# Supporting Seniors: How Low-Income Elderly Individuals Respond to a Retirement Support Program *

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**Abstract**

Longer life expectancy and insufficient savings expose individuals to financial vulnerability in older ages and prompt government support measures. We study a government cash subsidy program for the low-income elderly population in Singapore. Using comprehensive, high-frequency transaction data, we estimate a marginal propensity to consume (MPC) out of the subsidies of 0.7. More liquidity-constrained recipients exhibit a higher MPC of 1. They also increase their spending immediately after recurring subsidies. We find no evidence of labor supply reduction or other strategic behaviors. We discuss implications for eligibility criteria, payment frequency, and distribution form in policy design.

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## 1 Introduction

Many countries in the world face population aging due to lower birth rates and longer life expectancies. The global population aged 60 years or over numbered 962 million in 2017 and is expected to double by 2050 (United Nations, 2017). Across countries, the fraction of the population aged 65 or above in 2017 is particularly high among developed countries, with close to 16% in the United States and as high as 27% in Japan. The sheer size of the elderly population exerts pressure on the social security programs in meeting retirement spending needs. An added concern is that a large portion of the elderly may have insufficient liquid savings to prepare for their extended life (Laibson, Repetto, Tobacman, Hall, Gale, and Akerlof, 1998; Skinner, 2007). These factors prompt policymakers to consider support measures, e.g., direct fiscal transfers.

How the elderly's consumption respond to the transfer programs is an interesting question. Some elderly may over-spend due to behavioral factors, while some under-spend due to bequest motives. Hence, how do the elderly recipients adjust their consumption in response to the transfer programs and what factors affect the consumption response? Another pertinent question is the relative effectiveness of transfer programs across subgroups of the elderly population. Moreover, there is a simple but important policy design question: What is a good policy in terms of eligibility criteria, payment frequency, and distribution form? Answers to these questions are pertinent to the imminent policy need, yet little is known. Finding answers to the questions above is particularly important in the current pandemic. A key component of government economic rescue programs is to bring resources to the needy in a speedy, effective, and efficient manner that has the intended impact—elevating their depressed consumption.

In this paper, we study a government means-tested subsidy program targeting low-income elderly individuals in Singapore. Singapore is a developed economy that faces the aging challenge. According to the United Nations' projection, the fraction of Singapore's population aged 65 or above will reach 47% by 2050. Starting from 2016, the Ministry of Finance in Singapore rolled out one of the government's largest transfer programs, the Silver Support Scheme, that distributes a quarterly subsidy to eligible Singaporeans aged 65 and above. This means-tested subsidy program has features that facilitate highly reliable empirical investigations: (i) transparent means-testing in selecting recipients, (ii) accurate identification of recipients, and (iii) perfectly traceable passing of cash to target recipients. Specifically, elderly individuals with limited pre-retirement cumulative income, limited current family support, and residential status in public housing are eligible to receive the quarterly subsidies. A key component of the means testing is based on historical data which mitigates the concern that recipients might manipulate their behaviors to qualify for the program. This adds credence to our empirical results. The subsidies range from 300 to 750 Singapore Dollars (228 to 570 US Dollars) per individual per quarter and are higher for people living in smaller public housing units. The subsidies are directly deposited into recipients' bank accounts by the government. Around 150,000, or approximately the bottom 20%, elderly individuals receive the recurring subsidies. The annual cost of financing amounts to 230 million US Dollars in 2019.

We study how households respond to the subsidy program, using administrative transaction data of checking accounts, debit cards, and credit cards from DBS Bank, the largest bank in Singapore. The quarterly Silver Support subsidies are recorded with a designated transaction code in the bank's records. We use this designated transaction code to identify the recipients among all older adults and the timing and size of subsidies they receive.

Our analysis is based on an event-study design that compares the behaviors of a recipient before and after program inception, that is, the time she starts to receive the recurring subsidies. The timing of program inception depends on the recipients' age. Specifically, the quarterly subsidy starts in the quarter before the 65th birthday for an eligible individual and continues for as long as this individual remains eligible. We only include the recipients in our main analysis sample, thus isolating the potential selection effect. Our estimation compares a recipient's change in consumption since the start of receiving her subsidies, relative to the consumption changes of other subsidy recipients who start to receive the subsidies at different times. The staggered inception of the Silver Support subsidies allows us to include time fixed effects to control for unobserved aggregate confounding factors such as general seasonal variation in consumption expenditures.

We begin by examining the average change in consumption expenditures as an individual receives the subsidies. Recipients increase their total spending by 0.69 dollars per dollar of subsidy. This additional spending corresponds to approximately 16% of the average spending in the pre-subsidy period. More than 80% of the total spending increase after program inception is attributable to the spending increase using cash, followed by the increase in bill spending and debit card spending. Credit card spending, on the other hand, experiences a statistically insignificant decrease.

We address several concerns for attributing the observed changes in spending to the subsidies. We perform falsification tests using non-recipients that are matched to recipients based on observable characteristics such as age, gender, income, wealth, and housing status. By construction, these matched non-recipients are in the same age- and wealth-cohorts as the recipients, and their spending provide a useful reference for the impact of unobserved life cycle trends. We find that the matched non-recipients do not increase their spending upon the matched pseudo program inception. This reassures us that the spending response of recipients is unlikely to be driven by unobserved, age-cohort-specific, or wealth-cohort-specific life cycle trends. In addition, we reject the hypothesis that the observed spending response could simply be random using a bootstrap test.

To gauge the dynamic pattern of the spending response, we investigate the dynamic evolution of spending before and after program inception. We find no anticipatory effect on spending in the three months before program inception. Spending starts to increase after program inception. In the 29 months after program inception, the cumulative increase in spending on average reaches 5,200 dollars. We also investigate how recipients respond to the quarterly recurring subsidy payments. We track daily spending for twelve weeks after each subsidy payment and analyze the high-frequency dynamics. We find little anticipatory effect on spending in the four weeks prior to recurring subsidies. Once the individuals receive the payouts, they increase their spending immediately. By the end of the payout week, recipients have spent more than 0.2 dollars for each dollar of subsidy received, which accounts for approximately 40% of the cumulative spending response in the twelve-week horizon.

We find substantial heterogeneity in the consumption response to program inception across recipients. In particular, lower-liquidity (as measured by the pre-period bank balance scaled by income) recipients appear to have a much larger MPC relative to higher-liquidity individuals. The difference in the spending response of lower-income and higher-income individuals, on the other hand, is much more muted. Moreover, liquidity remains highly relevant in elevating the MPC when we hold income constant, whereas income differences do not appear to explain differences in MPC once we hold liquidity constant. We also examine the role of liquidity in driving the immediate spending response to recurring subsidy payments. Lower-liquidity recipients exhibit a stronger spending response. Moreover, they concentrate their additional spending in the first week since the recurring subsidy payments. On the contrary, higher-liquidity recipients have a much smaller first week response.

The characteristics of the spending response are also important for us to assess the efficacy of this subsidy program. The majority of the spending response is in the form of cash spending, consistent with the lower adoption of cashless payment instruments among the elderly. We analyze the locations of ATMs from which the recipients in our sample withdraw cash to sharpen our understanding of what the spending response might entail. We find that the recipients expand their geographic footprints upon receiving the subsidies. They also appear to increase their dining-out spending, as proxied for by ATM withdrawals near food courts. A separate analysis of retail purchases using the Nielsen Homescan dataset corroborates the increased food spending.

Next, we turn to other aspects of the recipients' behavioral responses to the subsidy program. Using real-time salary to measure labor supply, we find that there is no change in either the extensive or intensive margin of labor supply following program inception. As for the housing response, one might suspect that recipients strategically downsize their apartments to qualify for larger subsidies. We test this hypothesis with various measures for residential moves. We find that the likelihood of moving remains low and unchanged, implying that recipients do not downsize their apartments to qualify for larger subsidies.

We discuss the implications for policy design of our empirical findings. The Silver Support Scheme achieves its intended objective of stimulating consumption with little side effects on labor supply and housing. We also find no discernable strategic behaviors to qualify for the subsidy program before 65, implying that the eligibility criteria are well designed. The heterogeneity analysis shows that liquidity is consistently a more important driver for the consumption response than income. Individuals with lower levels of liquid assets may not be able to smooth consumption if they experience negative shocks. For such individuals, the increase in consumption is a rational response to the relaxation of liquidity constraints. Their MPC out of the subsidies reaches \$1. This finding has important implications for the policy design of elderly support programs: If the goal of the policy is to maximize consumption response, then a means test based on liquidity can correctly identify constrained individuals and may therefore be more effective than a means test based on income. In terms of payment frequency, our results imply that the government could improve consumption smoothing by splitting quarterly payments into smaller, more frequent payments. Lastly, the efficacy of a subsidy program can also depend on how subsidies are disbursed. We compare the consumption response to the Silver Support Scheme's direct cash approach with that to an earlier program in Singapore which targets the same elderly demographic group but takes the form of vouchers for medical and health insurance expenses. We find that even the most constrained recipients of the medical vouchers do not increase their spending upon receiving the vouchers, highlighting that a cash/bank transfer disbursement is more effective than a voucher disbursement in stimulating consumption.

Our paper contributes to the aging and retirement literature. Existing literature on the life cycle dynamics of consumption and savings suggests that individuals should save significantly for retirement from their early forties (Gourinchas and Parker, 2002). However, bounded rationality, hyperbolic discounting, and self-control problems can result in insufficient retirement savings in the working years (Laibson et al., 1998; Angeletos, Laibson, Repetto, Tobacman, and Weinberg, 2001). For instance, Poterba, Venti, and Wise (2012) document that approximately half of US retired households rely almost entirely on Social Security benefits for retirement support and have virtually no financial assets upon death. Furthermore, the recent trends of rising life expectancy and increasing health care costs for the elderly pose additional challenges to the retired who reasonably would not have anticipated these trends earlier in their lives. The government can influence retirement financial security through its policy designs of pension policies and transfer programs. Agarwal, Pan, and Qian (2020) show that early access to retirement savings relaxes liquidity constraints for the older population near their retirement. This paper documents a strong consumption response, mostly to meet daily needs, among the low-income elderly population to a quarterly cash subsidy. These findings provide supporting evidence on the efficacy of a cash-based means-tested transfer program to support the trapped elderly population.[1] The evidence also highlights the importance of taking into account liquid savings, in addition to income, to target the neediest elderly.

We also relate to the large literature on the consumption response to income shocks

[1] A closely related literature on the fungibility of money documents that equivalently valued cash and voucher transfers have differential impacts on household decision making (Hastings and Shapiro, 2013, 2018; Beatty, Blow, Crossley, and O'Dea, 2014; Benhassine, Devoto, Duflo, Dupas, and Pouliquen, 2015; Gelman, Gorodnichenko, Kariv, Koustas, Shapiro, Silverman, and Tadelis, 2019).

(Browning and Collado, 2001; Jappelli and Pistaferri, 2010). Existing studies find a large consumption response to expected and unexpected income shocks, especially for the liquidity-constrained consumers.[2] Our results reinforce the finding by providing additional estimates of the magnitude and dynamic characteristics of the consumption response among the elderly. In particular, the elderly subsidy recipients with lower levels of liquid savings spend the full dollar for each dollar of subsidy received; more than 40% of the spending response concentrates in the first week after recurring payouts. The recipients with higher levels of liquid savings, on the other hand, register a less intensive and less immediate response.

Our findings provide a useful reference for the policy design of government transfer programs. Amidst the COVID-19 pandemic, many fiscal programs have been developed to support the hardest-hit people and to provide economic stimulus. Our results are worthy of attention: Bringing cash to those facing liquidity stress produces efficient and effective help, which will instantly elevate the recipients' depressed consumption. We also document little reduction in labor supply or other strategic behaviors, highlighting the strength of the means testing criteria. The housing and pre-55 cumulative income criteria are costly to manipulate and thus the program does not distort incentives.

## 2 The Silver Support Scheme in Singapore

The Silver Support Scheme is a means-tested program for the elderly population in Singapore. This program directly distributes a quarterly cash subsidy to eligible Singaporeans aged 65 and above, who have had low income throughout life and who currently have a low level of family support. Specifically, a Singaporean aged 65 and above is eligible for the subsidy if the person meets all three of the following criteria. First, the total

[2] Examples include Zeldes (1989a,b); Carroll, Hall, and Zeldes (1992); Shapiro and Slemrod (2003a,b); Souleles (1999, 2000, 2002); Parker (1999); Hsieh (2003); Stephens (2003, 2006, 2008); Stephens and Unayama (2011); Aguiar and Hurst (2005, 2013); Agarwal and Qian (2014, 2017); Gelman, Kariv, Shapiro, Silverman, and Tadelis (2014); Di Maggio, Kermani, Keys, Piskorski, Ramcharan, Seru, and Yao (2017); Olafsson and Pagel (2018); Baker (2018).

contribution to the national pension savings system, the Central Provident Fund (CPF), does not exceed 70,000 Singapore Dollars (SGD) by the age of 55.[3] As both the CPF participation and contribution rates are mandatory for working Singaporeans, this criterion amounts to a criterion of low pre-retirement cumulative income effectively. Second, the monthly income per person in the household that this individual currently lives in does not exceed 1,100 SGD. Third, the individual should live in subsidized public residential housing, known as HDB, in an apartment up to 5 rooms. Homeownership is restricted to one HDB apartment up to 4 rooms. If an individual, or his/her spouse, owns a 5-room or larger HDB apartment, or a private property or multiple properties, the individual is ineligible (in Singapore, HDB households are typically less well-off than private property residents.) Thus, these three criteria limit the program eligibility to elderly people with low cumulative past income, living in a household with a low level of per capita income, and with limited housing wealth. The program covers about 150,000, or approximately the bottom 20%, elderly individuals in Singapore.

An eligible elderly individual receives quarterly subsidies according to the size of the HDB apartment this individual lives in. Specifically, the subsidy per quarter is 750 SGD for residents of 1- and 2-room HDB apartments, 600 SGD for residents of 3-room HDB apartments, 450 SGD for residents of 4-room HDB apartments, and 300 SGD for residents of 5-room HDB apartments. The annual cost of financing the subsidies stands at SGD 330 million in 2019.

The Silver Support Scheme was first introduced in August 2014 by Singapore's Prime Minister Lee Hsien Loong during the National Day Rally. Subsequently, the program was formalized by the Parliament in August 2015 and commenced in 2016. The Singapore government automatically reviews individuals' eligibility periodically and sends a notification letter to eligible individuals in advance of the first subsidy. Individuals are also able to check their eligibility using a government online portal. It is reasonable to

[3]For self-employed individuals, an additional requirement is that the average annual net trade income did not exceed 22,800 SGD when they were between the ages of 45 and 54.

assume that the subsidies are fully anticipated.

