:00 a.m. local time for each of the six rounds. Shaded areas highlight the time window during which there were still coupons available for claiming. In all six rounds, click traffic began to increase about ten minutes before the event, peaking exactly at 10:00 a.m. when the portal was activated for coupon claiming.[21] Traffic quickly declined but continued into the "after minutes" as users were still able to log onto the portal, only to find that the coupons were all gone (Appendix Figure B.3 shows an example screenshot from the Alipay app at three points in time: moments before the portal was activated, during the rush, and after coupons ran out). In all rounds, click traffic dropped to near zero after 10:20 a.m.. Figure 2 also suggests that the competitiveness of the rush grew over time. The final round, for example, all coupons were claimed within 128 seconds. A second useful feature of the program design is that, once claimed, a coupon expired in seven days, when the next round of Coupon Rush began (Section 2.2). This design ensures that "treated" and "control" groups are easy to define for each week.

Our research design compares coupon winning, usage, and next 7-day spending for consumers who first logged onto the Coupon Rush portal shortly before and after the moment when *last* coupon was claimed. For the sake of the discussion, we will call this moment "minute zero." Because minute zero is unknown to participants and the entire Rush only lasts minutes, the extent of users sorting around minute zero is low. Our estimation equation is:

$$Y_{it} = \alpha + \beta \cdot 1(Coupon)_{it} + \eta_i + \eta_t + \varepsilon_{it} \text{ for } i \in \text{logon time window } [-5, 5] \text{ minutes} \qquad (1)$$

where Y_{it} denotes individual i's spending in week t where a week is defined by the 7 days between a Friday and next Thursday to match the coupon's expiration schedule. $1(Coupon)_{it}$ is an indicator for whether user i won any coupon for the week. η_i are user-level covariates, including age, gender, average weekly account cash inflow in 2019 (or user fixed effects, depending on specification choice; more below). η_t are week (i.e., round) fixed effects. Our identification compares users close to the minute-zero cutoff. We focus on

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[21] During the second wave, the Coupon Rush portal was overwhelmed with excess traffic, which caused a momentary connection loss. Traffic quickly resumed once the issue had been fixed.

individuals logged on to the rush portal within the -5 to 5 minutes, the finest level of time information available to us. This sample includes about 958,920 individuals, or about 61% of all users who participated in the program over its duration. We test robustness with more liberal choice of time windows such as -10 to 10 minutes, all users up to 10 minutes, and all users up to 20 minutes.

We begin with a standard repeated cross-sectional approach to estimate equation (1). We construct six cross sections of program participants in each week, and the β estimate thus represents the difference between winners and non-winners spending in the 7 days following the Coupon Rush event. To interpret β as the causal effect of winning coupons on spending, the identification assumption must hold that those who logged onto the portal within plus or minus five minutes of "minute zero" are identical except for the coupon treatment. In practice, one might worry that users with different log-on timings, even if differing by mere minutes, might still be different in observable or unobservable ways. For example, those who are motivated enough to attempt the Coupon Rush portal minutes prior to when it opened may have a higher propensity to spend than those who logged on later. We assess the validity of our identification assumption in several ways.

Selection on observables. We first compare observable, pre-treatment characteristics, including age, gender, and account inflows, across the -5 to 0 group (winners) and the 0 to 5 group (non-winners). We then compare cross-sectional estimation results with and without controls for these characteristics. If there is no substantial selection on these observables, then we expect (1) the characteristics to balance as functions of log-on minutes, and (2) controlling for these characteristics in regressions is inconsequential for estimation results.

Selection on unobservables. Next, we use panel identification approach to address potential selection on unobservables. We first conduct the standard parallel trend test, comparing *trends* in spending among the winners and non-winners, before and after the Coupon Rush events. This exercise allows us to inspect whether the two groups have common trends in consumption prior to the coupon treatment, and how spending evolves as a consequence of winning coupons. In addition, the "shape" of spending trends can help inform anticipatory responses, e.g., whether users reduce this week's spending in anticipation of the possibility of winning coupons in the future.

Second, we estimate a panel data version of equation (1) using a full panel of users who participated in at least one of the six rush events within the -5 to 5 minute window. Here, $1(\text{Coupon})_{it}$ equals 1 if user i won any coupon in week t, or 0 otherwise (i.e., the user did not win the coupon, or the user did not participate that week). The primary advantage of the panel regression is the ability to control for user fixed effects, which allows us to compare spending of a *given* user across coupon winning and non-winning

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weeks, thus addressing confounds due to factors that are time-invariant at the individual level.[22] With the panel structure, we are also able to test the lagged impact of previous coupon-winning status, and the impact of *future* coupon-winning status as a "placebo" treatment to *this* week's spending. We implement these tests by augmenting equation (1) with leads and lags terms in $1(\text{Coupon})_{it}$.

As we detail in Section 4, these identification validity tests lend confidence to the identification assumption that users' minor difference in log-on time can serve as a source of exogeneous shocks for the purpose of our study. We find that observable characteristics differ little between winner and non-winner groups, that consumption pre-trends of the two groups match closely to each other, and that the effect estimates are similar across repeated cross-sectional and panel specifications, with and without individual-level covariates or user fixed effects. Unless noted otherwise, our preferred specification is the panel estimation version of equation (1) with individuals who logged on within the -5 to 5-minute window, with user fixed effects η_i and week fixed effects η_t.

Spending substitution. A deeper concern with the estimation of equation (1) is whether winning coupons triggers an increase in subsidized spending, but at the same time induces a compensating reduction in spending "elsewhere", thus overstating the *net* stimulus effect of the coupon program. We assess three types of potential spending substitution in this paper: subsidized versus unsubsidized spending substitution, intertemporal/anticipatory substitution between winning and non-winning weeks, and cross-platform substitution between Alipay and other payment venues. Once again, these tests hinge on our ability to observe coupon redemption choice at the transaction level, and to track the same user over time. We report the associated findings in Section 4 and, in particular, Section 4.3.

Before proceeding, it bears mentioning that we will focus on the impact of coupons on three measures of spending throughout this study. We define "total spending" as the sum of all spending made through Alipay in the subsequent week. We define "out-of-pocket spending" as total spending minus the amount subsidized by the coupon. Thus, if a user spent 1,500 yuan during the week, and redeemed a dining coupon of [¥30 off ¥90+] in a transaction of ¥100 and a shopping coupon [¥20 off ¥60+] for a transaction of ¥80, then the user's out-of-pocket spending that week is 1,500 – 30 – 20 = 1,450 yuan. Finally, we define "unsubsidized spending" as total spending net of the *transaction(s)* subsidized by coupons. Thus, to use the previous example, the user's weekly total unsubsidized spending is 1,500 – 100 – 80 = 1,320 yuan. We use these different spending measures to shed light on the mechanisms through which coupons affect consumption behavior.

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[22] The panel structure also allows us to cluster standard errors at the user level to address serial correlations in spending and coupon treatment.

4. Results

We now present evidence on the causal effect of the coupon program on spending. Section 4.1 reports statistics on coupon usage. Section 4.2 presents estimates of the effect of coupon winning on the subsequent week's spending. Section 4.3 assesses the degree to which the stimulus effect may be explained by spending substitution of various forms.

4.1. Coupon Redemption

During its six-week duration, the coupon program gave away over 3.4 million coupons, which represented subsidies of some 240 million yuan, to more than 1 million users. Redemption rates varied by coupon categories. (In all, 86% coupons were redeemed for shopping, 69% for dining, 39% for cellphones, 15% for both lodging and books, and 8% for gyms.) At the user level, 86% of coupon winners redeemed at least one coupon in the subsequent week, and the average subsidy value received by coupon winners was 73.3 yuan (Appendix Table B.1). The coupon program thus features a high "compliance" rate in that most coupon winners engaged in coupon-eligible transactions before their coupons expired. For simplicity, we next focus on the "intent to treat" effect of winning coupons, i.e., we compare spending patterns of winners and non-winners, regardless of actual coupon usage.

Figure 3 plots the distribution of value of subsidized transactions (i.e., transactions that involve coupon redemption). In each coupon category, we find that the value distributions exhibit spikes at exactly the minimum spending requirements levels. To make a comparison, we randomly match each subsidized transaction with an unsubsidized transaction that occurred at the same merchant on the same day. Figure 3 plots the distribution. Reassuringly, we do not see similar spikes for unsubsidized transactions. The overall patterns also suggest the distributions of subsidized and unsubsidized transactions are similar except near the coupon eligibility requirements.[23]

4.2. The Effect of Winning Coupons on Spending

As outlined in Section 3, our primary empirical strategy focuses on platform users who "barely" won with users who "barely" lost due to minor differences in the timing of logging onto the Coupon Rush portal. To illustrate the idea, Figure 4 summarizes users' coupon-winning status, redemption, and

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[23] One exception is cellphone-related transactions (panel F) where most unsubsidized transactions concentrate around the ¥0-200 range; the vast majority of transaction volume is for purchases of prepaid data plans and cellphone accessories.

subsequent week's spending as a function of the user's log-on time relative to "minute zero" (i.e., the moment when all coupons had been claimed). Panel A shows that users who logged on before time zero almost always won coupons, whereas those who logged on later than minute zero won coupons with a probability of zero.[24] This pattern suggests that a user's first log-on time is a near-perfect measure of whether the user wins any coupon. The redemption rate shows a similar jump from about 0.9 before minute zero to 0 after that point. The redemption rate for users who logged in even earlier – prior to the five-minute run-up to the coupons' runout time (the "< -5 minute" bin) – is slightly lower. Panel B reports average out-of-pocket spending (total spending minus the subsidy amount) and unsubsidized spending (total spending minus the transactions that involved coupon redemptions) by log-on time. We find a jump in coupon winners' out-of-pocket spending relative to non-winners. For coupon winners in the "< -5 minute" bin, the jump is smaller and proportional to the lower coupon redemption rate among that group. Apart from the jump in spending around minute zero, spending exhibits an upward-sloping trend for users within 15 minutes of minute zero, suggesting that users who logged on earlier in the rush have lower overall spending capacity. This pattern motivates us to compare users closest to the minute zero cutoff to tease out the causal effect of coupons.

To examine potential selection into treatment based on log-on time, Figure 5 repeats the exercise in Figure 4, but with observed user characteristics as the outcome variable. We examine three "pre-treatment" user characteristics that we have available in the database: age, gender, and weekly account cash inflow in 2019 (a proxy for wealth). Graphical patterns in Figure 5 suggest no apparent difference in characteristics around minute zero. In Appendix Table B.2, we report statistically significant, but small differences in age, gender, and income in the repeated cross sections. For example, we find weekly cash inflow in 2019 to be 22.04 yuan (standard error = 6.92 yuan) smaller among coupon winners than among those who did not win. This represents a nearly 2% difference from the non-winners group mean. We view the statistical difference as largely a consequence of our large sample size, and we believe any potential bias that would result from such differences in characteristics would be small.

To further address potential selection on observable or unobservable user characteristics, we report regression results from (1) repeated cross-sectional estimations with and without controls for age, gender, cash inflows, and week fixed effects; and (2) panel data estimation with user fixed effects and week fixed effects. Table 2 summarizes our main estimation results. As discussed in Section 3, our preferred specification focuses on users who participated in Coupon Rush events, and arrived within the -5 to 5

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[24] We draw coupon status and log-on time information from two separate databases, so the relationship is not entirely mechanical. As mentioned in Section 2.2, we find very small number of cases in which users did not win coupons even if the log-on time was before minute zero, and in which users won coupons although the log-on time was after minute zero. We treat these cases as random errors in coupon status.

minutes window. Columns 1 and 2 present repeated cross-sectional estimation results, where one cross section consists of winners and non-winners in a given round of Coupon Rush, repeated for six different rounds. Column 1 includes no control variables. Column 2 includes user characteristics (age, gender, and average weekly account cash inflow in 2019) and week fixed effects. Both specifications suggest that coupon winners increased total spending by 300 yuan relative to non-winners. Consistent with an average coupon subsidy of roughly 73 yuan (Appendix Table B.1), we find coupon winners' out-of-pocket spending increased by 225 yuan. We find unsubsidized transactions in the winners' group increase by about 30 yuan. Column 3 reports panel regression estimates with user fixed effects and week fixed effects. Column 3 shows the estimation results for both total and out-of-pocket spending are remarkably similar with those from cross-sectional estimations. We find a larger unsubsidized spending increase of 50 yuan in the panel estimation, which is about a 5% increase relative to the non-winners' group mean. This finding suggests the stimulus effect is not offset by reduction in unsubsidized transactions, therefore generating net increase in consumption. We discuss issues of consumption substitution in Section 4.3.

Figure 6 presents a parallel trend test comparing spending of the winners group (-5 to 0 minutes) and non-winners group (0 to 5 minutes) from ten weeks before to three weeks after the Coupon Rush event. We choose the 13-week event window to ensure the underlying estimation data is a balanced panel of users for which we can track spending patterns since the COVID shutdown.[25] Event week "0" (i.e., the treatment week) is the week of the Coupon Rush event. Lines on the graph represent simple averages across users in the corresponding group. Because some non-winning users at event week 0 could be coupon winners in previous and/or future weeks (and vice versa), we remove subsidized transactions in computing pre and post periods for both winning and non-winning trends, so that the trends reflect the net impact of winning a coupon at the treatment week.[26] Panel A (panel B) of Figure 6 suggests that out-of-pocket (unsubsidized) spending of winners and non-winners tracks each other closely except for a divergence that occurs at the treatment week, providing strong support to the identification assumption that the two groups are largely identical except for the treatment.

