# Consumption and Debt Response to Fiscal Stimuli: Evidence from a Large Panel of Consumers in Singapore

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**Abstract**

This paper uses a unique panel data set of consumer financial transactions to study how consumers respond to exogenous income shocks. Specifically, we study how their spending behavior on their credit card, debit card and bank checking account responds to a positive income shock. Our analysis is based on a difference-in-differences identification by exploiting the qualification criteria—foreigners do not qualify for the program. We find that consumption rose significantly subsequent to the fiscal policy announcement, for each dollar received, consumers on average spend 90 cents, during the ten months upon announcement. There was a moderate decrease in debt. We find a strong announcement effect -- consumers increase spending on their credit cards during the two-month announcement period, but they switched to debit cards after disbursement, before finally increasing spending on the credit card in the later months. Consistently, credit card debt dropped in the first months after disbursement and reverted back to the original level. Finally, consumption response is heterogeneous across spending categories and across individuals. Consumption rose primarily in the non-food, discretionary category. The consumption response is driven by liquidity constrained consumers, and the spending response of the credit constrained consumers is dominated by that of the liquidity constrained consumers.

Keywords: Consumption, Spending, Debt, Credit Cards, Household Finance, Banks, Loans, Durable Goods, Discretionary Spending, Fiscal Policy, Tax Rebates, Liquidity Constraints, Credit Constraints.

JEL Classification: D12, D14, D91, E21, E51, E62, G21, H31

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## 1. Introduction

A central implication of the life-cycle/permanent income hypothesis (LC/PIH) is that consumers should not respond to predictable and temporary changes in their income. The existing literature on the failure of the Permanent Income Hypothesis explains these declines in spending across time primarily through liquidity constraints and precautionary savings (Souleles, 1999; Carroll 2002; Johnson, Parker, and Souleles, 2006; Agarwal, Liu, and Souleles, 2007; Parker, Souleles, Johnson, and McClelland, 2013).

In this paper we use a unique panel data set of consumer financial transactions to study how consumers respond to exogenous income shocks.[1] Specifically, we use a representative sample of over 180,000 consumers in Singapore and study how their spending behavior in their credit card, debit card and bank checking accounts responded to a positive income shock. The positive income shock we analyze is the "Growth Dividend" program announced by the Singapore government in February 2011. The US$1.17 billion package distributed a one-time cash payout, ranging from US$78 to US$702, to 2.5 million adult Singaporeans. This represents a significant income bonus, corresponding to about 18% of monthly median income in Singapore in 2011. Our analysis is based on a difference-in-differences identification by exploiting the qualification criteria—foreigners do not qualify for the program and comprise the control group in the study. In addition to being able to identify the causal impact of the fiscal policy on consumption, richness of our data also allows us to study the response in the credit card spending, debit card spending, change in credit card debt, and change in banking transaction behavior in a period of 10 months after the policy announcement, which help us understand different channels of the consumption response.

As discussed by Gross and Souleles (2003), credit cards play an important role in consumer finances, so they can be quite useful for studying consumer spending behaviour. Half of consumers in the US have a credit card, and total credit card debt is close to a trillion dollars in 2012 with 40% of revolving debt (U.S. Census Bureau, Statistical Abstract of the United States:2012). Consumer credit plays an equally important role in Singapore. More than a third of consumers have a credit card in Singapore, and the total credit card debt as a percentage of GDP is over 2% in Singapore in 2011 (Department of Statistics Singapore, 2012). Hence, the ability of consumers to manage credit well has direct implications for the welfare impact of consumer credit proliferation. Agarwal, Liu, and Souleles (2007) point out the limitations of studying consumption dynamics with simply using credit card data, because credit cards potentially miss significant spending on other instruments (debit cards, cash, and checks).[2] For example, the purchase volume on debit cards is similar in magnitude as that on credit cards (2.1 trillion vs. 2.3

[1] While our objective is not to test any specific theoretical model, our results can also be interpreted as a test of the Life-Cycle/Permanent Income (LCPI) model. If the LCPI holds, we should not find significant increase in spending over a broad window due to a temporary and expected change in income.