The timing of the subsidies depends on the recipients' age. Specifically, the quarterly subsidy starts in the quarter before the 65th birthday of an eligible individual and continues for as long as this individual remains eligible. This staggered inception of the Silver Support subsidies allows us to compare recipients who start to receive the subsidies at different times to isolate the potential selection effect in our empirical analysis.

The subsidies are distributed by the government in the form of direct bank transfers and are recorded with a designated transaction code in bank records. We use this designated transaction code to identify the recipients among all elderly people and to accurately measure the timing and size of the subsidies they receive.

We focus on Singapore, which is an interesting country to study due to data quality and availability. There are several reasons to believe that the results from Singapore are relevant for understanding retirement care more generally. First, population aging is a widespread phenomenon seen in most developed countries and many developing countries. With both costs of living and life expectancy increasing substantially in Singapore over the past decades due to economic growth, many elderly individuals are left underprepared. Many fast-growing developing countries may face the same emerging class of needy elderly soon. Second, other countries have introduced means-tested programs to support the economically stressed elderly population. The empirical impact of Singapore's experience may apply to them. In section 7, we discuss the impact of program features in more detail.

## 3 Data and summary statistics

Our main dataset contains comprehensive records of banking transactions from the DBS Bank, the largest bank in Singapore. The data cover 250,000 individuals over a 36-month period from January 2016 to December 2018. This bank has more than 4.5 million customers or 80% of the entire population of Singapore as of 2017. The 250,000 individuals in the sample constitute a random, representative sample of this bank's consumer banking customers.

The first set of comprehensive records is the detailed transaction-level information about the bank accounts, debit cards, credit cards, and mobile wallets that individuals in the sample have with the bank. For each transaction, we observe the amount, date, and type (debit or credit). For bank account transactions, we also observe the transaction code that the bank assigns according to its transaction classification system. The granular transaction classification allows us to distinguish different types of inflow and outflow transactions. For instance, we can differentiate inflows due to salaries, investment returns, and different types of government transfers. For spending transactions using credit cards, debit cards, and mobile wallets, we also observe the merchant name and merchant category. To supplement the information on the characteristics of cash transactions (deposits and withdrawals), we use another set of bank records that contains the locations and timestamps of all transactions conducted through automatic teller machines (ATMs).

The data also contain the monthly statement information about each of the aforementioned accounts with the bank. The information includes the bank account balance, total transaction amount, types and amount of fees incurred, and credit limit, payments, and debt (for credit cards).

Lastly, the data include individual demographic characteristics, including age, gender, educational attainment, marriage status, income, property type (public or private housing), postal area,[4] nationality, ethnicity, and occupation.

The quarterly Silver Support subsidies are recorded with a unique transaction code that allows us to accurately identify the recipients among all elderly individuals. For our baseline analysis, we restrict the sample to Singaporeans who have received at least one Silver Support subsidy in their bank accounts during the sample time window. Since the subsidies are distributed to the bank accounts that are registered with the government

[4]In Singapore, a postal code is 6 digits in length and represents a building. A postal area corresponds to the first two digits of postal codes. There are 28 postal areas in total.

for receiving various government transfers, the recipients in the bank records likely have a primary or even exclusive relationship with the bank. In accordance with the eligibility criteria for the Silver Support scheme, we further exclude individuals who are less than 64.75 years old at the time of the first subsidy[5] and individuals who live in private properties as opposed to the public housing (HDB). Our final sample comprises 1,340 individuals.

We consider four categories of spending. Cash spending is computed by adding all cash withdrawals from automated teller machines (ATMs) and teller counters over all bank accounts for each individual. Debit card spending is computed by adding spending over all debit card accounts for each individual. Credit card spending is computed by adding spending over all credit card accounts for each individual. For individuals who do not have any credit card with the bank, we impute 0 for credit card spending. Bill spending is computed by adding all recurring bill payments across all bank accounts for each individual.

We report the summary statistics for spending, demographic, and financial characteristics in the pre-subsidy period in Table 1. The average monthly cash spending is 965.2 SGD, more than 68% of the average monthly total spending of 1,407.8 SGD.

## 4 Empirical approach

To test for the effect of a subsidy program, ideally one would randomly allocate the subsidies to a subset of elderly individuals. In this randomized setting, the difference in spending between recipients and non-recipients would be orthogonal to all individual characteristics and therefore reflect the impact of the subsidies. The actual implementation of the current subsidy program is different from this randomized setting; it relies on a means test to determine eligibility for receiving the subsidies. As a result, non-recipients

[5]This choice of age cutoff is to account for the one quarter lag from the timing of the first subsidy to the time when the eligible individual turns 65. For instance, an invididual who turns 65 years old in the first quarter of 2017 and satisfies the income and housing criteria will receive the first subsidy at the fourth quarter of 2016.

may not constitute a credible counterfactual for recipients even after observable characteristics are controlled for due to unobservable differences. We include only the recipients in our main analysis sample, thus alleviating this concern about the validity of using non-recipients as the control group.

Our estimation exploits the staggered program inception across recipients. Specifically, the quarterly subsidy starts in the quarter before the 65th birthday for an eligible individual and continues as long as this individual remains eligible. Table 2 reports the distribution of the timing of the first subsidy in our sample. We identify a recipient's starting time in receiving her subsidy. We then compare her change in consumption since the start of receiving her subsidies, relative to the consumption changes of other subsidy recipients who start to receive the subsidies at different times. The staggered inception of the subsidies allows us to include time fixed effects to control for unobserved aggregate confounding factors such as general seasonal variation in consumption expenditures. Hastings and Shapiro (2018) use a similar approach to analyze the consumption response to the adoption of SNAP vouchers.

First, we study the average daily response to the subsidy program inception using the following specification:

$$y_{i,t} = \mu_i + \pi_{ym} + \delta_{dow} + \beta \cdot Post_{i,t} + \varepsilon_{i,t} \tag{1}$$

$y_{i,t}$ is the dollar amount of total spending (further decomposed into cash, debit card, credit card, and bill spending) of individual $i$ on day $t$. The key variable of interest is $Post_{i,t}$, an indicator variable equal to 1 for the calendar days since the individual receives the first subsidy. We include a host of fixed effects to control for unobserved characteristics that are invariant in dimensions that one might think as confounding factors. Individual fixed effects $\mu_i$ are included to absorb unobserved cross-sectional heterogeneity such as individual consumption preference. Year-month fixed effects $\pi_{ym}$ are included to absorb seasonal variations in aggregate consumption expenditures and the average impact of all other concurrent aggregate factors. Day-of-week fixed effects $\delta_{dow}$ are included to control for the possibility that consumption expenditures for different days of the week differ. Standard errors in all regression analyses are clustered at the individual level.

In equation (1), the omitted period includes the days before the individuals receive their first Silver Support subsidy, the benchmark period against which our estimated response is measured. $\beta$ captures the impact of the Silver Support subsidies on daily spending and is estimated with only within-individual variation but not between-individual variation.

In addition to the average spending response to receiving the subsidies, we are also interested in the marginal propensity to consume (MPC) out of the subsidies, that is, for each dollar of subsidy, how much additional spending is. To gauge this MPC measure, we estimate the following specification:

$$y_{i,t} = \mu_i + \pi_{ym} + \delta_{dow} + \beta_{MPC} \cdot Post_{i,t} \cdot DailySubsidyAmount_i + \varepsilon_{i,t} \tag{2}$$

$DailySubsidyAmount_i$ is the daily-equivalent amount of Silver Support subsidies, calculated as the quarterly Silver Support subsidy divided by 90. $\beta_{MPC}$ captures the average change in daily spending per dollar of subsidy received. As for $\beta$ in equation (1), $\beta_{MPC}$ is estimated with only within-individual variation.

To analyze the dynamic response, we estimate the following distributed lag model:

$$y_{i,t} = \mu_i + \pi_{ym} + \delta_{dow} + \sum_{s=-3}^{T} \beta_s \cdot \mathbb{1}_{i,(sm)} + \varepsilon_{i,t} \tag{3}$$

where $\mathbb{1}_{i,(sm)}$ is an indicator variable for each of the months before and after an individual receives the first subsidy. For example, $\mathbb{1}_{i,(0m)}$ is an indicator for the exact month that an individual receives the first subsidy, while $\mathbb{1}_{i,(-1m)}$, $\mathbb{1}_{i,(-2m)}$, and $\mathbb{1}_{i,(-3m)}$ are indicator variables for each of the three months before an individual receives the first subsidy. Similarly, $\mathbb{1}_{i,(1m)}, \ldots, \mathbb{1}_{i,(Tm)}$ refer to each of the $T$ months after an individual receives the first subsidy. In this specification, the omitted period is the fourth and earlier months before an individual receives the first subsidy.

This dynamic specification can be interpreted as an event study, following Agarwal, Liu, and Souleles (2007) and Agarwal and Qian (2014). The coefficient $\beta_0$ measures the immediate dollar response in spending to program inception, relative to the baseline level in the fourth and earlier months before program inception. The post-period coefficients $\beta_1, \ldots, \beta_T$ capture the change in each of the $T$ months since the first subsidy, relative to the fourth and earlier months. By the same token, the pre-period coefficients $\beta_{-3}, \ldots, \beta_{-1}$ capture the difference in each of the three months prior to the first subsidy relative to the omitted period, and reflect the anticipatory effects in spending.

We define the *cumulative* coefficients $b_s \equiv \sum_{t=-3}^{s} 30 \cdot \beta_t$ for the cumulative response in spending after $s$ months. Note that the coefficient $b_s$ captures the cumulative spending response from month $-3$ (i.e., three months before program inception). Thus, the cumulative effect of spending at month $s$ upon receiving the subsidy is $b_s - b_{-1} \equiv \sum_{t=0}^{s} 30 \cdot \beta_t$ for $s \geq 0$. For instance, $\beta_0 = 4$ and $\beta_1 = 3$ imply that spending rises by 4 dollars per day in the month an individual receives the first subsidy, and after one month, spending rises by 3 dollars per day. The total increase in each of these two months amounts to $30 \cdot \beta_0 = 120$ and $30 \cdot \beta_1 = 90$ dollars, respectively. The cumulative spending effect at the end of month 1 is, therefore, equal to $b_1 - b_{-1} = 210$.

Our test of whether an individual is smoothing consumption before and after program inception corresponds to testing whether the $b'$s before $b_0$ are significantly different from zero. Significant increases in the cumulative spending in the months prior to the program inception imply that individuals are smoothing their consumption in anticipation of an increase in disposable income. Tracing out the $b'$s over longer horizons also shows whether the consumption stimulus persists beyond the initial subsidies.

## 5 Consumption response to the subsidy program

### A Average spending response to program inception

We begin by examining the average change in consumption expenditure as an individual receives the subsidies.

Table 3 shows the average spending response in terms of the dollar amount as estimated from equation (1). The first column shows the average response of daily total spending, i.e., the sum of cash spending, debit card spending, credit card spending, and bill spending, to receiving the subsidies. Overall, Silver Support recipients increase their total spending by 7.35 dollars per day. The effect is both statistically and economically significant; the additional spending corresponds to approximately 16% of the average daily spending in the pre-subsidy period, 46.9 dollars (one-thirtieth of 1,407.8 dollars, the average monthly spending in Table 1). More than 80% of the total spending increase after program inception are attributable to the spending increase using cash (5.87 dollars per day, column 2), while the remaining is due to bill spending (1.29 dollars per day, column 5) and spending on debit cards (0.46 dollars per day, column 3). The coefficient on credit card spending is -0.06 (column 4), which suggests that credit card spending experiences a 0.06 dollar decrease per day. But the effect is statistically insignificant. One potential reason for this lack of significance is the low fraction of credit card holders in the sample of recipients. Since credit cards provide liquidity to households, we examine the differential response of credit card holders and non-holders in the analysis of the impact of liquidity on the spending response in Section 5.E.

One potential measurement issue is that bill spending may include payment for credit card spending. If this is the case, total spending is inflated as it is subject to double-counting. However, since only 12% of recipients have credit card(s) with the bank, the extent of this double-counting is limited. Nonetheless, we remove such double-counting at the monthly level using the information on the payment amount from credit card statement records. We then estimate the average monthly response to the subsidies using the monthly analogue to equation (1) and report the results in Online Appendix Table OA.1. Using the alternative measurement frequency and specification, we find that the Silver Support recipients increase their total spending by 219.4 dollars per month or about 16% of the average monthly spending in the pre-subsidy period of 1,407.8 dollars.

The Silver Support subsidies, ranging from 300 to 750 SGD per quarter, represent a non-trivial source of additional income for the recipients who have per capita household income less than 3,300 SGD per quarter. To sharpen our understanding of the effectiveness of the subsidy program, we examine the MPC out of the subsidies.

Table 4 reports the estimates from equation (2). $SubsidyAmount_i$ is the daily-equivalent amount of the Silver Support subsidies, calculated as the quarterly subsidy divided by 90. $\beta_{MPC}$ captures the average daily post-period spending per dollar of subsidy received relative to the daily spending in the period before program inception. The first column shows that on average, Silver Support recipients increase their total spending by 0.69 dollars per dollar of subsidy received. 85% of the overall MPC out of the subsidies takes the form of cash spending (0.59 dollars per dollar of subsidy received, column 2), and the remaining is due to debit card spending (0.05 dollars per dollar of subsidy received, column 3) and bill spending (0.05 dollars per dollar of subsidy received, column 5). The coefficient on credit card spending change is -0.01 (column 4), which suggests that credit card spending experiences a 0.01 dollar decrease per dollar of subsidy received. Both the positive MPC in the form of bill spending and the negative MPC in the form of credit card spending are statistically insignificant.

### B Falsification tests

Before turning to additional results on the dynamics, heterogeneity, and characteristics of the spending responses, in this subsection, we address several key concerns with our empirical approach.

In attributing the observed changes in spending to the subsidies, one might be concerned that our estimated consumption changes reflect life cycle changes among individuals in the age cohorts of those eligible for the subsidies. To address this concern, we perform a falsification test among Singaporeans in the same age cohorts as those eligible but who do not receive the subsidies. To ensure that non-recipients are observationally similar to recipients in our sample, we adopt a propensity score matching approach and proceed with two steps. First, we narrow the set of potential matches to those who have a checking account with the bank and live in HDB housing. Second, we calculate propensity scores based on the following covariates: the natural logarithm of age, the natural logarithm of bank balance, gender, homeownership, ethnicity, and the number of years as a customer of the bank. We perform the nearest-neighbor matching based on the computed propensity scores. It is worth mentioning that we do not include income as a matching variable as income is one of the eligibility criteria. Instead, we rely on the bank balance variable to match non-recipients who have observationally similar levels of financial resources to those of recipients.