Besides the parallel pre-trends and an obvious jump of winners spending on the treatment week, there are several other data patterns worth noting. First, trends suggest that coupons have no obvious lagged effect following the treatment week. This pattern suggests limited intertemporal substitution, in which case we would have seen a reduction in winners' spending relative to non-winners after the treatment week. We present a more formal analysis of intertemporal spending patterns in Section 4.3. Second, trends of the non-

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[25] That is (from Figure 1), the first week of the provincial shutdown is the 10th week prior to the first round of Coupon Rush, and our data end the 3rd week following the last round of Coupon Rush, hence the balanced 10-week-before, 3-week-after event window.

[26] In unreported analysis, we have confirmed that parallel trends hold exactly without such adjustments.

winners group are smooth throughout the event window, suggesting little if any anticipatory spending responses (e.g., users who do not win coupons this round save consumption in anticipation of potential wins in future rounds).[27] Finally, although we examine raw trends in Figure 6, in Appendix Figure B.6 we report a panel regression analysis, augmenting equation (1) with leads and lags terms of the coupon-winning status $1(Coupon)_{it}$. This regression yields a stimulus-impact estimate – the current-week effect coefficient indicates 221.8 yuan increase in out-of-pocket spending – which is similar to the main estimate in Table 2, column 3; on the other hand, the leads and lags terms are in general small and statistically insignificant. The general pattern that emerges from both Figure 6 and Appendix Figure B.6 suggests that coupons' effect concentrates on the treated week, with limited evidence of anticipatory and lagged effects; this pattern supports our preferred estimation strategy that uses simple panel variation of $1(Coupon)_{it}$ within a given user across different weeks.

In Appendix Table B.3, we report the marginal effects of different types of coupons by replacing the $1(Coupon)_{it}$ indicator in equation (1) with four separate indicators for winning dining coupons, shopping coupons, gym/travel coupons (which always come as "suite" in a given coupon packet, and, thus, for which individual effects cannot be estimated separately), and books/digital devices coupons (which also come in "suite"). Not surprisingly, books/cellphones coupons have the largest spending boost due to the cellphones coupon's large minimum spending requirement. Because much of coupon redemption occurs in the dining and shopping sectors, these two categories comprise roughly 47% of spending stimulus. We also find precise impacts of coupons on unsubsidized spending, except for gym/travel coupons, for which the unsubsidized spending effect is close to zero, and statistically insignificant.

Figure 7 reports heterogeneous treatment effect by age groups (panel A), gender (panel B), and wealth deciles (panel C). The coupon program's effects are slightly larger for certain groups: those who are between the ages of 20 and 40, females, and those who are potentially wealthier – with the caveat that account cash inflows are imperfect measures of wealth. Overall, we conclude that the stimulus effect of winning coupons emerges across the board, and it does not appear to concentrate in particular subgroups of users.

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[27] The coupon program is widely expected due to the week-ahead announcement of its entire implementation schedule. Following Hsieh, Shimizutani, and Hori (2010), we note that there are no significant changes in spending during the week of March 25 when the program is announced. In unreported analysis, we find a similar stimulus effect for the final round of Coupon Rush event which is not subject to the anticipation concern. The lack of significant anticipation effect is consistent with coupons' small face value and the highly competitive nature of the Rush events.

Appendix Table B.2 reports additional robustness specifications in which we vary users included in the analysis samples using alternative log-on time windows (-5 to 5 minutes, -10 to 10 minutes, all users within 10 minutes, all users within 20 minutes). Our results are similar across the board.

4.3. Do Coupons Generate *Net* Increase in Spending?

One concern with the impact of the coupon program is that an increase in coupon winners' spending may be offset by a decrease in purchases "elsewhere", leading to an overstatement of the coupon program's *net* spending effect. In this subsection, we consider three different types of spending substitution, and assess the degree to which they might influence our interpretation of the stimulus effect.

Does increase in subsidized spending cause decrease in unsubsidized spending? No. Quite the opposite, as we mention earlier in Section 4.2, we find winners *increase* unsubsidized weekly spending by 25 to 50 yuan (Table 2). For example, if coupons have induced a consumer to make shopping trips that would not otherwise occur, the consumer may make "unplanned buying" during the trips.

To be clear, this finding is not mechanical – this is not the scenario where a consumer is at a store where she would like to redeem the Alipay coupon for *one* item so she would then use Alipay to pay for *all* the items in her basket. Because we define unsubsidized spending as spending not involving the *transaction* that uses coupon, the unsubsidized spending finding implies the consumers have made *separate* transactions using Alipay that would not otherwise take place.

Does increase in spending this week cause decrease in spending in future weeks? In Section 4.2 (Figure 6), we discussed spending pre-trends and their implications for *anticipatory* substitution. We next examine the possibility of *intertemporal* substitution of subsidized and unsubsidized spending by looking at whether coupon winners compensate for their initial spending increase by reduced spending in subsequent weeks. To operationalize this test, we construct "k-week" spending measures, defined as total, out-of-pocket, and unsubsidized spending in the k weeks following (and including) the current week. We then use the k-week spending as the outcome variable in equation (1). On the right-hand side of the equation we control additionally for the number of coupon-winning weeks in the corresponding look-ahead window. For example, in our 3-week specification, our outcome variable is the sum of spending in weeks, t, $t+1$, and $t+2$, our key dependent variable is whether the user won coupons in week t, and we control for the number of weeks (0, 1, or 2) that the user won coupons in weeks $t+1$ and $t+2$. Note that, if an initial spending increase in week 1 is compensated by a decline of spending in weeks 2 and 3, then the 1-week specification

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will show a positive effect, while the 3-week specification will show zero impact.[28] We only have 2 weeks of data following the final round of the Coupon Rush, so there are necessarily composition changes as we expand the look-ahead window. We compare our primary, 1-week specification results to 3-week and 6-week results. Note that the 6-week data essentially use treatment only from the first three rounds of the Coupon Rush events.

Table 3 summarizes the results. Column 1 repeats column 3 of Table 2. Columns 2 and 3 present 3-week and 6-week specifications. We find some evidence that the initial spending increase of coupon winners is partially offset in the subsequent weeks. Looking at out-of-pocket spending, we find a 12% reduction in the effect size about 3 weeks into the initial treatment, and a 23% reduction in 6 weeks. We find a larger reduction in unsubsidized spending, which drops by 50% in the 6-week regression (although still marginally significant). We interpret our results as suggestive of a mild intertemporal substitution. Still, our results provide strong indications that the coupon treatment does not increase spending once they are no longer in effect (i.e., we can strongly reject the hypothesis that the 3-week effect size is *larger* than the 1-week effect size). That is, the small-value coupons do not have a sustained effect in consumption stimulation that lingers after the subsidy ends.

Does increase in spending on Alipay cause decrease in spending on other platforms? Yet another potential concern about substitution is that winning a coupon may induce users to make transactions with Alipay which would otherwise have been made through different venues such as WeChatpay or cash payment, thus leading to an overestimation of the coupon program's net stimulus effect. We do not have data on these alternative venues which together account for about 28% of all consumption in Shaoxing. Rather, we exploit information on Coupon Rush program participants' characteristics and prior spending pattern to provide indirect tests of cross-platform substitution. The general idea is to hone in on subgroups that are less likely to exhibit cross-platform substitution because of winning a coupon.

We first examine heterogeneity of coupon's stimulus effects across individuals with different usage intensity. For a heavy user who is already making many transactions through Alipay, the coupon treatment – which worth about 73 yuan in face value (Appendix Table B.1) – should provide a smaller incentive for cross-platform substitution than an occasional user. To operationalize this test, we group program participants into deciles by the monthly transaction value on Alipay in 2019. Appendix Figure B.7 shows that usage intensity varies widely among the coupon program participants. Users in the second-least active group spent on average 486 yuan on Alipay, while users in the second-most active group spent an average

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[28] This method is commonly used in the medical and health economics literatures in studying, for example, the impact of one-time surgical treatment on individuals' medium-run survival.

7,669 yuan. We then estimate heterogeneous effects of winning a coupon across these spending deciles. Appendix Figure B.7 reports a similar stimulus impact for active users. In fact, the stimulus impact of winning a coupon, both in terms of out-of-pocket spending and unsubsidized spending, is similar across spending deciles.

Another way to concentrate on "spontaneous" users is to leave out individuals who signed up for Alipay just to participate in the Coupon Rush events. We find that dropping users who registered Alipay after January 2020 (about 3% of all participants) has no impact on our stimulus impact estimates.

In summary, our examination of active and non-active Alipay users provides no evidence that the coupon's stimulus impact is subject to substantial degree of cross-platform substitution. There are other channels of substitution that we cannot assess with our data. For example, we do not have information on users' family structure and thus cannot directly test for an intra-household substitution where, if one member of a couple wins the coupon, then the couple will be more likely to use that member's account to pay for purchases that they might otherwise have put on the other member's account.[29]

5. Business Impact and Stimulus Mechanism

5.1. Empirical Evidence

In this section, we use merchant information to cast light on the mechanisms underlying the coupon program's stimulus impact. We use transaction data to construct customer flow information of all shopping and dining merchants, which together comprise over 60% of all merchants registered with Alipay in the city. We then analyze how coupon participants flow among firms of different size, popularity, and price. Our primary analysis examines shopping merchants. We repeat the same analysis with dining merchants in the appendix, which shows qualitatively similar results.

Our merchant data can be considered as a simple reorganization of the transaction database by coupon-receiving merchants. A merchant in our data is a business that was registered with the Alipay platform on or before January 1, 2019, and made at least one transaction between the months of April and May 2020. Alipay's merchant platform is populated by a large group of inactive business users and a small group of actual users that make frequent transactions. To avoid overstating our effective sample size, and to minimize the influence of inactive users on our findings, we restrict our sample to the 12% of merchants (N=45,067) that collectively accounted for 90% of all revenues in 2019. We observe the firm's customer

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[29] We have examined effects of male participants under age 31 and female participants under age 29 – those below the average age of marriage in Shaoxing – and found similar stimulus impact relative to the population average effect.

pool, defined as consumers who made at least one transaction through Alipay in the merchant-week, for each merchant on each week between April 3 and May 14, 2020. We observe whether the customers participated in the week's Coupon Rush event, and if so, whether they won any coupons. Among coupon winners, we further distinguish those who made subsidized transactions from those who made unsubsidized transactions in the merchant-week.

We group merchants into decile bins of baseline (year 2019) revenue. For each bin, we calculate the composition of customers by coupon-winning and coupon-redeeming status. Figure 8, panel A plots the results. The dash-circle line shows fraction of customers who participated in the Coupon Rush during the week, but did not win any coupon ("Non-winners"). In a given week, roughly 3% of total customers are non-winners. The fraction of customers from non-winners is very similar across firm size bins. Next, we turn to coupon winners. We divide "winners" into two groups: those who made subsidized transactions, and those who made unsubsidized transactions. The dash-triangle line of Figure 8, panel A shows that winning customers who made unsubsidized transactions consist of roughly 8% of weekly customer flow, and are also quite stable across the various types of merchants. By contrast, the fraction of winner customers who redeemed coupons rose almost monotonically from near 0% in the smallest merchant-size bin, to above 8% for firms in the top decile bin.

In the rest of Figure 8, we "decompose" this pattern into heterogeneity by baseline transaction volume (panel B) and baseline "price" (i.e., revenue per transaction, panel C), where baseline is again defined using year 2019 data. Panel B shows that winners do not differentially favor more popular merchants. In contrast, panel C shows that coupon winners, when redeeming coupons, favor merchants that sell pricier goods. As in panel A, coupon winners or non-winners do not favor pricier options when making unsubsidized transactions.

The patterns in Figure 8 suggests a difference-in-differences-style interpretation. We are interested in how the coupon program affects the distribution of customers across merchants. We ask the question: what kind of merchants did program participants patronize when they (1) did not win coupons, (2) won coupons but did not intend to redeem any coupons, and (3) won coupons and intended to redeem coupons. Presuming that the coupon program has no impact on spending behavior of non-winners, the dash-circle line of Figure 8 provides a measure of the "natural" distribution of coupon participants customer in the absence of coupon treatment.[30] The dash-triangle line – the distribution of coupon winners who made

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[30] Note the line need not be flat. For example, the priciest firms may have a wealthier customer pool that is less represented in the Coupon Rush participants. If this is the case, the fraction of program participants will appear to be smaller. In our case, however, we do find that non-winners are almost equally represented in the shopping category, in terms of patronizing firms of different sizes and with different price levels.

unsubsidized transactions – provides a measure of the natural distribution of coupon winners without the intention to redeem coupon. Thus, the *level difference* between the dash-circle and dash-triangle lines reflects the odds of winning a coupon in the Coupon Rush (0.74 on average, consistent with the summary statistics of coupon-winning odds in Table 1); the *slope difference* between the lines reflects the pure effect of winning a coupon on the customer distribution. We find that the two lines are largely parallel to each other for firms in the smallest five deciles, while there is a slight uptick in winners flow to larger firms (especially those with higher transaction volumes, as shown in Figure 8, panel B). This pattern suggests that the coupon program has, at best, induced a mild shift of unsubsidized spending toward larger firms. Finally, the sharp slope difference of the connect-triangle line (i.e., share of coupon winners that made subsidized transactions in the merchant-week) from both non-winners and non-redeeming winners suggests a tremendous shift of consumer flows to larger firms when customers intend to redeem coupons.

In Appendix Figure B.8, we repeat the same analysis with dining firms. Different from shopping firms, dining firms in our data exhibit a wide price spread (top decile spending per transaction is 1,195 yuan, or about 171 USD per dining transaction, which likely captures luxury options). In the case of the dining sector, the lines representing both the "non-winners" and "winners, not redeeming coupons" are downward-sloping. This indicates that individuals who would patronize very expensive restaurants are less represented among the Coupon Rush participants. However, there remains parallel trend. Once again, we find evidence of substantial shift toward pricier options when customers intend to redeem coupons.