[2] Though, it is important to point out that disposable consumption is likely to be spent on the debt or credit cards and not using checks or other instruments.

trillion US dollars) in the U.S. in 2012 (U.S. Census Bureau, Statistical Abstract of the United States:2012). This is even more relevant for Singapore, where the dominant medium of disposable consumption is through the debit and credit cards. Virtually, everybody in Singapore has a debit card. Specifically, in Singapore, close to 30% of aggregate personal consumption is already being purchased using credit cards, and about another 30% of aggregate personal consumption is being purchased using debit cards. The combination of the two accounts for nearly half of household consumption. The fraction of checks and cash usage for consumption accounts for the remaining 40% in Singapore. However, since we also want to study debt dynamics of the households due to the income changes, credit cards represent the leading source of unsecured credit for most households.[3]

We estimate a distributed lag model using the announcement date of the dividend growth program as the exogenous event and observe the impulse response of credit card spending, debit card spending, and debt. Our findings are summarized as follows. First, consumers' consumption rose significantly after the fiscal policy announcement: for each dollar received, consumers on average spend 90 cents (aggregated across different financial accounts) during the ten months after announcement. On the other hand, consumers' credit card debt experienced a moderate decrease (so savings effectively increased). Second, we find strong announcement effect; consumers start to increase spending during the two-month announcement period before the cash payout. Third, consumption response is concentrated in debit card (or 25% of the total response) and credit card (or 75% of the total response) spending. As pointed out by Agarwal, Liu and Souleles (2007) we should expect consumption response to show up in credit card spending. More importantly, consumers started spending using credit cards during the announcement period, and then switched to debit cards after disbursement, before finally increasing significantly the credit card use. Consistently, credit card debt dropped in the first months after disbursement and reverted back to the original level. Lastly, consumption response is heterogeneous across spending categories and across individuals. Consumption rose primarily in the non-food, discretionary category. Liquidity constrained consumers respond strongly in their consumption response, whether or not they are credit-constrained.

We conduct a series of robustness tests to make sure that our results are not confounded with some other policy changes in Singapore. For instance, during the sample period there were two other policy changes that provide positive income shocks with potential implication on their consumption -- consumers above the age of 45 and all low income households (foreigners and locals) received these shocks. To be certain that this was not confounding our study, we drop the low income household from our analysis to isolate the consumption response to the Growth Dividend program. The second policy targeted older Singaporeans (age >= 45) by topping up their illiquid retirement medical accounts which can only be applied to hospitalization or certain out-patient care items and cannot be cashed out. To further validate our results, we carry out a

[3] Japelli, Pischke, and Souleles (1998) found that people with bankcards were better able to smooth their consumption past income fluctuations than were people without bankcards.

separate analysis on a subsample of consumers younger than 45 years old who are entitled only to the Growth Dividend program. Once again the results are qualitatively and quantitatively similar to those in the main analysis.

There is a vast literature on consumption response to income shocks. Some recent studies include Shapiro and Slemrod (1995, 2003a, 2003b), Souleles (1999, 2000, 2002), Parker (1999), Browning and Collado (2001), Hsieh (2003), Stephens (2003, 2005, and 2006), Johnson, Parker, and Souleles (2006), and Parker, Souleles, Johnson, and McClelland (2013). The literature finds mixed evidence, some studies find that consumption response is essentially zero, while other find that liquidity constrained consumers respond positively to the fiscal stimulus programs.

Our paper is most closely related to Agarwal, Liu and Souleles (2007). We also study the dynamics of consumption and debt as a function of an income shock. We find significant spending response working through the balance sheets of the consumers and we confirm that liquidity constraints matter. However, we document the dynamics of consumption response across different spending instruments, rise in credit card spending subsequent to announcement, then switching to debit card spending subsequent to the disbursement of the stimulus, and finally, switching back to the credit card in the later months. This implies that Agarwal et al. (2007) underestimate the spending response due to data limitation. Specifically, they are unable to measure spending using debit card instruments, which we show accounts for a significant portion of MPC, especially in the initial months after disbursement. We are also the first to document that the spending response of the credit constrained consumers is dominated by that of the liquidity constrained consumers. Credit constrained but liquidity unconstrained consumers do not respond to the stimulus, while liquidity constrained consumers with credit capacity respond strongly both in spending and debt.

More broadly, in relation to the prior literature, this study points out an important factor in understanding of the consumption response to fiscal stimuli. Since the specific stimulus program we study has an unambiguous announcement date, we are able to show that consumption responds upon announcement. This has a significant economic implication. In our study, 18% of the total consumption response occurs during the announcement period, implying the prior literature underestimates the consumption response to income shocks.

The rest of the paper flows as follows. Section 2 reviews the literature. Section 3, section 4, and section 5 discuss the fiscal policy experiment in Singapore, the data, and the econometric methodology respectively. The results appear in Section 6. Section 7 concludes.