We carry the actual recipients' program inception timing to their corresponding matched non-recipients. We then estimate the spending response to the pseudo program inception using equation (1). The results, reported in the first column of Table 5, show that matched non-recipients increase their spending by 1.18 dollars per day following the pseudo first subsidies. Not only is this estimated spending response much lower than that of actual recipients, it is also not statistically distinguishable from zero. Hence, life-cycle changes specific to the age cohort of the eligible do not drive our observed consumption changes.

As the welfare program targets lower-income and lower-wealth elderly individuals, matched non-recipients from the same age cohorts naturally have slightly higher levels of income than the recipients. The above falsification test, by design, cannot rule out the impact of unobserved wealth-specific trends. We, therefore, conduct another falsification test among Singaporean non-recipients who are between 60 years old and 65 years old (they are not yet old enough to be eligible for the Silver Support Program subsidies) but have similar income and wealth levels to the recipients. To create the sample used in the falsification test, we follow a similar two-step process. First, we narrow the set of potential matches from all non-recipients to those who are Singaporeans, are between 60 and 64.75 years old in December 2018, do not live in private housing, and have a checking account with the bank. Second, we calculate propensity scores based on the following covariates: the natural logarithm of income, the natural logarithm of bank balance, gender, homeownership, ethnicity, and the number of years as a customer of the bank. We perform the nearest-neighbor matching based on the computed propensity scores. Compared to the previous falsification test, income is added as a matching variable while age is removed. We carry the actual recipients' program inception timing to their corresponding matched non-recipients. We then estimate the spending response as in equation (1). The results, reported in the second column of Table 5, show that matched younger non-recipients increase their spending by 1.63 dollars per day following the pseudo program inception. Similar to the spending response in the first falsification test, this spending response is both much lower than that of the actual recipients and statistically indistinguishable from zero.

Could the observed response of spending to the Silver Support subsidies simply be random? The standard errors suggest not, but an alternative way to answer this question is to generate "pseudo recipients" many times in a bootstrap test and compare the coefficient obtained from the sample of recipients to the distribution of the coefficient in the bootstrapped sample. We randomly select individuals as "pseudo recipients" among all elderly people in our sample, defined as individuals who are at least 64.75 years old in December 2018. We allocate the actual subsidies received by the recipients to the "pseudo recipients" randomly and estimate the spending response. We repeat 500 times and plot the histogram of the bootstrapped coefficients in Figure 1. The estimated spending response in the sample of recipients, $7.35 per day after program inception (Column 1, Table 3) is at the 99.8th percentile of the distribution of the bootstrapped coefficient. Among the 500 iterations, the coefficient is higher than 7.35 only once.

## C Dynamic spending response

Results in Tables 3 and 4 show the average response to program inception. In addition, we investigate the dynamic evolution of spending from three months before program inception to $T$ months after program inception (equation (3)). We focus on the cumulative coefficients obtained from the dynamic specification to analyze the cumulative response in spending. In Figure 2, we plot the entire path of cumulative coefficients $b_s$ ($s = -3, -2, \ldots, T-1, T$) in the solid line and the corresponding 95% confidence intervals in the dotted lines. Standard errors used to construct the confidence intervals are calculated based on the standard errors of the marginal coefficients in equation (3), which are clustered at the individual level. The results can be interpreted as an event study with month 0 being the time of program inception. As noted before, the cumulative effect of the spending change at month $s$ upon program inception ($s \geq 0$) is measured by $b_s - b_{-1}$. For comparison purposes, we also plot the average cumulative subsidy amount in the figure.

Over the three months prior to when individuals first receive the subsidies, their cumulative spending change, relative to the baseline level which is measured at least four months before program inception, is insignificant both statistically and economically. In other words, there is little anticipatory effect on spending. Spending starts to increase after program inception. By the end of 29 months after program inception, the cumulative increase in total spending $(b_{29} - b_{-1})$ amounts to 5,200 dollars.

## D Spending response to recurring subsidy payments

We also investigate how recipients respond to the quarterly recurring subsidy payments. To this end, we estimate the change in spending after recurring subsidy payments. To avoid arbitrary choice of "pre-period" in recurring events, we use the days before program inception as the common "pre-period" for all subsidy payout events. We track daily spending for twelve weeks after each subsidy payment and adopt an empirical specification following Stephens (2003).

To analyze the high-frequency dynamic response, we estimate the weekly response to recurring subsidy payments using the following distributed lag model:

$$y_{i,j,t} = \mu_i + \pi_{ym} + \delta_{dow} + \sum_{s=-4}^{11} \beta_s \cdot \mathbb{1}_{i,j,(st)} \cdot SubsidyAmount_{i,j} + \varepsilon_{i,j,t} \tag{4}$$

where $\mathbb{1}_{i,j,(st)}$ is an indicator variable for each of the weeks before and after an individual receives the payout in payout event $j$. $SubsidyAmount_{i,j}$ is the amount of payout individual $i$ receives in payout event $j$. In this model, the *cumulative* coefficients $b_s \equiv \sum_{t=-4}^{s} 7 \cdot \beta_t$ correspond to the cumulative change in spending after $s$ weeks for every dollar of subsidy received.

Figure 3 presents the entire path of cumulative coefficients $b_s$ ($s = -4, -3, \ldots, 10, 11$) in the solid line and the corresponding 95% confidence intervals in the dotted lines. Standard errors used to construct the confidence intervals are calculated based on the standard errors of the marginal coefficients in equation (4), which are clustered at the individual level.

We find little anticipatory effect on spending: over the four weeks prior to recurring subsidies, the cumulative spending change is statistically indistinguishable from zero. Once the individuals receive the payouts, they increase their spending immediately. By the end of the payout week (week 0), recipients have spent more than 0.2 dollars for each dollar of subsidy received. In the twelve weeks since receiving one recurring subsidy payment, spending increases by 0.5 dollars for every dollar of subsidy received. The first week response accounts for approximately 40% of the cumulative spending response. In Online Appendix Table OA.2, we conduct additional analyses on the spending response to recurring subsidy payments. We find that the spending response to subsequent subsides is stronger than to the first subsidy, and also that inaugural recipients exhibit a stronger spending response than later recipients. As for the composition of spending, cash accounts for the majority of the spending response, which is consistent with the spending response to program inception.

## E Heterogeneity in the spending response

We further study whether the spending response varies across groups of recipients. To allow for heterogeneity in the spending response to program inception, we add interaction terms to equation (2):

$$y_{i,t} = \mu_i + \pi_{ym} + \delta_{dow} + \sum_{g=1}^{N} \beta_{MPC,g} \cdot \mathbb{1}_{i,g} \cdot Post_{i,t} \cdot DailySubsidyAmount_i + \varepsilon_{i,t} \qquad (5)$$

In this model, $N$ is the number of mutually exclusive groups that we decompose recipients into. By interacting the group identity indicators $\mathbb{1}_{i,g}$ for $g \in \{1, 2, \ldots, N\}$ with $Post_{i,t} \cdot DailySubsidyAmount_i$, we can flexibly estimate a different MPC out of the subsidies for each group.

The first column of Table 6 compares the MPC by gender. The MPCs of male and female recipients are very close to each other, different by only 0.01 dollars. The p-value of a test of equality is 0.95.

Previous studies have documented that low-income and low-liquidity individuals respond more strongly to positive disposable income shocks (e.g., Jappelli and Pistaferri, 2010). We study the impact of income and liquidity conditions on the MPC in columns 2–4 of Table 6.

We use the individual characteristics two months prior to program inception to construct income groups and liquidity groups. We define higher-income and lower-income groups based on whether the pre-subsidy monthly income in real December 2015 dollars is above or below the bottom tercile of the distribution, or 650.6 dollars. Our liquidity proxy is based on the ratio of bank account balance to monthly income two months prior to program inception. We define higher-liquidity and lower-liquidity individuals based on whether this ratio is above or below the bottom tercile of the distribution, or 1.[6]

Column 2 shows that higher-income individuals have an MPC of 0.68 dollars whereas lower-income individuals have an MPC of 0.73 dollars. The difference in MPC between the two income groups is statistically insignificant with a p-value of 0.77.

Column 3 shows that while higher-liquidity individuals have an MPC of 0.38 dollars, lower-liquidity individuals have an MPC which is approximately three times as large, of 1.12 dollars. The difference is highly statistically significant with a p-value of the equality test lower than 0.0001. In addition, the lower-liquidity individuals' MPC of 1.12 dollars is statistically indistinguishable from 1.

In column 4, we estimate an MPC for each of the four possible values of the income-liquidity pair—higher-income & higher-liquidity, higher-income & lower-liquidity, lower-income & higher-liquidity, and lower-income & lower-liquidity. Among the four groups, individuals in the lower-income & lower-liquidity group exhibit the strongest spending response, while individuals in the higher-income & higher-liquidity group exhibit the mildest spending response. Furthermore, we find that liquidity remains highly relevant in elevating the MPC when we hold income constant. Among higher-income individuals, the MPC difference between those with lower and higher liquidity amounts to 0.71 dollars and is highly statistically significant (p-value: 0.0005). Among lower-income individuals, the MPC difference between those with lower and higher liquidity equals 0.86 dollars and is also highly statistically significant (p-value: 0.0005). On the contrary, income differences do not appear to explain differences in MPC once we hold liquidity constant. Among higher-liquidity individuals, the MPC difference between those with higher

[6]We obtain similar results if (1) we use the first three months in our sample period (2016:01-2016:03) to measure income and liquidity, (2) we do not deflate nominal values, or (3) we use other percentiles (e.g. the median) to define the threshold.

and lower income, 0.04 dollars, is both economically small and statistically insignificant (p-value: 0.86). Similarly, among lower-liquidity individuals, the MPC difference between those with lower and higher income, 0.19 dollars, is statistically indistinguishable from zero (p-value: 0.40). Furthermore, the MPC difference between higher-income and lower-liquidity individuals (1.08 dollars) and lower-income and higher-liquidity individuals (0.41 dollars) is both statistically and economically significant. In this specification, both the higher-income and lower-liquidity individuals' MPC of 1.08 dollars and the lower-income and lower-liquidity individuals' MPC of 1.27 dollars are statistically indistinguishable from 1.

We also examine the role of liquidity in driving the immediate spending response to recurring subsidy payments. To do this, we add interaction terms to the post-payout weekly indicators in equation (4):

$$\begin{aligned} y_{i,j,t} = \mu_i + \pi_{ym} + \delta_{dow} + \sum_{s=-4}^{-1} \beta_s \cdot \mathbb{1}_{i,j,(st)} \cdot SubsidyAmount_{i,j} \\ + \sum_{s=0}^{11} \beta_{s,H} \cdot \mathbb{1}_{i,j,(st)} \cdot SubsidyAmount_{i,j} \cdot \mathbb{1}_{i,H} + \sum_{s=0}^{11} \beta_{s,L} \cdot \mathbb{1}_{i,j,(st)} \cdot SubsidyAmount_{i,j} \cdot \mathbb{1}_{i,L} \\ + \varepsilon_{i,j,t} \end{aligned} \tag{6}$$

where $\mathbb{1}_{i,H}$ and $\mathbb{1}_{i,L}$ are indicator variables for individuals in the higher- and lower-liquidity groups, respectively. We plot the cumulative response for the two groups along with the associated 95% confidence intervals in Figure 4.

Lower-liquidity recipients exhibit a stronger spending response, consistent with the earlier results based on program inception. Moreover, they concentrate their spending in the week of the recurring subsidy payments, rendering their cumulative spending concave. On the contrary, higher-liquidity recipients have a much smaller first week response.

## F Characteristics of the spending response

So far, we have documented a strong response to receiving the Silver Support subsidies–0.69 dollar additional spending for every dollar of subsidy received. The majority of the spending response is in the form of cash spending, consistent with the lower adoption of digital payments among the elderly. Cash spending leaves no digital footprint. We, therefore, turn to where the recipients obtain their cash through ATM cash withdrawals to investigate what the additional cash spending may entail.[7]

The first column of Table 7 shows the average response of daily ATM withdrawals to receiving the subsidies estimated based on equation (1). Overall, the recipients increase their ATM withdrawals by 3.44 dollars per day. Such an increase is lower than the response of overall cash spending, which is 5.87 dollars per day (Column 2 of Table 3), as cash spending includes cash withdrawals from both ATMs and bank counters.

We decompose total ATM withdrawals into different buckets based on the distance from home. We do not have the recipients' home addresses. We, therefore, create a home location (latitude and longitude) for each recipient using the centroid of all the ATMs from which this individual withdraws cash, weighted by withdrawal amount, in the three months before the first Silver Support subsidy. Using this measure of home location, we calculate the distance from home for each ATM withdrawal. For each individual, we measure her "daily ATM withdrawal close to home" by adding all withdrawals at ATMs within a 1km radius from home. We do the same to create "daily ATM withdrawals far from home" by defining ATMs outside of the 1km radius from home as far from home. The response of these two ATM withdrawal measures to receiving the subsidies are reported in columns 2 and 3 of Table 7, respectively. The decomposition of cash spending response by distance reveals an expansion of footprint by the recipients: While the increase of ATM withdrawal close to home is 0.72 dollars per day and not statistically sig-

[7] We find that both the number of cash withdrawals and the average withdrawal amount increase after the program inception.

nificant, the increase of ATM withdrawal far from home amounts to 3.18 dollars per day and is highly significant. Column 4 shows that recipients increase their cash withdrawals from ATMs near food courts, also known as hawker centers in Singapore, by 1.37 dollars per day upon receiving the subsidies. Dining spending, defined as the withdrawal from ATMs at most 200 meters from any food court, accounts for approximately 40% of the response of ATM cash withdrawals to the subsidies. These results suggest that the subsidies expand recipients' consumption footprint and support dining out consumption.

To gain further insights into what the additional spending in response to the subsidies entails, we conduct a separate analysis on retail purchases using the Nielsen Homescan dataset and present the results in Online Appendix Section B.3. Based on the available demographic information in the Nielsen dataset, we construct a treated group of low-income elderly individuals that act as a proxy for Silver Support recipients and a control group of low-income younger individuals.[8] Using a standard difference-in-differences framework, we find that the proxied recipients in the treated group increase their spending, especially on food items, and expand the product, brand, and category variety of their consumption.[9]

## 6 Labor supply and housing responses to the subsidy program

In this section, we turn to other aspects of the recipients' behavioral responses to the subsidy program. We focus on labor supply and housing status, both of which correspond to the program qualification criteria and are important components of the recipients' well-being.

