Consumer-Financed Fiscal Stimulus: Evidence from Digital Coupons in China∗

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Abstract

We study a new form of fiscal stimulus undertaken by municipalities across China starting in 2020: government-issued digital coupons designed to encourage spending in certain categories such as restaurants, groceries, and entertainment. Using unique account-level and transaction-level data from a large online shopping platform that distributed many of the government coupons, we estimate the effect of the coupons on spending for many different types of coupons with different spending thresholds (e.g., “Spend at least ¥X, get ¥Y off”). We identify the effects of the coupons on spending using a bunching estimator that uses the transaction-level spending distribution in the weeks before each coupon is distributed as the counterfactual, and we validate the bunching estimates by using the random assignment of a subset of the coupons in our data. We first present visual evidence of sharp bunching around coupon-specific thresholds during the weeks that the coupons are distributed, but not in the weeks before and after. We find that the coupons cause large and persistent increases in spending in the targeted spending categories, and we do not find evidence of any substitution away from spending on the platform in “non-targeted” spending categories. We estimate that the consumer spending increases by 2.7-2.8 yuan per yuan spent by the government. As a result, we conclude that the digital coupons increased spending substantially in the targeted spending categories at very low fiscal cost. We show that a standard consumption model can generate these results since the coupons’ spending thresholds create “notches” that lead to large spending responses from consumers. We calibrate the consumption model to match our empirical results, and we find that the coupons generate about half of the increase in consumer welfare as an equivalent amount of fiscal stimulus distributed as cash. We then use the calibrated model to simulate alternative coupon designs, and we find that lower coupon thresholds and higher coupon discounts would be less cost-effective but would deliver greater aggregate stimulus.

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1 Introduction

Countries all around the world distribute stimulus payments during economic downturns to increase consumption. In the United States, for example, the federal government distributed billions of dollars of stimulus payments to households in each of the last three recessions, and each time households used the payments to immediately increase their consumption (Johnson et al., 2006; Shapiro and Slemrod, 2009; Parker et al., 2022).

Many governments also design fiscal stimulus policies to target particular sectors of the economy. For example, during the 2008-2009 Great Recession the US government provided targeted financial support for the automobile industry through the “cash for clunkers” program and supported the real estate industry through a new first-time homebuyer tax credit (Mian and Sufi, 2012; Berger et al., 2020).

More recently, during the 2020-2021 COVID-19 recession provinces and municipalities across China carried out a novel form of targeted economic stimulus using government-issued digital coupons. The coupons were delivered online through smartphone apps, and they were designed to encourage spending in certain categories such as restaurants, food delivery, grocery stores, and entertainment. In China (like in many other parts of the world), these sectors were hit particularly hard during the early months of the global COVID-19 pandemic, and many provincial and municipal governments in China designed these coupons to stimulate spending in these sectors as their local economies re-opened following the initial wave of the virus.

In addition to the digital distribution, another major difference between the coupons and other forms of stimulus is that the coupons had fixed spending thresholds that needed to be reached before consumers received money from the government – for example, one coupon would give 18 yuan off of a food delivery order if the total transaction amount was at least 54 yuan (“Spend at least ¥54, get ¥18 off”).
In this paper, we estimate the effects of the digital coupons on consumer spending, and we evaluate the coupons’ effectiveness as fiscal stimulus. To do this, we assemble data covering several different types of coupons distributed across three cities in China. The different coupons have a range of different thresholds and apply to several different spending categories. Throughout this paper, we define the “coupon MPC” to be the increase in consumption caused by the coupons relative to the fiscal cost of the coupons. For example, if 200,000 “Spend at least ¥54, get ¥18 off” food delivery coupons were distributed in a city, and 100,000 of them were redeemed, then the direct fiscal cost is 18 × ¥100,000 = ¥1,800,000. If the total increase in spending caused by the coupons is ¥4,500,000, then we conclude that the coupon MPC is 2.5.

The reason the coupon MPC can be larger than one is that many consumers may need to increase their spending substantially in the targeted spending category in order to reach the threshold and be able to take advantage of the coupon. If they do not decrease their spending in other categories (which would “offset” the increase in spending in the “targeted” spending category), then total consumer spending would increase by more than the discount associated with the coupon, which is the amount financed by the local government. As a result, we call the digital coupons a new form of consumer-financed fiscal stimulus, since the increased spending caused by the government spending but is ultimately mostly paid for by consumers.

Our empirical analysis uses detailed account-level and transaction-level data from a large online shopping platform that distributed the coupons across many cities and provinces in China. The data set contains detailed information about each transaction including the spending amount and the time and date of each transaction. The account-level data also contains information on everyone who received coupons and whether or not the coupons were redeemed during the time window when the coupons were valid.

We begin our analysis by first presenting clear visual evidence of sharp “bunching” around coupon-specific thresholds during the weeks that the coupons could be used. We find no evidence of similar bunching in the weeks before and after the coupons were distributed. These results indicate a clear behavioral response to the coupon-specific spending thresholds.

We then build on these graphical results by developing a bunching estimator that compares the number and distribution of transactions before, during, and after the weeks when the coupons were available to be used. Under the assumption that the distribution of transaction-level spending in the weeks before the coupons were distributed represents a valid counterfactual estimate of the distribution of spending
in the weeks during and after the coupons were distributed, we can identify the effects of the coupons on spending by “differencing” the spending distributions and then integrating across the difference in spending distributions to recover the coupon MPC for each coupon. This empirical approach is broadly related to previous work in public economics and labor economics which uses a similar kind of “bunching estimator” to infer the behavioral responses to tax kinks, tax notches, and minimum wages (Best et al., 2020; Defusco et al., 2020; Cengiz et al., 2019). In our setting, the coupons create a notch in the consumer’s budget constraint, which means our methodological approach is most similar to the recent Kleven and Waseem (2013) analysis of tax notches in Pakistan.

Turning to our main results, we find coupon MPC estimates ranging from 1.4 to 3.7, with a weighted average of 2.8-2.9. These estimates are stable for at least several months after the coupons are distributed. We assess whether the large coupon MPCs we estimate come partly from substitution between “targeted” and “non-targeted” spending categories, and we find no evidence of meaningful cross-category substitution, suggesting that the coupons increased aggregate consumer spending in the short run. We also find very little intertemporal substitution in the short run, finding very large MPCs even going out several months after the coupons were distributed. This implies that simple re-timing of consumption in the short run is not likely to account for much of the large coupon MPCs we estimate.\footnote{This contrasts with the findings in the Mian and Sufi (2012) analysis of the “cash for clunkers” program, where the initial short-run increase in auto purchases from the stimulus program comes almost entirely from the re-timing of auto purchases rather than from an aggregate (net) increase in auto spending during the year of the policy.}

We show that our main results are robust to alternative ways of implementing the bunching estimator. We also support the causal interpretation of our results using an alternative empirical approach that exploits the explicit random assignment of coupons for a subset of the coupons in our data. In these cases, consumers were randomly assigned one of three different coupons, which allows us to calculate the increase in spending caused by being assigned a high (or medium) threshold coupon compared to a low threshold coupon. We show that the causal spending effects from the random assignment should be related to the bunching estimator estimates through an identity, which provides a direct test of the validity of our coupon MPCs recovered from the bunching estimator.