The findings in Figure 8 have important implications for both consumers and businesses. On the consumer side, it suggests that coupons stimulate spending by directing consumption toward pricier options that the consumers would not otherwise prefer in the absence of the coupons' minimum spending requirement. On the business side, because larger and pricier merchants comprise the bulk of the market share, most of the subsidy from coupon benefits necessarily accrues to those merchants. Our analysis reveals that the coupon program *disproportionally* favors merchants that are large and sell more expensive goods, i.e., these merchants receive more business from coupon winners even on a percentage basis. For example, for both shopping and dining firms, those in the bottom price decile typically receive almost zero benefits from the coupon program. This unequal allocation might not be optimal, for example, from an employment stimulus perspective if firms that sell less expensive goods and services also account for substantial share in the labor market.[31]

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[31] We do not have detailed firm size data for Shaoxing. However, in Zhejiang province (where Shaoxing located), a substantial share of employment belongs to enterprises "below designated size," i.e., firms deemed very small from a national economic account point of view. For example, retail enterprises below designated size (annual revenue less than 5 million yuan and/or with fewer than 50 employees) account for over 76% of industry-wide employment, and

In the next section, we formalize these arguments using a conceptual model of spending with coupon incentives. We then analyze gains from alternative coupon designs with less stringent minimum spending requirements.

5.2. A Model of Consumer Choice with Minimum-Spending Coupons

The empirical finding of consumption distortion and unequal business benefits distribution motivates the question of what can be done to reduce such distortion, and to improve consumer welfare. In this section, we present a conceptual model of consumer spending with coupons. To make clear how to think about distortionary effects, we use the simplest possible setting – a one-time shopping decision given a discount coupon with minimum spending requirement. We use a simple numerical example to show that our model can rationalize several key empirical findings, including the bunching around minimum spending requirements (Figure 3), the resulting spending stimulus (Figure 4), and preferences for redeeming coupons with more expensive merchants (Figure 8). We then use our model to analyze consumer welfare under counterfactual coupon designs. We note that the *optimal* design of coupons is beyond the scope of our paper; the main purpose of the conceptual model is to provide intuitions that facilitate our discussion of the stimulus mechanism.

Model Setup. Consider a situation in which consumer i must make a one-time shopping decision for a consumption occasion. We employ a discrete-continuous framework, in which the discrete choice is the merchant selected and the continuous choice is the number of units consumed.[32] We assume that there are N merchants with different price levels and are differentiated by quality. The consumer chooses the preferred choice set n (or merchants) from these N merchants, and the optimal amount of expenditure y within the choice set. For simplicity, we assume the consumer's preferred choice set contains exactly one merchant. That is, the consumer first picks the merchant, and then decides how much to spend of that merchant. The consumer has a non-negative endowment E_i drawn from a set E. We assume consumer utility follows a Cobb-Douglas function form and the consumer's utility maximization problem is:

$$\max_{n\in\{1,2,\dots,N\},y_n,z} u_n(y_n,z) = A_n(y_n)^{\alpha_n}z^{\beta}$$

$$\text{s.t. } y_n + z = E_i$$

$$y_i y_j = 0 \ \forall \ i \neq j$$

where $A_n(y_n)^{\alpha_n}$ is the utility of spending y_n yuan in choice set n, and z^β is the utility from the numeraire good. We denote n as a quality index such that $n_1 > n_2$ if and only if $\alpha_{n_1} > \alpha_{n_2}$ and $A_{n_1} < A_{n_2}$. These conditions imply that the first unit of a good with a lower index increases the utility more because of its lower price, but the marginal utility diminishes faster than higher quality goods. Following <u>Hanemann (1984)</u>, we set $y_i y_j = 0$, which ensures that each consumer could only choose one consumption set.

One can show that the indirect utility function of choice set n for consumer i is:

$$v_n(E_i) = A_n \frac{\alpha_n^{\alpha_n} \beta^\beta}{(\alpha_n + \beta)^{\alpha_n + \beta}} E_i^{\alpha_n + \beta}$$

and the optimal spending in choice set n is:

$$y_n^\star(E_i) = \frac{\alpha_n}{\alpha_n + \beta} E_i$$

and the consumer's optimal choice set is:

$$n^* = \text{argmax}_{n \in \{1,2,\dots,N\}}\{v_n(E_i)\}$$

Now consider the impact of a minimum-spending requirement coupon that returns t yuan if the spending exceeds x yuan. Intuitively, there are two groups of consumers whose choice will be barely affected. The first group is consumers whose original optimal spending $y_{n^*}^*$ is already far above x. For these high-income consumers, the coupon simply serves as a pure t-yuan increase in endowment which leads to a small increase in spending without changing the original choice set n^*. The second group is consumers whose $y_{n^*}^*$ is far below x. For these low-income consumers, the coupon's payment incentive t is not enough to cover the disutility of raising consumption to x, and thus it is of their best interest to not use the coupon. The primary consumers of interest are those fall in between these two groups. For these consumers, their original consumption choice $y_{n^*}^* < x$, but the coupon incentive t and the utility increase from consuming potentially higher-quality goods make it welfare-improving to deviate from the original consumption choice and reach the minimum-spending requirement x (in particular, to reach *exactly* x for some consumers).

To formalize these intuitions, it pays to first characterize, in isolation, how the consumer's choice set is affected by t (what happens to n^* upon a marginal increase in endowment), and by x (how does the consumer choose n^* if he or she has a spending target). Consider the following function:

$$g_n(E_i) = \frac{v_{n+1}(E_i)}{v_n(E_i)} = \frac{A_{n+1}}{A_n} \frac{\alpha_{n+1}^{\alpha_{n+1}}}{\alpha_n^{\alpha_n}} \frac{(\alpha_n + \beta)^{\alpha_n + \beta}}{(\alpha_{n+1} + \beta)^{\alpha_{n+1} + \beta}} E^{\alpha_{n+1} - \alpha_n}$$

Note that $g_n(\cdot)$ is monotonically increasing, and we let E_n denote the unique solution of $g_n(E_n) = 1$. Intuitively, E_n is an endowment cutoff beyond which consumer upgrades choice set from n to $n + 1$.[33] Similarly one can define:

$$h_n(x) = \frac{u_{n+1}(x; E_i)}{u_n(x; E_i)} = \frac{A_{n+1}}{A_n} x^{\alpha_{n+1} - \alpha_n}$$

$h_n(\cdot)$ is also monotonically increasing, with a unique solution x_n such that $h_n(x_n) = 1$. We make the following two simplifying assumptions to make our theoretical and numerical analyses tractable.

Assumption 1. Non-overlapping "upgrading" cutoffs.

$$E_1 < E_2 < \cdots < E_{N-1} < E_N \text{ and } x_1 < x_2 < \cdots < x_{N-1} < x_N$$

Assumption 1 implies that the consumer will choose set n if and only if E_i satisfies $E_{n-1} \le E_i < E_n$;[34] if the consumer aims to spend x, he or she will choose set n if and only if x satisfies $x_{n-1} \le x < x_n$.

Assumption 2. Increasing propensity to "upgrade" at higher endowment levels.

$$\frac{\partial}{\partial E_i} \frac{v_{n+1}(E_i + t)}{v_n(E_i)} > 0 \ \forall n \text{ and } \frac{\partial}{\partial E_i} \frac{u_{n+1}(x; E_i + t)}{u_n(x; E_i)} > 0 \ \forall n$$

Intuitively, Assumption 2 says that consumers with higher initial endowment (and thus closer to the upgrading cutoffs in the absence of coupon) will find it more attractive to take the coupon's incentive and "upgrade" their choice set. This assumption ensures that the likelihood of consumers' upgrading to higher-quality goods within any interval between two endowment (or spending) cutoffs can be ordered monotonically by consumers' initial endowment levels.

Proposition 1. *Under Assumptions 1 and 2, one can find endowment levels $E_1 < E_2 < E_3$ such that:*

   (1) for consumers with $E_i < E_1$, the original spending level is below the minimum requirement x, and they do not take up the coupon incentive;

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[33] Our setting is similar to <u>Allenby and Rossi (1991)</u> who develop a demand system for different brands of the same product where the indifference curves of the utility function are linear but rotate in slope as the level of utility increases. Therefore, as the attainable level of utility increases, the marginal utility of some brands will increase while that of other brands will decrease.

[34] This assumption ensures that choice set cutoffs depend solely on endowment, and so consumers in the entire economy can be clearly grouped into different choice sets without overlapping. A more generalized model may relax this assumption and allows the chosen set to depend on other individual characteristics in addition to endowment.

(2) for consumers with $E_1 \leq E_i < E_2$, the original spending level is below the minimum requirement x, and they take up the coupon incentive to raise spending to exactly x ("bunching");

(3) for consumers with $E_2 \leq E_i < E_3$, the original spending level is below the minimum requirement x, and they take up the coupon incentive to raise spending to a level greater than x;

(4) for consumers with $E_3 \leq E_i$, the original spending level is already above the minimum requirement x, and they treat the coupon as a pure discount by t;

(5) for consumers with $E_1 \leq E_i < E_3$, the coupon causes an upgrade to consumption with weakly higher quality.

Proposition 1 predicts a bunching of consumer spending around the coupon's minimum requirement x, and a shift of consumption towards more expensive choices for a set of consumers whose choices would not reach x in the absence of the coupon's minimum spending requirement. Having shown that agents in our model do respond to coupon incentive and favor more expensive goods and services, we now consider the effect of relaxation of the coupon's minimum spending requirement.

Proposition 2. *Relaxing coupon's minimum spending requirement x:*

(1) strictly increases the number of consumers who can use the coupon without upgrading to higher choice sets;

(2) weakly increases the total coupon redemption rate;

(3) strictly increases total consumer utility of the society.

Intuitively, relaxation of x reduces choice constraints and improves utility. Note that Proposition 2 does not ensure government revenue neutrality as reduced x might lead to reduced total stimulus amount. However, more consumers (from lower endowment groups) will be able to reach the minimum spending requirement, thus increasing the pool of agents who will participate in the coupon program.

A Numerical Example. Appendix A contains the proofs for Propositions 1 and 2. Here provide a simple parametrization of our conceptual model, and generate a numerical simulation of *Propositions 1 and 2*. Note that we do not attempt to "calibrate" the model according to moments in the real data. The numerical example is used to illustrate the basic intuition underlying our conceptual model of spending with coupons.

In practice, however, we have confirmed that our qualitative conclusions are robust to alternative parametrization of the model. We set $N = 4$, with $A_1 = 7, A_2 = 3.9, A_3 = 2, A_4 = 0.95, \alpha_1 = 0.08, \alpha_2 = 0.3, \alpha_3 = 0.5, \alpha_4 = 0.7$ and $\beta = 0.2$. We assume that consumer endowment follows a gamma distribution $\Gamma(8,5)$ with an upper bound of ¥80 and a lower bound of ¥20. The average endowment is ¥40.76. We simulate a total of 100,000 consumers, and we randomly assign 60% of the consumers with coupons. We run separate simulations with four different types of coupons; [¥5 off ¥15+], [¥10 off ¥30+] and [¥15 off ¥45+]. Notice that we fix the coupon's ¥t/¥x ratio to be 1/3. That is, on a per-user basis, the stimulus effect size is exactly 3 if the coupon is redeemed. Our goal is to analyze spending, customer flows, and consumer welfare with these coupons of different minimum spending requirement.

Figure 9, panel A displays the distribution of consumer spending under alternative coupons. Note the figure is analogous to the empirical patterns of Figure 3, the difference being that in our simulation we can observe transactions even if they do not meet the minimum spending requirement. Panel A provides a numerical representation of *Proposition 1*, featuring sharp bunching exactly around the spending requirements. Having shown that agents in our model do respond to coupons' minimum spending requirements, we now turn to the analysis of merchant customer flows. Figure 9, panel B provides an analogous plot to Figure 8, showing the fraction of business customers who made coupon-eligible purchases. Our simulation results indeed are consistent with the hypothesis of Section 5.1. With the highest minimum spending requirement coupon [¥15 off ¥45+], only merchants that sell the most expensive goods (choice set 4) receive business from coupon winners. With coupons that have lower minimum spending requirements, the *same* set of agents are more evenly spread across merchants. These simulation results confirm our conjecture of the mechanism underlying Figure 8's pattern: minimum spending requirements induce consumers to spend for more expensive options that they would not otherwise prefer. We discuss policy implications next.

5.3. Policy Implications

We offer several policy comments based on our empirical evidence and welfare analysis of the coupon program. First, both our empirical and theoretical analyses suggest that the coupon program leads to a disproportionate favor for large business that sell more expensive goods and services. Issuing coupons with smaller minimum spending requirements would alleviate such a distributional pattern, while at the same time increasing total consumer surplus. In principle, with a fixed budget, a government may issue more smaller-value coupons to achieve the same amount of spending stimulus achieved by offering fewer

higher-value coupons. Of course, this assumes that the additional coupons will be taken up by consumers. We believe that this is a reasonable assumption, given the excess demand for coupons (Figure 2).

Second, our model also casts light on an alternative, potentially easier, solution to distributional concerns by allowing consumers to spread a coupon's minimum spending requirement across multiple transactions. For example, one might imagine a coupon that returns ¥30 reimbursement once shopping spending accumulates to ¥90+. In theory, such a design is equivalent to decomposing the original [¥30 off ¥90+] coupon into a "use-all-or-lose-all" bucket of many small-value components (e.g., 10 coupons each with [¥3 off ¥9+] face value). Such a coupon design would preserve the stimulus magnitude while reducing the consumers' incentive to upgrade to a more expensive choice set because the minimum spending requirement would no longer need to be satisfied in a single transaction.

6. Discussion and Conclusion

6.1. Discussion

In this section, we briefly summarize the key properties of the coupon program. A tool purely designed to stimulate spending, the coupon stimulus model does not provide payment assistance and financial alleviations like many cash payment-based stimulus programs do. However, we hope that several unique features of the program – including its ability to quickly boost spending and to target specific sectors – can make it a useful addition to the policy maker's toolbox for economic stimulus.