Government tax policies and transfer programs directly affect individuals' labor supply decisions (see, e.g., Martinez, Saez, and Siegenthaler (2018); Gelber, Jones, Sacks, and

[8] The limitation of demographic information recorded in the Nielsen dataset introduces measurement error by including some non-recipients into the treated group and makes us underestimate the spending response. See Online Appendix Section B.3 for details.

[9] To complete the analysis, we also test and find no pass-through of the subsidy program to the retail prices of products consumed by the recipients (Online Appendix Figure OA.2).

Song (2020)). By providing a guaranteed income level, the Silver Support Scheme may reduce incentives to work and lead to a reduction of labor supply from the recipients. We test this hypothesis using the information on salary. We use the bank records to identify the individuals receiving salary paychecks among the Silver Support recipients and the timing and amount of their salary. The salary-based measures of labor supply are highly accurate and are free of any stale information.

The empirical literature on labor supply has distinguished two margins of labor supply responses (Heckman, 1993) – the intensive margin response (adjustment of the number of hours worked) and the extensive margin response (participation in the labor force). We separately examine these two margins and estimate the labor supply response to program inception using the monthly analogue to equation (1):

$$y_{i,ym} = \mu_i + \pi_{ym} + \beta \cdot Post_{i,ym} + \varepsilon_{i,ym} \tag{7}$$

where the individual and year-month fixed effects are included.

The estimates are shown in Columns 1 and 2 of Table 8. In the extensive margin analysis in Column 1, we use the indicator of receiving positive salary in a month as the dependent variable. We find no change in the likelihood of being a salaried employee before or after program inception. In the intensive margin analysis in Column 2, we restrict to the sample of salaried employees, who account for 44% of the recipients, and use the natural logarithm of monthly salary as the dependent variable. The estimated coefficient $\beta$, which represents the proportional change in salary, is small in magnitude and statistically indistinguishable from zero, implying that there is no discernable change in the intensive margin of labor supply.

Next, we turn to the housing response. The subsidy benefits are decreasing in the number of rooms in the public housing apartments. A natural question arises: do recipients downsize their apartments to qualify for larger subsidies?

We construct three measures for moving residence: (1) an indicator of changing residential postal area; (2) an indicator of changing dwelling type; and (3) an indicator of changing home ownership status. We estimate equation (7) for all three measures to examine moving behaviors and report the results in Columns 3–5 of Table 8. We find little change in housing adjustment regardless of the measure used. This series of analyses shows that the recipients do not move their residences according to these three different measures. Some forms of downsizing such as buying a smaller HDB apartment in the same postal area as the old one and selling the old apartment will not be reflected as a change in any of our measures, preventing us from fully ruling out the possibility of downsizing based on these analyses. Nonetheless, our measures collectively cover the common types of residential moves. The robustness of the results across different measures implies that the recipients do not downsize their apartments to qualify for larger subsidies.

## 7 Implications for policy design

### A Criteria in the means test

A well-known concern for government income support programs is that they may substantially reduce incentives to work and may result in large efficiency costs. This concern is especially relevant for subsidy programs that take the form of a guaranteed income level such as the Silver Support Scheme. This type of programs is viewed as responsible for the low working rates observed among welfare recipients in the United States (see, e.g., Murray (1984)). Contrary to the popular belief that the subsidies provide disincentives to work, we find no evidence of a reduction in labor supply in either the extensive margin or the intensive margin. Given that the subsidy benefits are decreasing in the number of rooms in public housing apartments, one might be concerned that recipients would downsize their apartments to qualify for larger subsidies. Using a variety of measures for residential moves, we find no evidence of this form of manipulation. Our analysis of the consumption, labor supply, and housing responses reveals that the subsidy program achieves the targeted support among the recipients with little side effects.

Another potential concern for the overall effectiveness of the program arises if individuals can strategically change their behaviors prior to their 65th birthdays to qualify for the subsidy program. To investigate whether this manipulation exists, we expand our analysis to investigate whether the younger cohorts change their labor supply and housing status prior to turning 65.

To allow for the adjustment time lag, we focus on the period from six months before an individual turns 64 years old to the 65th birth month and estimate the following regression model:

$$y_{i,ym} = \mu_i + \pi_{ym} + \beta \cdot Post64_{i,ym} + \varepsilon_{i,ym} \tag{8}$$

In this model, $Post64_{i,ym}$ is an indicator variable for the period from the 64th birth month to the 65th birth month of an individual $i$. In this specification, the omitted period is the six months before an individual turns 64 years old. In this equation, we include individual fixed effects $\mu_i$ as well as year-month fixed effects $\pi_{ym}$ and cluster standard errors at the individual level.

We divide the younger cohorts into two income groups based on whether the reported monthly income at the 64th birth month is above or below 1,300 SGD (in real December 2015 dollars). We separately estimate equation (8) for each group.[10]

We first examine the change in labor supply among people turning 65 years old in Panel A of Table 9. Columns 1 and 3 report the results for the extensive margin of labor supply, as measured by an indicator of receiving positive salary in a month. Neither lower- nor higher-income individuals change the extensive margin of labor supply af-

[10] We obtain similar results if (1) we use other income levels to define the threshold, (2) we measure income prior to the 64th birth month, or (3) we do not deflate the nominal income.

ter they turn 64 years old relative to the previous 12 months. Columns 2 and 4 report the results for the intensive margin of labor supply, as measured by the log-transformed monthly salary, in the higher- and lower-income samples of salaried employees. There is little change in the intensive margin of labor supply across income groups.

Turning to the second dimension of the program qualification criteria, housing, we examine the measures for moving residence in Panel B of Table 9. Across the three measures of residential moves, we find little change in housing across income groups.

In summary, we find no evidence of strategic behaviors prior to turning 65 years old, suggesting that the criteria used in the means test are likely to be manipulation-proof. This desirable feature is related to the criterion on cumulative income by age 55 in the means test, which is based on historical data and leaves no room for manipulation closer to 65.

In the heterogeneity analysis in Section 5.E, we find that liquidity is a more important driver for the consumption response than income in both program inception and recurring payment cycles. Individuals with lower levels of liquid assets may not be able to smooth consumption if they experience negative shocks. For such individuals, the increase in consumption is a rational response to the relaxation of liquidity constraints. This finding has important implications for the policy design of elderly support programs. If the goal of the policy is to maximize consumption response, then incorporating liquidity in the means test may be desirable as a means test based on liquidity can correctly identify constrained individuals.

## B Payment frequency

How the government should choose the frequency of benefit disbursements to those eligible is an important question for the design of public benefit programs. Keeping the total amount of benefits constant, frequent distribution of smaller benefits versus infrequent distribution of larger benefits may lead to different effects as the recipients do not fully smooth their consumption. We document a concave-shaped consumption response to recurring subsidy payments where the first week response accounts for approximately 40% of the 12-week cumulative spending response. Our results imply that the government could improve consumption smoothing by splitting quarterly payments into smaller, more frequent payments. Our results and implications are broadly consistent with existing studies. Dobkin and Puller (2007) and Mastrobuoni and Weinberg (2009) document that the infrequent distribution of public benefits has adverse effects on the health outcomes of the recipients who live "payment to payment". LaPoint and Sakabe (2019) conclude that the government could improve welfare by increasing payment frequency in a structural framework of the tradeoff between the administrative cost of providing more frequent benefits and the welfare gain from reducing deviations from full consumption smoothing.

### C Distribution form

The Silver Support Scheme distributes the subsidies in the form of direct bank transfers, which boosts the disposable income of the recipients and is fully fungible. On the contrary, many subsidy programs distribute vouchers that are usually restricted to specific uses and cannot be used to cover other expenses.

From the perspective of the government or the funding agency, the cash/bank transfer disbursement and the voucher disbursement have very similar costs. But the impacts on recipients, especially the consumption implications, can be very different. On the one hand, cash/bank transfer disbursements have lower administrative costs and give recipients more freedom, including overcoming sudden negative shocks. On the other hand, unrestricted disbursements can result in excessive present consumption at the expense of future security at an older age.

Comparisons across programs can be difficult as they have to accommodate differences over time and across societies. We compare consumption responses to the Silver

Support Scheme's direct cash approach with that to an earlier program in Singapore that targets the same elderly demographic group but takes the form of vouchers for medical and health insurance expenses. Using card spending data, we find that even the most disadvantaged recipients of the medical vouchers do not increase their spending upon receiving the vouchers significantly, economically or statistically (Online Appendix Section B.5). These results imply that the medical and health insurance expenditure vouchers do not stimulate consumption. This comparison highlights that a cash/bank transfer disbursement is more effective than a voucher disbursement in stimulating consumption due to its flexibility and fungibility.

## 8 Conclusion

We study the consumption, labor supply, and housing response to a government means-tested subsidy program for low-income elderly individuals in Singapore using several unique panel datasets of consumer financial transactions. We adopt an event-study design that compares the behaviors of a recipient of the subsidy program before and after program inception. On average, the recipients increase their spending by 0.69 dollars for each dollar received. More than 80% of the spending response is in the form of cash spending, consistent with the lower adoption of cashless payment instruments (e.g. debit card, credit card) among the elderly population. We find evidence that the recipients expand their geographic footprints, raise their food spending, and increase variety of their retail purchases.

Liquidity is an important driver of the consumption response. Individuals with lower liquid savings show a strong and immediate response to subsidies while individuals with higher liquid savings register a much smaller and less immediate response. Lower-income individuals do not necessarily exhibit a larger spending response than their higher-income peers. The Silver Support Scheme achieves its intended objective of stimulating consumption with little side effects on labor supply and housing. In addition, younger individuals do not engage in strategic behaviors to qualify for the subsidy program at their 65th birthdays. We also show that the spending response of this subsidy program can be partly attributable to its disbursement form of direct bank transfers, which adds to the recipients' disposable income and provides more flexibility than the alternative disbursement form of vouchers.

Our findings have significant implications for the policy design of elderly support programs. If the goal of the policy is to maximize consumption response, then a means test based on liquidity may be more effective than a means test based on income. The major concern of consumer over-spending with the cash/bank transfer disbursement may be unwarranted. On the contrary, in our context, we find that providing the subsidies in the form of bank transfers may allow liquidity-constrained consumers to better smooth consumption.

Finally, we ponder the question of why the program does not lead to strategic behaviors. One explanation is that the means test is set in such a way that gaming the system can be costly. For example, downsizing by one room leads to an additional subsidy of S$600 per year. The gains may be lower than the relocation costs and the increase in costs of living. Likewise, the means test examines the cumulative income by age 55 which is unaffected by short term income changes closer to the qualification age 65. As the means test uses criteria that are costly to manipulate, the program does not distort incentives.

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Figure 1: **Distribution of spending response from the bootstrap falsification test**

This figure plots the histogram of the coefficients obtained in the bootstrap falsification test. We randomly select individuals as “pseudo recipients” among all elderly people in our sample, defined as individuals who are at least 64.75 years old in December 2018. We allocate the actual subsidies received by the recipients to the selected “pseudo recipients” randomly and estimate the spending response. We repeat 500 times. The red vertical line denotes the estimated spending response, 7.35 dollars (column 1 of Table 3).

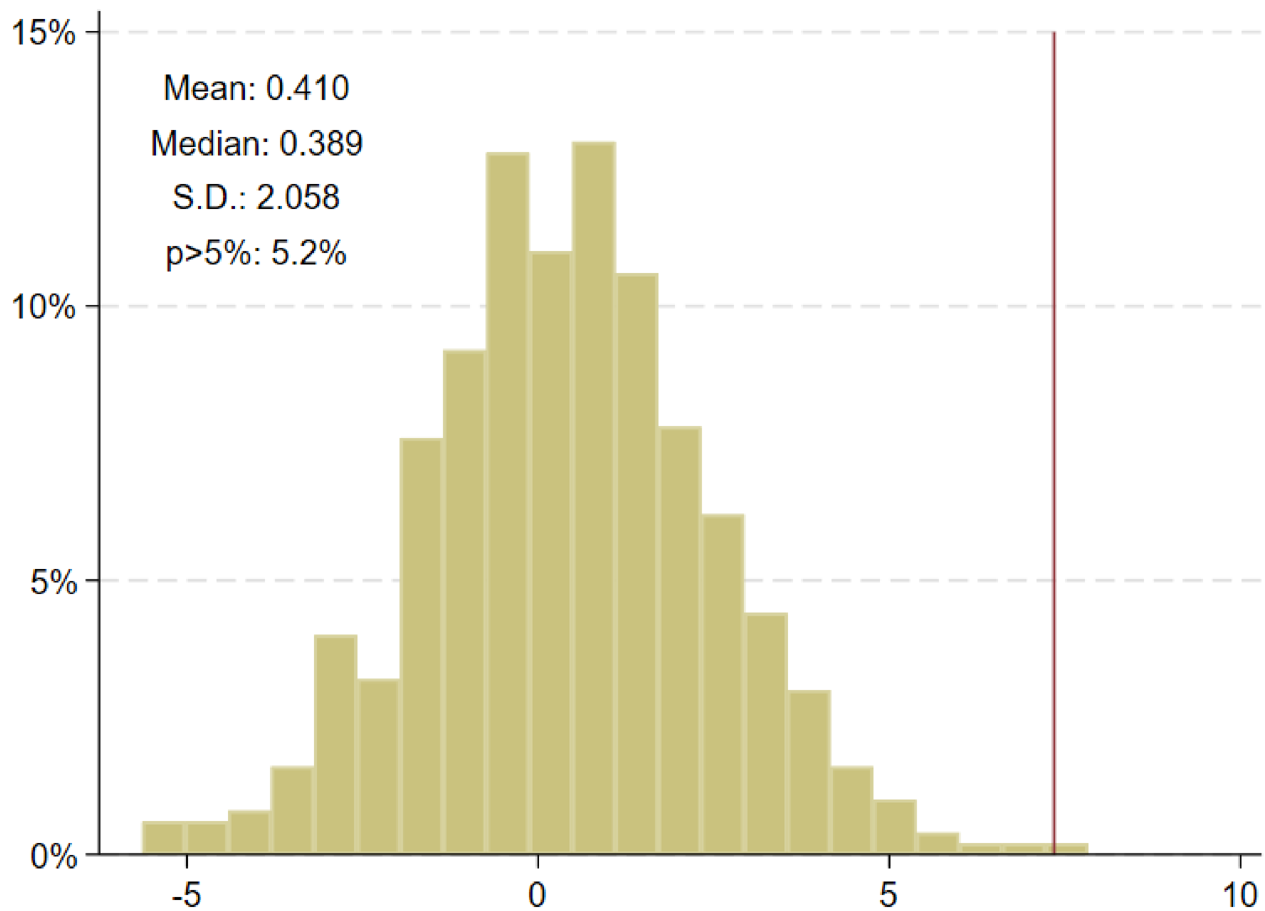


Figure 2: **Estimated spending response dynamics**

This figure plots the entire path of cumulative coefficients $b_s \equiv \sum_{t=-3}^{s} 30 \cdot \beta_t$, for $s = -3, -2, \ldots, T-1, T$ along with their associated 95% confidence intervals of total spending as estimated from equation (3). Standard errors used to construct the confidence intervals are calculated based on the standard errors of the marginal coefficients in the dynamic regression, which are clustered at the individual level. The *x-axis* denotes the months before and after program inception; the *y-axis* shows the dollar response.