In the final part of the paper, we describe a simple model of consumer spending to understand the economics behind our reduced-form results. We use the model to derive closed-form expressions for the coupon MPC and the MPC out of cash. We are not aware of any existing estimates of the average MPC out of cash in China, but we expect it to be similar – or perhaps slightly smaller than – the recent estimates in the U.S. during the same time period (see, e.g., Parker et al. (2022)). We calibrate our
simple model and show that it can match both the very large coupon MPCs we estimate as well as a small MPC out of cash. The key to matching the results is that the consumers need to be willing to substitute consumption across time (i.e., intertemporal elasticity of substitution in consumption cannot be too low), and the coupon threshold needs to be set higher than the spending many consumers would have wanted to choose in the targeted sector in the absence of the coupon.

We use the calibrated model to illustrate how the coupon MPC varies with the coupon’s threshold and discount amount, and we also use it to calculate the welfare cost to consumers from receiving a coupon instead of cash. We estimate that consumers get about 50 percent of the surplus they would get from equivalent amount of fiscal stimulus distributed as cash, but the targeted sector receives much more spending from coupons compared to cash, highlighting the targeting properties of this novel form of stimulus. Lastly, we use the calibrated model to simulate alternative coupon designs, and we find that lower coupon thresholds and higher discount amounts would be less cost-effective but would deliver greater aggregate stimulus.

Taken together, our empirical and theoretical results suggest that the digital coupons may be a particularly cost-effective way to provide targeted fiscal stimulus to specific sectors. The coupon MPCs that we estimate are large and persistent, implying that the increased spending is achieved at very low fiscal cost compared to other forms of stimulus. As a result, we conclude that the digital coupons represent a technological innovation in stimulus policy that may be particularly attractive when there are specific sectors that need targeted support during economic downturns.

When it comes to fiscal stimulus, at least, the highly non-linear incentives created from the notch-based coupon design may be a feature rather than bug. Just as tax notches sometimes create unusually large behavioral responses by taxpayers, the digital coupons we study in this paper consistently create unusually large spending responses because the thresholds temporarily create notches in the household’s budget constraint. While tax notches are usually seen as a “design flaw” in public finance (since it’s difficult to imagine any optimal tax policy featuring a tax notch), in our setting the coupon-specific spending thresholds create large behavioral responses in a way that may deliver cost-effective stimulus to targeted sectors compared to direct cash payments to households or even direct subsidies to the targeted industry.

Our paper contributes to three main areas of research. First, the paper contributes to a large and active literature on the consumption responses to different types of fiscal stimulus. Much of this literature in recent years has focused on spending responses to direct cash payments, but there are also papers
studying other forms of fiscal stimulus such as the “cash for clunkers” and first-time homebuyer credit policies mentioned above, as well as recent related work studying shopping coupons in Japan and shopping vouchers in Taiwan (Kan et al., 2017; Hsieh et al., 2010). Relative to these studies, our focus is on novel digital coupons during the COVID-19 recession that had coupon-specific spending thresholds, and we develop a model to explain why these thresholds appear to be primarily responsible for the particularly large coupon MPCs compared to these other policies.

Second, this paper is related to recent papers studying behavioral responses to “notches”. Tax notches create strong incentives for behavioral responses to avoid dominated choices. The same kind of incentives are created by the digital coupons we study in this paper. For households receiving the coupons, as long as there is “free disposal” there is no reason for households to spend just below coupon threshold when a coupon is available. Unlike in Kleven and Waseem (2013), where the dominated choices are used to reveal the extent of optimization frictions, in our setting the share of households with coupons who make dominated choices in the same way is extremely small. Some of this may be due to the fact that households had a choice about whether to try to get a coupon, and for the households who chose to try to receive the coupons, they very rarely ended up choosing transaction amounts just below the threshold needed to unlock the discount. This is arguably another benefit of the coupon stimulus policy, which is that the coupons are only “taken up” by households who are interested and able to increase spending enough to take advantage of the threshold-based benefit.

Lastly, this paper is most closely related to two other recent studies of digital coupons using different data sets and different empirical approaches. Xing et al. (2021) study digital coupons in a single large Chinese city and find an average MPC of around 3.0 comparing consumers who just barely missed out on getting a coupon (“near miss”) to consumers who just barely received a coupon. These estimates are broadly similar to our own main results, and we see the two projects as highly complementary since the papers have different methodologies and identifying assumptions, but similar coupon MPC estimates. Liu et al. (2021) use administrative data on coupons issued on Alibaba in Hangzhou and Guangxi and find that the marginal propensity to consume (MPC) to the range of 3.4-5.8. This paper takes a difference-in-difference approach comparing consumers who received coupons to a random sample of individuals who tried but failed to get a coupon. The approach is similar in spirit to the Xing et al. (2021) approach, One benefit of the “near miss” approach is that it also rules out anticipatory behavior as a source of the large coupon MPCs. The fact that our results are similar to the results in Xing et al. (2021) suggests that anticipatory behavior is not a major reason for the large MPCs in our setting. Xing et al. (2021) also studies how the coupons cause consumers to shift consumption between firms and find that the coupons cause consumers to spend more at larger firms that sell pricier goods and services.

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although it is not set up as a “near-miss” design, so it requires somewhat stronger identifying assumptions, and still implicitly relies on there being excess demand for coupons so that the limited offering of coupons is “binding.”

Relative to both of these papers, our analysis covers a larger number of cities and studies more coupons. Our bunching estimator approach is also a distinct research design, and we use explicit random assignment of coupon thresholds, which is not used in either of the two previous papers. We are also the first study we are aware of that estimates coupon MPCs using explicit random assignment of coupons, which provides validation of both our bunching estimates and the other estimates in the literature. Lastly, we develop and calibrate a model that can simultaneously fit the large estimated coupon MPCs alongside a small MPC out of cash, which we use to measure the consumer surplus from coupons relative to cash and to evaluate alternative (counterfactual) coupon designs.

The next section provides background on the digital coupons that we study. Section 3 describes our data and sample construction. Section 4 describes our empirical approach and formally defines the coupon MPC concept we use throughout the paper. Section 5 describes our main results, assesses the importance of intertemporal substitution and substitution to other spending categories, and validates our results using random assignment of coupons. Section 6 presents a simple model of spending responses to the digital coupons and cash and calibrates the model for welfare analysis and counterfactual scenarios. Section 7 concludes.