Cost and Effectiveness. The coupon program features a small treatment size per person. The average subsidy value received by coupon winners is 73.3 yuan (Appendix Table B.1), which is about 0.13 percent of the annual per capita income of Shaoxing in 2019. Although a small treatment size *per se* is not an advantage of the program, it does allow the program to reach a big swath of the city population while at the same time remain fiscally feasible to the city government.

Although the treatment size is small, coupons' spending incentives prove to be effective in generating quick and strong spending responses. The use-it-this-week-or-lose-it design prompts an immediate increase in spending. For every 1 yuan of government subsidy, out-of-pocket spending increases by 3 yuan. From a purely fiscal cost-effectiveness perspective, such a rate of return is much higher than most cash payment-based stimulus programs, where estimated consumer spending per dollar of government subsidy ranges between 0.2 to 0.8.[35] In total, the coupon program itself generated 850 million yuan (121

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[35] This range is based on the marginal propensity to consume (MPC) estimates from the following programs: 1999 Japan shopping coupon program (Hsieh, Shimizutani, and Hori, 2010), the 2001 U.S. tax rebates (Shapiro and Slemrod,

million USD) spending in six weeks. This corresponds to a recovery of 13% of the Alipay platform-wide spending loss and 8% of the city-wide consumption loss in 2020Q1.

Targeting. Coupons can be designed to target business sectors that are hit hardest in the economic downturn, such as shopping and restaurants. On the consumer side, the high coupon redemption rate (89%) suggests the Rush mechanism helps land coupons into the hands of those actually want to use them.

Consumption Distortion. Coupons' minimum spending requirements distort consumers toward pricier goods and services that they would not otherwise choose. Such a choice distortion can be alleviated by setting low minimum requirements or by allowing separate transactions to add up to the minimum requirement.

Scalability. Whether the program's take-up rate and stimulus impact can remain high among a wider swath of the population (or when coupons are issued in larger quantities) has yet to be determined as more cities adopt similar programs. We note, however, that a unique nature of the coupon program financing is that the government can provide subsidy to businesses *ex post*, meaning it does not need to pay for coupons that are not redeemed. This feature could open up the possibility of policy experimentations and lessen the fiscal burden usually associated with traditional stimulus programs for which the government must provide subsidies *ex ante*.

6.2. Conclusion

We have provided an evaluation of one of the first large-scale spending stimulus programs that employ digital coupons as an economic stimulus tool, and we have offered suggestions about ways in which the use of such policy measures could be improved. Our findings show that small-value, "use-it-or-lose-it" coupons provided a significant and immediate spending boost at a low cost. In practice, consumers "upgraded" consumption toward pricier options to satisfy coupons' minimum spending requirements. Our results show that this aspect of the program led to potentially undesirable distributional impacts that favored large firms selling more expensive goods and services. Relaxing coupons' minimum spending requirements could alleviate such distributional concerns without sacrificing consumer welfare. The program can be tractably administered through a mobile payment platform, can be done by a local government with a relatively small budget, and can be tailored to boost spending in specific sectors. We conclude that such a digital coupon program might be new option to add to the policy makers' toolbox for economic recovery.

2003; Johnson, Parker, and Souleles, 2006), the 2008 U.S. tax rebates (Shapiro and Slemrod, 2009), the 2009 Taiwan shopping voucher program (Kan, Peng, and Wang, 2017), the 2011 Singapore growth dividend program (Agarwal and Qian, 2014), and the 2020 U.S. Coronavirus Aid, Relief, and Economic Security (CARES) Act (Chetty et al., 2020; Baker et al., 2020).

Compared to conventional cash-based stimulus plans that aim for deeper, longer-term recovery, the coupon model can be especially useful as an instrument to trigger swift spending response against a sudden economic downturn.

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savings data." University of Chicago, Becker Friedman Institute for Economics Working Paper 2020-82 (2020).

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Figure 1. Consumption Trends, October 2019 - May 2020
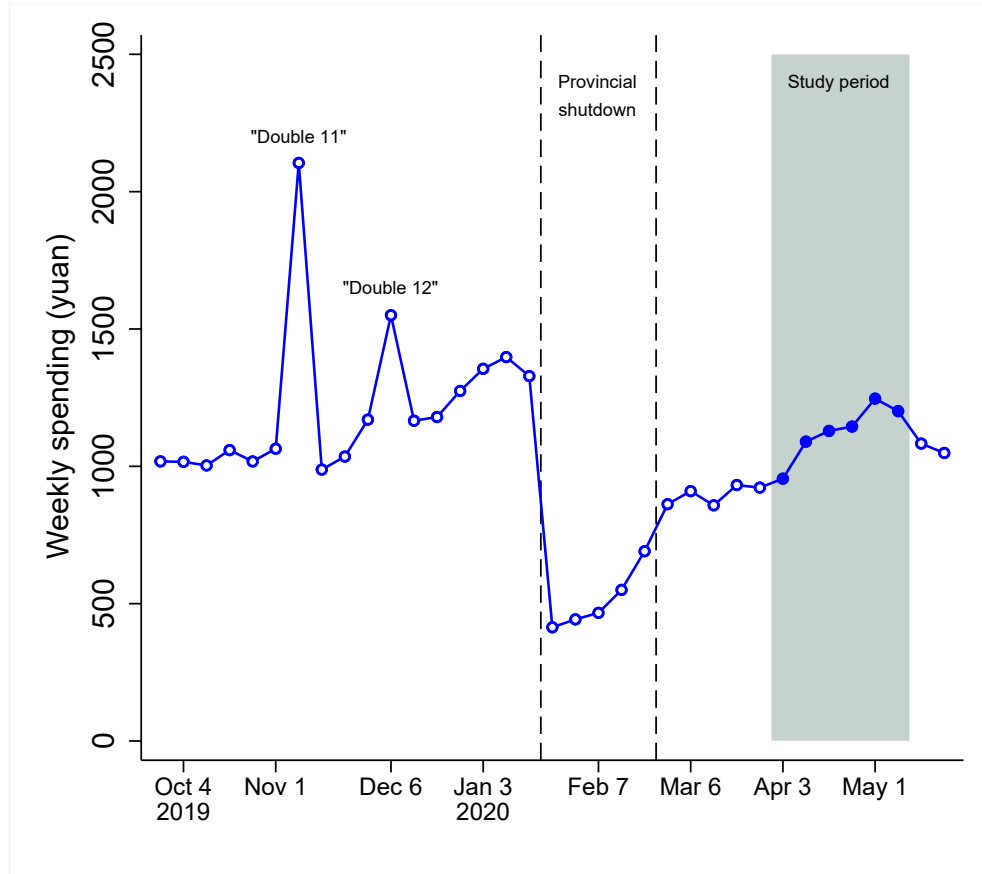
Notes: This graph shows per user weekly total consumption made through Alipay. Sample restricts to a balanced panel of all 1.57 million users who participated in the Coupon Rush events. The two major spikes correspond to the week of the November 11 Singles' Day shopping holiday ("Double 11") and its December 12 spin-off ("Double 12"). "Provincial shutdown" indicates the period between Zhejiang province's COVID-19 shelter-in-place order issuance and Shaoxing city's re-opening date. "Study period" highlights the six weeks with Coupon Rush events. 1000 CNY ≈ 144 USD in 2019.

Figure 2. Click Traffic During Coupon Rush Events
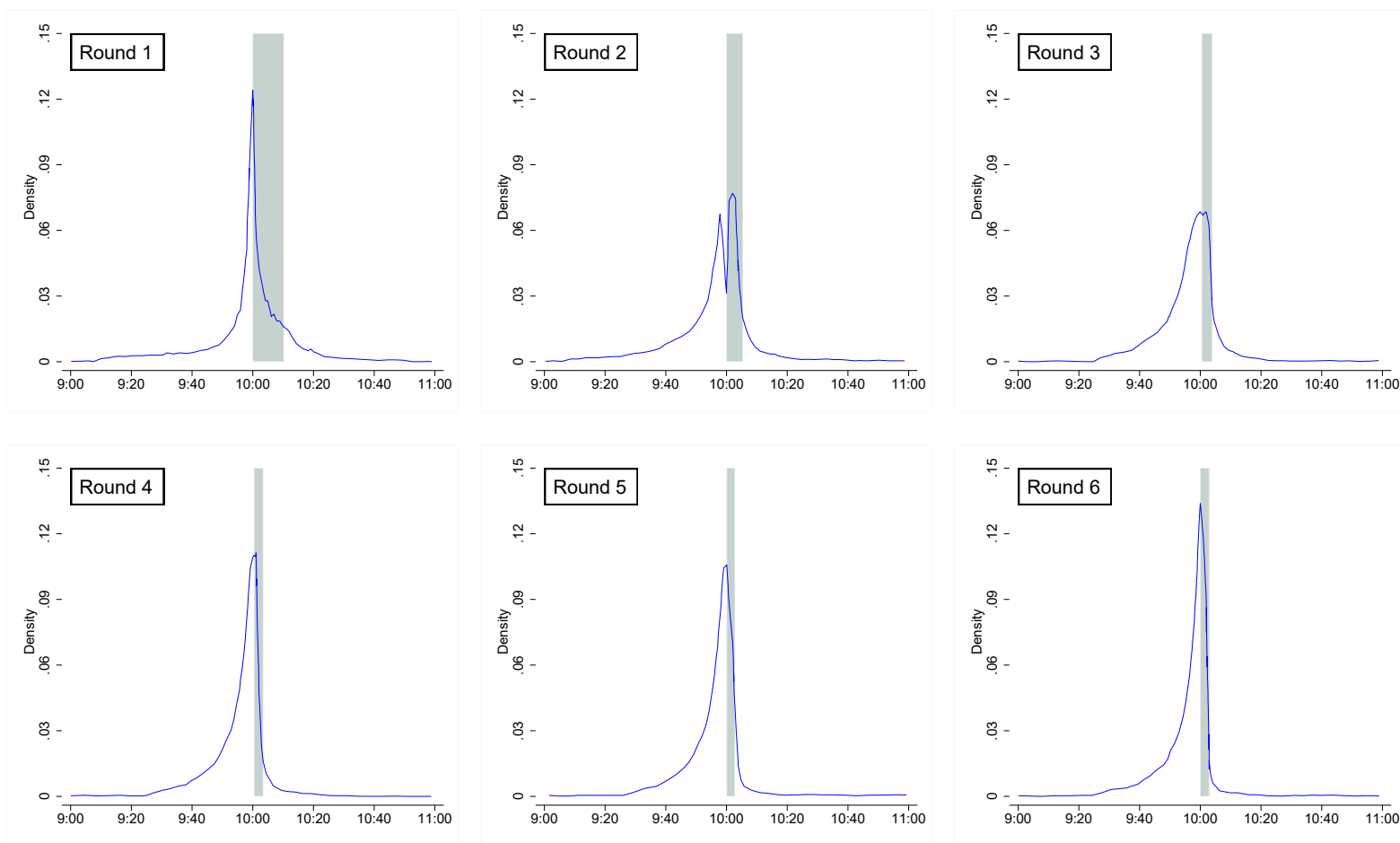
Notes: Graphs show click traffic of Alipay's Coupon Rush portal. Horizontal axis is time in hh:mm (am). Panels show the first event (Friday, April 3, 2020) through the sixth event (Friday, May 8, 2020). Highlighted area indicates the period between the Coupon Rush event activation (10:00 am) and the moment when the last coupon is claimed. Round 2's traffic dips shortly before the activation time in a momentary connection loss due to web traffic overload.

Figure 3. Value of Transaction with Coupon Redemption (Subsidized) and without Coupon Redemption (Unsubsidized)
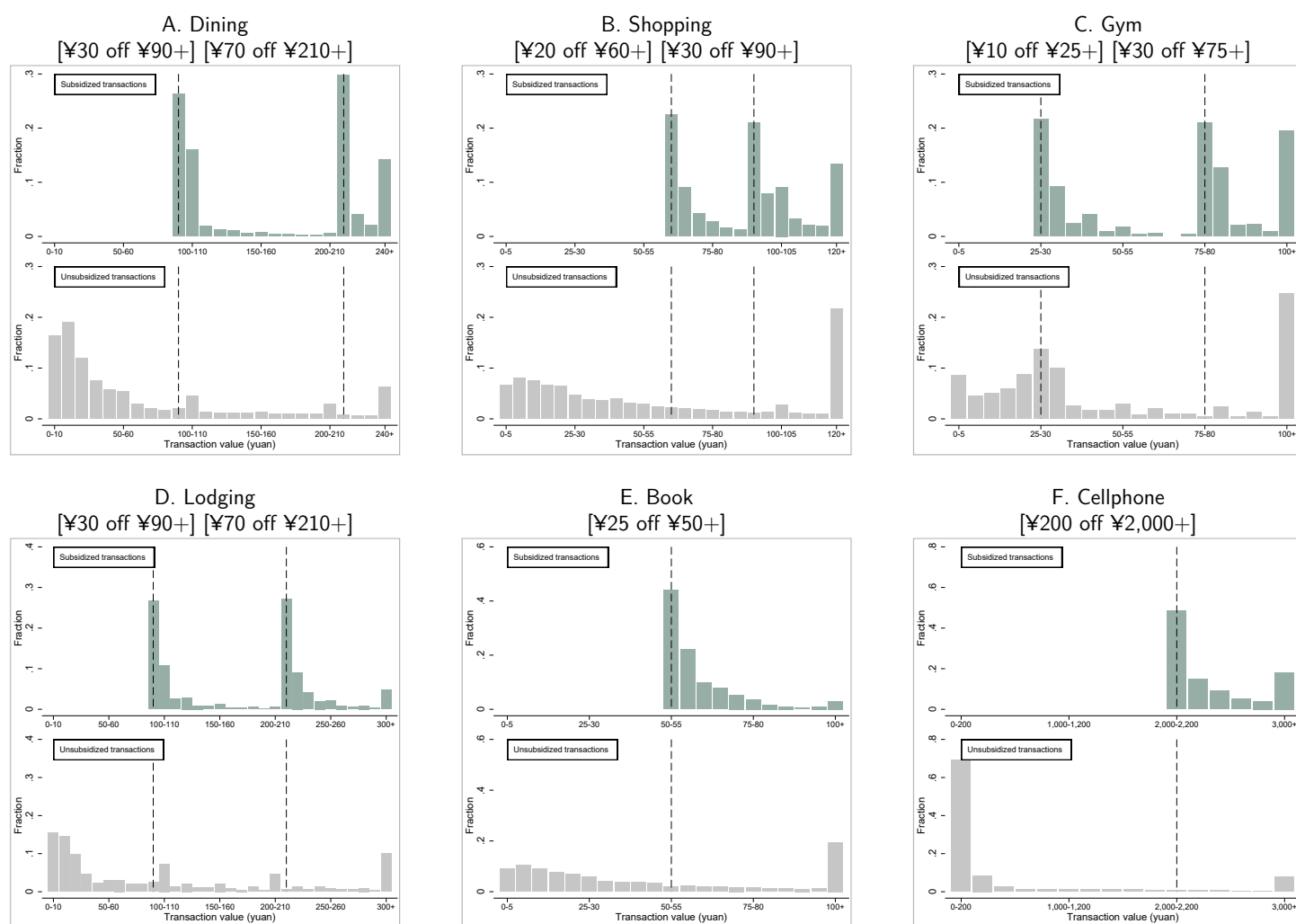
Notes: Graphs show distributions of transaction value by whether a coupon was redeemed ("subsidized transaction"). For each subsidized transaction, we randomly match it with a transaction that didn't involve coupon redemption and occurred at the same merchant on the same day ("unsubsidized transaction"). Panels correspond to different coupon categories. Coupon specifications (e.g., ¥30 off purchase over ¥90) are listed in the panel title. Vertical dashed lines mark the coupons' minimum consumption requirements.

