"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. Coupon-winning consumers practice intertemporal substitution by moving up purchases that would have been made months in the future. 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 about 1.57 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 address endogenous selection – the concern that early- and late-arriving consumers might be different in observable or unobservable ways – in a series of tests: comparing observable characteristics including age, gender, and previous-year account cash inflows (i.e., a proxy for income) across winners and non-winners; controlling for these observable characteristics in regressions; testing for common trends in spending prior to the coupon treatment; estimating panel-data models that exploits *within*-individual variation in coupon-winning status by controlling for user fixed effects; estimating dynamic panel-data specifications that test for the "placebo" treatment effect of *future* coupon-winning on *this* week's spending. Together, these familiar causal inference tools to test for both selection on observables (the first two approaches) and selection on unobservables (the latter three) provide support to the identification assumption that users' minor difference in log-on time can serve as a source of exogeneous variation in coupon assignment.

Our study has five sets of results. 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, and coupon 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. 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.[4]

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 during the week of the coupon treatment. This effect size partly 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 608 million yuan (92 million USD) spending in six weeks, which corresponds to a recovery of 10% of the Alipay platform-wide spending loss and 6% of the city-wide consumption loss in 2020Q1.

Third, we analyze the persistence of the program's stimulus effect by tracking spendings of both coupon winners and non-winners after the coupon program has ended. We find evidence of intertemporal substitution of spending where the week-of increase in spending among the coupon winners is explained by expedited consumption that would otherwise have occurred in the following months. Consistent with prior literature, we find stronger evidence of intertemporal substitution among users receiving shopping

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[4] Small-value subsidies help keep coupon redemption rates high as households are unlikely to be liquidity constrained to exercise the coupons. As we will detail in Section 2.2, over the course of the six-week program, the average winner (i.e., those who won coupons in at least one of the six weeks) received a total subsidy of about $31 in 2020 USD. This represents a small share compared to a per capita annual disposable income of 53,839 yuan in Shaoxing as of 2019 (about $8,000 in 2019 USD). We also note that the Shaoxing coupon subsidy value is smaller than most stimulus programs that dispense cash or cash equivalents: in the Japan shopping coupon program (Hsieh, Shimizutani, and Hori, 2010), the shopping coupons are 20,000 Japan yen in total value (about $340 in 2019 USD); in the Taiwan shopping voucher program (Kan, Peng, and Wang, 2017), vouchers totaled 3,600 New Taiwan dollars in value (about $145 in 2019 USD); U.S. tax rebates were in the order of $600 to $1,200 per household (e.g., Johnson, Parker, and Souleles, 2006; Shapiro and Slemrod, 2009; Parker, Souleles, Johnson, and McClelland, 2013).

coupons (semi-durables) and books and digital product coupons (durables) than for users receiving dining coupons (non-durables and services). Overall, we estimate that the six-week coupon program triggers a stimulus effect that lasts for about four months. To put such a time frame in context, the citywide overall spending has recovered to pre-pandemic level in about seven months after the shutdown order was lifted. The persistence of coupon program's stimulus effect is therefore significant/meaningful in curbing the pandemic recession.

Fourth, we try to rule out "leakage effects": the possibility 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 true stimulus effect. 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 potentially due to consumption/shopping complementarity. Second, we explore variation in user's historical spending intensity on Alipay to shed light on potential cross-platform substitution, the concern that winning a coupon induces users to make transactions with Alipay which would otherwise have been made through different venues such as WeChatpay (another popular mobile payment platform in China) or cash payment. We find that winning a coupon has a similar stimulus effect for heavy users who were already 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, or across different payment venues.

Fifth, 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 disproportionally 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.

Our paper demonstrate that digital coupons stimulus can be a policy option that supplements 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) and cash-equivalent spending vouchers (Hsieh, Shimizutani, and Hori, 2010; Kan, Peng, and Wang, 2017). Several unique advantages of the coupon-based stimulus model have become apparent during Shaoxing's economic recovery from the COVID-19 episode. The coupon program achieves an immediate spending stimulus response of ¥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] 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 stimulus effect persists for months, long enough in the context of Shaoxing's COVID recovery. Unlike sector-neutral stimulus tools such as cash, coupons can be designed to target specific sectors, such as in-person services, and thus can help businesses that need the most help during the recovery from a pandemic recession. Together, these features make digital coupons a useful countercyclical fiscal tool, especially in context where a near-zero interest rate limits the scope for conventional monetary policy interventions.

The coupon program also exhibits significant administrative flexibility that is worth noting: (a) several key aspects of the coupon design – such as the minimum spending requirements, coupon expirations, and sector targeting – can be tailored by the government to influence the expected stimulus effects and to

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[5] Evaluations in the context of welfare 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).

better fit local economic recovery needs;[6] and (b) because coupons are not storable and there are no fiscal costs to the government for coupons that are *not* redeemed, the government need not worry about "over-issuing" coupons that will be absorbed into household savings. This could be an attractive feature for governments with relatively small budgets looking for a stimulus program that offers the best bang for the buck. Overall, Shaoxing's experience indicates the coupon program can be tractably administered by the local government. In contrast, most prior stimulus programs we are aware of are financed and administered at the federal level.[7]

Our analysis also 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).

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[6] For example, it seems reasonable to think that reducing the minimum spending requirements may reduce the OOP-per-subsidy metric but encourages more participation; adopting a longer coupon expiration may generate a less immediate consumption response but a more persistent stimulus effects; issuing more coupons for a specific sector may lead to a larger consumption boost in that sector so long as the demand is not yet saturated.

[7] Our paper is among the first evaluations of the digital coupon-based stimulus model. A concurrent research project (Liu et al., 2021) evaluates a similar digital coupon program in Hangzhou. Reassuringly, a part of their analysis also finds large consumption effect in response to coupon subsidy. Shaoxing and Hangzhou are among the first cities that pioneered the digital coupon programs; in the wake of these initiatives, more than 50 cities in China have adopted 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, 2021; Chetty et al., 2020; Coibion, Gorodnichenko, and Weber, 2020; Cox et al., 2020; Eichenbaum, Rebelo, and Trabandt, 2021; Guerrieri et al., 2020) or economic shocks of similar nature. 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 (disposable 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 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,

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[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%).
[9] https://www.forbeschina.com/lists/15

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.

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

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[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.

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

million registered merchants.[14] 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.[15]

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. 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+][16] 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 10,001st 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

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[14] That is, there are 0.6 million merchants in Shaoxing that registered with Alipay. Among these firms, those that operate in the six categories subsidized by the coupons (dining, shopping, gym, lodging, books, digital products) are the ones that can potentially benefit from the stimulus program.

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

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

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. There are 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. This event is announced in May 17, which is after the final round of coupons in our study have expired. Both the transportation coupons and comeback events 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.[17]

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.[18] For each participant, we observe all transactions made for the 52 weeks between Friday, September 27, 2019 and Thursday, September 24, 2020. 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 aggregate transaction-level data to user-weekly level. To match coupons' expiration schedule, we define weeks as the seven days from a Friday to the next Thursday (Section 2.2). Figure 1 plots weekly consumption made through Alipay for the average user throughout our sample period.

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 (see Section 3). Our primary analysis focuses on the six consecutive weeks (April 3 to May 14, 2020) during which the coupon program was in

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

place. We will use data on all available weeks in several specifications where we look at longer-term effects, which enables us to examine spending patterns up to 20 weeks after a user won coupons. We also observe the following user-level information: age, gender, Alipay account cash inflow in 2019 (as a proxy for wealth), and total value and frequency of transactions in 2019.[20]

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 (Figure 1). 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).[21] We discuss the external validity of our results with these caveats in mind.

3. Empirical 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) due to minor difference in log-on timing. 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

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[20] 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.

[21] In Appendix Figure B.5, we summarize age profile of the coupon program participants. 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.

the event, peaking exactly at 10:00 a.m. when the portal was activated for coupon claiming.[22] 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 the *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 seven 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 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 958,920 individuals, or about 61% of all users who participated in the program over its duration.

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

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[22] 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.

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, winners might be *positively selected* if those who are motivated enough to attempt the Coupon Rush portal early have a higher propensity to spend than those who logged on later. Alternatively, winners might be *negative selected* if those most eager to win have lower budget in the first place, and therefore they would spend less relative to non-winners in the absence of coupon treatment; for example, overall spending is slightly higher for non-winners who logged on at later times (Figure 4, panel B).[23] We use a series of tests to evaluate potential selection on observables and unobservables, which we summarize below.

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.

A related exercise is to relax the -5 to 5 minute bandwidth, and see how observable characteristics and the stimulus effect estimates would change as a result. In Table 1 column 2, we tabulate statistics for users who logged on up to 20 minutes after coupons ran out; in column 3, we report statistics for those who ever attempted the portal, regardless of log-on time. We find that average spending, coupon redemption, as well observable characteristics are broadly similar across these alternative bandwidths. In Appendix Table B.2, we report that the stimulus effect estimates are robust to alternative choices of time windows.

Selection on unobservables. Next, we use panel identification approaches to address potential selection on unobservables. We first conduct a staggered event study approach, comparing *trends* in spending among the winners and non-winners prior to the coupon treatment. In the absence of selection into winners and non-winners, we expect the pre-trends in spending between the two groups to match each other (i.e., both in levels and in trends).[24] The event study also allows us to inspect how spending evolves as a consequence of winning coupons. In addition, the "shape" of spending trends can help inform

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[23] We note that in practice, small differences in log-on time also likely reflect idiosyncratic factors such as internet connection, hallway conversations, commuting, or many other events that may distract the users from logging onto the portal on time on a workday morning.

[24] This is stronger than the evaluation of the parallel trend assumption in a standard difference-in-differences estimation which allows for a potential difference in the *levels* of pre-trends.

anticipatory responses, e.g., whether non-winners 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 its ability to control for user fixed effects, which allows us to compare spending of a *given* user across coupon winning and non-winning weeks, thus addressing confounds due to factors that are time-invariant at the individual level; we are also able to cluster standard errors at the user level to address serial correlations in spending and coupon treatment. With the panel structure, we are also able to test the lagged impact of winning coupons in previous rounds, and the impact of *future* coupon-winning as a "placebo" treatment to *this* week's spending. We implement these tests by augmenting equation (1) with leads and lags terms in $1(\text{Coupon})_{it}$.[25]

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 variation for coupon assignment. 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. These evidence motivate us to choose as our preferred specification the simple panel data 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, cross-platform substitution between Alipay and other payment venues, and intertemporal substitution over time. Note that the first two types of substitutions are "bad" because they may lead us to overstate the true stimulus effect of the program. The third type – intertemporal substitution – does not necessarily pose threats to our analysis; in fact, the point of a stimulus tool is to bring aggregate demand forward to stimulate a weak economy today while hoping that the intervention does not cause additional stimulus and inflation

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[25] The dynamic leads and lags specification also helps to tease out the pure effect of this week's coupon treatment by controlling for potential lasting impacts from previous treatments. See more discussion on intertemporal spending substitution in this section and in Section 4.2.

after the recovery. For policy makers, the key question is whether the stimulus effects can last long enough to fight the recession. We will empirically examine these issues in Section 4 and, in particular, Section 4.2.