## 2. Literature Review

A number of papers have studied consumers' response to changes in a permanent predictable change in income, as a means of testing whether households smooth consumption as predicted by the rational expectation life-cycle permanent-income hypothesis.

Much of the previous literature on this topic uses aggregate data. For example, Wilcox (1989) finds that aggregate consumption rises in months when Social Security benefits per beneficiary rise. Because benefit increases are mandated by Congress, they are known well in advance. However, it is not clear if it is the increase in Social Security benefits or something else that causes consumption to rise. As a result, his estimates are sensitive to how he implements the seasonal adjustments.

More recent studies use micro data, which overcome the problems associated with aggregate data. Shea (1995) tests whether consumption increases in response to income mandated years earlier in union contracts. Because he uses the Panel Study of Income Dynamics, he is forced to look at food consumption only. He finds that a 10% increase in income leads to almost a 10% increase in food consumption. Gross and Souleles (2002), use a unique data of credit card accounts and test the response to spending and debt to changes in credit limit. They interpret the change in credit limit as a permanent increase in income. They find an MPC of 13% and for accounts that had an increase in credit limit, they find that debt levels rise by as much as $350. Their results are consistent with models of liquidity constraint and buffer stocks.

More recently, two papers have exploited the end of debt contracts to identify predictable changes in disposable income. Coulibaly and Li (2006) find that when mortgages end, households do not alter their consumption on non-durable goods but increase their spending in durable goods such as furniture and entertainment equipment. Stephens (2006) uses the completion of vehicle loan payments and finds that a 10% increase in discretionary income leads to a 2 to 3% increase in non-durable consumption. Thus there is some contention about the size and composition of the spending change from this identification strategy. Other papers have looked at the consumption response to the social security checks (Stephens, 2003), food stamp receipts (Shapiro, 2005), and the Alaska Permanent fund (Hsieh, 2003).

Finally, Aaronson, Agarwal, and French (2012) study the impact of a minimum wage hike on spending debt. Specifically, they find that following a minimum wage hike, households with minimum wage workers often buy vehicles. On average, vehicles spending increases more than income among impacted households. The size, timing, persistence, composition, and distribution of the spending response are inconsistent with the basic certainty equivalent life cycle model. However, the response is consistent with a model in which impacted households face collateral constraints.

There is perhaps even more disagreement over the consumption response to transitory income changes. This contention goes back to just after the publication of Friedman's (1957) PIH, when Bodkin (1959) used insurance dividends paid to WWII veterans to reject the PIH but Kreinen's (1961) study of restitution payments to certain Israelis could not reject the PIH. Among more recent studies, Paxson (1993), Browing and Collado (2001), and Hsieh (2003) fail to reject, but Shea (1995), Parker (1999), and Souleles (1999) all reject the PIH.

A number of previous papers have also studied consumers' response to tax cuts and other windfalls. Modigliani and Steindel (1977), Blinder (1981), and Poterba (1988) studied the 1975 tax rebate. They found that consumption responded to the rebate, though they came to somewhat different conclusions regarding the relative magnitude of the initial versus lagged response. All three studies used aggregate time-series data, but there are a number of advantages to using micro-level data . First, it is difficult to analyze infrequent events like tax cuts using time-series data.[4] For example, time-series analysis of the 2001 rebate is complicated by the recession, changes in monetary policy, the September 11th tragedy, and other concurrent macro events. Second, with micro data one can investigate consumer heterogeneity in the cross-section, for instance by contrasting the response of potentially constrained and unconstrained households. Early papers using micro data include Bodkin (1959), who studied the insurance dividends the U.S. paid to WWII veterans, and Kreinen (1961), who studied restitution payments from Germany to Israelis. Among more recent related studies, Souleles (1999) found that consumption responds significantly to the federal income tax refunds that most taxpayers receive each spring. Gross and Souleles (2002) found that exogenous increases in credit-card limits (*i.e.*, windfall increases in liquidity) lead to significant increases in credit card spending and debt. Both of these papers found evidence of liquidity constraints.[5] There have been four recent studies, using micro data, by Shapiro and Slemrod (2003a and 2003b), Johnson, Parker, and Souleles (2006) and Agarwal, Liu, and Souleles (2007) on the 2001 tax rebates. As mentioned earlier, this paper directly builds on the results of the last of these four studies. Shapiro and Slemrod (2003a) found that only 21.8% of their survey respondents report they will mostly spend their rebate, a result they calculate is consistent with an average marginal propensity to consume of about one third. They found no significant evidence of liquidity constraints. Shapiro and Slemrod (2003b) used a novel follow-up survey in 2002 to try to determine whether there was a lagged response to the rebate. They found that, of respondents who said they initially mostly used the rebate to pay down debt, most report that they will "try to keep [down their] lower debt for at least a year". Johnson, Parker, and Souleles (2006) find that consumers spent only about a third of the rebate initially, within a quarter. But they also find evidence of a substantial lagged consumption response in the next two quarters. The consumption response was greatest for illiquid households, which is indicative of liquidity constraints. Agarwal, Liu, and Souleles (2007) find that consumers initially saved much of the rebates, on average, by increasing their credit card payments and thereby paying down debt. But soon afterwards spending temporarily increased, offsetting the initial extra payments, so that debt eventually rose back near its original level. For people whose most intensively used credit card account is in the sample, spending on that account rose by over $200 in the nine months after rebate receipt, which represents over 40% of the average household rebate. Finally, others have