Figure 4. Coupon-Winning and Subsequent Week's Spending

A. Coupon-winning and coupon redemption
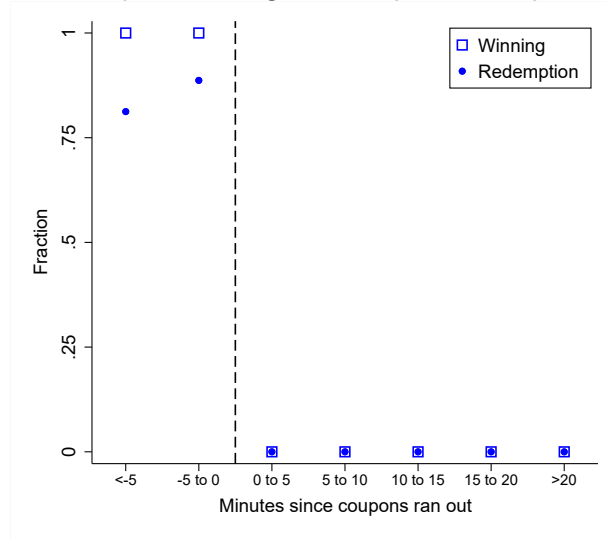
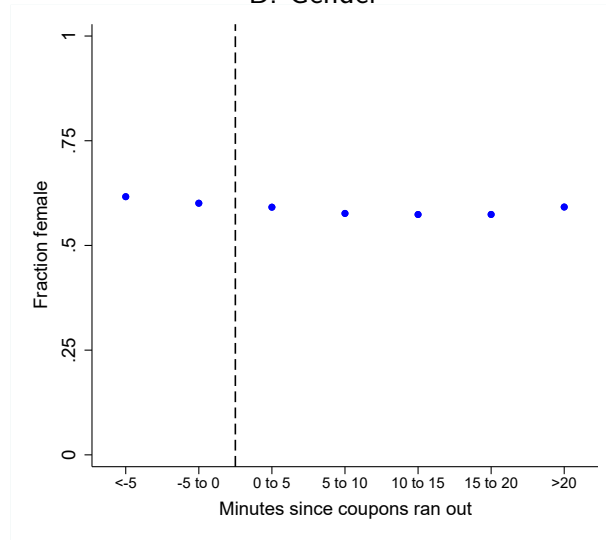## B. Spending in the subsequent week
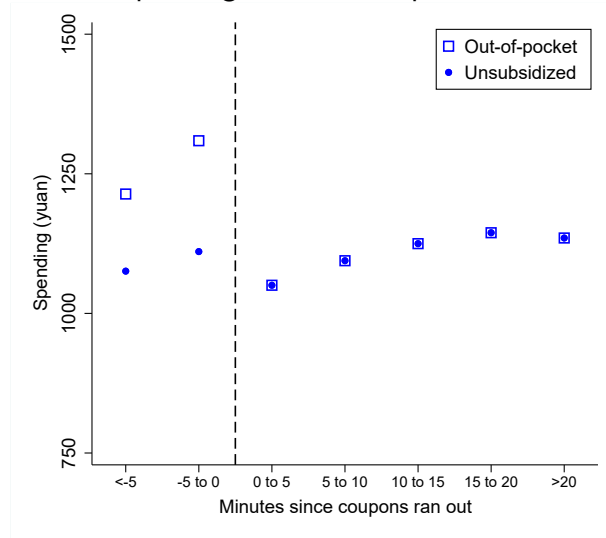
Notes: Graphs show coupon-winning, redemption, and subsequent week's spending as a function of relative time of a user's first attempt to click and log onto the Coupon Rush portal during the event day (0 = the minute when the last coupon was claimed). Over 0.95 million users (out of 1.57 million participants) fall in the "-5 to 0" and "0 to 5" minute bins. "Winning" is the fraction of users winning at least one coupon. "Redemption" is the fraction of users redeeming at least one coupon. "Out-of-pocket" spending is total spending minus the portion paid by the coupon. "Unsubsidized" spending is total spending excluding transactions that redeemed any coupon.
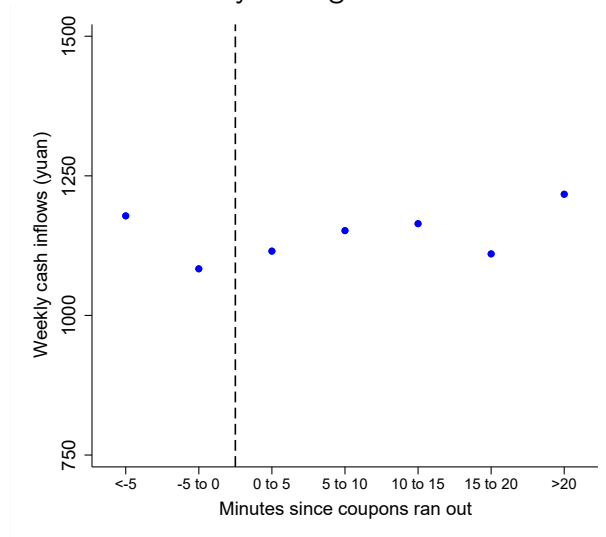
Figure 5. Coupon Rush Participants' User Characteristics

A. Age
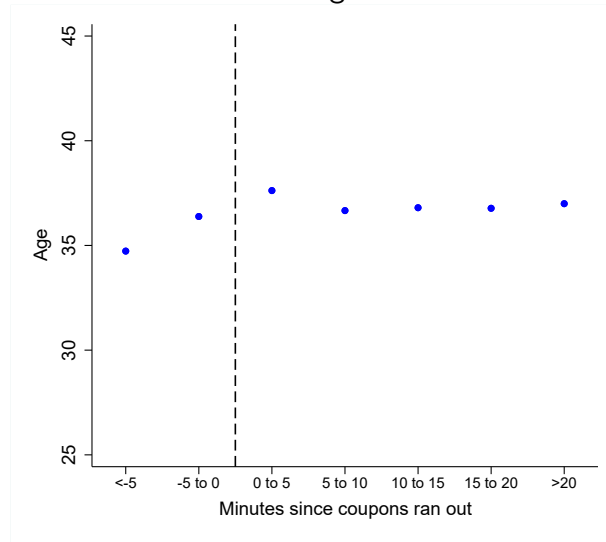
B. Gender

### C. Account weekly average cash inflow in 2019

Notes: Graphs show age, gender, Alipay account cash inflow (i.e., a proxy of wealth) as a function of relative time of a user's first attempt to click and log onto the Coupon Rush portal during the event day ($0 =$ the minute when the last coupon was claimed). Over 0.95 million users (out of 1.57 million participants) fall in the "-5 to 0" and "0 to 5" minute bins.

Figure 6. Event-Time Trends in Weekly Spending

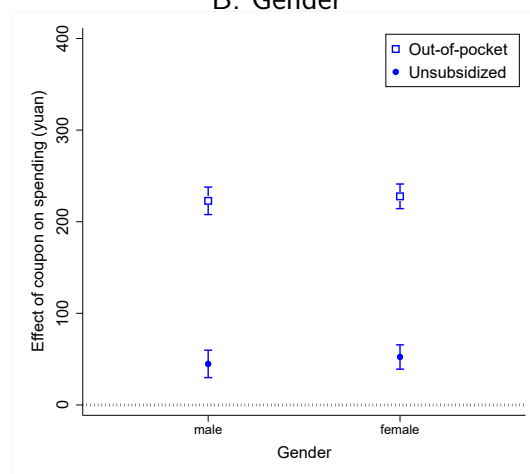A. Out-of-pocket spending
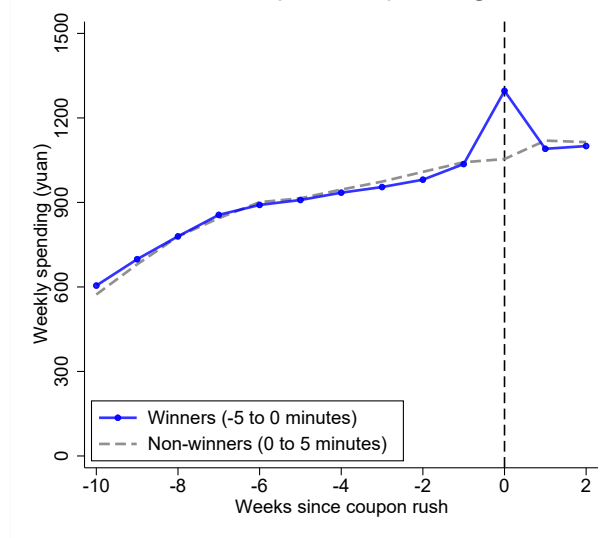
B. Unsubsidized spending
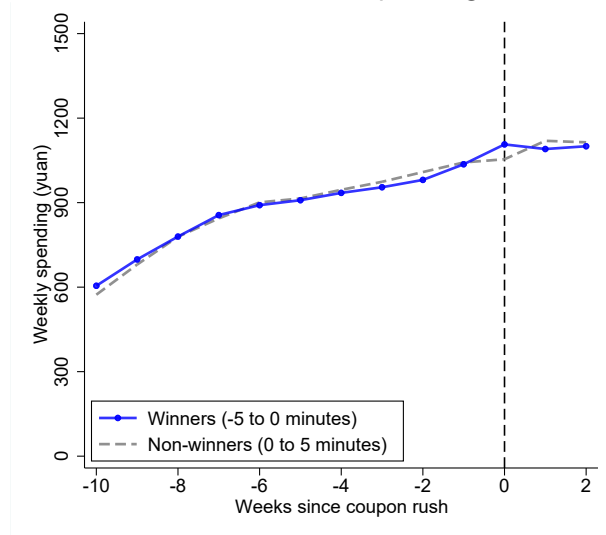
Notes: Graphs show weekly spending as a function of weeks relative to the Coupon Rush event. The underlying data is a balanced panel of users who participated in each of the six rounds of coupon rush events. For each round, the data include participants who logged onto the Coupon Rush portal -5 to 0 minutes (winners) and 0 to 5 minutes (non-winners) since the moment when coupons ran out. The lines represent weekly spending of these two groups of users averaged across six rounds of coupon rush events. Event week "0" represents the Coupon Rush event. Both winning and non-winning trends control for serial correlation in coupon treatment (i.e., winning coupons in previous and future rounds) by removing subsidized transactions in pre and post periods. "Out-of-pocket" spending is total spending minus the portion paid by the coupon. "Unsubsidized" spending is total spending excluding transactions that redeemed any coupon.