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.

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 consumer spending. Section 4.3 provides a comparison of the stimulus effects with the prior literature. Section 4.4 assesses the degree to which the stimulus effect may be explained by spending leakage.

4.1. Coupon Redemption

During its six-week duration, the coupon program gave away over 3.4 million coupons, which represented a total face value of some 240 million yuan of subsidies, 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. Total realized government subsidy spending is 148.6 million yuan.) 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 in a given week 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, 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. 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.[26]

4.2. The Effect of Winning Coupons on Spending

Response of 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 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.[27] 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.

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[26] 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.

[27] 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.

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, weekly cash inflow in 2019 is 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 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), coupon winners' out-of-pocket spending increased by 225 yuan, and 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. The small but positive effect on unsubsidized spending has important implications for substitution between subsidized and unsubsidized consumption and whether the coupon treatment generates net stimulus. We discuss issues of potential spending leakages in Section 4.4.

Figure 8 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.

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.

As we detailed in Section 3, a more powerful test of *selection on unobservable* is to compare trends of spending among winners and non-winners prior to coupon treatment. We will discuss these results next together with the analysis on intertemporal substitution.

Intertemporal substitution. Consumers can move spending forward to periods when they won coupons. This is indeed the general goal of stimulus tools: bringing aggregate demand forward to stimulate a weak economy today while hoping that the intervention does not cause additional stimulus and inflation after the recovery. For policy makers, a key question is whether the stimulus effects can last long enough to fight the recession.

Our empirical setting allows us to directly examine this question by tracking spending of coupon winners and non-winners long after the coupon program has ended. Figure 6 plots spending of the winners group (-5 to 0 minutes) and non-winners group (0 to 5 minutes) from 10 weeks before to 20 weeks after the Coupon Rush event. We choose the 30-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.[28] 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.[29]

Panel A (panel B) of Figure 6 suggests that out-of-pocket (unsubsidized) spending of winners and non-winners tracks each other closely, followed by 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.[30] Trends of the non-winners group are smooth throughout the pre-treatment window,

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[28] 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 20th week following (and including) the last round of Coupon Rush, hence the balanced 10-week-before, 20-week-after event window.

[29] In unreported analysis, we confirm that the treated and control pre-trends match exactly without these adjustments.

[30] In a related test, we report in Appendix Figure B.6 a panel regression analysis, augmenting equation (1) with leads and lags terms of the coupon-winning status $1(\text{Coupon})_{it}$. This regression yields a stimulus-impact estimate – the

suggesting little if any anticipatory spending responses, e.g., users who do not win coupons this round reduce consumption in anticipation of potential wins in future rounds.[31] Besides the common pre-trends and a jump of winners spending on the treatment week, Figure 6 shows that winners' overall spending is slightly lower than that of non-winners following the treatment week. Starting around week 9 (i.e., two months after the treatment), winners' spending begins to show a sizable decrease relative to the spending of non-winners. Spending patterns of the two groups match each other again starting in week 16.

In Figure 7, we use the event trends estimates to calculate the total, citywide stimulus effect of the program over time. The shaded area highlights the six weeks during which the coupon program was in place. The six red bars show total government subsidies paid for redeemed coupons for each week. The hollow bars show the *period* stimulus effect of the coupon program on out-of-pocket spending implied by the event-time trends shown in Figure 6. That is, for the first week (i.e., the week starting April 1), the bar simply represents the immediate stimulus effect of coupons won in round 1; for the second week, the bar corresponds to the immediate stimulus effect for winners in the second round subtracted by the amount of intertemporal substitution from winners in the first round, and so forth. The coupon program ended the week of May 14; from that point, therefore, the hollow bars began to turn negative. The blue line shows the *cumulative* stimulus effect, adding up the heights of all previous bars. This figure thus provides a visualization of how the coupon program leverages a relatively small amount of government spending (the red bars) to displace future consumptions forward (the hollow bars). In cumulative terms, the out-of-pocket stimulus effect of the program peaks on week 6 (i.e., the final round of coupon dispensing) at over 460 million yuan; this effect gradually dies off over time and lasts a total of about four months. To put such a time frame in context, the citywide overall spending has recovered to pre-pandemic level in about seven months after the shutdown order was lifted. The persistence of coupon program's stimulus effect thus seems significant in curbing the pandemic recession.

Durability. The intertemporal substitution of the stimulus effect may depend on the durability of the underlying products and/or services purchased. Some prior studies have found strong evidence of

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current-week effect coefficient indicates 227.8 yuan increase in out-of-pocket spending – which is similar to the main estimate in Table 2, column 3 (point estimate = 225.7 yuan); on the other hand, the leads and lags terms are economically small in size. In particular, the first lead "placebo" coefficient suggests that winning coupons in the next week is associated with a change of this week's spending by -14.1 yuan (95% CI = -24.1 yuan to -4.0 yuan). Note that the estimate is an order of magnitude smaller than the main, current-effect estimate even if we take the lower bound of the 95% confidence interval. The coefficients on the second and third leads are even smaller and statistically indistinguishable from zero.

[31] 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.

reversal after a stimulus of durable spending (e.g., Mian and Sufi, 2012; Baker, Johnson, and Kueng, 2021).[32] In our study context, estimating the effects of coupons on durable and non-durable goods spendings is less straightforward because coupons are sector-specific by design. For example, winners of dining coupons can only redeem the coupons in restaurants but not towards shopping consumption. Our transaction data do not contain information on itemized spending, and therefore we also cannot examine, say, the impact of winning shopping coupons on purchases of durable and non-durable products within a purchase at a shopping center.

However, we can still make progress by leveraging the fact that different types of coupons likely subsidize consumption of varying "overall" degrees of durability. Recall from Section 2.2 that program participants can win combination(s) of six types of coupons: [dining], [shopping], [gym, lodging], [books, digital products] where brackets reflect the fact that gym/lodging and books/digital products coupons are always won as sets. It seems reasonable to assume that restaurant, gym, and lodging coupons are more likely than shopping coupons to subsidize spending on **non-durable goods** and **services**. By contrast, books and digital coupon sets would subsidize spending that is more **durable** in nature. Our analysis therefore examines how the intertemporal substitution of the stimulus effects vary across different types of coupons.

Table 3 summarizes the analysis. Begin with columns 1 and 2, which examine the effect of winning coupons on the current week's spending. Column 1 repeats the stimulus effect estimate on out-of-pocket spending in Table 2 column 2 row 2 (corresponding to estimation equation 1). The number in the bracket reports the ¥OOP-per-¥1-subsidy metric obtained by dividing the spending effect coefficient (¥225.36) by the average subsidy coefficient (¥73.31) in Appendix Table B.1 column 2. In column 2, we report the marginal effects of different types of coupons by replacing the $1(\text{Coupon})_{it}$ indicator in equation (1) with four separate indicators for winning dining coupons, shopping coupons, gym/travel coupons (which always come as a set in a given coupon packet, and, thus, for which individual effects cannot be estimated separately), and books/digital devices coupons (which also come in a set). Analogous to column 1, we calculate the ¥OOP-per-¥1-subsidy metric for each coupon category using category-specific subsidy coefficients in Appendix Table B.1, column 3. We find that OOP spending stimulus effects are about ¥196 for winning dining coupons, ¥94 for shopping, ¥27 for gym/travel, and ¥949 for books/digital products. The coefficient for the gym/travel category coupons is imprecisely estimated likely due to low take-up rate (8% and 15%, respectively).[33]

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[32] Intuitively, if a subsidy induces a consumer to purchase a shirt this week, the consumer is less likely to need another shirt the following week; but the same need not be true for food consumption.

[33] 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.

It is tempting to conclude from estimates in column 2 that the stimulus effects and the ¥OOP-per-¥1-subsidy metrics appear to be substantially larger in some categories than others. However, we note that this difference is largely driven by the design of the coupons. For example, given the digital product coupon's face value of "¥200 off purchase over ¥2,000 this week" (Section 2.2), it is not surprising that the book/digital coupons category has a large spending effect in absolute value and with a ¥OOP-per-¥1-subsidy metric near 10. Therefore, differences in the current-period stimulus effects across coupon categories do not necessarily inform us about heterogeneity with respect to consumption durability.

We can, however, assess how the stimulus effect changes over time, and relate these changes to differences in consumption durability across categories. To do so, we construct a multi-week spending measure, defined as out-of-pocket 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). We first examine the medium-run, six-week spending response in which the outcome variable is the sum of spending in weeks, t, t+1, …, t+5, and the key dependent variable is whether the user won coupons in week t. We also examine spending response 20 weeks into the future, which is the longest we can observe given the time span of our data. To tease out the pure effect of this week's coupon-winning status on longer-term outcome, in addition to the user and week fixed effects, we also control for the number of coupon-winning weeks in the corresponding look-ahead window separately by coupon categories, the number of coupon "comeback" events between the weeks of May 22 and June 18 of 2020 (recall from Section 2.2), and whether the user won coupons during the prior three weeks in the spirit of Appendix Figure B.6. Note that the multi-week analysis captures the cumulative effect on spending: if an initial spending increase in week 1 is compensated by a decline of spending during weeks 2 through 19, then the 1-week specification will show a positive effect, while the 20-week specification will show no impact.[34]

In columns 3 and 5, we estimate the effect of winning coupons this week on 6-week and 20-week spending. We find a 27 percent reduction (95% CI: 16 to 38 percent) in the effect size about 6 weeks into the initial treatment, and an 80 percent reduction (95% CI: 62 to 98 percent) in 20 weeks. These estimates are broadly consistent with the trends evidence in Figures 6 and 7. Columns 4 and 6 present coupon category-specific estimates for the 6-week and 20-week outcomes. We find that the stimulus effect of dining coupons appears persistent: over 83% of the stimulus effect still remains by week 20 since the initial treatment. This is consistent with prior evidence that little spending reversal is found for the consumption stimulus of nondurable products (Johnson, Parker, and Souleles, 2006; Agarwal, Liu, and Souleles, 2007). In contrast, coupons for more durable consumptions saw much quicker spending substitutions over time.

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[34] 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.

For books and digital products, we observe that about 30% of stimulus effect remains by week 20. Faster spending reversal is observed for shopping coupons; we find that 58% of the stimulus effect remains by week 6, and the effect estimate turns negative by week 20 (point estimate = -¥44.6, 95% CI = -¥83.5 to -¥5.6). This pattern can be potentially explained by the fact that shopping coupons cover a wide variety of products, and therefore it is easier for consumers to practice intertemporal substitution for consumption of a more planned nature. Due to low redemption rates and small coupon face values, gym/travel coefficients do not exhibit systematic patterns, and tend to be noisy.

4.3. Comparison with Prior Literature

We discuss key features of coupon program and how they relate to the prior literature. We navigate the discussion along three dimensions we mentioned at the beginning of the paper: the magnitude of the stimulus impact, the ability to target specific sectors, and the duration of the stimulus effects.