[4] Blinder and Deaton (1985) found smaller consumption responses when they considered jointly the 1975 rebate along with the 1968-70 tax surcharges. Nonetheless they found consumption to be too sensitive to the pre-announced changes in taxes in the later phases of the Reagan tax cuts. Overall they concluded that the time-series results are "probably not precise enough to persuade anyone to abandon strongly held a priori views".

[5] Other related studies include Wilcox (1989, 1990), Parker (1999), Souleles (2000, 2002), Browning and Collado (2001), Hsieh (2003), and Stephens (2003), among others.

looked at the effect of the 2008 tax rebates on payday loans payments (Bertrand and Morse, 2009) and the 2001 and 2008 tax rebates on bankruptcy filing (Gross, Notowidigdo, and Wang, 2012).

### 3. The Growth Dividend Program in Singapore

The Ministry of Finance in Singapore announced on February 18th, 2011 during the annual budget speech that, as an attempt to share the nation's economic growth in 2010, the government is distributing a one-time pay out of Growth Dividends to all adult Singaporeans over 21 years old in 2011. While the amount each Singaporean receives depends on his wealth, on average 80% of all Singaporeans receive US$428 to US$ 624 in Growth Dividends. This represents a significant income bonus, corresponding to about 18% of monthly median income in Singapore in 2011. The payments of the Growth Dividend program totalled US$ 1.17 billion, which corresponds to 12% of Singapore's monthly aggregate household consumption expenditure in 2011.

Eligible Singaporeans receive the payment by the end of April, 2011, typically via direct bank transfer. The amount of Growth Dividend an individual receives is jointly determined using income and annual value of home. The annual value is the estimated annual rent of the property if it were to be rented out, excluding the furniture, furnishings and maintenance fees, and is determined by IRAS, Singapore's tax authority, on an annual basis. While we do not have data on the exact annual value of home for each individual in our data, we make use of the fact that the government uses the annual value of home criteria to identify less well-off Singaporeans living in the government housing (a.k.a. HDB). Thus, we use the property type (HDB or private) together with income to identify the size of the Growth Dividend for each qualified Singaporean. In addition, Singaporean adult men who are serving or have served in the army receive an additional Growth Dividend of $100, in recognition of their contributions to the nation. The average Growth Dividend amount each qualified individual receives in our sample is SG $ 522, or equivalently US$407. Please refer to Table 1A for the exact pay out schedule.

There are other stimulus programs being announced at the same time in February 2011, and we focus on the Growth Dividend for the following reasons. Compared to other stimulus packages, the Growth Dividend program is the largest. It also has features that allow better identification of the consumption response. It is the only one with cash payment (as opposed to, for example, illiquid retirement account) and a targeted population—adult Singaporeans—for us to have clean identification by using the foreigners as the control group, and is unprecedented and unanticipated by the population. To control for the confounding effects of other stimulus packages, we drop individuals who qualify for the other cash stimulus package—Workfare Special Bonus—in our analysis.[6] We also perform other robustness checks to verify our result.

[6] The qualification criteria for Workfare Special Bonus is Singaporean citizens who are aged 35 or older by December 2010, and who work for at least 3 months out of any 6 month period in 2010 with a monthly income lower than SG$1700.