Figure 7. Heterogeneous Effects of Winning a Coupon on Subsequent Week's Spending

A. Age
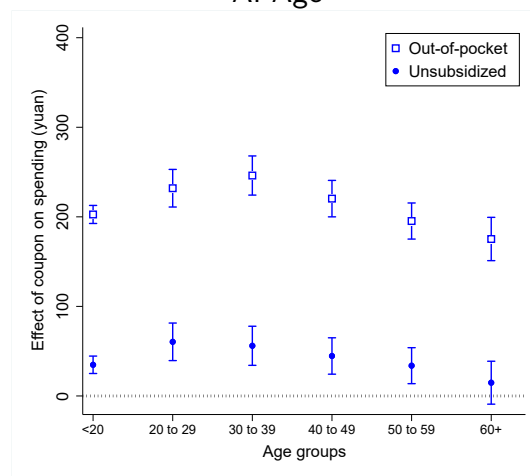
B. Gender

C. Account weekly average cash inflow in 2019

Notes: Graphs report interaction coefficients of coupon-winning and indicators for user characteristics group. "Out-of-pocket spending" is total spending minus the portion paid by the coupon. "Unsubsidized spending" is total spending excludin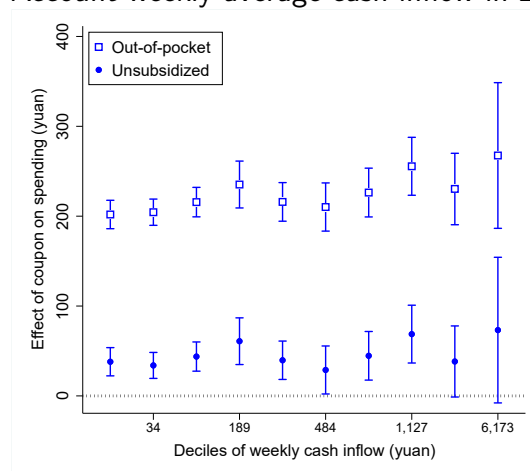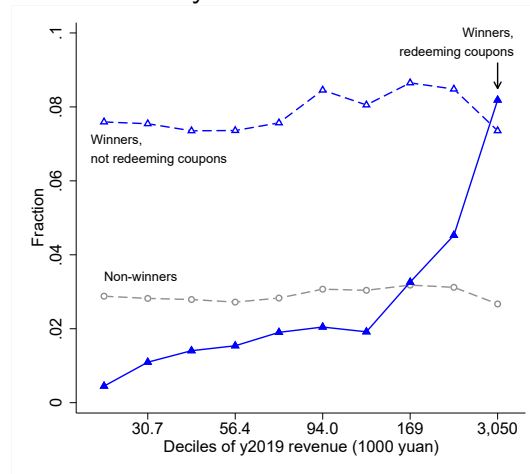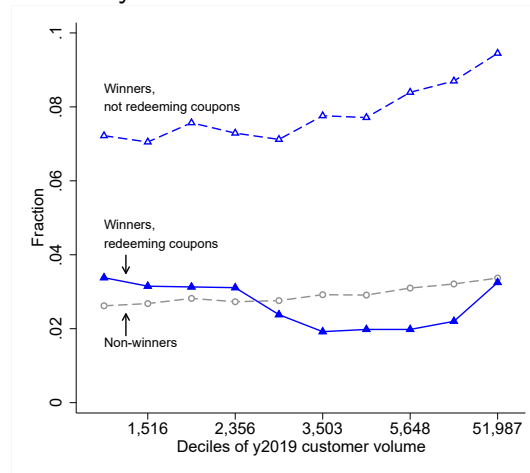g transactions that redeemed any coupon. Panel C horizontal axis shows mean weekly cash inflow within decile bins. Bars show 95% confidence interval constructed using standard errors clustered at the user level.
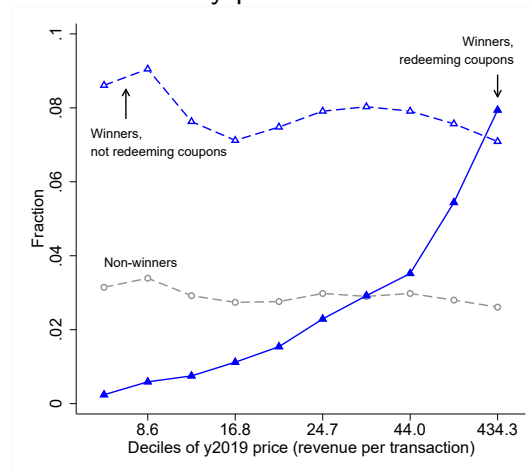
Figure 8. Shopping Merchants' Weekly Customer Distributions by Coupon-Winning Status

A. By revenue in 2019

B. By transaction volume in 2019

C. By price in 2019

Notes: Graphs report distributions of firm's weekly customer distributions by coupon-winning status. "Non-winners" are fraction of customers that participated in the week's Coupon Rush but did not win any coupon. "Winners, not redeeming coupons" are fraction of customers that won coupon(s), but did not make any coupon-eligible transactions. "Winners, redeeming coupons" are fraction of customers that won coupon(s), and made coupon-eligible transactions. "Price" is defined by the firm's average revenue per transaction in year 2019.

Figure 9. Numerical Example of the Conceptual Model: Alternative Coupon Minimum Spending Requirements

A. Consumer spending

B. Merchants' customer distribution
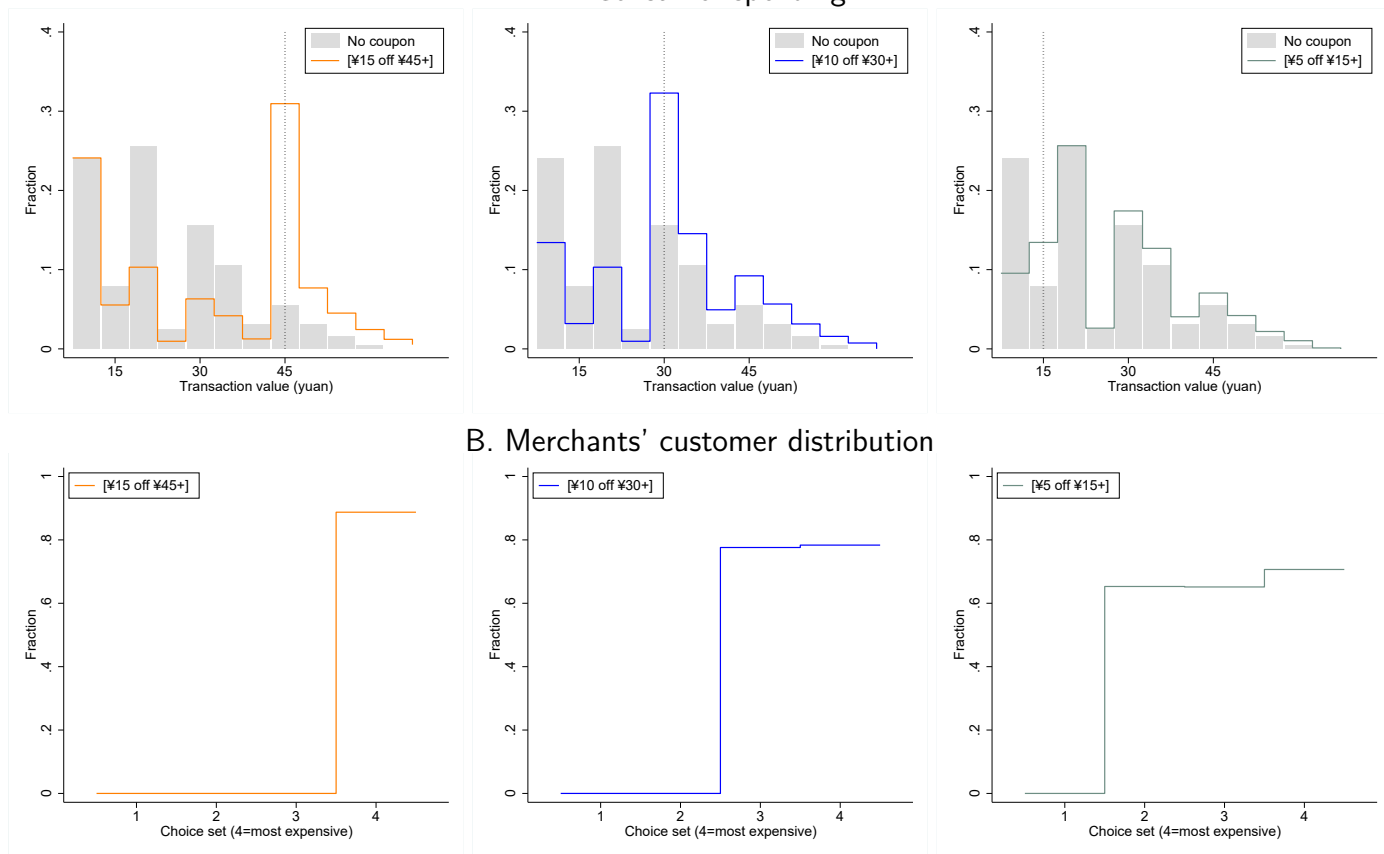
Notes: This figure shows results from a simulation of our conceptual model with alternative coupon designs. Panel A shows the distribution of consumer spending. Panel B shows the fraction of customers redeeming coupons by merchant type. See Section 5.2 for more details.

Table 1. Summary Statistics

	(1)	(2)	(3)
User log-on time window (minutes):	[-5,5]	(–,20]	All

A. Panel

Total spending	1,035.29	1,038.64	1,057.82
	[10,634.45]	[10,493.67]	[6,662.11]
Coupon: any	0.324	0.307	0.300
Coupon: dining	0.134	0.127	0.125
Coupon: shopping	0.310	0.294	0.287
Coupon: gym, travel	0.051	0.049	0.048
Coupon: books, digital	0.021	0.020	0.019
Observations	5,753,520	5,944,530	9,390,690

B. Repeated cross-sections

Total spending	1,300.06	1,298.05	1,296.39
	[6,715.09]	[6,677.17]	[6,669.66]
Coupon: any	0.744	0.732	0.726
Coupon: dining	0.305	0.304	0.301
Coupon: shopping	0.711	0.701	0.695
Coupon: gym, travel	0.117	0.117	0.116
Coupon: books, digital	0.047	0.047	0.046
Age	36.55	36.52	36.53
	[11.57]	[11.58]	[11.58]
Female	0.601	0.599	0.598
Weekly cash inflow (y2019)	1.099.81	1,103.37	1,104.29
	[3,865.38]	[3,884.62]	[3,903.85]
Observations	2,473,939	2,567,066	2,590,146

Notes: Panel data (panel A) include all Coupon Rush participants (i.e., users who participated in at least one round of Coupon Rush) over six weeks. Repeated cross-section data (panel B) include Coupon Rush participants during weeks in which they actually participated in the event. In panel B column (1), observation numbers are 2,470,699 ("Age"), 2,473,939 ("Female"), and 2,075,636 ("Weekly cash inflow"). For these variables, similar variations in observations exist for columns 2-3 depending on data availability. Spending variables are in CNY. 1000 CNY ≈ 144 USD in 2019.

Table 2. The Effect of Winning a Coupon on Subsequent Week's Spending

	(1)	(2)	(3)
Total spending	303.61	283.69	299.34
	(11.46)	(11.28)	(5.13)
Out-of-pocket spending	224.76	225.36	225.68
	(11.46)	(11.99)	(5.13)
Unsubsidized spending	32.16	25.08	49.31
	(11.45)	(11.98)	(5.12)
User characteristics		✓	
User fixed effects			✓
Week fixed effects		✓	✓
Data structure	repeated CS	repeated CS	panel
Standard error adjust.	robust	robust	user clst.
¥OOP per ¥1 subsidy	3.07	3.07	3.08
No-coupon group mean	1,053.57	1,189.09	1,031.87
Observations	1,679,728	1,679,728	5,753,520

Notes: This table shows regression coefficients and standard errors (in parentheses) of spending on an indicator for coupon-winners of the week. Each cell corresponds to a separate regression. "Out-of-pocket spending" is total spending minus the portion paid by the coupon. "Unsubsidized spending" is total spending excluding transactions that redeemed any coupon. "User characteristics" include age, indicator for female, and weekly cash inflow in 2019. "repeated CS" means a repeated cross-section data structure. "user clst." means the standard error is clustered at the user level. "¥OOP per ¥1 subsidy" shows the amount of out-of-pocket consumption stimuli per 1 CNY of coupon subsidy.

Table 3. The Effect of Winning a Coupon on Longer-Term Spending

	(1)	(2)	(3)
	1-week	3-week	6-week
Total spending	299.34	273.82	240.30
	(5.13)	(9.28)	(13.60)
Out-of-pocket spending	225.68	200.30	173.56
	(5.13)	(9.28)	(13.60)
Unsubsidized spending	49.31	23.97	20.09
	(5.12)	(9.27)	(13.59)
User fixed effects	✓	✓	✓
Week fixed effects	✓	✓	✓
No-coupon group mean	1,031.87	3,125.67	6,325.56
Observations	5,737,520	5,737,521	2,876,760

Notes: This table shows regression coefficients and standard errors (in parentheses) of spending in the next k weeks (including the current week) on an indicator for coupon-winners of the week. Each cell corresponds to a separate regression. "Out-of-pocket spending" is total spending minus the portion paid by the coupon. "Unsubsidized spending" is total spending excluding transactions that redeemed any coupon. Standard errors are clustered at the user level.

Appendix A. Conceptual Model Details

A.1. Proof of Proposition 1

We make the following observation about consumer spending:

Remark 1. The optimal spending is monotonically increasing in endowment E_i; total spending increases for larger n (higher quality).

We characterize the endowment cutoffs $E_1 < E_2 < E_3$ with the following four groups of consumers.

Group 1. Natural beneficiaries. If a consumer's optimal spending in their original choice set exceeds x before the introduction of the coupon or with the coupon subsidy, he or she could redeem the coupon without changing the choice set. The subsidy becomes a lump-sum transfer of endowment. These consumers are characterized by the following condition:

$$y_o^\star(E_i + t) = \frac{\alpha_o}{\alpha_o + \beta}(E_i + t) \geq x$$

where o denotes the original (no coupon) choice set. According to Remark 1, we could define a cutoff (lower bound) of this group as E_3 which is defined by

$$y_n^\star(E_3 + t) = \frac{\alpha_n}{\alpha_n + \beta}(E_3 + t) = x$$

where choice set n is defined by $E_{n-1} \leq E_i + t < E_n$. Consumers with endowment $E_i \geq E_3$ belong to Group 1.