2 Background on the Chinese Coupon Programs

The Covid-19 pandemic at the beginning of 2020 dramatically slowed China’s economy. In response to this unexpected macroeconomic shock, provincial and municipal governments in China issued short-term Internet-based digital coupons to stimulate the economy from the demand side\(^3\). The digital coupons were distributed through pre-existing consumer spending technology platforms such as Alibaba, Meituan, and JingDong. The coupons were distributed directly to consumers through multiple waves in many cities across China. The first city issuing coupons was Jinan, the capital of Shandong Province, whose government offered a total of ¥20 million worth of coupons on March 2, 2020.

The stated aim of the stimulus policy was to promote consumption of local individuals and enhance

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\(^3\)Other demand-side Chinese stimulus policies during this time period included shopping festivals and subsidies for purchasing durables. On the supply side, Chinese policies included tax cuts and fee cuts for firms and the provisions of preferential loans to firms to help the firms resume production in the so-called “street-stall” and “night-time” economy.
the demand of the local economy at relatively low fiscal cost in response to the Covid-19 pandemic and the subsequent economic recession. Different types of coupons could only be used in their specific categories in order to help the recovery of those industries hit hardest by the pandemic (such as restaurants and tourism). The central government in China only gave general guidance to the local governments that they ought to undertake these policies, which meant that the final coupons that were released by local governments differed across locations in terms of important features such as issuing volume and the types of consumption targeted. However, most of the issued coupons were in one of the following seven categories: catering, retail, cultural tourism, automobiles, home appliances, sports, and information. Additionally, all of the coupons had thresholds and discount amounts – i.e., “Spend at least ¥X, get ¥Y off” – and all of the coupons had a fixed, short time period when the coupons needed to be used before they expired (“use it or lose it”).

We now describe the coupons that we analyze in more detail. Our data cover coupons distributed in three different cities and cover a range of spending categories. We anonymous the cities in order to help protect the anonymity of the platform that provided the data for our study. Throughout this paper we describe coupons with a spending threshold $X$ and a discount $Y$ as “$X$-$Y$” coupons.

2.1 City A Coupons

In February 2021, the City A municipal government announced that digital coupons would be rolled out during the Spring Festival through mobile platforms, with the objective to stimulate the local economic recovery after COVID-19 pandemic and to reduce residents’ outbound travels during the Spring Festival. There were two waves of coupons. Each wave included nine types of vouchers: “24-8”, “54-18”, “84-28” supermarket coupons which can only be redeemed in online supermarkets; “54-18”, “84-28”, “114-38” life service coupons which can be redeemed in food delivery, movies, hotel booking, entertainment and restaurants; and “84-28”, “174-58”, “324-108” shopping coupons which can be redeemed in physical shopping malls. We focus on the supermarket and life service coupons because of implementation issues with the shopping mall coupons (see Online Appendix for more details).

All residents in City A were eligible to take up one coupon through the mobile platform in each wave. The number of coupons in each wave is limited. Residents in City A had to acquire the coupons from the online platform on a

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4 We focus on food delivery, restaurants, and supermarkets, and exclude the shopping coupons that could be used at shopping malls, hotels, and for other types of entertainment. The reason is that these coupons were essentially “exchanged” for store-specific or shopping-mall-specific coupons that could be used in the future, and those coupons had longer duration. This was controversial behavior since it is a kind of “duration arbitrage”, but it also makes it impossible to reliably measure the timing of actual spending. We only see the “exchange” of the government coupons into retail coupons in our data.
“first-come-first-service” basis. The first-wave coupons were released on February 8 and were valid for redemption between February 8 and February 16; the second-wave coupons were issued on February 17 and expired on February 26.

A unique feature of the City A coupons is that the residents acquired life services or supermarket coupons without knowing the threshold and discount of the coupon they were getting; the residents only knew it would be one of the three types listed above. After taking up the life services or supermarket coupons, the threshold and discount was randomly assigned by the platform.

2.2 City B Coupons

The City B municipal government handed out ¥2.89 million worth of food delivery coupons. All residents in City B were eligible for a coupon package distributed through the platform between July 30 and August 6, 2021. Each coupon package included two identical “30-15” coupons that were valid for 15 days. The coupons were redeemable in any online food delivery order in City B when a purchase met the minimum requirement of ¥30.

2.3 City C Coupons

In the last quarter of 2021, the City C municipal government rolled out ¥3.3 million worth of digital coupons in two waves, from October 20 to October 29 and from October 30 to November 8, respectively. Each coupon wave included two types of coupons: 100-40 and 200-100. Residents could choose only one type of coupon and redeem it in food delivery, hotel booking, or restaurants. Take-up of coupons in City C was particularly high. For example, in the second release it took only 4 seconds before all the “200-100” coupons were claimed, and it took only 16 seconds before all “100-40” coupons were claimed.

3 Data

We use detailed transaction data from one of the large Chinese shopping platform that distributed the coupons. This e-commerce platform (henceforth, “the platform”) has had substantial market share for spending categories including entertainment, dining, and food delivery for several years. By 2018, the platform had more than 600 million registered users with more than 290 million of them actively using its service. The platform has roughly 35 daily users. Our data cover coupons issued in the three cities
described in the previous section.\footnote{The data was provided under a data use agreement that allowed us to carry out this research study as long as the platform and the cities were anonymity. The platform reviewed the study prior to public dissemination, but only for factual inaccuracies, confidential information, and trade secrets. All of the researchers had access to the “binned” transaction data that forms the basis of the bunching estimator described in more detail below.}

For each transaction in the sample, we observe the consumer’s de-identified account number, transaction number, transaction time, transaction amount, and transaction spending category. We have access to transactions for three months before and after the coupons were distributed.

We merge the transactions data with the coupon database, which records each coupon holder’s de-identified account number, the time the coupon was acquired, the coupon face value, and the coupon threshold. The coupon database identifies each coupon holder in each coupon wave. We also observe coupon redemption information in a separate coupon redemption database. For each redeemed coupon, we observe the transaction number, transaction amount, coupon id, discount amount, and the actual payment.

By merging the transactions data with the coupon database using the account numbers, we are able to get all of the transactions for all of the coupon holders each coupon wave, whether or not the coupons were actually used. This level of detail is important because the coupon redemption rate is often much less than 100 percent for all of the coupons in our data.

Most of our analysis proceeds using the distribution of spending at the transaction level, focusing on the full set of consumers who acquired coupons each coupon wave. To minimize the influence of outliers, we winsorize the spending amounts at the 0.5 and 99.5 percentiles of the spending distribution, although this has no effect on any of our results, since the bunching estimator uses data on spending around the coupon thresholds, which are always set pretty far from the tails of the spending distribution.