## 4. Data

We use in our analysis a unique, proprietary dataset obtained from the leading bank in Singapore with over 4 million customers, or 80% of the entire population in Singapore. Our sample contains consumer financial transactions data of over 180,000 individuals in a period of 24 months between 2010:04 and 2012:03, which is a random, representative sample of the bank's customers. For each individual in our sample period, we have information on the monthly statement of each of their credit cards, debit cards and checking accounts with the bank, including balance, total debit and credit amount (for checking accounts), spending (for credit and debit cards), credit limit, payment and debt (for credit cards). At the disaggregate level, the data contains transaction level information of the individual's credit card and debit card spending, including the transaction amount, transaction date, merchant name and merchant category for each account. The data also contains a rich set of demographics information about each individual, including age, gender, income, property type (HDB or private), property address zip code, nationality, ethnicity, and occupation.[7]

This dataset offers several advantages. Relative to traditional household spending data sets in the U.S. such as the Survey of Consumer Finance, our sample is larger with little measurement error, and allows high frequency analysis. Compared to studies that use micro-level credit card data (e.g., Gross and Souleles 2002, Agarwal et al., 2007, and Aaronson et. al., 2012), we have more complete information on consumption of each individual in our sample. Rather than observing a single credit card account, we have information on every credit card, debit card and checking accounts of those individuals with the bank. Although we do not have information of accounts individuals have with other banks in Singapore, we suspect the measurement error is negligible given the market share of the bank. For example, an average Singaporean consumer has 3 credit cards, which is also the number of credit cards an average consumer has in our data set. In other words, we are picking up the entire consumption of these households using the spending on the credit and debit card at this bank. In addition, the richness in the transaction level information as well as the individual demographics allows us to better understand heterogeneity in consumers' consumption response to the positive income shock.

For our purpose, we aggregate the data at the individual month level. Credit card spending is computed by adding monthly spending over all credit card accounts for each individual. Credit card debt is computed to be the difference between the current month's credit card payment and the previous month's credit card balance. Debit card spending is computed by adding monthly spending over all debit card accounts for each individual. For the checking account, we compute the aggregate number of debit (outflow) transactions for each individual every month. We exclude dormant/closed accounts, and accounts that remain inactive (i.e., with no transactions) in

[7] Unlike the US where a zip code represents a wide area with a large population, a zip code in Singapore represents a building. Specifically, there is a unique zip code for a single family house as well as a building with 10 apartment units.

the six months before the announcement of the Growth Dividend program (i.e., 2010:08-2011:01).

[Insert Table 1 About Here]

Table 1 provides summary statistics of demographics and financial information for the treatment and control group in our sample. Panel A shows the demographics of the treatment and control group. The control group (non-Singaporeans) is not directly comparable with the treatment group (Singaporeans) along several key dimensions. For example, the control group on average has a considerably higher income than the treatment group and is much less likely to live in government subsidized housing (HDB). This suggests that the treatment group is less wealthy and may have an inherently different spending pattern than the control group. Furthermore, the amount of the growth dividend depends on the wealth level, which requires individuals in the treatment and control group to be comparable in their wealth levels to reliably identify the policy effect. Therefore, we perform propensity score matching, based on the observed demographics, including age, gender, income in 2010, ethnicity, property type and occupation (please refer to Table 2A in the Appendix for the propensity score matching result). After matching, the difference between the treatment and control group in income and property type becomes statistically and economically indistinguishable from zero (Panel A, Table 1). Differences for other characteristics also shrink significantly. In addition to the mean statistics, distributions of monthly income in 2010, age, and checking account balance of the treatment and control group after matching are also similar and comparable (Figure 1). While we report the results after the propensity score matching the control and treatment groups, but the bias should go in the opposite direction. The control group is wealthier and so their spending will be higher, which implies a likely under-estimation of the response.

[Insert Figure 1]

## 5. Methodology

We analyze the response of credit card spending, debit card spending, and checking account balances as a function of the fiscal policy stimulus, beginning with the monthly individual-level data. First, we study the average monthly spending response to the stimulus using the following specifications:

$$Y_{i,t} = \beta \times \$benefit_i \times 1_{post} + \alpha_i + \alpha_t + \epsilon_{i,t} \tag{1}$$

$$Y_{i,t} = \beta_a \times \$benefit_i \times 1_{announce} + \beta_d \times \$benefit_i \times 1_{disburse} + \alpha_i + \alpha_t + \epsilon_{i,t} \tag{2}$$

The dependent variable, $Y_{i,t}$, represents the dollar amount of total card spending, debit card spending, credit card spending and credit card debt held for individual *i* at the end of month *t*. Because the Growth Dividend is a temporary event and debt is a stock variable, to allow for potentially persistent effects of the stimulus on debt, the specification for debt uses the change in debt as the dependent variable. Since spending is a flow variable, it is accordingly analyzed in levels.