Group 2. Upgraders. For this group of consumers, their spending level is less than the minimum spending requirement under the current choice set, even with an increase of endowment of t. But if they upgrade to a higher quality set, it is welfare improving to increase spending above x. These consumers satisfy:

$$y_o^\star(E_i + t) = \frac{\alpha_o}{\alpha_o + \beta}(E_i + t) < x$$

and there exists a choice set j, which satisfies the following conditions:

$$y_j^\star(E_i + t) = \frac{\alpha_j}{\alpha_j + \beta}(E_i + t) \geq x$$

$$\frac{v_j(E_i + t)}{v_o(E)} = \frac{A_j}{A_o} \frac{\alpha_j^{\alpha_j}}{\alpha_o^{\alpha_o}} \frac{(\alpha_o + \beta)^{\alpha_o + \beta}}{(\alpha_j + \beta)^{\alpha_j + \beta}} \frac{(E_i + t)^{\alpha_j + \beta}}{E_i^{\alpha_o + \beta}} \geq 1$$

From Assumption 1, the with-coupon choice set is thus $k = \min_{j}\{j > n\}$, which is the lowest indexed choice set such that the upgrading is welfare-improving. Notice that when endowment gets larger, the expenditure on the same set j strictly increases. By Assumption 2, there exists a lower bound E_2 such that the consumers with $E_2 \leq E_i < E_3$ belong to Group 2.

Group 3. Bunching group. Like group 2, consumers in this group have a spending that is slightly smaller than the minimum purchase requirement of the coupon even with an increase of endowment of t. But they may still be willing to increase spending to exactly x in order to redeem the coupon, since the coupon subsidy could at least cover the welfare loss from the deviating from their optimal choice. Given Assumption 1, all these consumers will choose set m where $x_{m-1} \leq x < x_m$, and they satisfy the following conditions:

$$y_o^\star(E_i + t) = \frac{\alpha_n}{\alpha_n + \beta}(E_i + t) < x,$$

$$y_j^\star(E_i + t) = \frac{\alpha_j}{\alpha_j + \beta}(E_i + t) < x, \forall j \in N,$$

$$\frac{u_m(x; E_i + t)}{v_o(E_i)} = \frac{A_m}{A_o} \frac{x^{\alpha_m}(\alpha_o + \beta)^{\alpha_n + \beta}}{\alpha_o^{\alpha_n}\beta^\beta} \frac{(E_i + t - x)^\beta}{E_i^{\alpha_o + \beta}} \geq 1,$$

Note Assumption 2 ensures the existence of a lower bound E_1 such that all the consumers with $E_1 \leq E_i < E_2$ belong to Group 3.[*]

Group 4. Non-users. The remaining set of consumers do not belong to any of the above groups, and increasing consumption to the minimum spending requirement will reduce utility no matter which choice they pick. Therefore, they choose not to redeem the coupon and keep their original expenditure.

Note that, overall, coupons induce consumers toward higher quality choice sets (part 5 of Proposition 1). In particular, group 2 consumers upgrade their choice set to reach the minimum purchase requirement, i.e., $j > o$ and $y_j^\star(E_i + t) > x > y_o^\star(E_i + t)$.

---

[*] We have assumed away the possibility that group 3 consumers will downgrade to a lower-indexed set when given the coupon treatment. Either of the following two scenarios could rule out the possibility of downgrading: a) The minimum purchase requirement is sufficiently low such that the optimal expenditure in choice sets with a higher index than m already exceeds the requirement x; b) consumers whose original choice set has a higher index than m do not find it welfare-improving to downgrade to choice set m to redeem the coupon.

A.2. Proof of Proposition 2

The consumers who will use the coupon while remaining in the original choice set are characterized by

$$y_n^\star(E_i + t) = \frac{\alpha_n}{\alpha_n + \beta}(E_i + t) \geq x$$

$$E_{n-1} \leq E_i < E_i + t < E_n$$

These conditions still hold when x decreases, so the fraction of consumers who could use the coupon while keeping their original quality level will not decrease.

Only Group 4 consumers were not able to use the coupon. Therefore, to show that relaxing the minimum spending requirement x weakly increases the total coupon redemption rate, it suffices to show there will be no more Group 4 consumers when x decreases. We have shown that the size of Group 1 consumers will never decrease. Group 2 consumers satisfy:

$$y_o^\star(E_i + t) = \frac{\alpha_o}{\alpha_o + \beta}(E_i + t) < x$$

$$y_k^\star(E_i + t) = \frac{\alpha_j}{\alpha_j + \beta}(E_k + t) \geq x$$

$$\frac{v_k(E_i + t)}{v_o(E)} = \frac{A_k}{A_o}\frac{\alpha_k^{\alpha_k}}{\alpha_o^{\alpha_o}}\frac{(\alpha_o + \beta)^{\alpha_o + \beta}}{(\alpha_k + \beta)^{\alpha_k + \beta}}\frac{(E_i + t)^{\alpha_k + \beta}}{E_i^{\alpha_o + \beta}} \geq 1$$

The second and third conditions still hold when x gets smaller. If $y_o^\star(E_i + t) = \frac{\alpha_o}{\alpha_o + \beta}(E_i + t) < x$ no longer holds, those consumers will move to Group 1, who are still able to redeem the coupon.

Group 3 satisfies the following condition:

$$\frac{u_m(x; E_i + t)}{v_o(E_i)} = \frac{A_m}{A_o}\frac{x^{\alpha_m}(\alpha_o + \beta)^{\alpha_o + \beta}(E_i + t - x)^\beta}{\alpha_o^{\alpha_o}\beta^\beta}\frac{(E_i + t - x)^\beta}{E_i^{\alpha_o + \beta}} \geq 1$$

When x decreases, m will reduce to a lower index. If we could show that $x^{\alpha_m}(E_i + t - x)^\beta$ is monotonically decreasing in x holding m fixed, then this inequality will still hold if m changes.

Since $x > y_m^\star(E_i + t)$, we know

$$\frac{\alpha_m x^{\alpha_m - 1}(E_i + t - x)^\beta}{\beta x^{\alpha_m}(E_i + t - x)^{\beta - 1}} = \frac{\alpha_m}{\beta}\frac{E_i + t - x}{x} < \frac{\alpha_m}{\beta}\frac{E_i + t - y_m^\star(E_i + t)}{y_m^\star(E_i + t)} = 1$$

where $y_m^\star(E_i + t) = \frac{\alpha_m}{\alpha_m + \beta}(E_i + t)$. Taking derivative of $x^{\alpha_m}(E_i + t - x)^\beta$ with respect to x, we get

$$\alpha_m x^{\alpha_m - 1}(E_i + t - x)^\beta - \beta x^{\alpha_m}(E_i + t - x)^{\beta - 1} < 0$$

That is, a smaller x still makes the consumers who originally belong to Group 3 satisfy $\frac{u_m(x;E_i+t)}{v_o(E_i)} \geq 1$. The only reason for Group 3 consumers to deviate is to become Group 1 or 2, and thus the fraction of Group 4 will never increase.

Parts 3 of Proposition 2 follows the arguments above. When the purchase requirement decreases, the optimal choice set and expenditure under the original coupon requirement scenario are still attainable. Therefore, a decrease in x will not decrease the utility level of the consumers. From above, we know that there will be more consumers who can maintain their optimal choice while redeeming the coupon. Therefore, the utility level is strictly raised for the entire society.
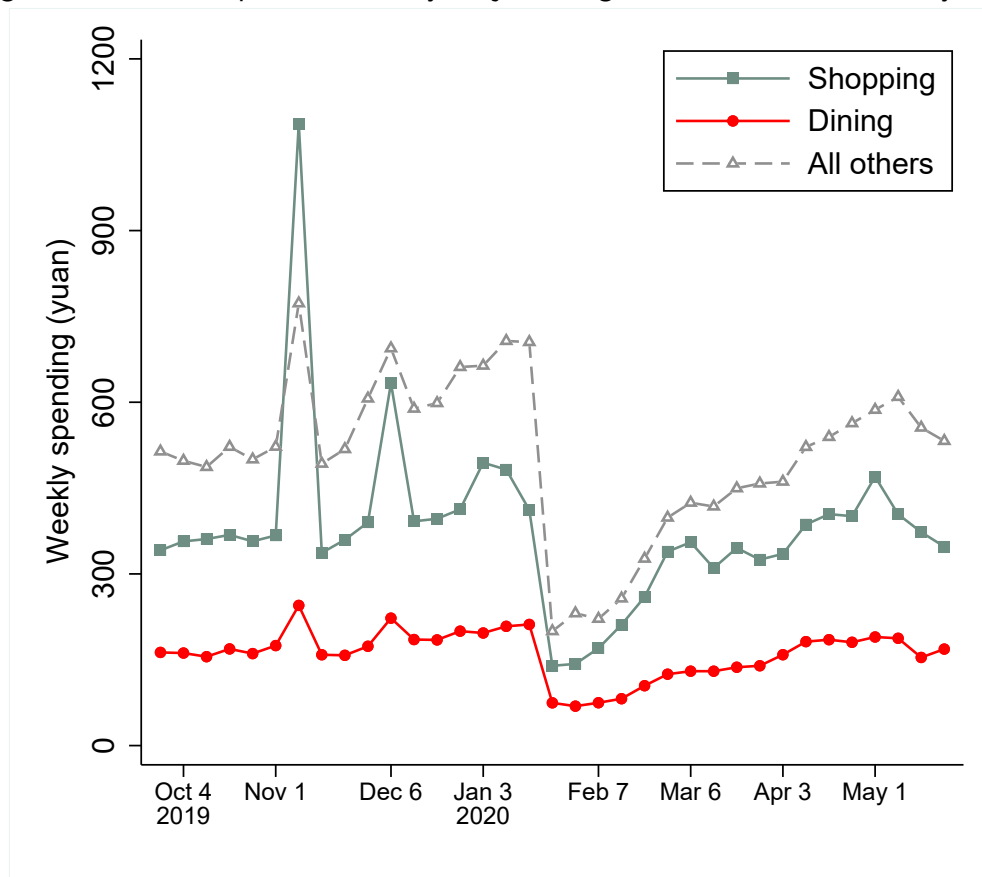
Appendix B. Additional Figures and Tables

Figure B.1. Location of Shaoxing Prefecture and Zhejiang Province


Notes: This map shows location of Zhejiang province (light blue) and the prefecture-city of Shaoxing (deep blue). Lines are provincial borders.

Figure B.2. Consumption Trends by Major Categories, October 2019 - May 2020

Notes: Consumption by receiving merchants' business category. Sample restricts to a balanced panel of all 1.57 million users who participated in the Coupon Rush events. The two major spikes correspond to the week of the November 11 Singles' Day shopping holiday and its December 12 spin-off.

Figure B.3. Example Screenshots of The Coupon Rush Portal
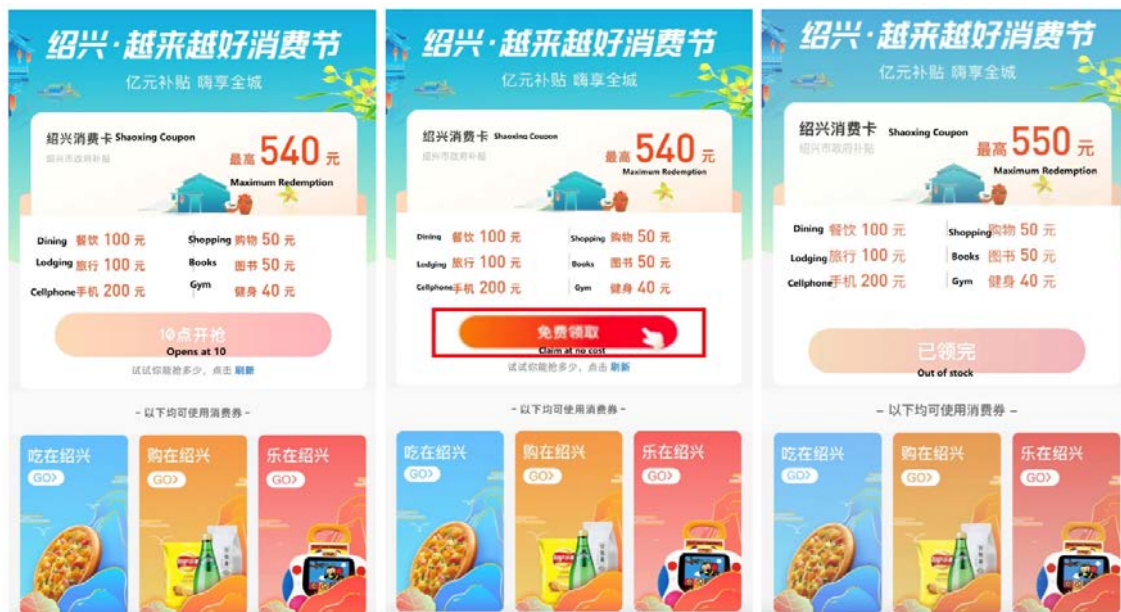
Notes: Screenshots show Alipay app's Coupon Rush portal when logged on before it is activated (left, red button text = "Opens at 10"), after it is activated but before coupons are all gone (middle, red button text = "Claim at no cost"), and after coupons are all gone (right, red button text = "Out of stock"). English translations were added by the authors. Source: weibo.com.

Figure B.4. Example Screenshot of Coupon Redemption

Notes: This screenshot shows an example transaction of ¥100 that met the requirement of a [¥30 off ¥90+] coupon. English translations were added by the authors. Source: weibo.com.