Table 1 presents summary statistics for the coupons in our data and reports the total coupons available, the coupons taken up, and the coupons redeemed. Table 2 converts these statistics into take-up rates and redemption rates. There is variation in both the take-up rate and redemption rate across coupons. The redemption rate is always below 50 percent, which means that most coupons taken up by consumers are not used.

Table 2 shows that the take-up rate is virtually identical across the supermarket and food delivery coupons in City A. This is consistent with strict random assignment of the coupons within a coupon category and wave in this subset of coupons. The variation in redemption rate is consistent with a causal impact of the coupon threshold and discount amount on the likelihood that the consumer chooses to use the coupon during the time window.
Figure 1 shows the range of coupon thresholds and discounts in our data. Almost all of the coupons have fairly low threshold (below ¥120), and the discounts are always set between 25 and 50 percent of the coupon threshold. In other words, when cities offered coupons with higher thresholds, they tended to choose higher discounts, as well.\footnote{In interviews with employees of the platform, they described the municipalities as trying to hit a certain “leverage ratio” which they defined as the ratio of the coupon threshold to the coupon discount amount. This ratio is similar but not quite the same as the closed-form expression for the \( \text{MPC}^\text{coupon} \) that we derive in Section 6 below. See the Online Appendix for more institutional details we learned from these interviews.}

To create our final analysis data set, we define the period length for each coupon to be the coupon’s period length (i.e., the number of days each consumer had to use the coupon before it expired), and we make sure to include the same days of the week as the coupon period to account for any possible day-of-week effects. For example, if a coupon’s period length lasted 5 days from Tuesday to Saturday, then we define our first pre-period to be the Tuesday to Saturday in the prior week. For some cities that experience multiple coupon waves in a row, we will take the pre-period prior to the first wave as the pre-period for all waves, in order to avoid overlap between any coupon treatment and the pre-period. When we examine spending during post-periods (i.e., the periods after the coupon wave), we define the post-periods similarly. Appendix Figure ?? illustrates the pre-periods, coupon waves, and post-periods for each of our analyzed coupons.

4 Empirical Approach

We begin by describing our bunching estimator, which is our main empirical approach. We then describe how we translate our bunching estimates into a coupon MPC estimate. Lastly, we describe how we use the random assignment of a subset of the coupons in our data to validate the bunching estimates.

4.1 Bunching Estimator

To estimate the effects of the coupons on spending, we use a modified bunching estimator that takes the distribution of spending in the periods before the coupons are distributed to be a plausible counterfactual distribution of spending in the absence of coupons. This approach follows Best et al. (2020), Defusco et al. (2020), and Cengiz et al. (2019) by using pre-treatment distributions to form the counterfactual. This approach avoids relying on strong parametric functional form assumptions that are needed to estimate behavioral responses in a single cross-section (see, e.g., Saez (2010); Chetty et al. (2011); Kleven and Waseem (2013); Kleven (2016); Blomquist et al. (2021)). Specifically, we take the distribution of purchases...
for coupon-receivers during the pre-period immediately prior to coupon recipient to take the advantage of the fact that our dataset tracks transactions of each individual account over time.

Given this setup, our bunching estimator takes as an input the distribution of spending in various time periods grouped into ¥1 bins. We then calculate the effects of the coupons on spending by calculating the “excess mass” of transactions above the coupon threshold and the “missing mass” of transactions below the coupon threshold. We do this by comparing the number of transactions in different bins during the coupon wave and the pre-period. This results in the following bunching estimators:

\[
\hat{B}_\tau = \sum_{j=\tau}^{\tau+H} (n_j^{WAVE} - n_j^{PRE}) \\
\hat{M}_\tau = \sum_{j=1}^{\tau-1} (n_j^{WAVE} - n_j^{PRE})
\]

where \(\hat{B}_\tau\) is the “excess mass” of transactions above the coupon’s spending threshold, and \(\hat{M}_\tau\) is the “missing mass” of transactions below the coupon’s spending threshold. The parameter \(\tau\) denotes the coupon-specific spending threshold, \(n_j^{PRE}\) is the number of transactions with spending amounts between \(j\) and \(j+1\) yuan in the pre-period, and \(n_j^{WAVE}\) is the number of transactions with spending amounts between \(j\) and \(j+1\) observed during the coupon wave period. The parameter \(H\) is a tuning parameter that defines the upper limit of the bunching window. Effectively, this parameter rules out the coupons having any effects on the spending distribution at spending levels greater than \(\tau + H\).\(^7\) We choose \(H = ¥50\) for all of the coupons in our data, but all of our main results are very robust to alternative upper limits (see Online Appendix).

The excess mass estimate \(\hat{B}_\tau\) contains a mix of intensive and extensive margin responses. Some of the additional transactions contributing to the excess mass represent spending that would not have occurred at all in the absence of a coupon (extensive margin), while some transactions contributing to this excess mass represent intensive margin responses, because consumers decided to spend more than they otherwise would have in order to be able to use the coupon (intensive margin). The sum of the excess mass and missing mass estimates, \(\hat{B}_\tau + \hat{M}_\tau\), is thus the total effect of the coupons on the total number of transactions.

\(^7\)Intuitively, for consumers who would have spent amounts greater than \(H\) in the absence of a coupon, the coupon represents a pure cash transfer, with a “face value” given by the coupon’s discount. If there were large effects in the upper tail of spending distribution, we would interpret this as a likely violation of the research design under the assumption that any income effects are trivially small.
4.2 Estimating $MPC_{\text{coupon}}$

The previous subsection described how to estimate the effect of coupons on the total number of transactions. This approach leads to a simple visual presentation of sharp bunching of transactions at the coupon threshold and tests the null hypothesis of no behavioral response to the coupons.

To quantify the magnitude of the behavioral response, we calculate additional bunching estimates that give the total increase in spending caused by the coupons. Instead of calculating the effects of coupons on the number of transactions, we calculate the effects of the coupons on total spending in the spending category targeted by the coupons. This leads to two additional bunching estimators:

$$
\hat{B}_\tau = \sum_{j=\tau}^{\tau+H} (n_j^{\text{AVE}} - n_j^{\text{PRE}}) \cdot j
$$

$$
\hat{M}_\tau = \sum_{j=1}^{\tau-1} (n_j^{\text{AVE}} - n_j^{\text{PRE}}) \cdot j
$$

where the net increase in spending is given by $\hat{B}_\tau + \hat{M}_\tau$.