Magnitude. We first consider the magnitude of the immediate spending response. In our study, each yuan of government subsidy spending triggers out-of-pocket spending of 3 yuan in the corresponding week; the total OOP stimulus effect peaked at 460 million yuan after the government had spent a total of 149 million yuan in subsidies. As we discussed previously, the ¥OOP-per-¥1-subsidy metric cannot be given a conventional MPC interpretation because coupons do not directly increase the winner's income. That said, from the perspective of a return on government investment (i.e., "how much of a stimulus in OOP can be achieved from one yuan of government subsidy"), the ¥OOP-per-¥1-subsidy metric can be directly compared to MPC estimates from prior studies.

Hsieh, Shimizutani, and Hori (2010) study the 1999 Japan shopping coupon program and find an MPC of 0.1-0.2 during the month of coupon distribution, and a cumulative MPC of 0.41 during the five months after the coupons were dispensed (before the coupons expired in the sixth month); Kan, Peng, and Wang (2017) study the 2009 Taiwan shopping vouchers program and found an MPC of 0.24; Shapiro and Slemrod (2003), Johnson, Parker, and Souleles (2006), and Agarwal, Liu and Souleles (2007) study the 2001 U.S. tax rebates, finding that roughly two-thirds of the rebate was spent cumulatively during the period between receipt of the rebate and the subsequent three months (an MPC of 0.3); Shapiro and Slemrod (2009) and Parker et al. (2013) show that the 2008 U.S. tax rebates had an implied MPC ranging from 0.3 to 0.52; Agarwal and Qian (2014) study Singapore's Growth Dividend Program and find that households spent $0.8 for every $1 received during the 10 months after receiving the payment (an MPC of 0.8); Baker et al. (2020) study the Coronavirus Aid, Relief, and Economic Security (CARES) Act stimulus payments distributed in April and May 2020 amid the COVID-19 pandemic recession, and they show an MPC of 0.25 to 0.35 within

a month of payment receipt; related studies using alternative data sources have reached similar conclusions (e.g., Chetty et al., 2020; Cox et al., 2020; Karger and Rajan, 2020). Berger, Turner, and Zwick (2020) report an MPC of 0.48-0.67 in the context of the 2008-2010 U.S. First-Time Home-Buyer Credit program in the context of home purchases.

From a pure OOP-per-subsidy perspective, the Shaoxing coupon program achieves much higher rate of return (an "MPC" of 3) than other programs studied by the literature, and the stimulus effects emerge within the week that the coupons were dispensed. The large and quick response can be explained by coupon's minimum spending design (e.g., ¥30 off ¥90 or more) and by the tight, seven-day period of time consumers had to use the coupons before they expired. These features differ from those of most previously studied programs that provided cash subsidies or as cash equivalents, which either featured long periods in which to spend the subsidies, or no expiration dates. For example, neither the 1999 Japan shopping coupon program or the 2009 Taiwan voucher program had minimum spending requirements. The coupons/vouchers from these programs were used as cash equivalents; both programs featured a much longer period to use the coupons: six months for the Japan program, and eight months for the Taiwan program. Fast spending responses have also been observed in other programs where expirations are tight (Mian and Sufi, 2012; Fetzer, 2022).[35]

Of course, these design features alone do not ensure successful reception by the consumers. Our analysis also uncovers the mechanisms underlying the stimulus effects by characterizing *how* consumers respond to the spending incentives. First, we have shown that coupon-winning consumers practice intertemporal substitution by moving up purchases that would have been made months in the future to the time in which they had coupons in hand. This is likely explained by the fact that coupons result in changes in effective prices of the subsidized consumption category across weeks for coupon winners which, combined with a rapid expiration design, creates strong incentives for consumers to frontload consumption, moving eligible purchases forward. Similar intertemporal substitution effects have been documented in the context of tax changes and subsidies for durable goods (Mian and Sufi, 2012; Bachmann et al., 2021; Baker, Johnson, and Kueng, 2021). Second, as we will discuss in Section 5.1, we find evidence that, when redeeming coupons in both shopping and dining contexts, consumers chose to spend in pricier merchants than they would have typically chosen. This evidence suggests the large stimulus response is also explained by consumers' desire to leverage the coupons to "upgrade" consumption quality, which may be another

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[35] The U.K. Eat-Out-to-Help-Out (EOHO) program subsidized the cost of meals and non-alcoholic drinks up to 50% during Mondays-Wednesdays on August 3 to August 31, 2020. The discount was capped at a max of 10 GBP per person. The program design would thus induce an OOP-to-subsidy ratio of 1 for eligible meals worth less than 20 GBP.

reason why the size of the stimulus effect is larger than that found in prior programs, in which subsidies were used towards planned consumption (e.g., Kan, Peng, and Wang, 2017).[36]

Several other facts might also have contributed to the large, quick stimulus response. The competitive coupon-dispensing mechanism (the Rush) might cause coupons to land in hands of those who really wanted to spend them. This differs from many other programs, in which stimulus was distributed to most citizens (e.g., the 2009 Taiwan shopping vouchers, the 2001/2008 U.S. tax rebates, the 2011 Singapore Growth Dividend Program), many of whom may not have had a high propensity to spend. Another potential contributing factor is that the Shaoxing coupon program was implemented during a pandemic recession caused by a five-week shutdown of the city. The transient shock might have had a limited impact on the real economy, but it also may have led to pent-up consumer demand. Thus, the economic situation in this case could differ from the situation faced in a typical recession in which earnings and consumers' ability to spend have substantially deteriorated.

Again, we caution that the comparison with other stimulus tools is solely based on the stimulus-per-dollar-of-subsidy metric rather than from a welfare perspective. While we cannot provide a direct quantification of welfare and comparison across different programs in this paper, it seems reasonable to expect welfare gains to be larger for a consumer who receives a sizeable check than if the consumer receives small-value discount coupons.

Targeting. A second feature of the coupon program is sector targeting: coupons are designed to be sector-specific, which nudges individuals to spend in those sectors that need the most help. We found that redemption rates were highest for dining and shopping (69% and 86%, respectively). The coupons for digital products had a redemption rate of 39%. By contrast, the redemption rates for service coupons, such as for gyms and travel, were relatively lower (8% and 15%, respectively). These lower rates could be explained by low baseline consumption in these categories, the fact that gym visits and travels typically take longer than a week to plan, or potential pandemic-related concerns. Most sector coupons have a ¥OOP-per-¥1-subsidy metric (our "MPC" metric) of nearly 3, except for the case of book/digital product coupons, for which we observe an OOP stimulus of 10 yuan per 1 yuan of subsidy (Table 3, column 2).

We contrast these results with consumption responses observed in stimulus programs in which subsidies (or direct cash stimulus) were not designed to target specific sectors. The closest comparison to our work is that of Kan, Peng, and Wang (2017), who report both the take-up and MPC information in

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[36] We recognize that, in addition to economic explanations, coupons may also be successful in inducing consumer spending through psychological channels such as mental accounting (Liu et al., 2021). See, for example, Leone and Srinivasan (1996) and DelVecchio, Henard, and Freling (2006) for the related marketing literature.

their analysis of the impact of the 2009 Taiwan shopping vouchers program. They report that 70% of respondents used vouchers to purchase necessities, and 58% of respondents used vouchers on durable goods, and 23% of respondents used vouchers on services.[37] The estimated category-specific MPC is 0.19 for necessities, 0.38 for durables, and 0.43 for services.

Though sector-specific redemption rates and MPC estimates are not always available from other studies, we attempt to provide a high-level summary of the qualitative patterns that emerge in the literature. For example, the study of Japan's 1999 shopping coupon program by Hsieh, Shimizutani, and Hori (2010) shows that redemption of the coupons was concentrated in consumption of semidurable goods, such as clothing, sporting goods, video games, and books. Johnson, Parker, and Souleles (2006) show that the 2001 U.S. income tax credits were spent on semi- and non-durable products. Baker et al. (2020) find that the largest increases in spending from the Coronavirus Aid, Relief and Economic Security (CARES) Act stimulus payments were for food, non-durable goods, and rent and bill payments. Sector-neutral stimulus may also generate large spending effects on durable goods when the face value of the stimulus is large, such as was the case of the 2008 U.S. tax rebate program (Parker et al., 2013). Spending on durable goods may also increase when the stimulus is targeted specifically at consumption of durable goods, such as was the case with the Car Allowance Rebate System ("cash for clunkers") program (Mian and Sufi, 2012; Green et al., 2020) and the First-Time Home Buyer Credit program (Berger, Turner, and Zwick, 2020).

Our analysis of the Shaoxing coupon program suggest that these coupons were at least as effective as sector-neutral subsidies – such as cash – in targeting different sectors of the economy. The redemption rates were substantial for coupons that targeted durable goods (e.g., digital products) and semi-durable/non-durable goods (e.g., dining and shopping), suggesting that coupons are not only good for stimulating consumption of particular types. On the other hand, it can be argued that coupons provide a more flexible tool for sector targeting in that (a) the relative strength of subsidies can be *designed* by the government; for example, the government may decide to issue twice as many shopping coupons than dining coupons, and can naturally expect a larger consumption boost in the shopping sector as a result of such efforts so long as the demand for shopping in the city has not yet been saturated; and (b) the government need not worry about "over-issuing" coupons to the extent that coupons are not storable, and that there is no fiscal costs to the government for coupons that are not redeemed.

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[37] The durable products category used in Kan, Peng, and Wang (2017) includes both long-lasting durable products, such as furniture, and semi-durable goods, such as apparel and books. The purchase rate for long-lasting durables (e.g., consumer electronics, furniture, electrical appliances, cookware, automobiles, bicycles) is 29%.

Persistence. Finally, we have shown that the coupon program triggered consumption stimulus of a substantial but not prolonged period of time: a week of stimulus consumption boost that dies off over a period of about four months. We find evidence that the stimulus effect on dining out is persistent – suggesting that coupons do not simply *replace* a planned, future restaurant trip, but that they rather *generate* a dining trip that would not otherwise have occurred in the near future. By contrast, the effect of shopping and digital products is characterized by a quick reversal.

Comparing the persistence of the coupon stimulus with the findings of the existing literature is not straightforward because persistence is partly determined by how the expiration structure of the stimulus is set. In our study setting, because all coupons expire in one week, we can separate the stimulus effect during the "treated" week (i.e., the seven-day window after winning coupons when we expect to observe the main stimulus effect) from intertemporal substitution effects during "post-treatment" weeks. This distinction is often less clear-cut in other programs' settings in which the stimulus had either long expiration periods or, in many cases, never expired because the stimulus offered was cash. When a stimulus has a long period during which it can be used, it is often challenging to estimate cumulative consumption responses in the long run as the longer after the initial treatment one attempts to estimate the cumulative effect, the more likely it is that unobservable factors unrelated to the stimulus affect consumption.