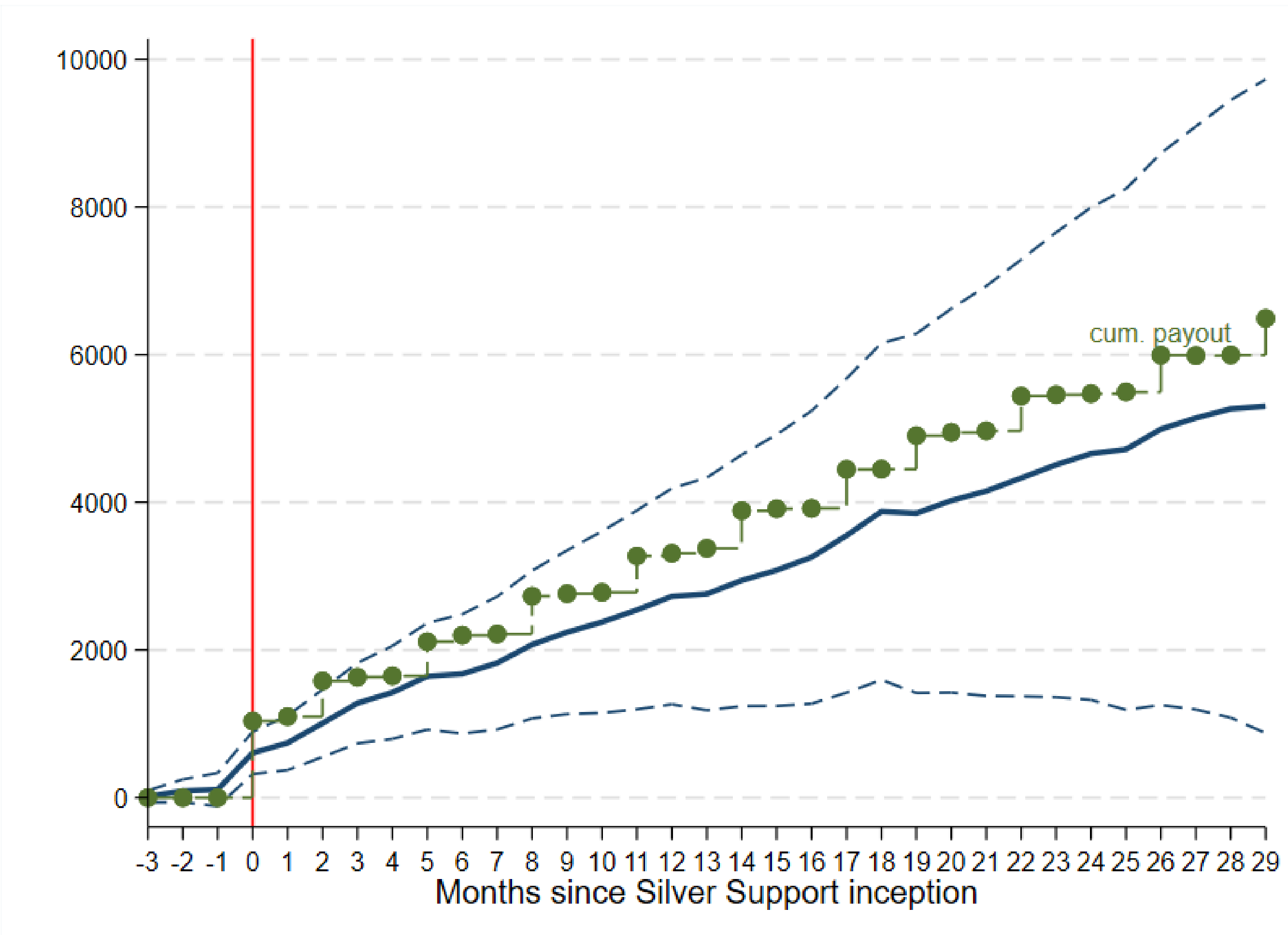


Figure 3: **Estimated spending response dynamics in recurring subsidy payment events**

This figure plots the entire path of cumulative coefficients $b_s \equiv \sum_{t=-4}^{s} 7 \cdot \beta_t$, for $s = -4, -3, \ldots, T-1, T$ along with their associated 95% confidence intervals of total spending as estimated from equation (4). Standard errors used to construct the confidence intervals are calculated based on the standard errors of the marginal coefficients in the dynamic regression, which are clustered at the individual level. The *x-axis* denotes the weeks before and after a recurring subsidy; the *y-axis* shows the dollar response (for every dollar received).

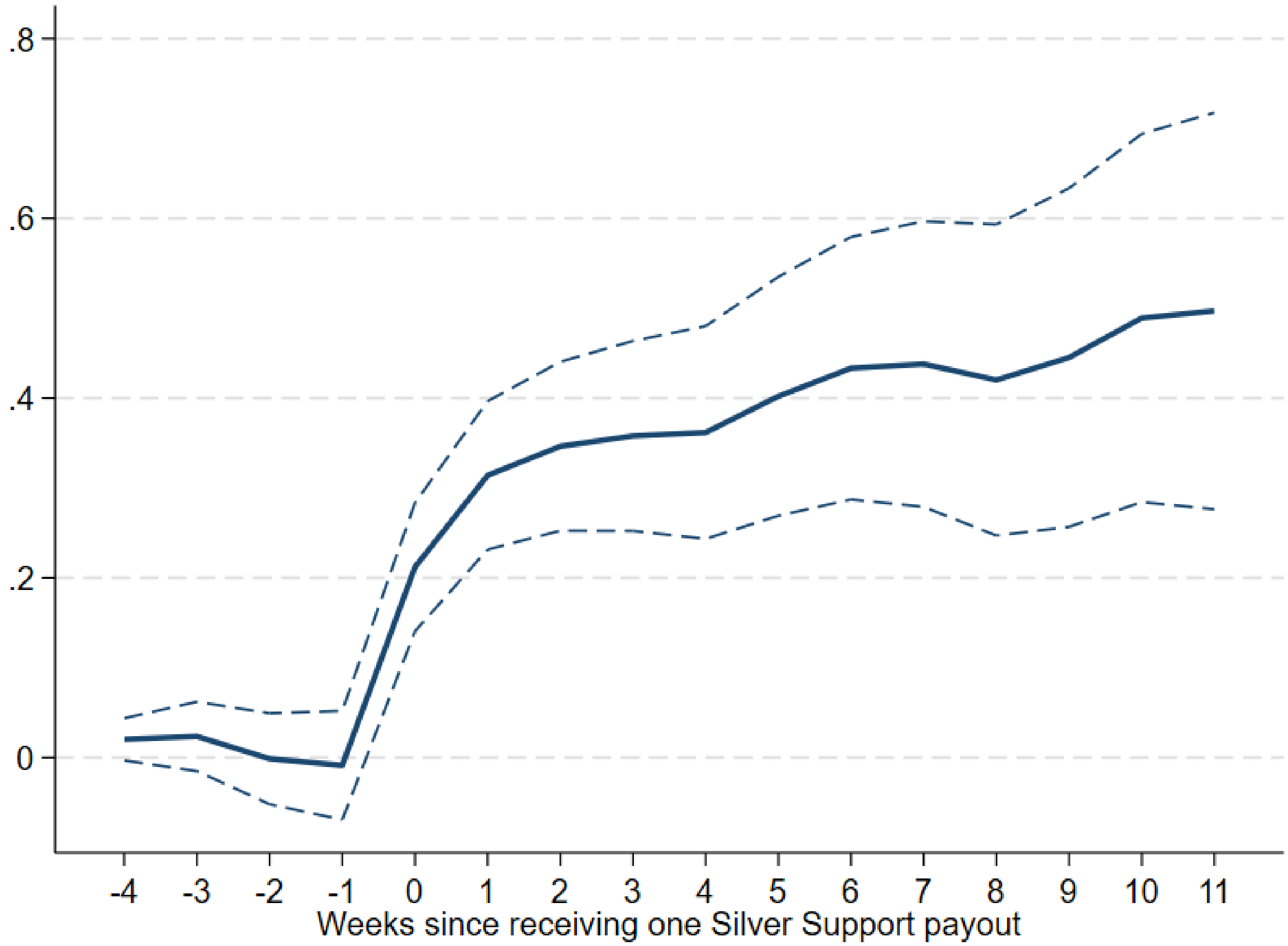


Figure 4: **Estimated spending response dynamics in recurring subsidy payment events by liquidity**

This figure plots the cumulative spending responses of higher- and lower-liquidity groups, along with their associated 95% confidence intervals, to recurring subsidy payments as estimated from equation (6). Standard errors used to construct the confidence intervals are calculated based on the standard errors of the marginal coefficients in the dynamic regression, which are clustered at the individual level. The *x-axis* denotes the weeks before and after a recurring subsidy; the *y-axis* shows the dollar response (for every dollar received).

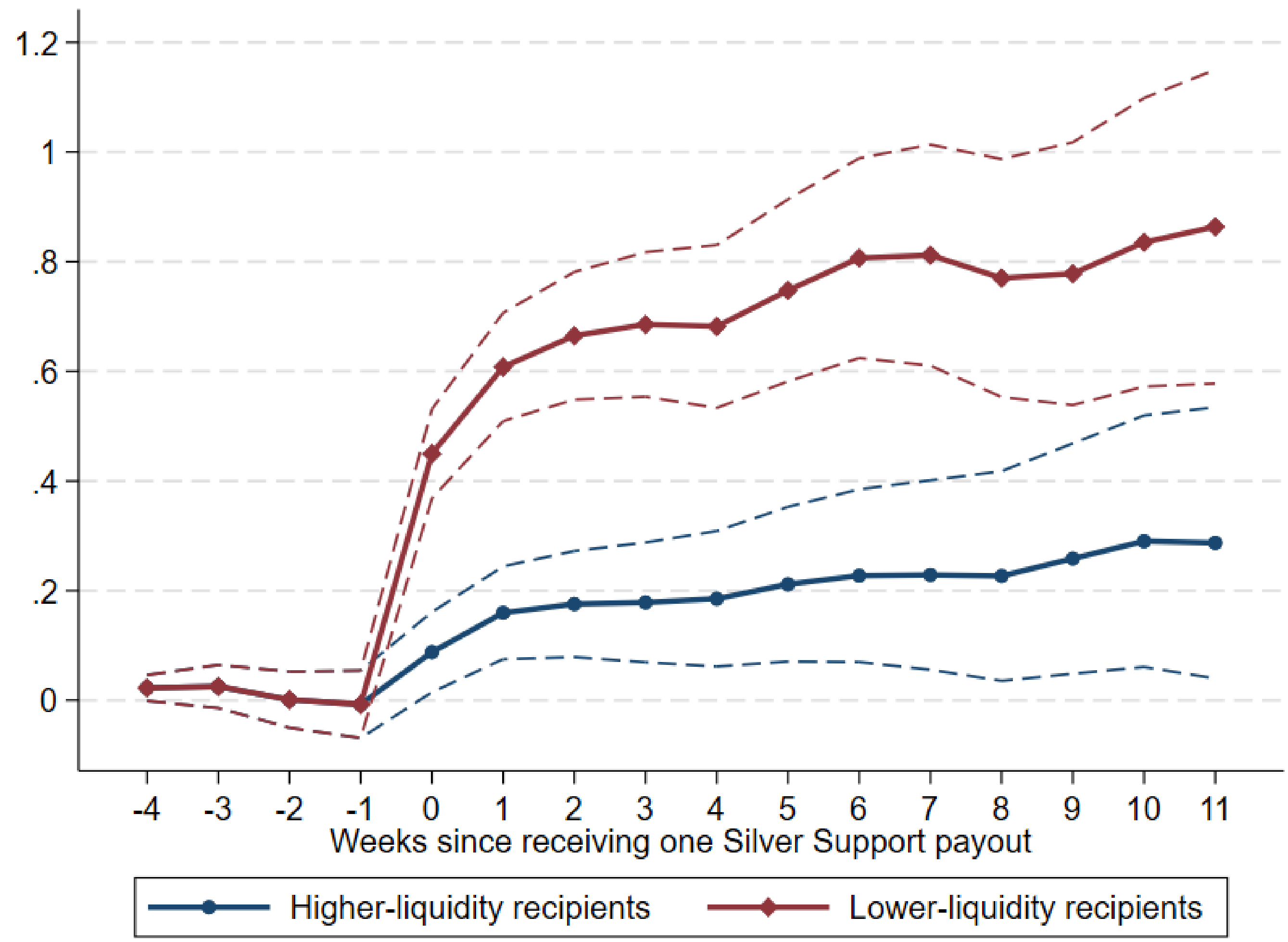


Table 1: **Summary statistics of the subsidy recipients**

This table reports the summary statistics for spending, demographic, and financial characteristics of the subsidy recipients two months prior to the first subsidy. The monetary amount is in the local currency Singapore Dollar (SGD) and 1 SGD = 0.76 USD as of January 2018.

| | Mean | Std. Dev. | 25% | 50% | 75% |
|---|---|---|---|---|---|
| *Total spending and its composition:* | | | | | |
| Monthly total spending (SGD) | 1407.8 | 4056.8 | 100 | 634.8 | 1578.0 |
| Monthly cash spending (SGD) | 965.2 | 1771.3 | 0 | 500 | 1200 |
| ... including ATM cash withdrawal (SGD) | 630.9 | 965.2 | 0 | 215 | 1000 |
| Monthly debit card spending (SGD) | 114.2 | 287.4 | 0 | 0 | 64 |
| Monthly credit card spending (SGD) | 33.1 | 249.0 | 0 | 0 | 0 |
| Monthly bill payment (SGD) | 295.3 | 3390.5 | 0 | 0 | 65.8 |
| *Demographic characteristics:* | | | | | |
| Age | 71.3 | 6.14 | 66.2 | 69.4 | 75.5 |
| Is female | 0.56 | 0.50 | 0 | 1 | 1 |
| Is married | 0.58 | 0.49 | 0 | 1 | 1 |
| Is ethnic Chinese | 0.77 | 0.42 | 1 | 1 | 1 |
| *Financial access and financial resources:* | | | | | |
| Years as the bank's client | 21.3 | 4.67 | 17.5 | 19.0 | 26.8 |
| Monthly income (SGD) | 1257.8 | 1551.1 | 521.5 | 911.2 | 1442.3 |
| Has credit card(s) | 0.12 | 0.33 | 0 | 0 | 0 |
| Has salary crediting in bank account | 0.28 | 0.45 | 0 | 0 | 1 |
| Bank account balance (SGD) | 22618.5 | 49361.4 | 336.9 | 4022.4 | 24284.6 |
| *Credit card characteristics (N=167):* | | | | | |
| Credit limit | 16608.4 | 20117.2 | 6000 | 12000 | 20000 |
| Has deliquent 30+ days debt | 0 | 0 | 0 | 0 | 0 |
| Observations | 1340 | | | | |