We define the coupon MPC ($MPC_{\text{coupon}}$) to be the net increase in spending divided by the total amount of spending by the municipal government on the coupons:

$$
MPC_{\text{coupon}} = \frac{\hat{B}_\tau + \hat{M}_\tau}{S_\tau}
$$

where $S_\tau$ to denote the total amount of subsidy spending by the government on coupons with threshold $\tau$, which equals the per-coupon subsidy $d$ times the total number of coupons that were redeemed during the coupon wave.\(^8\)

For each coupon, we carry out statistical inference on the $MPC_{\text{coupon}}$ estimate using a bootstrap procedure. Specifically, we simulate the underlying distribution of transactions from the “binned” that comes from grouping the transaction-level data into ¥1 bins. We simulate the underlying distribution by replacing the “binned” values with uniform random draws within each ¥1 bin.

Next, we carry out 1000 bootstrap replications. Each replication samples from the simulated distribution with replacement, and then we calculate the $MPC_{\text{coupon}}$ within each sample. The bootstrapped standard error is calculated as the standard deviation across the 1000 bootstrap samples.

\(^8\)For example, the 24-8 coupon has a threshold $\tau = 24$ and a per-coupon subsidy $d = 8$. Table 1 reports that 20,846 of the 24-8 coupons were redeemed. Therefore, the total government subsidy to this coupon type was $S_{\tau=24} = 8 \times 20,846 = ¥166,768$ RMB. See Appendix Table OA.1 for the subsidy calculations for the other coupons.
4.3 Validating Bunching Estimates Using Random Assignment

In a subset of the coupons, the coupons are randomly assigned within a spending category. This means that conditional on acquiring a coupon, the threshold and discount is chosen randomly from one a set of three options. The residents did not know which coupon they would receive. As a result, we can estimate the causal effect of being assigned one coupon relative to another coupon by simply comparing the distribution of spending in the coupon wave. This leads to a different \( MPC_{\tau - \tau'}^{\text{coupon}} \) estimate based on comparison of spending of residents assigned the coupon with threshold \( \tau \) to the residents randomly assigned the coupon with threshold \( \tau' \). We construct this alternative coupon MPC estimator as follows:

\[
MPC_{\tau - \tau'}^{\text{coupon}} = \frac{\sum_{j=1}^{H} (n_{j, \tau}^{\text{WAVE}} - n_{j, \tau'}^{\text{WAVE}}) \cdot j}{S_{\tau} - S_{\tau'}^{l}}
\]

where \( n_{j, \tau}^{\text{WAVE}} \) is the number of transactions with spending amount between \( j \) and \( j + 1 \) for the residents randomly assigned coupon with threshold \( \tau \).

This MPC estimate can be used to validate the bunching estimates \( MPC_{\tau}^{\text{coupon}} \), because if both estimates are valid then they should be related according by the following accounting identity:

\[
MPC_{\tau - \tau'}^{\text{coupon}} = \frac{S_{\tau}}{S_{\tau} - S_{\tau'}^{l}} MPC_{\tau}^{\text{coupon}} - \frac{S_{\tau'}^{l}}{S_{\tau} - S_{\tau'}^{l}} MPC_{\tau'}^{\text{coupon}}
\]

In words, the identity above says that the MPC between any two pairs of randomly assigned coupons can be decomposed into a particular weighted average of the coupon MPCs estimated using bunching estimators. Suppose that both of the coupon MPCs are similar according to the bunching estimator (i.e., \( MPC_{\tau}^{\text{coupon}} \approx MPC_{\tau'}^{\text{coupon}} \)), then the formula above implies that the MPC estimated by comparing pairs of randomly assigned coupons should be approximately equal to the individual coupon MPCs. If these are not approximately equal (up to sampling error), then we would conclude that the bunching estimators are providing biased estimates of the coupon MPCs.

There is also a useful economic implication of the identity above, which is that if two coupons are equally cost-effective based on the coupon MPC estimate, then this implies that the government could have increased total spending by randomly assigning a greater share of the coupons to the coupon with the higher threshold.
5 Main Results

We begin by presenting visual evidence of sharp bunching at the coupon-specific thresholds during the coupon wave but not during other time periods. We then turn to quantifying the effects of the coupons on spending. We estimate effects of coupons on targeted spending categories, non-targeted spending categories, and overall spending, and we also assess the importance of intertemporal substitution by calculating how the coupon MPCs evolve dynamically over time.

5.1 Graphical Evidence

We begin by presenting clear visual evidence of bunching at the coupon-specific thresholds. For concreteness, we focus on the 54-18 food delivery coupon offered to City A residents in the second coupon wave. Recall that our analysis sample is the set of residents who acquired the coupons, tracking all of their spending on the platform in the periods before, during, and after the coupons were distributed.

Panel A of Figure 2 shows the transaction-level spending distribution for the consumers who acquired the 54-18 in the two periods before the coupons were distributed. The similarity in the distributions shows that there are no potentially confounding trends in overall spending happening in the pre-periods.

Next, Panel B of Figure 2 shows the spending distribution in the coupon wave period (t) relative to the pre-period (t − 1). This figure shows clear visual evidence of “bunching” at the coupon-specific threshold, which is consistent with coupon redemptions leading to an increase in spending. Moreover, to the left of the coupon-specific threshold, there is some visual evidence of “missing mass”, which implies that some consumers are spending more than they otherwise would have in order to be able to redeem the coupon and earn the discount.

Lastly, Panel C of Figure 3 compares the spending distributions for the period following the coupon wave (t + 1) to the pre-period (t − 1), and the distributions are fairly similar, with perhaps some very slight evidence of fewer transactions across the distribution, which would be consistent with a very small amount of intertemporal substitution.

All of these results preview the main bunching estimates. As described in the previous section, these results can be used to reject the null hypothesis of no behavioral response to the coupons. Using the pre-period spending distribution as a counterfactual, we conclude that consumers using the coupons appear to be spending more than they otherwise would have. Figure 4 shows that the pre-period distributions are quite stable for several periods in a row leading up to the coupon wave, which means that our results
are not sensitive to which pre-period we choose or whether we take an average of several pre-periods.

Figure 5 shows separate estimates of the “excess mass” and “missing mass” estimates for the 54-18 coupons by taking the difference between the period $t$ and $t - 1$ spending distributions. This figure also provides an additional way of assessing the validity of the research design, by assessing whether there is any positive (or negative) mass in the upper right tail of the spending distribution. We label this area the “excluded region” because it does not contribute to either the excess mass or the missing mass estimates. If there were confounding trends that affected the entire spending distribution, then this would lead to a positive or negative area in the excluded region. Since there is no mass in the excluded region, this gives us more confidence that the difference in distributions reflects the genuine causal effect of the coupons.

The Online Appendix reports the analogous figures for the other coupons in the data, and the same patterns tend to emerge: clear visual evidence of bunching at the coupon thresholds, excess mass that is much larger than the missing mass, and no mass in the excluded region in the upper right tail.