$\$benefit_i$ is the amount of the Growth Dividend individual *i* received, and is equal to zero for the control group. $1_{post}$ is a binary variable equal to one for months after the announcement of the Growth Dividend program (i.e., later than 2011:01). $\alpha_t$ is the year-month dummy, used to absorb the seasonal variation in consumption expenditures as well as the average of all other concurrent aggregate factors; and $\alpha_i$ is the individual dummy included to absorb difference in consumption preferences at the individual level. The $\beta$ in Equation (1) captures the average monthly spending (or debt) response per dollar received for a treated individual after the announcement of the stimulus program, relative to the change in spending (or debt) of the control group. We also divide the post-policy window into the announcement period and the disbursement period, to compare the policy effect in these two windows separately. $1_{announce}$ is a binary variable equal to one for months during the announcement window (2011:02-2011:03), and $1_{disburse}$ is a binary variable equal to one for months after the disbursement of the Growth Dividends (i.e., later than 2011:04). Therefore, the coefficients $\beta_a$ and $\beta_d$ in Equation (2) capture the average monthly spending (or debt) response per dollar received, relative to the change in spending (or debt) of the control group, for a treated individual during the announcement period and after the disbursement respectively.

In addition, we study the dynamics of the spending (or debt) response. Specifically, we estimate a distributed lag model of the following form:

$$Y_{i,t} = \beta_0 \times \$benefit_i \times 1_{post\ m0} + \cdots + \beta_9 \times \$benefit_i \times 1_{post\ m9} + \alpha_i + \alpha_t + \epsilon_{i,t} \qquad (3)$$

Following Agarwal, Liu, and Souleles (2007), the results can be interpreted as an event study. The coefficient $\beta_0$ measures the immediate dollar response per dollar dividend received of the dependent variable to the dividend growth announcement in the announcement month,. The *marginal* coefficients $\beta_1$, …, $\beta_9$ measure the *additional* responses 1 month after the dividend growth announcement, …, and 10 months after the announcement, respectively. Therefore, for spending and debt, the *cumulative* coefficients $b_s \equiv \sum_{t=0}^{s} \beta_t$ give the cumulative change in spending and in debt after *s* months, *s = 0-9*. To gauge the expansionary impact of the fiscal stimulus, the response of spending is of central interest, especially the long-run cumulative response $b_9$. For instance, if spending rises by $\beta_0$=6 cents on a dollar of Growth Dividend in the announcement month and after 1 month spending rises by $\beta_1$=9 cents on a dollar of Growth Dividend, then the cumulative effect on spending after month 1 is $b_1 =$ 15 cents on a dollar of Growth Dividend. The response of debt is of independent interest, and can also help shed light on the response of spending.

Unless indicated otherwise, equations (1) – (3) are estimated by ordinary least squares (OLS), with individual and calendar month fixed effects and the standard errors adjusted for heteroscedasticity across accounts as well as serial correlation within accounts. The individual fixed effects will help us study the within individual consumption response before and after the growth dividend program and the month fixed effects will capture the consumption pattern due to aggregate fluctuations (Christmas, etc.). We will also study the heterogeneity in the response to the Growth Dividend differs across different groups of individuals (e.g. liquidity constrained vs. unconstrained consumers) using the following specification:

$$Y_{i,t} = \sum_{s=0}^{9} \beta_s \times 1_{g1} \times \$benefit_i \times 1_{post\ ms} + \cdots + \sum_{s=0}^{9} \beta_s \times 1_{g(N-1)} \times \$benefit_i \times 1_{post\ ms} + \alpha_i + \alpha_t + \epsilon_{i,t} \quad (4)$$

where N is the number of subgroups of consumers that we decompose into.

## 6. Results

We begin by estimating the average response of spending (in various financial accounts), and debt to the Growth Dividend government program. We will later analyze dynamics using the distributed lag model, and heterogeneity in response across different spending categories and different types of individuals, which will sharpen the results. In the main analysis, we focus on the matched sample in the sample period of 6 months before and 10 months after the announcement of the Growth Dividend Program (2010:08-2011:11).[8] To further address the possibility that individuals spend via financial instruments issued by other banks, we include in our main analysis only individuals who have a bank account, debit card and credit card account with the bank at the same time.