Table 2: **Timing of the first subsidy**

This table reports the distribution of the timing of the first subsidy in our sample of subsidy recipients.

| | Freq | % | Cumulative % |
|---|---|---|---|
| July 2016 | 869 | 64.85 | 64.85 |
| September 2016 | 46 | 3.43 | 68.28 |
| December 2016 | 44 | 3.28 | 71.57 |
| March 2017 | 28 | 2.09 | 73.66 |
| June 2017 | 27 | 2.01 | 75.67 |
| September 2017 | 28 | 2.09 | 77.76 |
| December 2017 | 99 | 7.39 | 85.15 |
| March 2018 | 28 | 2.09 | 87.24 |
| June 2018 | 32 | 2.39 | 89.63 |
| September 2018 | 27 | 2.01 | 91.64 |
| December 2018 | 112 | 8.36 | 100.00 |
| Total | 1,340 | 100.00 | |

Table 3: **The average spending response to the welfare program**

This table shows the average spending response to receiving the subsidies among recipients (equation (1)). The data are at the individual-daily level from January 2016 to December 2018. *Post* is an indicator that is equal to 1 for the calendar days since the individual receives the first subsidy. Individual, year-month, and day-of-week fixed effects are included and denoted at the bottom. Standard errors are clustered at the individual level; the corresponding t-statistics are reported in brackets. We use $^{***}$, $^{**}$ and $^{*}$ to denote significance at 1%, 5% and 10% level (two-sided), respectively.

| | (1) Total spending | (2) Cash spending | (3) Debit card spending | (4) Credit card spending | (5) Bill payment |
|---|---|---|---|---|---|
| Post | 7.348$^{***}$ | 5.868$^{***}$ | 0.463 | -0.058 | 1.286$^{***}$ |
| | [6.17] | [5.95] | [1.63] | [-0.47] | [2.66] |
| Individual FEs | Yes | Yes | Yes | Yes | Yes |
| Day of week FEs | Yes | Yes | Yes | Yes | Yes |
| Year-Month FEs | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.0866 | 0.0460 | 0.0458 | 0.0466 | 0.215 |
| No. of observations | 1,463,272 | 1,463,272 | 1,463,272 | 1,463,272 | 1,463,272 |

Table 4: **Marginal Propensity to Consume (MPC) out of the subsidies**

This table shows the marginal propensity to consume (MPC) out of the subsidies among recipients (equation (2)). The data are at the individual-daily level from January 2016 to December 2018. *Post* is an indicator that is equal to 1 for the calendar days since the individual receives the first subsidy. *Daily Subsidy Amount* is the daily-equivalent amount of the Silver Support subsidies, calculated as the quarterly Silver Support subsidy divided by 90. Individual, year-month, and day-of-week fixed effects are included and denoted at the bottom. Standard errors are clustered at the individual level; the corresponding t-statistics are reported in brackets. We use $^{***}$, $^{**}$ and $^{*}$ to denote significance at 1%, 5% and 10% level (two-sided), respectively.

| | (1)<br>Total<br>spending | (2)<br>Cash<br>spending | (3)<br>Debit card<br>spending | (4)<br>Credit card<br>spending | (5)<br>Bill<br>payment |
|---|---|---|---|---|---|
| Post $\times$ Daily subsidy amount | $0.693^{***}$ | $0.586^{***}$ | $0.049^{**}$ | -0.006 | 0.054 |
| | [7.06] | [7.13] | [2.19] | [-0.61] | [1.35] |
| Individual FEs | Yes | Yes | Yes | Yes | Yes |
| Day of week FEs | Yes | Yes | Yes | Yes | Yes |
| Year-Month FEs | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.0866 | 0.0460 | 0.0458 | 0.0466 | 0.215 |
| No. of observations | 1,463,272 | 1,463,272 | 1,463,272 | 1,463,272 | 1,463,272 |

Table 5: **Falsification tests of the spending response using matched non-recipients**

This table shows the average spending response to receiving the pseudo subsidies among non-recipients (equation (1)). The data are at the individual-daily level from January 2016 to December 2018. We perform a propensity score matching procedure to construct two samples of matched non-recipients based on observable characteristics. The sample of matched old non-recipients contains non-recipient individuals in the same age cohorts as the recipients; the sample of matched young non-recipients contains non-recipient individuals who are younger than but in the same wealth and income cohorts as the recipients. We carry the actual recipients' program inception timing to their corresponding matched non-recipients. *Post* is an indicator that is equal to 1 for the months since the individual receives the first pseudo Silver Support subsidy. Individual and year-month fixed effects are included and denoted at the bottom. Standard errors are clustered at the individual level; the corresponding t-statistics are reported in brackets. We use $^{***}$, $^{**}$ and $^{*}$ to denote significance at 1%, 5% and 10% level (two-sided), respectively.

| | (1)<br>Using old<br>non-recipients | (2)<br>Using young<br>non-recipients |
|---|---|---|
| Post | 1.183 | 1.634 |
| | [0.88] | [1.45] |
| Individual FEs | Yes | Yes |
| Day of week FEs | Yes | Yes |
| Year-Month FEs | Yes | Yes |
| $R^2$ | 0.0757 | 0.0657 |
| No. of observations | 1,516,461 | 1,517,830 |

Table 6: **Heterogeneity of Marginal Propensity to Consume (MPC) out of the subsidies**

This table shows the heterogeneous marginal propensity to consume (MPC) out of the subsidies among recipients (equation (5)). The data are at the individual-daily level from January 2016 to December 2018. We group individuals by gender, income, and liquidity. We measure income and liquidity two months prior to program inception. We use the bottom tercile of the distribution of pre-subsidy monthly income in real December 2015 dollars (the ratio of bank account balance to monthly income) to split individuals into higher- and lower-income (liquidity) groups. Individual, year-month, and day-of-week fixed effects are included and denoted at the bottom. Standard errors are clustered at the individual level; the corresponding t-statistics are reported in brackets. We use $^{***}$, $^{**}$ and $^{*}$ to denote significance at 1%, 5% and 10% level (two-sided), respectively.

| | By gender | By income & liquidity | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *MPC out of the subsidies of* | | | | |
| Male recipients | 0.700$^{***}$ | | | |
| | [6.14] | | | |
| Female recipients | 0.690$^{***}$ | | | |
| | [5.01] | | | |
| Higher-income recipients | | 0.676$^{***}$ | | |
| | | [6.38] | | |
| Lower-income recipients | | 0.727$^{***}$ | | |
| | | [4.30] | | |
| Higher-liquidity recipients | | | 0.383$^{***}$ | |
| | | | [3.45] | |
| Lower-liquidity recipients | | | 1.123$^{***}$ | |
| | | | [7.66] | |
| Higher-income & higher-liquidity recipients | | | | 0.369$^{***}$ |
| | | | | [3.11] |
| Higher-income & lower-liquidity recipients | | | | 1.078$^{***}$ |
| | | | | [6.16] |
| Lower-income & higher-liquidity recipients | | | | 0.414$^{**}$ |
| | | | | [2.09] |
| Lower-income & lower-liquidity recipients | | | | 1.274$^{***}$ |
| | | | | [7.09] |
| Individual FEs | Yes | Yes | Yes | Yes |
| Day of week FEs | Yes | Yes | Yes | Yes |
| Year-Month FEs | Yes | Yes | Yes | Yes |
| $R^2$ | 0.0866 | 0.0866 | 0.0866 | 0.0866 |
| No. of observations | 1,463,272 | 1,463,272 | 1,463,272 | 1,463,272 |

Table 7: **ATM cash withdrawals by location**

This table shows the average spending response, in the form of ATM cash withdrawals, to receiving the subsidies among recipients (equation (1)). The data are at the individual-daily level from January 2016 to December 2018. The dependent variables examined here include daily total ATM withdrawal amount and its composition by location. *Post* is an indicator that is equal to 1 for the calendar days since the individual receives the first subsidy. Individual, year-month, and day-of-week fixed effects are included and denoted at the bottom. Standard errors are clustered at the individual level; the corresponding t-statistics are reported in brackets. We use $^{***}$, $^{**}$ and $^{*}$ to denote significance at 1%, 5% and 10% level (two-sided), respectively.

| | (1) Total ATM withdrawal | (2) Close to home | (3) Far from home | (4) Close to food courts |
|---|---|---|---|---|
| Post | 3.437$^{***}$ | 0.725 | 3.184$^{***}$ | 1.368$^{***}$ |
| | [4.73] | [1.32] | [4.47] | [2.76] |
| Individual FEs | Yes | Yes | Yes | Yes |
| Day of week FEs | Yes | Yes | Yes | Yes |
| Year-Month FEs | Yes | Yes | Yes | Yes |
| $R^2$ | 0.0468 | 0.0430 | 0.0519 | 0.0339 |
| No. of observations | 1,463,272 | 1,090,820 | 1,090,820 | 1,463,272 |

Table 8: **The average labor supply and housing responses to the welfare program**

This table shows the average labor supply and housing responses to program inception among recipients (equation (7), the monthly analogue to equation (1)). The data are at the individual-monthly level from January 2016 to December 2018. *Post* is an indicator that is equal to 1 for the months since the individual receives the first subsidy. Individual and year-month fixed effects are included and denoted at the bottom. Standard errors are clustered at the individual level; the corresponding t-statistics are reported in brackets. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

| | Labor supply | | Residential moves | | |
|---|---|---|---|---|---|
| | (1) Receive positive salary | (2) Log salary | (3) Change postal area | (4) Change dwelling type | (5) Change ownership status |
| Post | -0.00639 | 0.0255 | 0.000275 | -0.000199 | -0.000335 |
| | [-0.56] | [1.17] | [0.36] | [-0.42] | [-0.50] |
| Individual FEs | Yes | Yes | Yes | Yes | Yes |
| Year-Month FEs | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.742 | 0.791 | 0.0351 | 0.990 | 0.0429 |
| No. of observations | 49,558 | 11,843 | 48,169 | 48,169 | 48,169 |

Table 9: **Estimated change in labor supply and housing prior to 65**

This table reports the estimated change in labor supply and housing among the individuals turning 65 (equation (8)). The data are at the individual-monthly level from the six months before an individual turns 64 years old to the 65th birth month. We group individuals turning 65 by income. We split individuals into higher- and lower-income groups based on whether the reported monthly income at the 64th birth month in real December 2015 dollars is above or below 1,300 SGD. Individual and year-month fixed effects are included and denoted at the bottom. Standard errors are clustered at the individual level; the corresponding t-statistics are reported in brackets. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

Panel A: Estimated change in labor supply prior to 65

| | Lower-income people turning 65 | | Higher-income people turning 65 | |
|---|---|---|---|---|
| | (1) Receive positive salary | (2) Log salary | (3) Receive positive salary | (4) Log salary |
| Post the 64th birth month | -0.0114 | -0.00215 | -0.00260 | 0.0108 |
| | [-1.20] | [-0.10] | [-0.81] | [1.14] |
| Individual FEs | Yes | Yes | Yes | Yes |
| Year-Month FEs | Yes | Yes | Yes | Yes |
| $R^2$ | 0.808 | 0.828 | 0.910 | 0.816 |
| No. of observations | 14,799 | 4,805 | 61,822 | 22,702 |

Panel B: Estimated change in housing prior to 65

| | Lower-income people turning 65 | | | Higher-income people turning 65 | | |
|---|---|---|---|---|---|---|
| | (1) Change postal area | (2) Change dwelling type | (3) Change ownership status | (4) Change postal area | (5) Change dwelling type | (6) Change ownership status |
| Post the 64th birth month | -0.000641 | -0.0000591 | 0.000161 | 0.00106 | -0.000246 | 0.000659 |
| | [-0.43] | [-0.05] | [0.12] | [1.31] | [-0.35] | [0.54] |
| Individual FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-Month FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.0584 | 0.918 | 0.0778 | 0.0714 | 0.874 | 0.0806 |
| No. of observations | 14,799 | 14,799 | 14,799 | 61,822 | 61,822 | 61,822 |

**Online appendix**

This appendix contains supplementary material, tables, and figures.

## A Timing details of the Silver Support Scheme

The Silver Support payouts typically occur in March, June, September, and December, with the exception of the inaugural payout in July 2016. The inaugural recipients received the first Silver Support payout at the end of July 2016, and received the second payout two months later at the end of September 2016. Most later recipients wait three months between two consecutive payouts.

All recipients receive a subsidy payout on the same day in a quarter. Payout days, however, are neither known to the recipients nor stable over time. Figure OA.1 shows that payout days can fall on either the middle of a month or the end of a month, and can fall on Tuesdays, Thursdays, or Fridays. In other words, although recipients can anticipate the arrival of a recurring payout in March, June, September, and December, they cannot fully anticipate the exact dates.

## B Additional results

### B.1 Monthly average response to program inception

One potential measurement issue is that bill spending may include payment for credit card spending. If this is the case, total spending is inflated as it is subject to double-counting. However, since only 12% of recipients have credit card(s) with the bank, the extent of this double-counting is limited. Nonetheless, we remove such double-counting at the monthly level using the information on the payment amount from credit card statement records. We construct the spending variables at the individual-monthly level and estimate the average monthly response to program inception using equation (7), the monthly analogue to equation (1). The estimates are shown in Table OA.1.

Despite the differences in measurement frequency and in the set of included fixed effects, the estimates for the average monthly response are remarkably consistent with the estimates for the average daily response in terms of the economic magnitude. The first column of Table OA.1 shows that the Silver Support recipients increase their total spending by 219.4 dollars per month or about 16% of the average monthly spending in the pre-subsidy period of 1,407.8 dollars. The size of the additional spending relative to the spending in the pre-subsidy period is identical to the estimate at the daily frequency (Table 3). When we decompose the monthly total spending into different components in columns 2–5, we obtain estimates that are consistent with their daily counterparts in Table 3 in terms of both statistical significance and economic magnitude.