5.2 Empirical Estimates of $MPC_{\text{coupon}}$

To quantify the spending effects of the coupons, we estimate equation (1) to recover the coupon MPCs for each coupon. The results are reported in Table 3 and summarized graphically in Panel A of Figure 5, which correlates the coupon-specific MPCs with the coupon thresholds. Both Table 3 and Figure 5 (Panel A) show that the estimated MPCs range from 1.4 to 3.7, with a weighted average of 2.7.

As discussed above, these MPC estimates are fairly similar to the two existing estimates of coupon MPCs in the literature, and these estimates are also much larger than the estimates of other stimulus programs. Figure 6 compares the coupon MPCs from China’s digital coupon program to MPCs from other programs such as tax rebates, stimulus payments, and other shopping coupon programs that did not feature spending thresholds like the China coupons. The main takeaway from Figure 6 is that the coupon MPCs are unusually large compared to other forms of fiscal stimulus.

To try to understand the reasons for the large estimated coupon MPCs, we first consider two possible explanations: (1) substitution between spending in the targeted category (i.e., the spending category targeted by the specific coupon) and spending in other categories; and (2) intertemporal substitution.

5.2.1 Substitution Between Spending Categories

Since we observe all of the spending on the platform for all of the consumers in our analysis sample, we can also calculate the coupon MPCs for spending in the non-targeted spending categories. For example,
if we are looking at a food delivery coupon, we can look for evidence of substitution away from spending at supermarkets or restaurants, or entertainment spending. Table 4 shows that we find no evidence of any statistically or economically significant effects of coupons on the spending in non-targeted spending categories.

This implies that if we aggregate total spending across all spending categories and re-estimate equation (1) using all platform spending rather than spending in the targeted category, we should find similar results. Figure 6 shows graphically that we see the same pattern of results for all spending for the same 54-18 coupon, and Table 5 shows that we find similar coupon MPCs when looking at total platform spending. This rules out substitution to other spending categories on the platform as an explanation for the large coupon MPCs.

### 5.2.2 Intertemporal Substitution

We next assess the role of short-run intertemporal substitution by re-estimating equation (1) for multiple additional periods before and after the coupons are distributed. These results are shown in Figure 7, which shows no evidence of substantial intertemporal substitution. There is a very slight decrease in spending in the following period, but this is nowhere near large enough to offset the substantial increase in spending in the coupon wave.

As a result, we conclude that the large coupon MPCs do not come primarily for substitution across different spending categories or from short-run intertemporal substitution. We thus conclude that the coupons successfully increased total consumer spending for at least a couple of months, as consumers increased spending to reach the coupon thresholds.

### 5.2.3 Robustness and Heterogeneity

We assess the robustness of these main results in two main ways. First, we re-estimate equation (1) with different values of $H$ (which is the “tuning parameter” for the bunching estimator). We find very similar results for different values of $H$, which is not very surprising given the visual evidence presented above (see Appendix Table 2). We also estimate coupon MPCs exploiting the strict random assignment of coupons in the subset of coupons in our data. Figure 8 Panel A shows the extremely similar pre-period spending distributions for consumers who were randomly assigned different coupons. The similarity in distributions is consistent with strict random assignment. Panel B of Figure 8 shows that during the coupon wave the sharp bunching lines up with the coupon threshold for each subsample. Using the
identity in equation (2) above, we find that the estimates based on strict random assignment are always very close to the implied estimates from the bunching estimates. The differences in magnitudes are always less than 10 percent, which supports the validity of the bunching estimates.

We also explore heterogeneity across consumers. We divided consumers into two roughly equal groups by age (above and below 35), and we find similar MPC estimates across the two groups (see Appendix Figure 2 and Appendix Table 3). We also divide consumers based on how often they used the platform prior to the coupon waves, and we also find fairly similar results across the three groups (Appendix Figure 3 and Appendix Table 4). The fact that we find broadly similar coupon MPCs for the “frequent users” (who are defined as consumers in the top 5 percent of spending distribution in the months prior to coupon issuance) partially addresses concerns about possible bias from not measuring “offline” consumption if this subsample contains a greater share of consumers with a large share of their overall spending in the targeted spending category observable on the platform.

Overall, our results consistently point toward large estimated coupon MPCs that do not come primarily from reduced spending in other categories or from short-run intertemporal substitution. Why then are the estimated coupon MPCs so large? The next section goes through a simple theoretical model of consumer spending to understand the economics behind these results.

6 Consumption Model

We begin by presenting a simple consumption model to understand the economic determinants of the coupon MPC compared to the MPC out of an “equivalent” amount of cash provided by the government. We then calibrate this model to match our empirical results, and we simulate alternative coupon designs using the calibrated model.

6.1 Model Setup

The model is a $T$-period model with perfect foresight, no uncertainty, and exogenous income. Consumers can freely borrow, save, and allocate consumption across time periods and sectors ($c_t^A$ and $c_t^B$). The consumer’s per-period utility function is given by the following:

$$u(c_t^A, c_t^B) \equiv \frac{1}{1-\gamma} (\alpha (c_t^A)\rho + (1-\alpha) (c_t^B)\rho )^{(1-\gamma)/\rho}$$

where $\sigma = 1/(1-\rho)$ is the consumer’s elasticity of substitution between consumption in sectors A and B.
B, $1/\gamma$ is the intertemporal elasticity of substitution, and $\alpha$ is a share parameter that (along with $\sigma$) determines the share of spending in each period devoted to sector A.

The consumer’s lifetime utility function is given by the following:

$$U(c_1^A, c_1^B) + \frac{1}{1+\delta} u(c_2^A, c_2^B) + \ldots + \frac{1}{(1+\delta)^{T-1}} u(c_T^A, c_T^B)$$

The consumer maximizes lifetime utility subject to the following lifetime budget constraint:

$$c_1^A + c_1^B + \frac{c_2^A + c_2^B}{1+r} + \ldots + \frac{c_T^A + c_T^B}{(1+r)^{T-1}} \leq \sum_{t=1}^{T} \frac{y_t}{(1+r)^{t-1}}$$

where $\delta$ is the consumer’s subjective discount rate, $r$ is the exogenous interest rate, and $y_1, y_2, \ldots, y_T$ is the consumer’s exogenous income.

### 6.2 $MPC^{\text{cash}}$ versus $MPC^{\text{coupon}}$

If the government distributes cash in period 1 to the consumer, this is equivalent to an exogenous increase in $y_1$. In this case, we define $MPC^{\text{cash}} = \Delta(c_1^A + c_1^B)/\Delta(y_1)$. This can be solved in closed-form and depends on $r$, $\delta$, $T$, and $\gamma$, but does not depend on $\sigma$.