### *6.1. The average response of debit card and credit card spending and credit card debt*

Panel A of Table 2 shows the results on the average response from applying equation (1) to spending and the change in credit card debt. The first column of Table 2, Panel A shows the average response of the monthly total card spending (i.e., debit card spending + credit card spending) of the treatment group. Overall, individuals in the treatment group increase their card spending by 8.9 cents per month for every dollar of the Growth Dividend received. The effect is both statistically and economically significant. It corresponds to a total increase of 89 cents per dollar received. Over 2/3 of the total spending increase after the stimulus program announcement is attributable to the spending increase on credit cards (67 cents per dollar received, column 2 of Table 2, Panel A), and less than 1/3 is due to spending on debit cards (22 cents per dollar received, column 3 of Table 2, Panel A). Credit card debt experiences a 1.1 cents decrease per month or 11 cents decrease in total per dollar received, for the treatment group after the announcement, but the effect is less statistically significant.

[8] We are restricted by data availability to look at 10 months after the growth dividend program, but it is sufficient for our purposes as the consumption response converges over this time period. Agarwal et al. (2007) also use a similar lag structure.

[Insert Table 2 About Here]

### *6.2. Announcement vs. disbursement effect*

The Growth Dividend program is a one-off stimulus program that is unprecedented and unanticipated by the population in Singapore. In addition, the program is announced with full information on the eligibility, timing, and size of the pay out in February 2011, two months before qualified Singaporeans receive them in April 2011. As a result, this offers a great opportunity to investigate the announcement effect separately from the disbursement effect. We thus estimate Equation (2) by decomposing the post-policy window into the announcement period and the disbursement period (Table 2, Panel B).

There is a significant increase in the total card spending in both windows: individuals spend 8 cents per month for every dollar received in the two-month announcement period and spend 9.2 cents per month for every dollar received during the disbursement period. Interestingly, there is a significant difference in the means of spending for the two windows. For the announcement period, the increase in spending is primarily concentrated in credit cards (7.1 cents per month for one dollar received), while there is no statistically or economically significant change in debit card spending for the treatment group in this period. Debit card spending increases mostly in the disbursement window, and the credit card spending continues to be higher than the pre-policy period for the treatment group during the disbursement window. Similarly, there is little change in the credit card debt during the announcement period and consumers start to pay down their credit card debt after they receive the Growth Dividend (consistent with Agarwal, Liu, and Souleles, 2007).

In summary, consumers start spending the stimulus money upon announcement before the actual receipt. Compared to the disbursement window, they increase spending in the announcement period by a similar amount, primarily through credit card use. After the dividend receipt, they can and do use their debit cards along with credit cards to increase spending. At the same time, consumers start to pay down debt after receiving the money.

### *6.3. Response in the bank checking accounts*

We then study the debit transactions of consumer’s bank checking accounts before and after the announcement of the Growth Dividend program. Since we do not have transaction-level data on debit transactions in the checking accounts, we use the number of debit transactions as the dependent variable to investigate whether consumers in the treatment group increase the number of debit transactions significantly after the program. Table 3 shows the regression results. There is no significant change in the number of checking accounts’ debit transactions after the stimulus program for the treatment group. We also decompose debit transactions into ATM, branch and online transactions, and find no significant change in the activity in any of the three categories for the treatment group after the program. This result suggests that most likely consumers increase their spending through card spending, either with debit or credit cards.

[Insert Table 3 About Here]

### *6.4. Heterogeneity in spending response: by spending category*

The existing literature documents heterogeneity in the type of spending response to positive income shocks (e.g., Parker, Souleles, Johnson, and McClelland, 2013). We select several major spending categories, into which we decompose the total monthly card spending for each individual. Table 4 shows the estimation result of the average spending response by spending category. Same as Table 2 and 3, we use the dollar amount of spending as the dependent variable in Panel A of Table 4, so the coefficient should be interpreted as the spending response in dollars for every dividend dollar received. Discretionary spending items, such as apparel and travel, respond the most to the stimulus program. For each dollar of Growth Dividend received, consumers spend 1.6-1.7 cents per month, or 16-17 cents in total in our sample period, on apparel or travel purchases. Consumers also seem to increase their spending on other categories such as supermarket, dining, entertainment, and transportation, but the economic and statistical effect is weaker than the increase in apparel and travel.