Figure B.5. Age Distribution of Coupon Program Participants
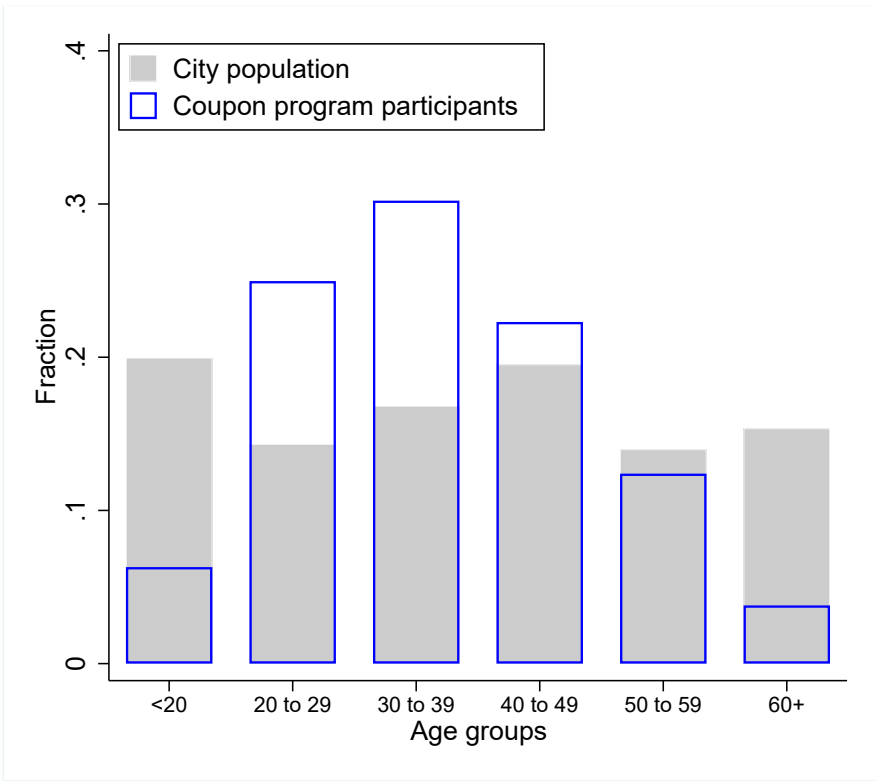
Notes: City population age distribution is sourced from Shaoxing's 2019 Yearbook.

Figure B.6. The Effect of Winning a Coupon on Weekly Spending: Leads and Lags of Coupon-Winning Status
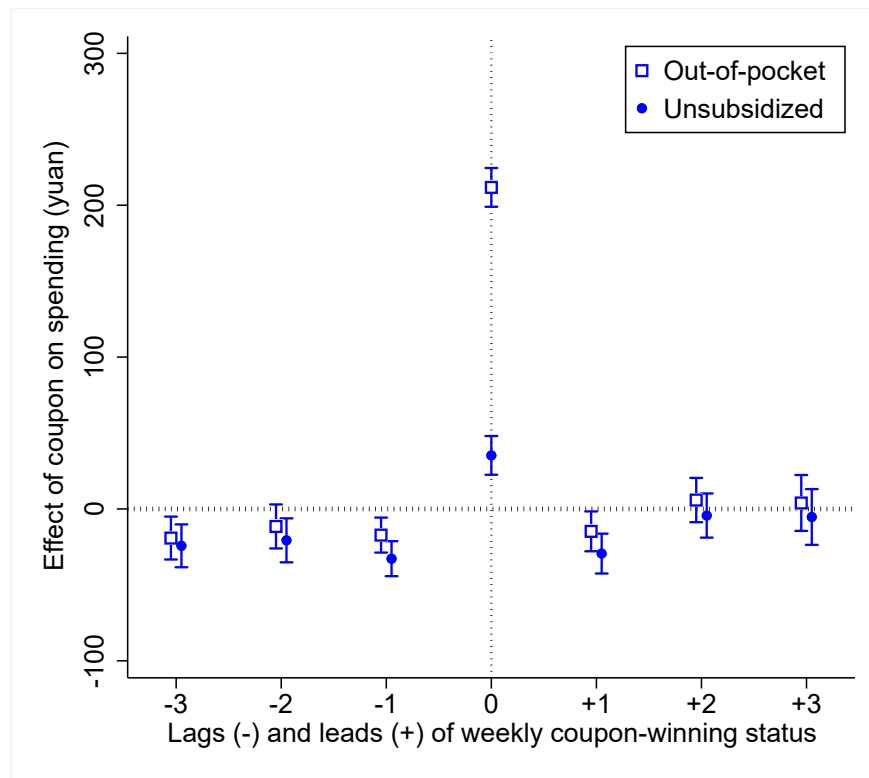
Notes: This figure reports a version of the main panel estimation (equation 1) with additional controls for three leads and three lags of the coupon-winning indicator $1(\text{Coupon})_{it}$. "Out-of-pocket" spending is total spending minus the portion paid by the coupon. "Unsubsidized" spending is total spending excluding transactions that redeemed any coupon. Bars show 95% confidence interval constructed using standard errors clustered at the user level.

Figure B.7. Heterogeneous Effects of Winning a Coupon by Monthly Average Spending in 2019
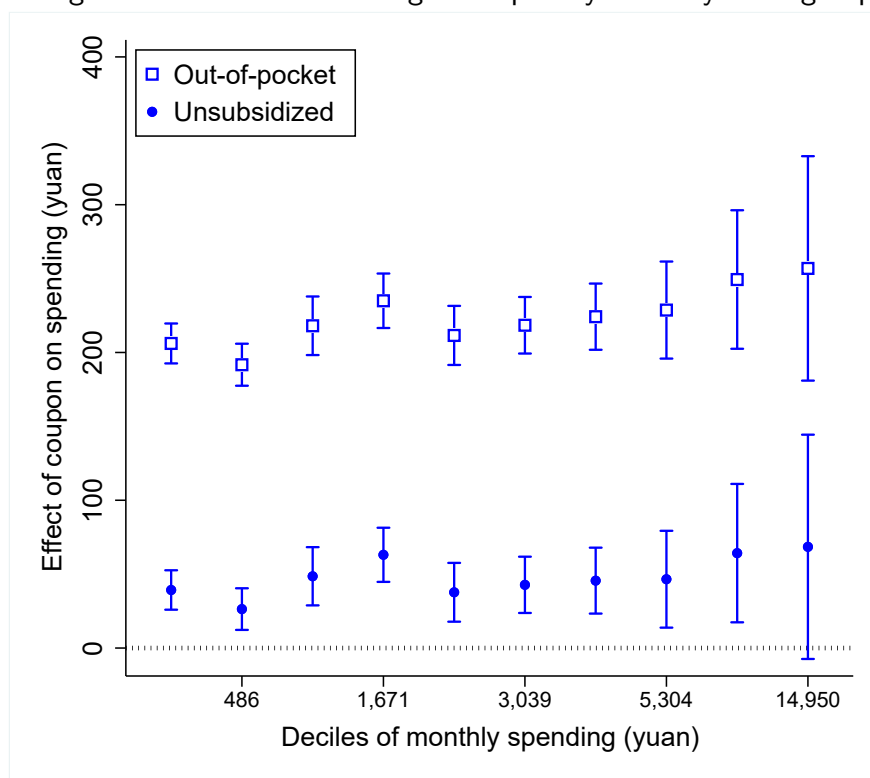
Notes: Graphs report interaction coefficients of coupon-winning and indicators for user's 2019 monthly average spending on Alipay. "Out-of-pocket spending" is total spending minus the portion paid by the coupon. "Unsubsidized spending" is total spending excluding transactions that redeemed any coupon. Horizontal axis shows midpoints of decile bins. Bars show 95% confidence interval constructed using standard errors clustered at the user level.
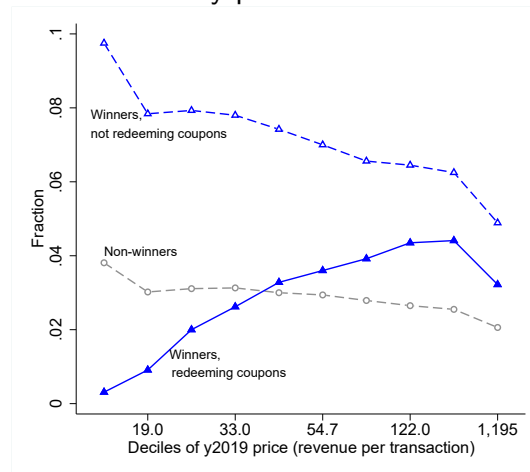
Figure B.8. Dining Merchants' Weekly Customer Distributions by Coupon-Winning Status

A. By revenue in 2019
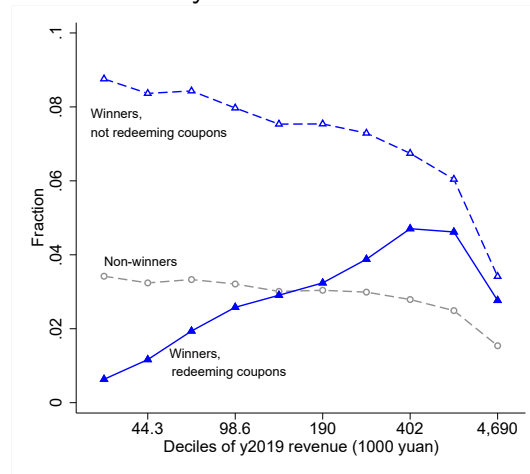
B. By transaction volume in 2019
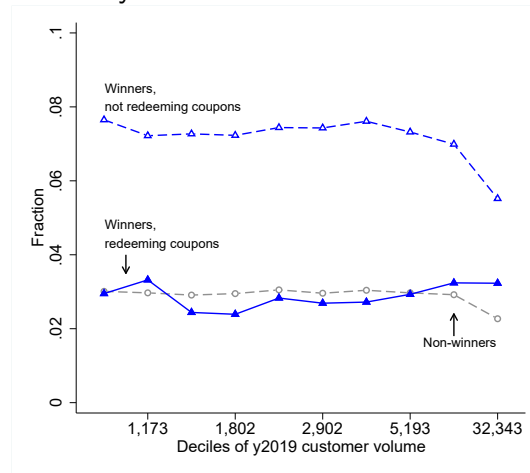
C. By price in 2019

Notes: Graphs report distributions of firm's weekly customer distributions by coupon-winning status. "Non-winners" are fraction of customers that participated in the week's Coupon Rush but did not win any coupon. "Winners, not redeeming coupons" are fraction of customers that won coupon(s), but did not come in to make any coupon-eligible transactions. "Winners, redeeming coupons" are fraction of customers that won coupon(s), and came in to make coupon-eligible transactions. "Price" is defined by the firm's average revenue per transaction in year 2019.

Table B.1. The Effect of Winning a Coupon on Coupon Redemption

	(1)	(2)	(3)
	1(redemption)	¥redemption	¥redemption
Coupon: any	0.859	73.31	
	(0.0003)	(0.06)	
Coupon: dining			73.03
			(0.08)
Coupon: shopping			40.51
			(0.03)
Coupon: gym, travel			15.84
			(0.18)
Coupon: books, digital			94.81
			(0.02)
User fixed effects	✓	✓	✓
Week fixed effects	✓	✓	✓
Observations	5,753,520	5,753,520	5,753,520

Notes: Each column shows a separate regression. Outcome variable is if any coupon is redeemed in the subsequent week (column 1), and the amount of subsidy (columns 2-3). Standard errors are clustered at the user level.

Table B.2. Effect of Winning a Coupon on Subsequent Week's Spending: Robustness

	(1)	(2)	(3)	(4)
User log-on time window (minutes):	[-5,5]	[-10,10]	(−,10]	(−,20]

Panel A: Spending (panel)

Total spending	299.34	298.30	296.49	296.62
	(5.13)	(5.13)	(5.09)	(5.09)
Out-of-pocket spending	225.68	225.02	223.65	223.77
	(5.13)	(5.12)	(5.08)	(5.08)
Unsubsidized spending	49.31	49.58	49.27	49.36
	(5.12)	(5.11)	(5.07)	(5.07)
User fixed effects	✓	✓	✓	✓
Week fixed effects	✓	✓	✓	✓
No-coupon group mean spending	1,031.87	1,013.33	1,015.11	1,027.23
Observations	5,753,520	5,944,530	6,123,804	6,009,042

Panel B: User characteristics (repeated cross sections)

Age	-0.846	-0.761	-0.818	-0.786
	(0.020)	(0.018)	(0.018)	(0.017)
Female	0.0116	0.0105	0.0119	0.0133
	(0.0009)	(0.0008)	(0.0008)	(0.0008)
Weekly cash inflow (y2019)	-22.04	-35.81	-36.92	-36.75
	(6.92)	(6.54)	(6.51)	(6.20)
Week fixed effects	✓	✓	✓	✓
No-coupon group mean age	36.44	36.33	36.33	36.29
No-coupon group mean gender	0.604	0.602	0.602	0.601
No-coupon group mean cash	1,117.8	1,125.2	1,125.1	1,125.3
Observations	1,679,728	1,935,402	2,046,857	2,099,168

Notes: This table shows regression coefficients and standard errors (in parentheses) of spending on an indicator for coupon-winners of the week using alternative user log-on time windows. For example, "(−,10]" means all users who logged onto the coupon-claiming portal within 10 minutes after the moment when all coupons are claimed. Each cell corresponds to a separate regression. "Out-of-pocket spending" is total spending minus the portion paid by the coupon. "Unsubsidized spending" is total spending excluding transactions that redeemed any coupon.

Table B.3. The Effects of Winning a Coupon by Subsidy Category

	(1)	(2)	(3)
	Total	OOP	Unsubsidized
Coupon: dining	268.09	195.79	51.67
	(10.60)	(10.59)	(10.59)
Coupon: shopping	134.61	94.28	15.28
	(5.97)	(5.96)	(5.96)
Coupon: gym, lodging	42.74	27.00	-3.76
	(17.75)	(17.75)	(17.74)
Coupon: books, cellphone	1042.84	948.62	217.45
	(22.85)	(22.78)	(22.50)
User fixed effects	✓	✓	✓
Week fixed effects	✓	✓	✓
No-coupon group mean	1,031.87	1,031.87	1,031.87
Observations	5,753,520	5,753,520	5,753,520

Notes: Each column corresponds to a separate regression. Each coefficient shows the marginal effect of winning a certain type of coupon on subsequent week's spending. "OOP" spending is total spending minus the portion paid by the coupon. "Unsubsidized" spending is total spending excluding transactions that redeemed any coupon. Standard errors are clustered at the user level.