We can nevertheless provide some perspective on some patterns that have frequently emerged in previous studies. One broad finding of the prior literature is that the stimulus effect on non-durable consumption exhibits slow, if any, reversal: Hsieh, Shimizutani, and Hori (2010) found no evidence of significant reversal of semi-durable consumption effects from Japan's 1999 shopping coupon program within the first four months after the coupons were dispensed (i.e., two months before the coupons were due to expire). Johnson, Parker, and Souleles (2006) reported no reversal of spending on semi- and non-durable goods in the second three-month period following receipt of the 2001 U.S. income tax credits. Fetzer (2022) tracks restaurant visits in the month after the U.K.'s "Eat-Out-To-Help-Out" Scheme ended, and he reports no apparent reversal of visits within that time horizon.[38]

On the other hand, stimulus to boost durable consumption is more often associated with forward displacement of planned expenditures, although the speed of such displacement depends on the specific consumption context. Baker, Johnson, and Kueng (2021) show that households strongly respond to a looming increase in sales tax by increasing the purchases of storable and durable products in the month

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[38] Fetzer (2022) does find evidence that, while it is in place, the EOHO scheme changed the intra-week timing of restaurant visits by shifting some trips from weekend to weekdays during which the discount was available. Such intra-week substitution, however, can only explain a minor share of the overall stimulus effect (meaning that the majority of the stimulus effect is explained by the scheme incentivizing restaurant visits that would not have occurred within the week in the absence of the discounts), which does not reverse in the month after the scheme ended.

prior to the tax increase – an effect that immediately reverses in the month of tax change; Mian and Sufi (2012) and Green et al. (2020) show that an initial boost of auto purchases spurred by the Car Allowance Rebate System (CARS) ("cash for clunkers") program reversed within six months, suggesting that the program worked by moving up auto purchases that consumers had planned to make within the next six months. Berger, Turner, and Zwick (2020) show that a surge in home sales during the 17 months when the First-time Home Buyer Credit provisions were in place did not reverse for at least two years following the policy period. Instead, demand appears to have come from several years in the future. Parker et al. (2013), on the other hand, find no substantial reversal of durable spending effects of the 2008 U.S. income tax credit.

Our finding of a faster reversal of the spending boost for those coupons that target the consumption of durable goods rather than nondurable goods is thus broadly consistent with the prior literature. The way that the Shaoxing coupon program was designed – including a very short coupon expiration and large quantities of small-value coupons – made it a particularly suitable measure to address the particular type of recession the city was facing, where the government sought to immediately encourage consumption from a large group of citizens to spur economic recovery from the effects of a transient lockdown policy. Our results suggest that governments should think about the stimulus objectives and length of time that they want the stimulus effects to carry on. For example, this may help them to decide the length of time that coupons should be available for use, and the number of coupons available to directly target certain goods (durable, semi-durable and non-durable products) and services.

4.4. Spending Leakages

Before proceeding, we discuss one additional concern with a potential "spending leakage" effect: the possibility 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 true spending effect. We consider two different types of spending leakages, 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, 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. Our finding is related to Baker, Johnson, and Kueng (2021) who showed that both taxable and tax-exempt spendings responded to sales tax changes, a finding that is explained by shopping complementarity especially among households facing high fixed costs of shopping trips.

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 subsidy value on average (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. Figure 9A shows that usage intensity varies widely among the coupon program participants. Users in the lower 20th-percentile active group spent on average 486 yuan on Alipay, while users in the upper 20th-percentile active group spent an average 7,669 yuan. We then estimate heterogeneous effects of winning a coupon across these spending deciles. Figure 9A 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. To address a potential concern that large spenders could just be richer households rather than frequent users, in Figure 9B, we repeat the exercise but grouping users by monthly Alipay transaction frequencies in 2019. Once again, we find little difference in stimulus effects across spending frequency deciles.

Another way to get at frequent users is to leverage our ability to observe *weekly* transaction activities since October 2019. For each coupon program participant, we calculate the fraction of weeks with positive Alipay transactions during the three months from October to December 2019. Figure 9C reports heterogeneous stimulus effects by four roughly equal groups of users with respect to this frequency metric. Notice from the horizontal axis that the distribution is heavily skewed because many users in our data made

Alipay transactions each and every week during the three-month period. Once again, Figure 9C shows little evidence that the stimulus effects differ by active and inactive users.

A third way we tried to concentrate on spontaneous users is to focus on those who signed up for Alipay before 2020 – users that are unlikely to have signed up for Alipay just to participate in the Coupon Rush events. In Figure 9D, we estimate stimulus effects by year of Alipay registration. We show that the stimulus effect for users who joined in 2020 is not statistically distinguishable from that of users joined in the previous years. There is some suggestive evidence that stimulus effects are larger for users joined Alipay prior to 2010, which likely captures wealth differences between older and younger users.

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.[39]

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.[40] 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

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[39] 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.
[40] We note that all merchants included in our analysis are Alipay participants and therefore there is no variation regards access to payment technologies (such as QR codes) across merchants.

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 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 10, 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 10, 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 10, 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 10 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 10 provides a measure of the "natural" distribution of coupon participants customer in

the absence of coupon treatment.[41] The dash-triangle line – the distribution of coupon winners who made 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. 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 10, 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.7, 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, there is evidence of substantial shift toward pricier options when customers intend to redeem coupons.

The findings in Figure 10 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

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[41] 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.

employment stimulus perspective if firms that sell less expensive goods and services also account for substantial share in the labor market.[42]

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 10). 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.[43] 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

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[42] 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 dining enterprises below designated size (annual revenue less than 20 million yuan and/or with fewer than 100 employees) account for over 57% of industry-wide employment.

[43] Our model follows the discrete/continuous consumer choice framework of Hanemann (1984), Dubin and McFadden (1984), and Hendel (1999).

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 Hanemann (1984), 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 $n+1$.[44] 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 $E_{n-1} \le E_i < E_n$;[45] 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.

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[44] Our setting is similar to Allenby and Rossi (1991) 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.

[45] 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.

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;

(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 11, 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 11, panel B provides an analogous plot to Figure 10, 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 10'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. Implications for Coupon Design