### B.2 Additional analysis of the spending response to recurring subsidy payments

We examine the spending response to recurring payout events using the following specification:

$$y_{i,j,t} = \mu_i + \pi_{ym} + \delta_{dow} + \beta \cdot Post_{i,j,t} \cdot SubsidyAmount_{i,j} + \varepsilon_{i,j,t} \tag{9}$$

In this equation, $SubsidyAmount_{i,j}$ is the amount of payout individual $i$ receives in payout event $j$. As the unit of observation is at the individual-daily level, additional spending amounts to $84 \times \beta$ for every dollar of payout received in the twelve weeks after receiving one recurring payout (inclusive of the payout week, week 0).

Column 1 of Table OA.2 Panel A shows the estimates. A coefficient of 0.008 implies that during the twelve subsequent weeks, for each \$1 received, recipients on average spent \$0.67 ($0.008 \times 84$). In column 2, we allow for differential response to the first and subsequent payouts by adding interaction terms to equation (9). We find the spending response to subsequent recurring payouts is stronger than to the first payout. Using a similar approach, we find that inaugural recipients exhibit a stronger spending response than later recipients in column 3.

Panel B decomposes the total spending into different components. As in the spending response to program inception, the majority of the spending response to recurring subsidy payments takes the form of cash spending.

### B.3 Analysis on the characteristics of spending using the Nielsen Homescan dataset

To gain further insights into what the additional spending in response to the subsidies entails, we conduct a separate analysis on retail purchases using a separate dataset: the Nielsen Homescan dataset. The Nielsen dataset tracks the purchases of a broad basket of consumer packaged goods from all retail outlets for a demographically and geographically representative sample of households. It enables us to observe the product-level information on retail purchases made by tracked households, such as brand, product name, product code, price, portion, and quantity. We use this detailed product-level information to study the composition of the spending response to receiving the subsidies.

The Nielsen dataset reports the age and income information as categorical variables. For the age information, each household is categorized as being in one of the four age groups (34 and below, 35–44, 45–54, or 55 and above). For the income information, each household is categorized as being in one of the three income groups (3,500 dollars or below, 3,501–7,000 dollars, or 7001 dollars or above). Silver Support recipients, who are low-income elderly individuals, are in the eldest age group (55 and above) as well as the lowest income group (3,500 dollars or below). To study the spending response to receiving the subsidies, we adopt a differences-in-differences methodology where we compare the change in spending behaviors of potential Silver Support recipients (the treated households) relative to non-recipients (the control households). The treated group consists of households who are in the lowest income group (3,500 dollars or below) and in the eldest age group (55 and above). The control group consists of households that have similar levels of income to treated individuals but are younger. Specifically, the control group comprises households who are in the lowest income group (3,500 dollars or below) and in the second eldest age group (45–54) in the control group. We also restrict both the treated group and the control group to HDB residents, in accordance with the Silver Support eligibility criteria.

The treated group contains the earliest Silver Support recipients who received the first subsidy in July 2016 as well as later recipients. Since we do not observe their banking transactions, nor do we know their particular ages, we proxy the timing of the first subsidy by July 2016, the first-ever Silver Support subsidy. This conservative choice of subsidy timing makes us underestimate the spending response as some of the actual pre-subsidy months are classified as post-subsidy months for later recipients. We also note that the coarsely defined age groups and income groups introduce measurement errors for the treated group. Specifically, in our treated group there are low-income households aged between 55 to 64 years who are too young to receive the subsidies. Households with relatively higher income in the 3,500 dollars or below income group are similarly misclassified. This over-inclusion of households into the treated group introduces measurement error and renders our estimate of the spending response less precise.

We estimate the following regression specification:

$$y_{i,ym} = \mu_i + \pi_{ym} + \beta \cdot \left(Treated_i \times Post_{ym}\right) + \varepsilon_{i,ym} \tag{10}$$

$y_{i,ym}$ measures the spending behavior of household $i$ in year-month $ym$. The key variable of interest is the interaction term between $Treated_i$, an indicator variable that equals 1 if household $i$ is in the treated group and 0 if household $i$ is in the control group, and $Post_{ym}$, an indicator for post-subsidy months. Its coefficient $\beta$ measures the impact of the Silver Support subsidies on monthly spending. Consumer fixed effects $\mu_i$ remove unobserved cross-sectional heterogeneity and time fixed effects $\pi_{ym}$ remove unobserved timevarying heterogeneity. This specification augments a standard difference-in-differences specification by taking a flexible and agnostic approach to account for the treatment assignment (subsumed by individual fixed effects) and the post indicator (subsumed by time fixed effects). The regression thus compares changes in spending behaviors within individuals instead of comparing changes across individuals. As in previous regression specifications, standard errors are clustered at the consumer level.

Table OA.3 reports the results for total spending and its components. The first column shows that the households in the treated group increase their total retail spending by 19.84 dollars per month relative to the households in the control group; this additional spending corresponds to close to 7% of the average total spending among the treated individuals of 255.4 dollars. Columns 2 & 3 show the results for food and non-food spending separately. The increase in food spending (15.07 dollars per month) accounts for 76% of the total spending response. Non-food spending increases by 4.78 dollars per month in the relative terms, but the effect is statistically insignificant.

We continue to examine how the variety of retail spending responds to the subsidies, as reported in Table OA.4. We measure the variety of retail spending by the number of unique products purchased (product variety, column 1), the number of unique brands purchased (brand variety, column 2), and the number of unique product categories purchased (category variety, column 3). The estimates show that these different variety measures consistently respond positively to the subsidies. The treated households significantly increase the variety of their retail spending according to all three variety measures.[11]

### B.4 Does the subsidy program affect retail prices?

To complete the analysis, we also investigate whether the subsidy program in our setting affects retail prices of products consumed by the recipients using the Nielsen dataset. We measure the exposure to the subsidy program as the expenditure share by the treated households in the period from January to June 2016 for each product in the Nielsen dataset. We then split products into high- and low-exposure groups based on this exposure measure. We then examine whether the price of high-exposure products increases

[11] Table OA.3 and OA.4 report results obtained in the unbalanced panel of household-month observations. We also re-run the regressions in the subsample of households that are present in all 24 months to isolate the effect of entries and exits. The results remain similar.

faster relative to low-exposure products using the following regression:

$$y_{j,ym} = \mu_j + \pi_{ym} + \sum_{ym} \gamma_{ym} \left( \mathbb{1}_{ym} \times \mathbb{1} \left( HighExposure_j \right) \right) + \varepsilon_{j,ym} \tag{11}$$

The dependent variable $y_{j,ym}$ is the log of the quantity-weighted average price of product $j$ in month $ym$, i.e., total monthly revenue divided by the monthly total number of units sold. $\mathbb{1}_t$ are monthly indicators. In this log-linear specification, the coefficient for the interaction between month $ym$ and the high exposure indicator $\gamma_{ym}$ corresponds to the incremental change in the price level of month $ym$ of high-exposure products relative to low-exposure products.

We include only products that appear consistently in 2016 and 2017 in this analysis to make sure that product creation and turnover do not affect our results. We define products whose exposure to treated households exceeds 20% as high-exposure products and the remaining products as low-exposure products.[12] We plot $\gamma_{ym}$ and the associated 95% confidence intervals in Figure OA.2. In both the overall sample and the subsample of food products, we find no evidence that high-exposure products experience a larger price increase than low-exposure products.

### B.5 Consumption response to the MediSave program

Starting in 2014, this program distributes annual medical vouchers to Singaporeans born in 1949 or earlier, known as the Pioneer Generation, every July. The medical vouchers are deposited by the government directly into the recipients' medical accounts of the Central Provident Fund (CPF), the national pension savings system, and can be used to cover medical and health insurance expenses. The amount of an annual voucher is higher for older cohorts but has remained constant over time for the same age cohorts. Specifically, the annual voucher amount is 800 SGD for individuals born in 1935 or earlier, 600 SGD for individuals born from 1935 to 1939, 400 SGD for individuals born from 1940 to 1944, and 200 SGD for individuals born from 1945 to 1949. Similar to the Silver Support Scheme, the Pioneer MediSave program was announced in the Budget far in advance of the first annual voucher. Hence, it is reasonable to assume that the arrival of the vouchers is fully anticipated.

Unlike the Silver Support Scheme, the Pioneer MediSave program covers all Singaporeans who were born in 1949 or earlier, and all eligible elderly individuals receive the voucher at the same time. This program structure precludes us from studying its con-

[12] 20% corresponds to the top quartile of the distribution. We obtain similar results if we use other percentiles (e.g. the median) to define the high and low threshold.

sumption response in the same way we study the Silver Support Scheme as we will not be able to rule out the possibility that concurrent aggregate conditions drive the variation in consumption patterns. We, therefore, switch to a difference-in-differences framework where we use foreigners in the same birth-year cohorts as the control group. Unlike in many other countries, foreigners in Singapore constitute close to 40 percent of the population and are well represented across age, income, wealth, and other demographics.

To examine the consumption response associated with the Pioneer MediSave program, we use data on card spending from the payment processing company Diners Club, for the period between January 2013 to August 2017.[13] In this data, we observe card spending (charge cards and credit cards) of cardholders, Singaporeans and non-Singaporeans, born in 1949 or earlier. In the sample of elderly individuals, dormant cards might be a concern. To prevent dormant card users from biasing our results, we report the estimates obtained in the sample of active users, defined as individuals having at least 10 months of non-zero credit card spending. Our results are robust to other ways in filtering active users or no filtering at all.

We aggregate the credit card spending to the monthly level for all individuals and estimate the following equation to gauge the marginal propensity to consume (MPC) out of the voucher:

$$y_{i,ym} = \mu_i + \pi_{ym} + \beta \cdot \left(Treated_i \times Post_{ym} \times VoucherAmount_i\right) + \varepsilon_{i,ym} \tag{12}$$

$y_{i,ym}$ is the total card spending of individual $i$ in year-month $ym$. $Treated_i$ is an indicator for Singaporeans. $Post_{ym}$ is an indicator for the months since July 2014, the inaugural MediSave voucher. $VoucherAmount_i$ is the monthly-equivalent amount of the Pioneer MediSave voucher, calculated as the annual voucher amount divided by 12 for treated individuals and zero for control individuals. The coefficient of the triple-interaction term captures the average change in monthly card spending per dollar of the voucher and is estimated with within-individual variation as opposed to between-individual variation.

Since both the Silver Support Scheme and the medical voucher program provide transfers to the same demographic group (the elderly population) in Singapore, their differential impacts are unlikely to be driven by institutional, cultural, or demographic factors.

Table OA.5 reports the results. Following the results in Table 6, we first focus on in-

[13]We are unable to study the Pioneer MediSave program using the more comprehensive DBS data that is used in our main analysis as the DBS data (2016–2018) only cover the post period of the Pioneer MediSave program and thus render a difference-in-differences analysis impossible. Also, the voucher program does not affect our identification of the effect of the Silver Support program as our estimates are only based on Silver Support recipients and all of these recipients are eligible to receive the MediSave vouchers.

dividuals with the worst liquidity constraint: a credit limit of zero. (Close to 40% of the elderly active users are charge card users and have a credit limit of zero.) Singaporeans in this group should have a high MPC out of the voucher. Column 1 shows that the estimated MPC out of the voucher for them is 0.18 dollars and is statistically indistinguishable from zero. This result sharply contrasts those reported in Table 6.

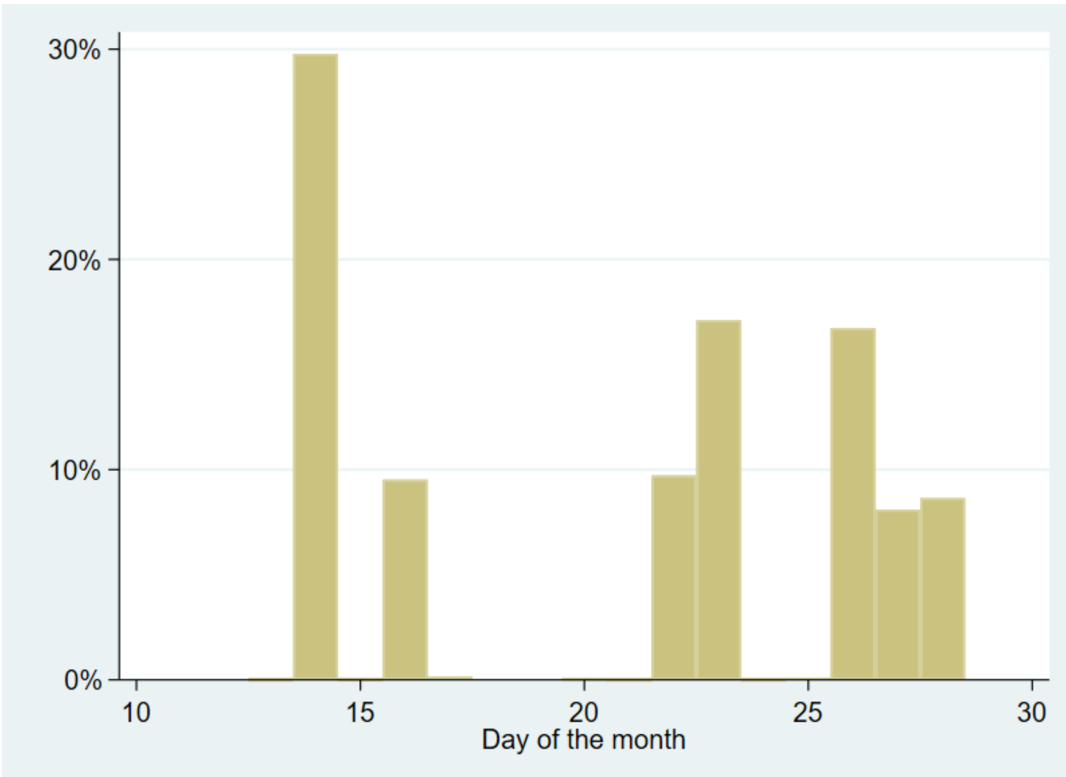
Again, following the results in Table 6, we focus on individuals with the worst liquidity constraint (zero credit limit) and the lowest income, defined as being at the bottom tercile of the income distribution of the elderly active users, in column 2. We estimate that Singaporeans in this group have an MPC out of the voucher of 0.18 dollars which is statistically indistinguishable from zero. The result also sharply contrasts those reported in Table 6.

The two different filters ensure that we are comparing the segment of MediSave recipients who are comparable to Silver Support recipients in terms of income and liquidity and are among the recipients most likely to increase spending in response to receiving vouchers. The comparability reassures that the differential impacts we have documented are unlikely to be driven by the different eligibility criteria of the two programs. Also, since both the Silver Support Scheme and the medical voucher program provide transfers to the same demographic group (the elderly population) in Singapore, their differential impacts are unlikely to be driven by institutional, cultural, or demographic factors. The contrast in consumer responses in Table 6 and OA.5 are attributable to the differences in the disbursement form of these two programs. This comparison highlights that a cash/bank transfer disbursement is more effective than a voucher disbursement in stimulating consumption expenditures due to its flexibility and fungibility.