Now consider the government offering a coupon that offers $\mathreff d$ off if the consumer spends more than $\mathreff D$ in sector A. The consumer can decide whether or not to take up the coupon, but it must be used in period 1 (i.e., the coupon is “use it or lose it”). We assume the consumer takes up and uses the coupon if and only if it increases their lifetime utility. If the consumer takes up and uses the coupon, we can define $MPC^{\text{coupon}} = \Delta(c_1^A + c_1^B)/d$.

We cannot solve for $MPC^{\text{coupon}} = \Delta(c_1^A + c_1^B)/d$ in closed-form in general, but we prove in the Appendix that if $D < c_1^A + c_1^B$ then $MPC^{\text{coupon}} = MPC^{\text{cash}}$. In this case, the coupon is fungible with cash, and so the equivalence comes immediately from fungibility. If $D > c_1^A + c_1^B$, then the consumer may or may not take up the coupon, but if consumer takes up the coupon then we expect $MPC^{\text{coupon}} > MPC^{\text{cash}}$.

If we define $c_1^{A*}$ to be the optimal consumption choice in period 1 in sector A in the absence of the coupon, then if we assume that the consumers prefers to take up and use the coupon, then we can define the $MPC^{\text{coupon}}$ as follows:

$$MPC^{\text{coupon}} = \frac{D - c_1^{A*}}{d} + \frac{\Delta(c_1^B)}{d}$$

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This shows that if the change in consumption in sector B is small (i.e., \( \Delta(c^B_t) \approx 0 \)), then \( MPC^{\text{coupon}} \approx (D - c^A_t)/d \). This shows that the coupon MPC is increasing in the coupon threshold and decreasing in the coupon discount.

### 6.3 Model Calibration

We calibrate the model with the following parameters:

- \( T = 10 \)
- \( y_t = 1 \)
- \( r = \delta = 0 \)
- \( \rho = 0.45 \)
- \( \gamma = 0.5 \)
- \( \alpha = 0.25 \)

The parameters above imply that \( c^A_t \approx 0.10 \forall t \). We also can see immediately that \( MPC^{\text{cash}} = 1/T = 0.10 \) since \( \delta = \delta \). We solve for \( MPC^{\text{coupon}} \) numerically and Figure 8 shows how the cash and coupon MPCs vary with the threshold (as the threshold goes from 0.05 to 0.25).

Specifically, Figure 8 shows that as long as the threshold is set below 0.10, the coupon MPC is equal to the cash MPC, consistent with fungibility. As the threshold increases between 0.10 and 0.20, the coupon MPC increases approximately linearly. This figure also shows the change in consumer utility from taking up and using the coupon. The figure shows that eventually the coupon’s threshold is high enough that the consumer has higher utility from not using the coupon at all. Intuitively, the difference between preferred consumption in sector A in period 1 is much lower than the consumption needed to achieve the coupon’s discount, and this distorts consumer’s preferred consumption bundle by enough that the positive effect of discount on consumer utility is not large enough to outweigh the utility loss from the distorted consumption. In the range of the coupon MPCs we estimate (1.5-3.7), the calibration above shows that this reduces consumer utility by about 50% relative to a benchmark where the government simply sent the coupon discount as cash (i.e., unconditional cash transfer).

Next, in Figure 9 (Panel A) we build on the same model simulation and decomposes the coupon MPC into sector A and sector B spending. The figure shows that as the coupon MPC increases (as threshold
increases), there is always very little substitution away from – or towards – sector B. In other words, the parameters chosen above lead to the coupon MPC being almost entirely driven by increased spending in sector A with the (net) increase in period 1 consumption coming almost entirely from this sector.

Lastly, in Panel B of Figure 9, we show that the previous result is sensitive to parameters. In particular, if we increase $\gamma$ to 4 so that the intertemporal elasticity is 0.25, then we find that the coupon leads the consumer to reduce sector B consumption when using the coupon in period 1. Intuitively, this is because the consumer would rather substitute across spending categories than substitute consumption in both sectors over time. The coupon MPC ends up smaller because the total increased spending in sector A is a very large over-estimate of the total increase spending in period 1 because spending in sector B goes down substantially in the period the coupon is used. Our large coupon MPC estimates and lack of substitution away from other spending categories is consistent the baseline model simulation with a larger intertemporal elasticity.

7 Discussion and Conclusion

[To be completed]
References


Table 1: Coupon Summary Statistics

<table>
<thead>
<tr>
<th>City</th>
<th>Spending Category</th>
<th>Coupon Wave</th>
<th>Coupon</th>
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<th>Coupons Taken Up</th>
<th>Redemptions in Any Category</th>
<th>Redemptions in Spending Category</th>
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This table gives detailed summary information on the coupons analyzed in our paper. “City” is the city that the coupon was available in. “Coupon Category” is the category of spending in which the coupon could be redeemed. “Analyzed Category” is the category of spending that we analyze (which is either the same as, or a subset of “Coupon Category”). “Wave” is a (city-specific) number that sequences each release of coupons. “Coupon” displays the threshold and discount of the coupon. For example, a “24-8” coupon gives its holder 8 RMB off if they spend at least ¥24. “Coupons Available” is the number of coupons made available on our platform for the given coupon in the given wave period. “Coupons Taken Up” is the number of the coupons that were claimed by users of the platform. “Coupons Redeemed” is the number of coupons that were redeemed within the “Analyzed Category” (which, in cases in which “Coupon Category” and “Analyzed Category” differ, may be less than the total number of redemptions across all spending categories.)
### Table 2: Coupon Take-Up and Redemption Rates

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<tr>
<th>City</th>
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<th>Wave</th>
<th>Coupon</th>
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<th>Redemption Rate in Any Category</th>
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This table gives detailed summary information on the coupons analyzed in our paper. “City” is the city that the coupon was available in. “Coupon Category” is the category of spending in which the coupon could be redeemed. “Analyzed Category” is the category of spending that we analyze (which is either the same as, or a subset of “Coupon Category”). “Wave” is a (city-specific) number that sequences each release of coupons. “Coupon” displays the threshold and discount of the coupon. For example, a “24-8” coupon gives its holder ¥8 off if they spend at least ¥24. “Take-Up Rate” is the fraction of coupons made available on our platform that were claimed by users of the platform. “Redemption Rate” is the fraction of taken-up coupons that were redeemed within the “Analyzed Category” (which, in cases in which “Coupon Category” and “Analyzed Category” differ, may be less than the total number of redemptions across all spending categories.)
### Table 3
#### Bunching Estimates of Coupon MPCs