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. 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. Coupon-winning consumers practice intertemporal substitution by moving up consumption from purchases that would likely have been made months in the future to the time in which they had coupons in hand. As a consequence, the program stimulus the economy by bringing aggregate demand forward to stimulate a weak economy today. We find evidence that 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. 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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Figure 1. Consumption Trends, October 2019 - October 2020
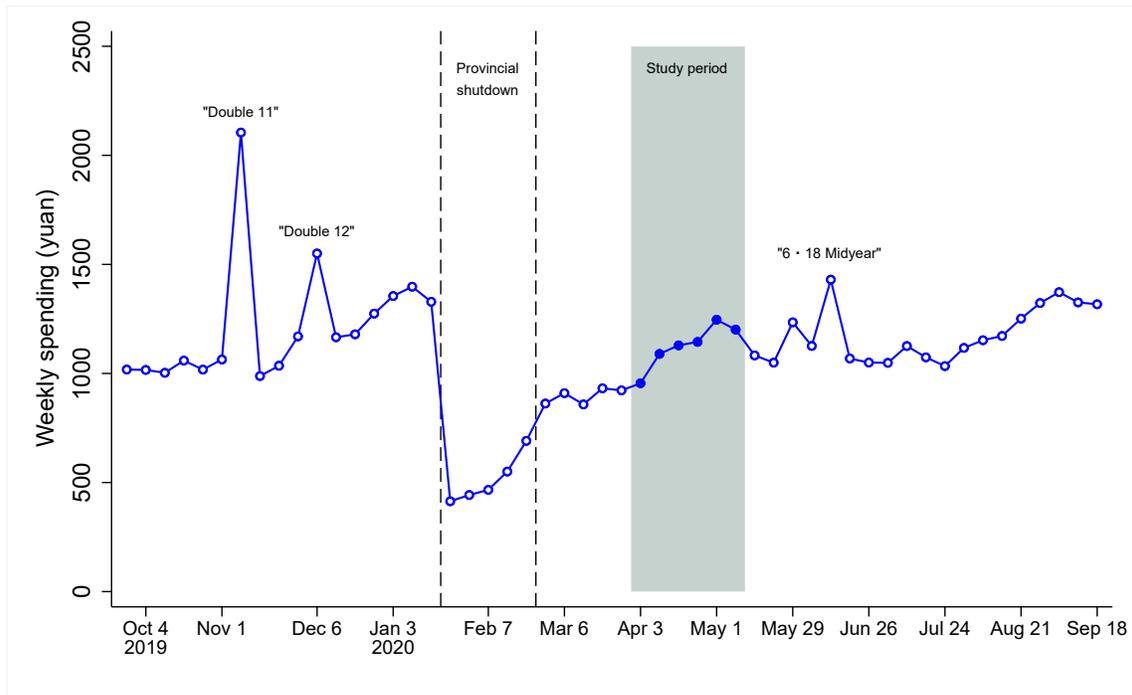
Notes: This graph shows per user weekly total consumption made through Alipay. The sample is restricted to a balanced panel of all 1.57 million users who participated in the Coupon Rush events. The two major spikes in 2019 correspond to the week of the November 11 Singles' Day shopping holiday ("Double 11") and its December 12 spin-off ("Double 12"). The two smaller spikes in 2020 coincide with the June 6 ("Ju Hua Suan") and June 18 midyear shopping holidays. "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
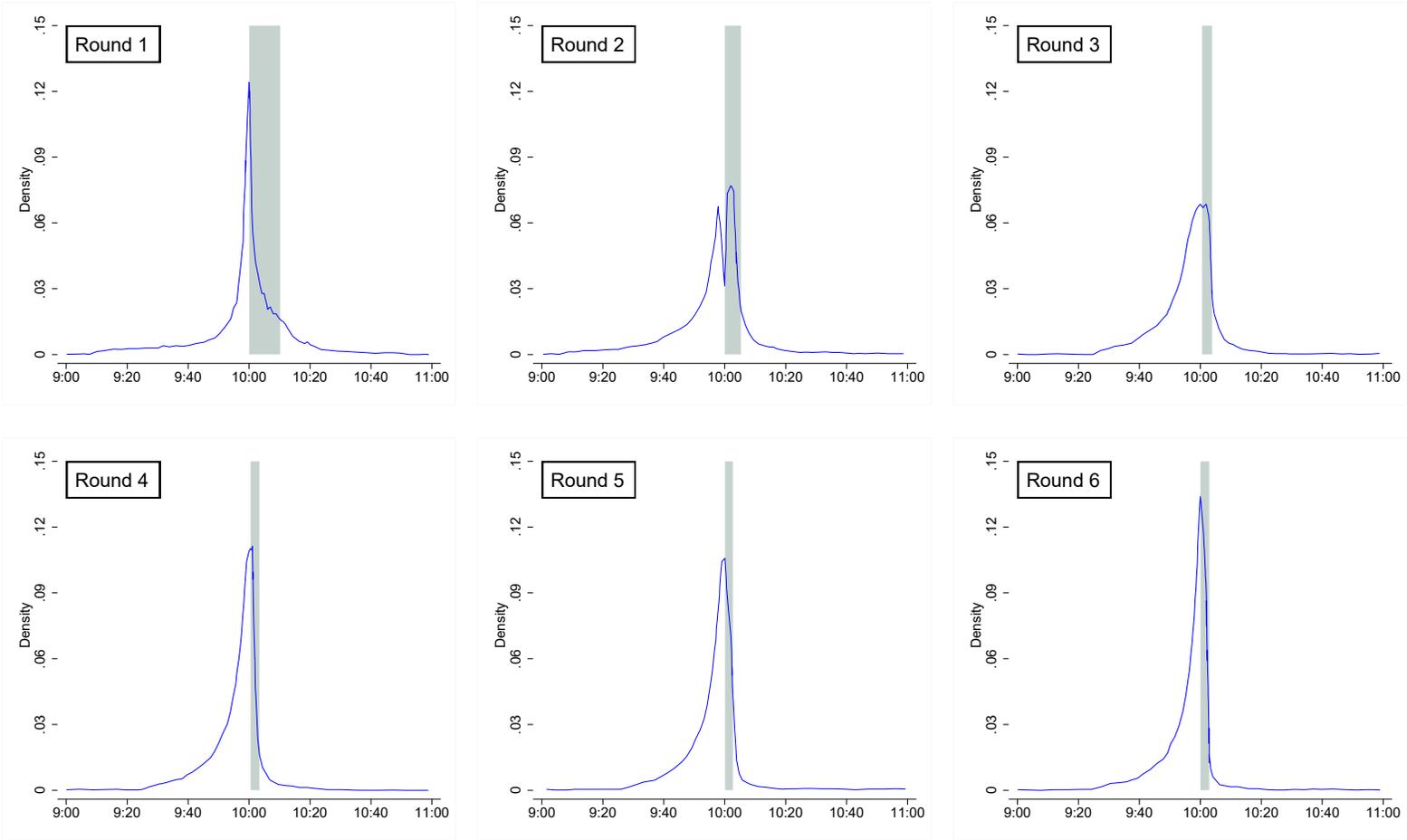
Notes: Graphs show click traffic of Alipay's Coupon Rush portal. Horizontal axis is time in hh:mm (am). Panels show the first event (Friday, April 3, 2020) through the sixth event (Friday, May 8, 2020). Highlighted area indicates the period between the Coupon Rush event activation (10:00 am) and the 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)
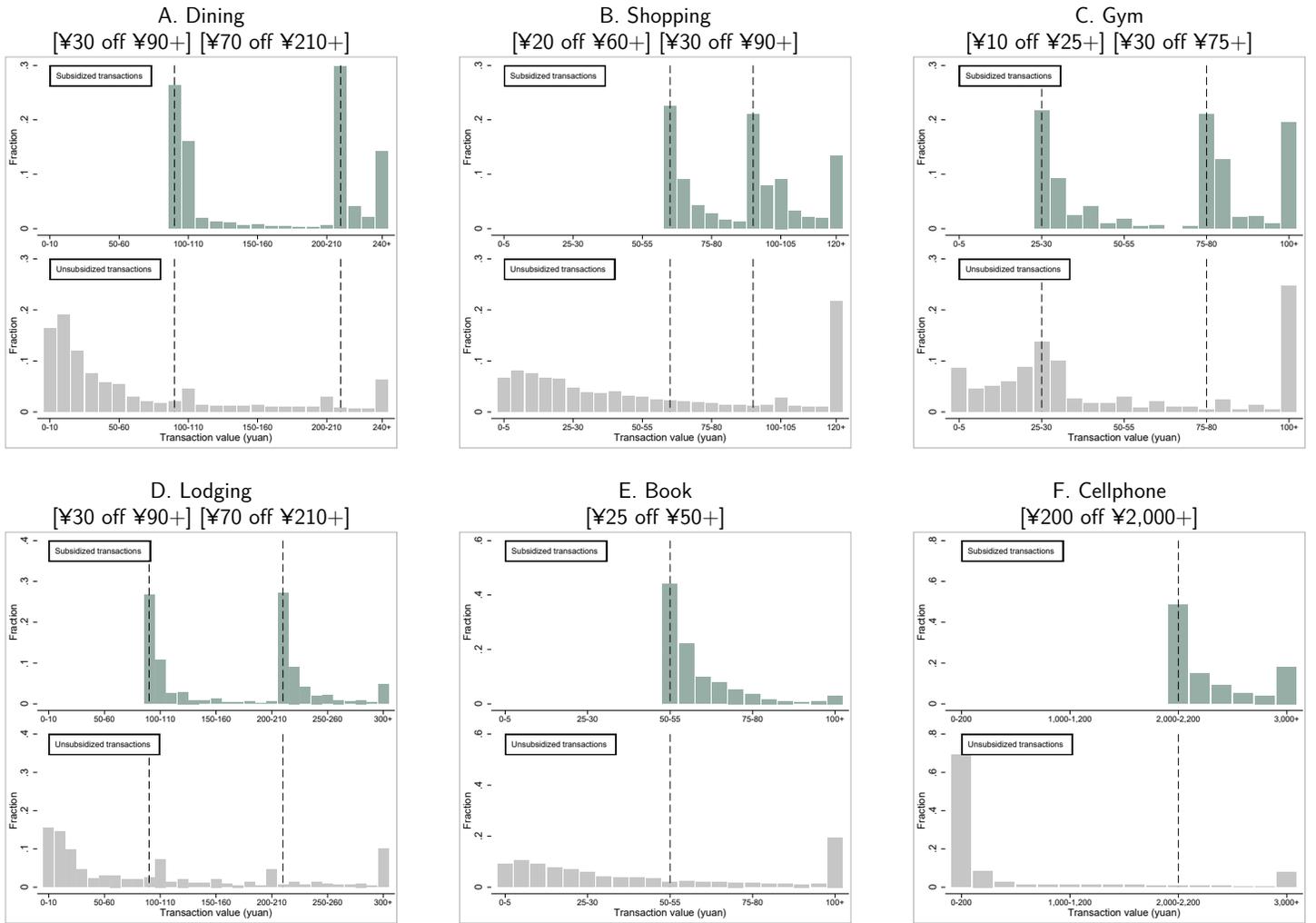
Notes: Graphs show distributions of transaction value by whether a coupon was redeemed ("subsidized transaction"). For each subsidized transaction, we randomly match it with a transaction that didn't involve coupon redemption and occurred at the same merchant on the same day ("unsubsidized transaction"). 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
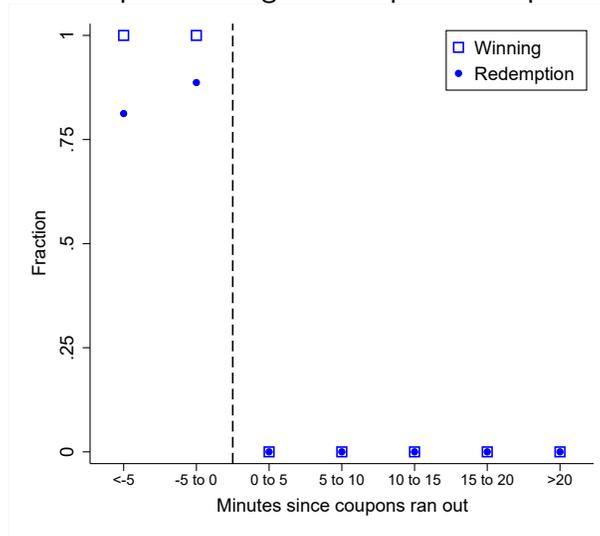
B. Spending in the subsequent week
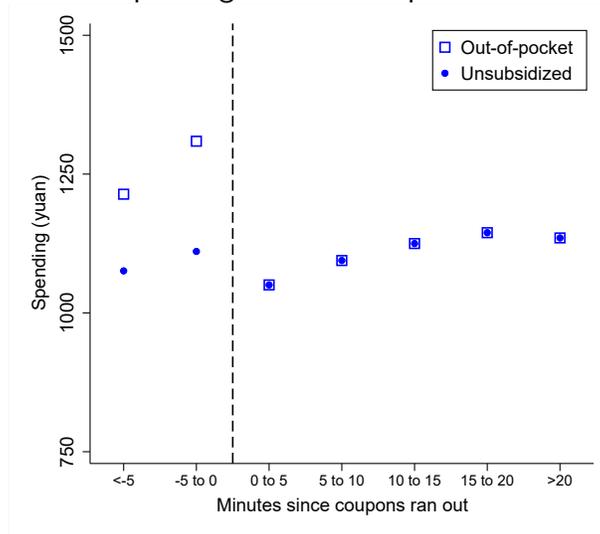
Notes: Graphs show coupon-winning, redemption, and subsequent week's spending as a function of relative time of a user's first attempt to click and log onto the Coupon Rush portal during the event day (0 = the minute when the last coupon was claimed). Over 0.95 million users (out of 1.57 million participants) 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
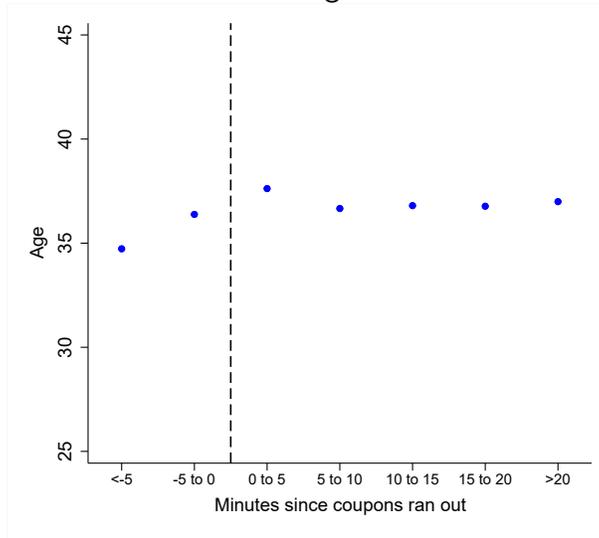
B. Gender
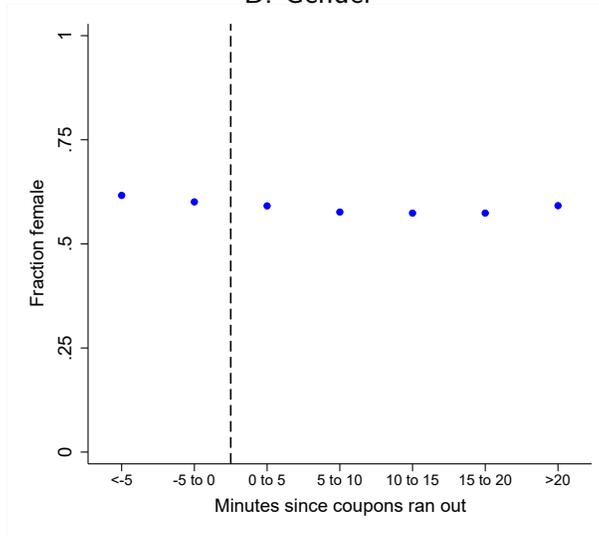
C. Account weekly average cash inflow in 2019
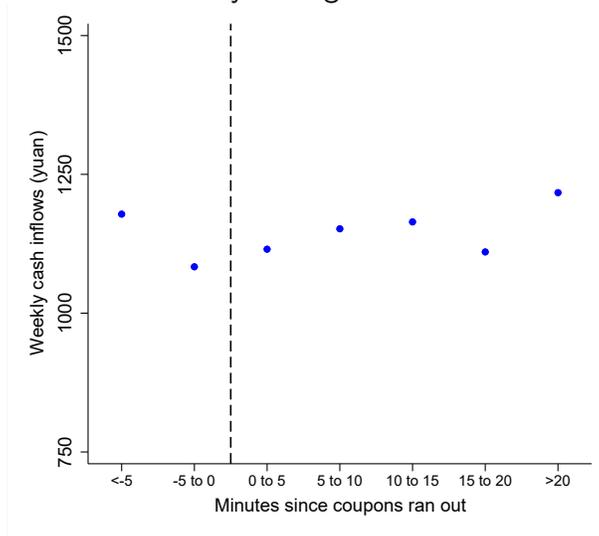
Notes: Graphs show age, gender, Alipay account cash inflow (i.e., a proxy of wealth) as a function of relative time of a user's first attempt to click and log onto the Coupon Rush portal during the event day (0 = the minute when the last coupon was claimed). Over 0.95 million users (out of 1.57 million 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
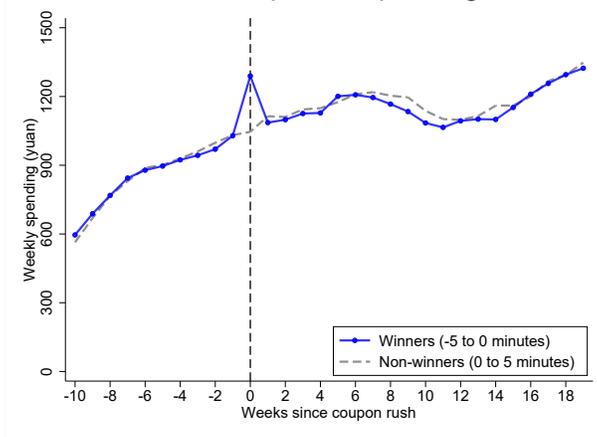