Figure OA.1: **Dates of recurring payouts**

This figure shows the histogram of the dates of recurring payouts by day of the month (Panel A) and by day of the week (Panel B) in our sample of subsidy recipients.

(a) Day of the month




(b) Day of the week

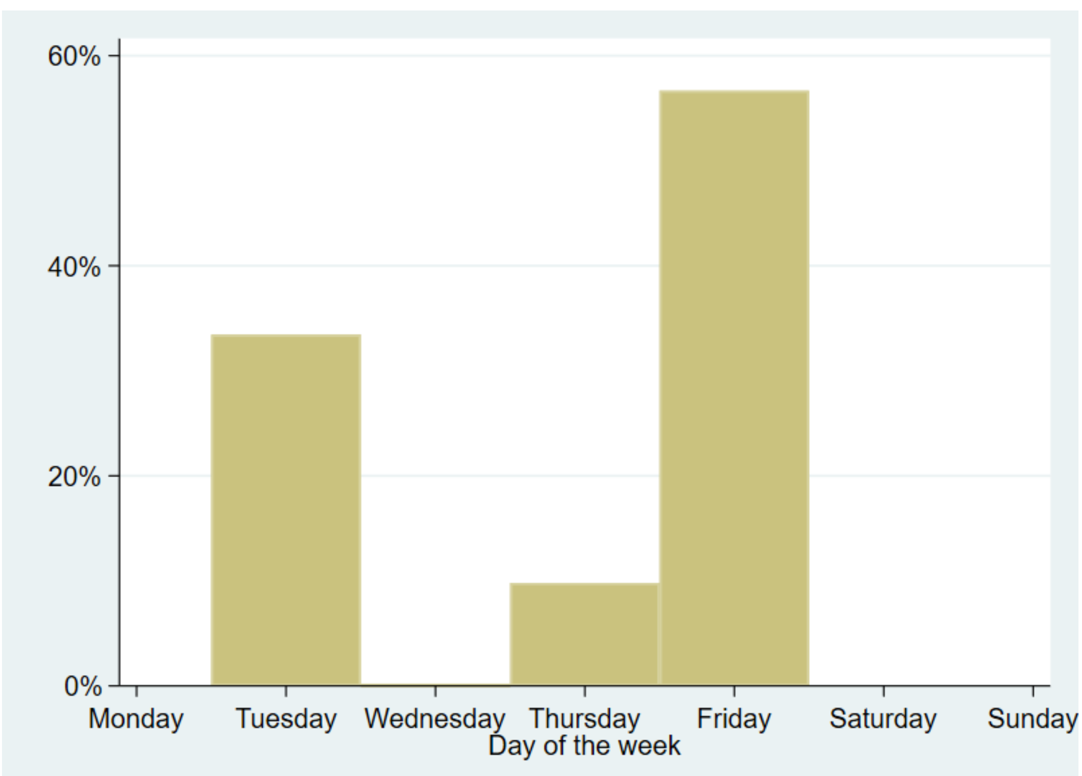


Figure OA.2: **Price level of Nielsen products by exposure to treated individuals**

This figure shows the price level of products captured in the Nielsen dataset, sorted by their exposure to the treated individuals, at a monthly frequency. For each product, we calculate the expenditure share of low-income households whose grocery buyers are at least 55 years old in the period from January to June 2016; we then use 20% as the cutoff to split products into high- and low-exposure groups based on this exposure measure. The figure plots coefficients $\gamma_{ym}$ in equation (11), the proportional change in the price level of month $t$ (normalized by the price level in January 2016) of high-exposure products relative to low-exposure products, and the associated 95% confidence intervals. The *x-axis* denotes the calendar month; the *y-axis* shows the proportional change in the price level.

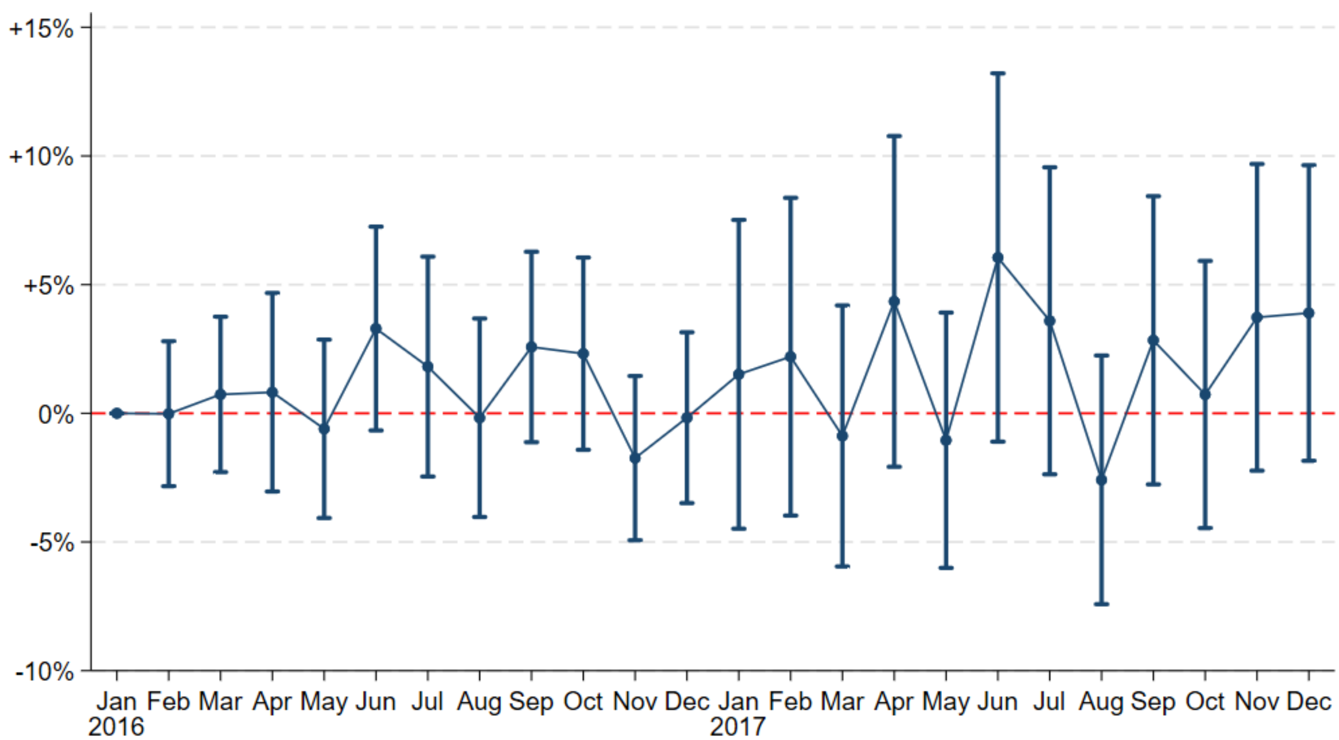


Table OA.1: **The average monthly spending response to the welfare program**

This table shows the average monthly spending response to program inception among recipients (equation (7), the monthly analogue to equation (1)). The data are at the individual-monthly level from January 2016 to December 2018. In constructing individual-monthly observations, we remove double-counting of payment for credit card spending in bill counting. See the text for details on the procedure. *Post* is an indicator that is equal to 1 for the months since the individual receives the first subsidy. Individual and year-month fixed effects are included and denoted at the bottom. Standard errors are clustered at the individual level; the corresponding t-statistics are reported in brackets. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

| | (1) Total spending | (2) Cash spending | (3) Debit card spending | (4) Credit card spending | (5) Bill payment |
|---|---|---|---|---|---|
| Post | 219.366*** | 171.281*** | 7.278 | -1.533 | 29.077*** |
| | [4.75] | [4.59] | [0.94] | [-0.35] | [2.59] |
| Individual FEs | Yes | Yes | Yes | Yes | Yes |
| Year-Month FEs | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.529 | 0.441 | 0.474 | 0.508 | 0.699 |
| No. of observations | 48,064 | 48,064 | 48,064 | 48,064 | 48,064 |

Table OA.2: **The average spending response to recurring subsidy payouts**

This table shows the average spending response to recurring payouts among recipients (equation (9)). The data are at the individual-daily level from January 2016 to December 2018, covering twelve weeks after each subsidy payout event (inclusive of the payout week). Individual, year-month, and day-of-week fixed effects are included and denoted at the bottom. Standard errors are clustered at the individual level; the corresponding t-statistics are reported in brackets. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

Panel A: Spending response by subsidy timing and recipient cohort

| | (1) Total spending | (2) Total spending | (3) Total spending |
|---|---|---|---|
| 0–83 days after subsidy receipt | | | |
| × Subsidy amount | 0.008*** | | |
| | [6.96] | | |
| 0–83 days after subsidy receipt | | | |
| × Subsidy amount × First subsidy | | 0.007*** | |
| | | [6.36] | |
| 0–83 days after subsidy receipt | | | |
| × Subsidy amount × Subsequent subsidies | | 0.010*** | |
| | | [5.24] | |
| 0–83 days after subsidy receipt | | | |
| × Subsidy amount × Inaugural recipients | | | 0.009*** |
| | | | [6.40] |
| 0–83 days after subsidy receipt | | | |
| × Subsidy amount × Later recipients | | | 0.007*** |
| | | | [4.21] |
| Individual FEs | Yes | Yes | Yes |
| Day of week FEs | Yes | Yes | Yes |
| Year-Month FEs | Yes | Yes | Yes |
| $R^2$ | 0.0869 | 0.0869 | 0.0869 |
| No. of observations | 1,361,332 | 1,361,332 | 1,361,332 |

Panel B: Spending response by spending instrument

| | (1) Total spending | (2) Cash spending | (3) Debit card spending | (4) Credit card spending | (5) Bill payment |
|---|---|---|---|---|---|
| 0–83 days after subsidy receipt | | | | | |
| × Subsidy amount | 0.008*** | 0.007*** | 0.001** | -0.000 | 0.001 |
| | [6.96] | [7.22] | [2.35] | [-0.55] | [1.52] |
| Individual FEs | Yes | Yes | Yes | Yes | Yes |
| Day of week FEs | Yes | Yes | Yes | Yes | Yes |
| Year-Month FEs | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.0869 | 0.0458 | 0.0466 | 0.0479 | 0.221 |
| No. of observations | 1,361,332 | 1,361,332 | 1,361,332 | 1,361,332 | 1,361,332 |

Table OA.3: **The average spending response (estimates from the Nielsen dataset)**

This table shows the average monthly spending response to receiving the subsidies, estimated using the Nielsen dataset (equation (10)). The sample covers low-income households whose grocery buyers are at least 45 years old in the Nielsen dataset from January 2016 to December 2017 and contains observations at the individual-monthly level. The dependent variables include the total monthly spending in dollars and its composition by category. *Treated* is an indicator that is equal to 1 for households with a grocery buyer at least 55 years old and 0 for households with a grocery buyer between 45 to 54 years old. *Post* is an indicator that is equal to 1 for the months since July 2016. Individual and year-month fixed effects are included and denoted at the bottom. Standard errors are clustered at the individual level; the corresponding t-statistics are reported in brackets. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

| | Total spending | Food spending | Non-food spending |
|---|---|---|---|
| Treated × Post | 19.843** | 15.067* | 4.776 |
| | [2.15] | [1.80] | [1.46] |
| Individual FEs | Yes | Yes | Yes |
| Year-Month FEs | Yes | Yes | Yes |
| $R^2$ | 0.603 | 0.614 | 0.373 |
| No. of observations | 5,564 | 5,564 | 5,564 |

Table OA.4: **Response of purchase variety (estimates from the Nielsen dataset)**

This table shows the average response of purchase variety measures to receiving the subsidies, estimated using the Nielsen dataset (equation (10)). The sample covers low-income households whose grocery buyers are at least 45 years old in the Nielsen dataset from January 2016 to December 2017 and contains observations at the individual-monthly level. *Product/Brand/Category variety* is the number of unique products/brands/categories that a household purchases in the given month. *Treated* is an indicator that is equal to 1 for households with a grocery buyer at least 55 years old and 0 for households with a grocery buyer between 45 to 54 years old. *Post* is an indicator that is equal to 1 for the months since July 2016. Individual and year-month fixed effects are included and denoted at the bottom. Standard errors are clustered at the individual level; the corresponding t-statistics are reported in brackets. We use $^{***}$, $^{**}$ and $^{*}$ to denote significance at 1%, 5% and 10% level (two-sided), respectively.

| | Product variety | Brand variety | Category variety |
|---|---|---|---|
| Treated × Post | 1.994$^{***}$ | 1.216$^{***}$ | 1.087$^{***}$ |
| | [3.15] | [2.64] | [3.02] |
| Individual FEs | Yes | Yes | Yes |
| Year-Month FEs | Yes | Yes | Yes |
| $R^2$ | 0.687 | 0.672 | 0.674 |
| No. of observations | 5,564 | 5,564 | 5,564 |

Table OA.5: **Spending response of a voucher program (the Pioneer MediSave program)**

This table shows the average monthly spending response to receiving the MediSave annual vouchers (equation (12)). The sample contains individual-monthly card spending from January 2013 to August 2017 by all active Diners Club charge card and credit card users that were born in 1949. *Treated* is an indicator that is equal to 1 for Singapore citizens and 0 for foreigners. *Post* is an indicator that is equal to 1 for the months since July 2014, the inaugural MediSave voucher. *Voucher Amount* is the monthly-equivalent amount of the Pioneer MediSave voucher, calculated as the annual voucher amount divided by 12 for the treated individuals and zero for the control individuals. Low-income individuals are defined as individuals whose monthly income in May 2014 (two months prior to the first voucher) is in the bottom tercile of the income distribution. Low-liquidity individuals are defined as individuals whose credit limit is zero. Individual and year-month fixed effects are included and denoted at the bottom. Standard errors are clustered at the individual level; the corresponding t-statistics are reported in brackets. We use $^{***}$, $^{**}$ and $^{*}$ to denote significance at 1%, 5% and 10% level (two-sided), respectively.

| | Outcome variable: monthly card spending | |
|---|---|---|
| | (1) | (2) |
| | Sample: low-liquidity individuals | Sample: low-liquidity & low-income individuals |
| Treated × Post × Voucher Amount | 0.182 | 0.185 |
| | [0.58] | [0.58] |
| Individual FEs | Yes | Yes |
| Year-Month FEs | Yes | Yes |
| $R^2$ | 0.405 | 0.425 |
| No. of observations | 69,168 | 65,647 |