<table>
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<th>City</th>
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<td>Food Delivery</td>
<td>2</td>
<td>30-15</td>
<td>1.96 (0.52)</td>
</tr>
<tr>
<td>City C</td>
<td>Food Delivery</td>
<td>1</td>
<td>100-40</td>
<td>2.33 (0.79)</td>
</tr>
<tr>
<td>City C</td>
<td>Food Delivery</td>
<td>1</td>
<td>200-100</td>
<td>1.30 (0.84)</td>
</tr>
<tr>
<td>City C</td>
<td>Food Delivery</td>
<td>2</td>
<td>100-40</td>
<td>2.36 (0.68)</td>
</tr>
<tr>
<td>City C</td>
<td>Food Delivery</td>
<td>2</td>
<td>200-100</td>
<td>1.86 (0.54)</td>
</tr>
</tbody>
</table>

#### Panel B: Weighted-Average Coupon MPCs

- Weight by Number of Coupons Distributed: 2.81
- Weight by Number of Coupons Taken Up: 2.77
- Weight by Number of Coupons Redeemed: 2.92

**Notes:** This table presents coupon MPC estimates using the bunching estimator described in the main text. Column (1) reports the anonymized city the coupon was distributed in, and columns (2) through (4) describe additional details of the coupon. Column (5) reports the coupon MPC estimate and the standard error in parentheses. All standard errors based on 1,000 bootstrap replications.
Table 4
Effects of Coupons on Spending in Other Spending Categories

<table>
<thead>
<tr>
<th>Spending Category</th>
<th>City A, Wave 2, 24-8</th>
<th>City A, Wave 2, 54-18</th>
<th>City A, Wave 2, 84-28</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food Delivery Spending</td>
<td>3.62</td>
<td>3.71</td>
<td>3.50</td>
</tr>
<tr>
<td></td>
<td>(0.20)</td>
<td>(0.05)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>All Other Spending</td>
<td>-0.62</td>
<td>0.12</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>(0.85)</td>
<td>(0.34)</td>
<td>(0.18)</td>
</tr>
<tr>
<td>Supermarket</td>
<td>-0.93</td>
<td>-0.17</td>
<td>-0.15</td>
</tr>
<tr>
<td></td>
<td>(0.63)</td>
<td>(0.22)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>Dining</td>
<td>0.03</td>
<td>0.02</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>(0.37)</td>
<td>(0.21)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>Entertainment</td>
<td>-0.03</td>
<td>-0.02</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(0.21)</td>
<td>(0.10)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Hotel</td>
<td>0.03</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.08)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Total Spending</td>
<td>3.00</td>
<td>3.83</td>
<td>3.62</td>
</tr>
<tr>
<td></td>
<td>(0.94)</td>
<td>(0.42)</td>
<td>(0.23)</td>
</tr>
</tbody>
</table>

Notes: This table presents coupon MPC estimates using the bunching estimator described in the main text for each coupon and category of spending separately, focusing on the Wave 2 coupons distributed in City A. All of these coupons were food delivery coupons.
Notes: This figure shows the distribution of coupon thresholds and discounts in our data. The dashed lines indicate the set of coupon discounts that corresponds to 25 percent and 50 percent of the coupon thresholds. All of the coupons lie between the two rays, which implies that when municipalities chose higher coupons, they chose higher coupon discounts to keep the ratio of the discount to the threshold between 25 and 50 percent. All values are in ¥.
Figure 2: Illustration of Bunching Estimator for 54-18 Coupon in City A

(a) Comparing Pre-Periods $t - 2$ to $t - 1$

(b) Bunching in Period $t$ Compared to $t - 1$

(c) Comparing Periods $t + 1$ to $t - 1$

Notes: This figure illustrates the bunching estimator by comparing the distribution of spending between periods around the time the coupons were distributed. Panel (a) compares the distribution of spending in the two pre-periods immediately before the coupons were distributed. Panel (b) shows the distribution of spending during the coupon wave. Panel (c) shows the distribution of spending in the period immediately after coupons were distributed. In all panels the pre-period $t - 1$ distribution is shown for reference.
Figure 3: Sensitivity of Bunching Estimator to Alternative Pre-Periods for 54-18 Coupon in City A

Notes: This figure illustrates the sensitivity of our bunching estimator to different pre-periods by comparing the distribution in the coupon wave period to four pre-periods ($t - 1$ through $t - 4$).
This figure “differences” the transaction distributions between the periods $t$ and $t-1$ as shown in panel (b) of Figure 2. The area below the coupon threshold is the “missing mass” and the area above the threshold ($\tau$) and below the assumed upper bound ($\tau + H$) is the “excess mass”. The difference in distributions above the upper bound is the excluded region and is assumed to be equal to zero if the research design is valid.
Figure 5: Effects of Coupons on Total Platform Spending

(a) Bunching in Period $t$ Compared to $t - 1$

(b) Comparing Periods $t + 1$ to $t - 1$

Notes: This figure reproduces the panels in Figure 2 using the distribution of total spending on the platform instead of the distribution of spending in the spending category targeted by the coupon. The similarity in figures across the analogous panels is consistent with the estimates in Table 5 showing limited effects of coupons on consumption in “non-targeted” spending categories.
Figure 6: Evolution of Coupon MPC estimates Over Time

Notes: This figure reports coupon MPC estimates over time for the three coupons distributed in wave 2 in City A. The small coupon MPC estimates after the coupon wave period is consistent with a very small amount of short run intertemporal substitution.
Figure 7: Estimating $MPC_{\text{coupon}}$ by Exploiting Random Assignment of Coupons

(a) Comparing Spending in Pre-Period $t - 1$

(b) Comparing Spending in Coupon Period $t$

(c) Comparing Spending in Post-Period $t + 1$

Notes: This figure reports panels analogous to Figure 2 except that the identification is based on comparing the consumers who were randomly assigned different coupons in Wave 2 in City A. Panel (a) compares the distribution of spending between the two groups of consumers assigned either the 54 – 18 or the 84-28 coupon. The distributions are nearly identical which is consistent with the strict random assignment of the coupons. Panel (b) compares the distribution of spending during the coupon wave; there is clear bunching at the coupon thresholds for each group, and there is greater overall spending for the consumers randomly assigned the higher-threshold/higher-discount coupon. Panel (c) shows the distribution of spending in the period immediately after coupons were distributed; the similarity is consistent with limited amount of intertemporal substitution, since the greater spending in coupon wave period does not show up as lower spending in the following period.
Figure 8: Model Simulation of $MPC^{coupon}$

Notes: This figure shows how the model-based $MPC^{coupon}$ varies with the coupon threshold. See main text for more details on the simulation.
Figure 9: Sensitivity in Model to Different Values of the Intertemporal Elasticity of Substitution

(a) Model Simulation with $\gamma = 0.5$

(b) Model Simulation with $\gamma = 0.5$

Notes: This figure shows how the model-based simulation results vary with the intertemporal elasticity of substitution $(1/\gamma)$. 

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