B. Unsubsidized spending
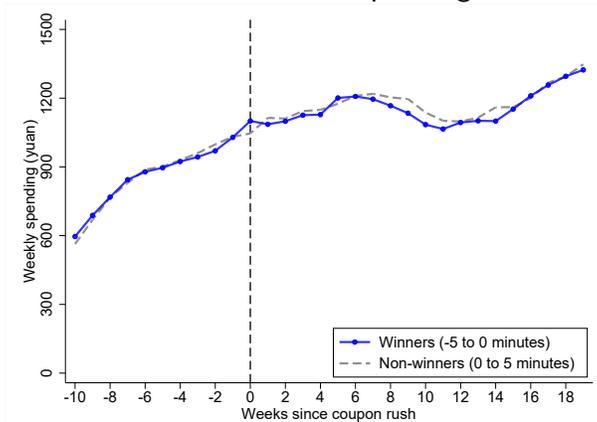
Notes: Graphs show weekly spending as a function of weeks relative to the Coupon Rush event. The underlying data is a balanced panel of users who participated in each of the six rounds of coupon rush events. For each round, the data include participants who logged onto the Coupon Rush portal -5 to 0 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. Citywide Stimulus Effects
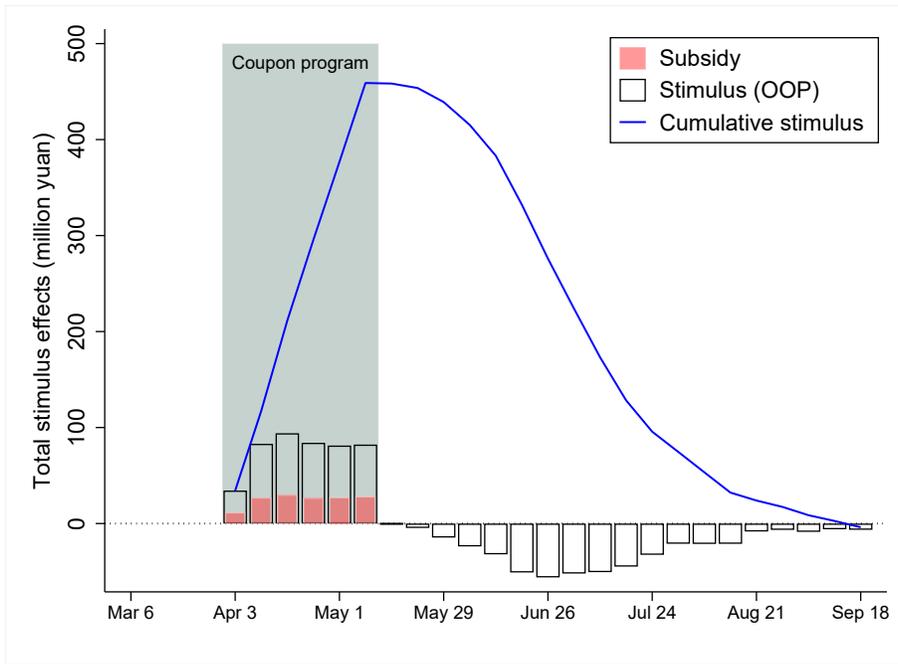
Notes: This graph shows the effect of the coupon program on citywide out-of-pocket (OOP) spending as a function of time. The shaded area highlights the six weeks during which the coupon program was in place. Red filled bars show government subsidy of the corresponding week. Black hollow bars show stimulus effects on OOP spending for the corresponding week. The blue line shows the cumulative OOP stimulus effect. 1 million CNY ≈ 0.144 million USD in 2019.

49

Figure 8. Heterogeneous Effects of Winning a Coupon on Subsequent Week's Spending


A. Age
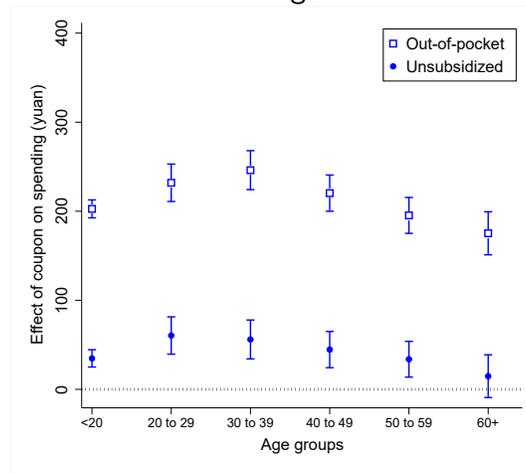
B. Gender
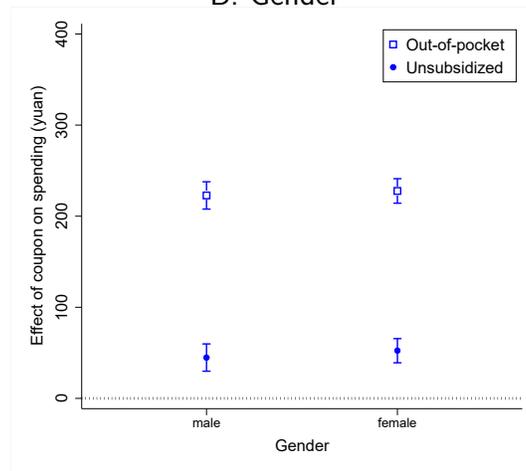
C. Account weekly average cash inflow in 2019
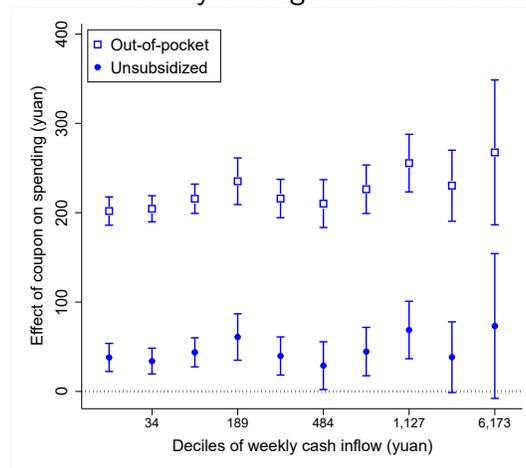
Notes: Graphs report interaction coefficients of coupon-winning and indicators for user characteristics group. "Out-of-pocket spending" is total spending minus the portion paid by the coupon. "Unsubsidized spending" is total spending excluding transactions that redeemed any coupon. Panel C horizontal axis shows mean weekly cash inflow within decile bins. Bars show 95% confidence interval constructed using standard errors clustered at the user level.

Figure 9. Heterogeneous Effects of Winning a Coupon by Intensity of Alipay Usage
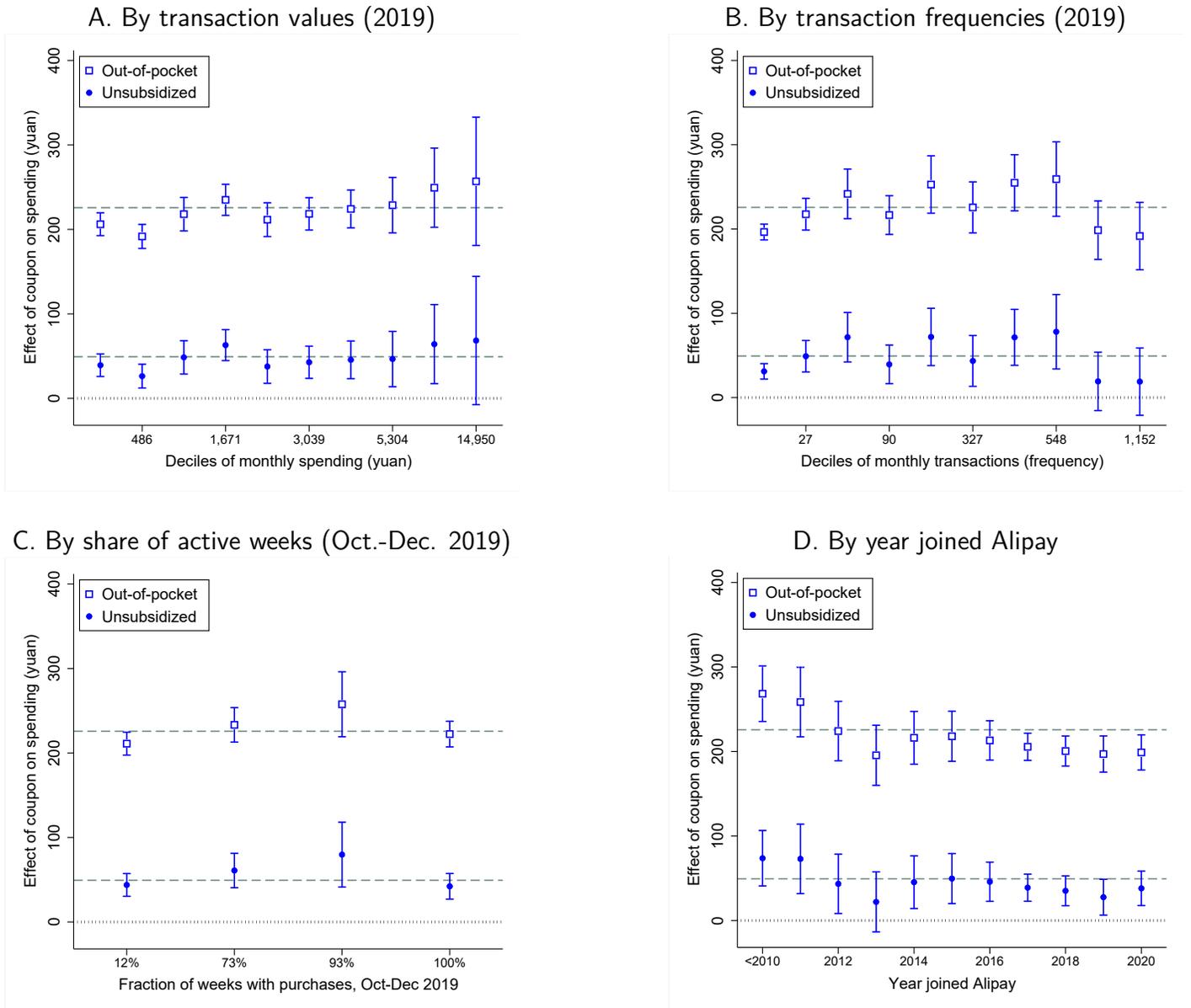
Notes: Graphs report interaction coefficients of coupon-winning and indicators for user's 2019 monthly Alipay average spending values (panel A) and frequencies (panel B), share of weeks between October and December of 2019 (panel C), and year the user joined Alipay (panel D). "Out-of-pocket spending" 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. Dashed lines show the average effect estimates for the effect of winning coupons on out-of-pocket and unsubsidized spending. Bars show 95% confidence interval constructed using standard errors clustered at the user level.

Figure 10. Shopping Merchants' Weekly Customer Distributions by Coupon-Winning Status

A. By revenue in 2019
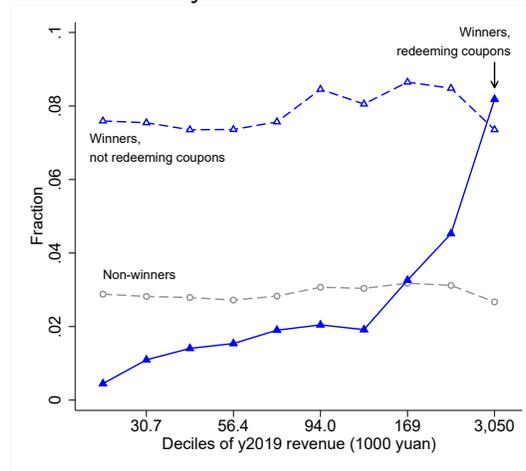
B. By transaction volume in 2019
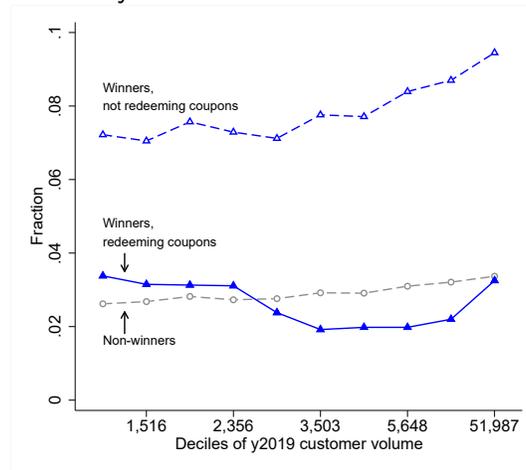
C. By price in 2019
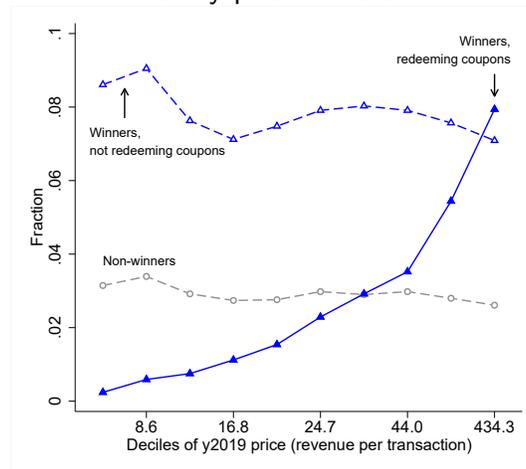
Notes: Graphs report distributions of firm's weekly customer distributions by coupon-winning status. "Non-winners" are fraction of customers that participated in the week's Coupon Rush but did not win any coupon. "Winners, not redeeming coupons" are fraction of customers that won coupon(s), but did not 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 11. Numerical Example of the Conceptual Model: Alternative Coupon Minimum Spending Requirements

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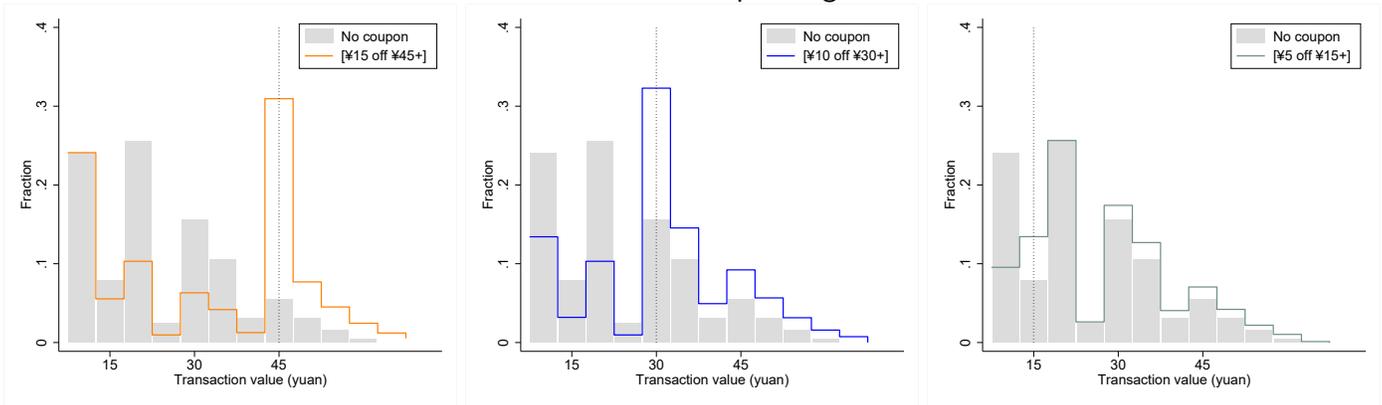
B. Merchants' customer distribution
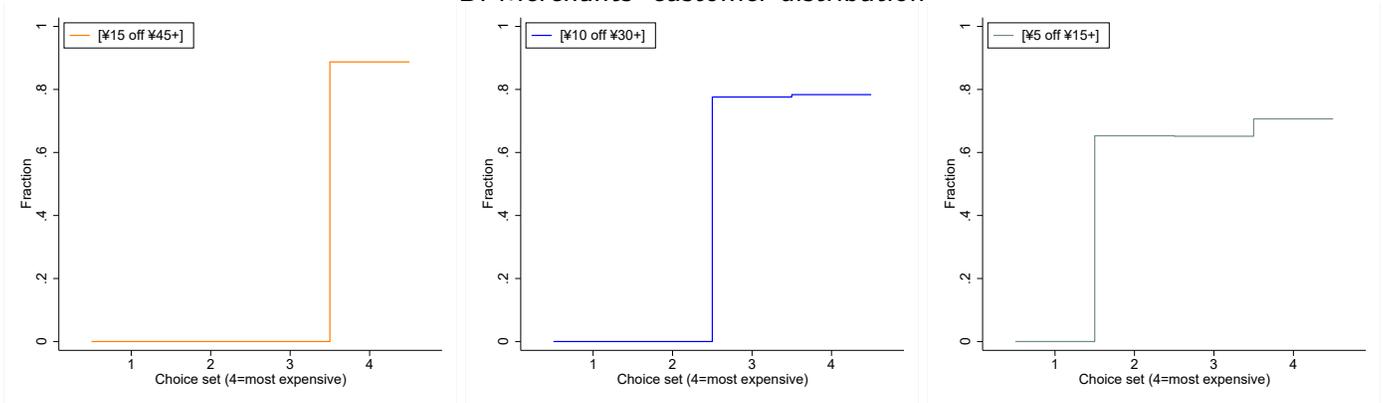
Notes: This figure shows results from a simulation of our conceptual model with alternative coupon designs. Panel A shows the distribution of consumer spending. Panel B shows the fraction of customers redeeming coupons by merchant type. See Section 5.2 for more details.

Table 1. Summary Statistics

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

A. Panel

Total spending	1,035.29 [10,634.45]	1,038.64 [10,493.67]	1,057.82 [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 [6,715.09]	1,298.05 [6,677.17]	1,296.39 [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 [11.57]	36.52 [11.58]	36.53 [11.58]
Female	0.601	0.599	0.598
Weekly cash inflow (y2019)	1.099.81 [3,865.38]	1,103.37 [3,884.62]	1,104.29 [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 Coupon Redemption

	(1)	(2)	(3)	(4)	(5)	(6)
	1-week		6-week		20-week	
Coupon: any	225.36		164.4		45.16	
	(11.99)		(12.89)		(20.98)	
	[3.07]		[2.24]		[0.62]	
Coupon: dining		195.79		164.95		163.37
		(10.59)		(25.41)		(25.01)
		[2.68]		[2.26]		[2.24]
Coupon: shopping		94.28		54.77		-44.56
		(5.96)		(15.06)		(19.88)
		[2.33]		[1.35]		[-1.10]
Coupon: gym, travel		27.00		-15.57		81.29
		(17.75)		(43.09)		(39.90)
		[1.70]		[-0.98]		[5.13]
Coupon: books, digital		948.62		899.82		285.62
		(22.78)		(50.52)		(51.56)
		[10.01]		[9.49]		[3.01]
User fixed effects	✓	✓	✓	✓	✓	✓
Week fixed effects	✓	✓	✓	✓	✓	✓
Observations	5,753,520	5,753,520	5,753,520	5,753,520	5,753,520	5,753,520

Notes: This table shows the effect of current week's coupon-winning status on out-of-pocket spending in the next k weeks (including the current week). Each column shows a separate regression. For each regression we report the regression point estimates and standard errors (in parentheses). We also calculate the implied ¥ OOP per ¥subsidy (in brackets) by dividing the point estimate by the average subsidy level associated with the category from Appendix Table B.1 (¥73.3 for the average coupon, ¥73.0 for dining coupons, ¥40.5 for shopping coupons, ¥15.8 for gym/travel coupons, and ¥94.8 for books/digital product coupons). Multi-week regressions also control for coupon-winning status in the corresponding look-ahead window and prior three weeks. 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.

<u>Group 3. Bunching group.</u> 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.[*]

<u>Group 4. Non-users.</u> 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:

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

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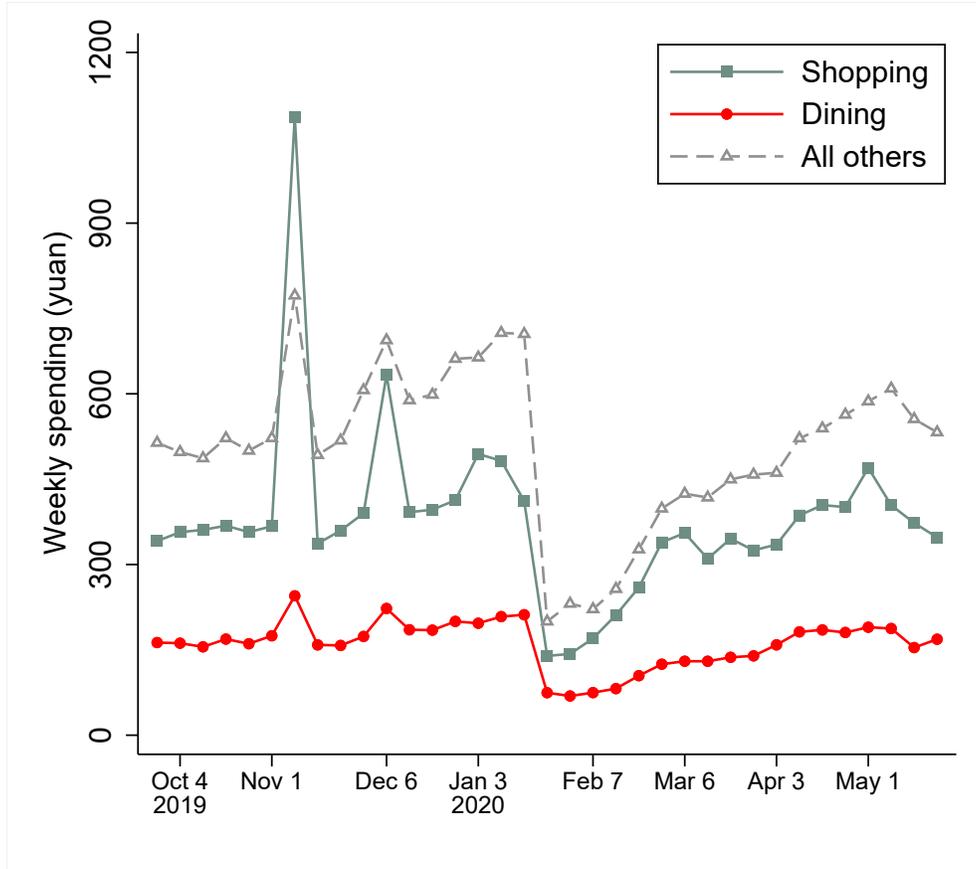
Notes: Consumption by receiving merchants' business category. Sample restricts to a balanced panel of all 1.57 million users who participated in the Coupon Rush events. The two major spikes correspond to the week of the November 11 Singles' Day shopping holiday and its December 12 spin-off.

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
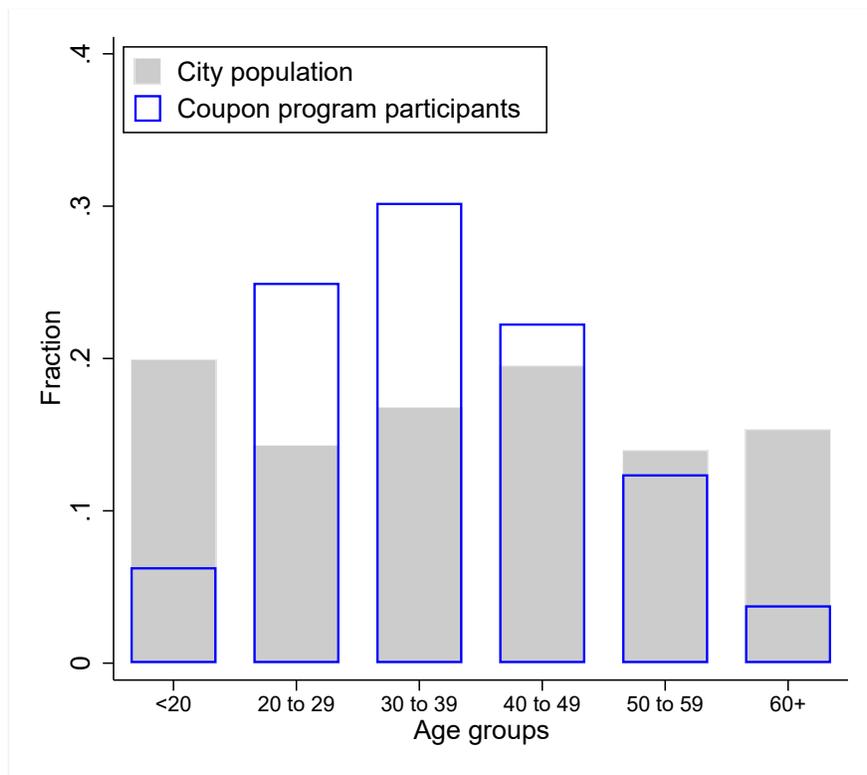
Notes: City population age distribution is sourced from Shaoxing's 2019 Yearbook.

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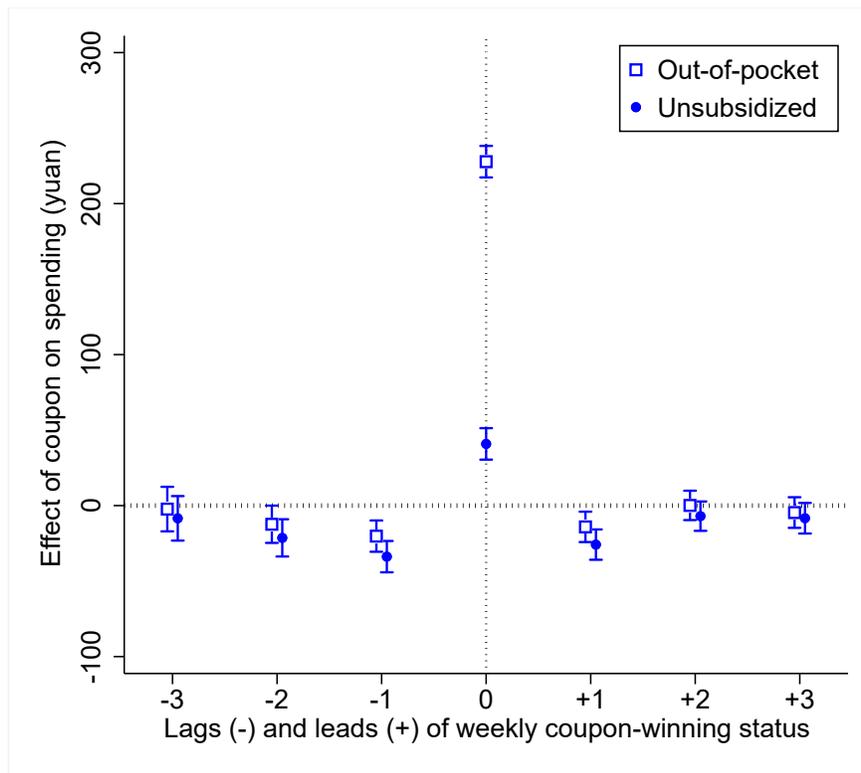
Notes: This figure reports a version of the main panel estimation (equation 1) with additional controls for three leads and three lags of the coupon-winning indicator $1(\text{Coupon})_{it}$. "Out-of-pocket" spending is total spending minus the portion paid by the coupon. "Unsubsidized" spending is total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

Figure B.7. Dining Merchants' Weekly Customer Distributions by Coupon-Winning Status

A. By revenue in 2019
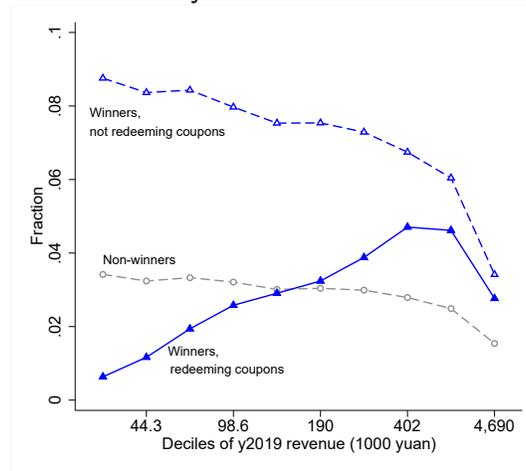
B. By transaction volume in 2019
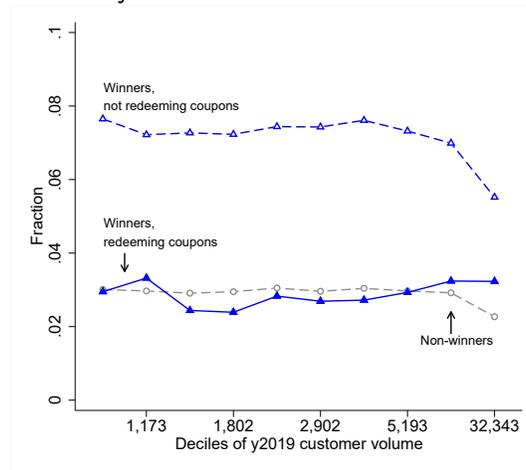
C. By price in 2019
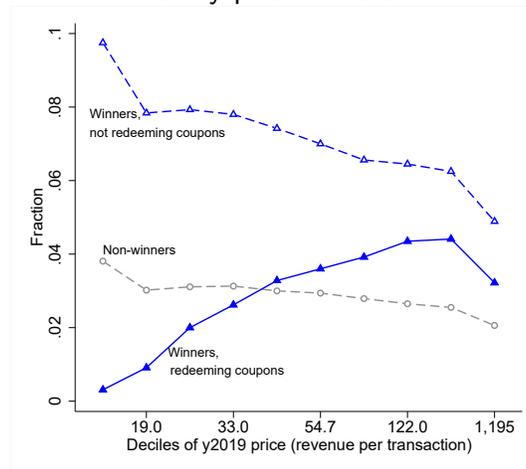
Notes: Graphs report distributions of firm's weekly customer distributions by coupon-winning status. "Non-winners" are fraction of customers that participated in the week's Coupon Rush but did not win any coupon. "Winners, not redeeming coupons" are fraction of customers that won coupon(s), but did not 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: Spending Effect Robustness and Balancing Tests

	(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.