[Insert Table 4 About Here]

In Panel B of Table 4, we use the log of spending as the dependent variable, and the key explanatory variable is the interaction term of the treatment dummy and post-announcement dummy. The coefficient in this specification should be interpreted as the % change in spending after the stimulus program relative to the pre-stimulus spending level in that category. Overall, consumer spending increase in the treatment group is 13.5% in apparel, 8.8% in travel, 7.6% in transportation and 11.1% in entertainment. These results are statistically significant (1% or 5%) and economically large. Particularly, although consumers do not appear to spend a significant amount (in absolute term) on entertainment, the spending increase is large as a proportion of their pre-stimulus spending in entertainment. In summary, spending responds to the stimulus program extensively across spending categories, but the effect is strongest in the discretionary spending category (entertainment, apparel and travel).

### *6.5. The dynamics of the spending and debt response*

Results in Table 2-4 show the average monthly response of spending and debt to the stimulus program. In addition, to gauge the expansionary impact of the fiscal stimulus, we investigate the dynamic evolution of the spending and debt response during the 10 month period upon the program announcement (Equation (3)). Table 5 reports the marginal coefficients, $\beta_s$, $s$ = 0-9. The figures graph the entire paths of cumulative coefficients $b_s$, $s$ = 0-9, along with their corresponding 95% confidence intervals. The results can be interpreted as an event study, with month 0 being the time of rebate receipt, $s$ = 0 in event time.

[Insert Table 5 About Here]

[Insert Figure 2 About Here]

Starting with the point estimates for spending, in the stimulus announcement month, (monthly) total card spending rises by $\beta_0 = b_0$ = 6.2 cents for every dollar of Growth Dividend received. One month later, spending rises, compared to the pre-announcement period, by $\beta_1$ = 9.9 cents on a dollar of dividend received, so the cumulative increase $b_1$ = 16.1 cents per dollar received in the announcement period. For the first month of the disbursement period, total card spending increases by another 15.2 cents per dollar, making the cumulative increase rise to $b_2$ = 31.3 cents per dollar received. Both the marginal and cumulative effects are statistically significant at the 1% level. By the end of nine months after the announcement, the cumulative increase in total card spending is $b_2$ = 89 cents per dollar received. However, the increase in total card spending between month 3 and month 9 (after announcement) is not evenly distributed. In month 3 and 4 after announcement, the marginal increase in total card spending continues but by a smaller amount and less statistically significant (only at 10%). In month 5, 6 and 7 after announcement, the total card spending increases by a significant amount, ranging from 9-13.7cents per dollar received, before dying off in month 8 to 9 after announcement.

Decomposing the debit card and credit card spending gives more insight on the spending response dynamics. There is no spending response in debit card spending during the announcement month, so the total spending response is attributable to an increase in credit card spending in the month when the Growth Dividend program is announced. In the first month after announcement, debit card spending starts to rise but by a considerably smaller amount compared to credit card spending increase. After disbursement, consumers in the treatment group primarily use their debit cards to increase their spending in the earlier period, since the marginal effect coefficients are statistically insignificant for credit card spending in month 3 and 4 after announcement. In the later period, debit card spending increase gradually plateaus by month 8 after announcement, but credit card spending increase picks up again and there is still evidence of marginal increase in credit card spending in month 8 and 9. A formal statistical test shows that debit card spending response is more front-loaded, as the cumulative increase in debit card spending in the first five months is larger than that in the last five months (statistically significant at the 10% level). On the other hand, the cumulative increase in credit spending in the first five months is statistically indistinguishable from that in the last five months.

The point estimates in debt response show that consumers start to reduce their debt when they receive the Growth Dividend (in month 2 after announcement), by 3.7 cents per dollar received, and they continue to reduce their debt in the next month by 2.6 cents per dollar received. The cumulative debt decrease by month 4 after announcement is $b_4$ = 9.9 cents per dollar received, and a formal test of the sum of coefficients suggests that $b_4$ is statistically significant at the 1% level. After that, the credit card debt stops decreasing, and experiences a significant increase in month 8 after announcement. By month 9 after announcement, the cumulative credit card debt decreases by $b_9$ = 10.8 cents per dollar received, and it is only marginally statistically significant

(10%). We also perform a statistical test: the difference between the cumulative credit card debt changes in the first 5 months compared to that in the last 5 months is -0.09 cents (per dollar) and is statistically significant at the 5% level. This suggests that the credit card debt decrease concentrates in the earlier period, especially after the disbursement of the Growth Dividend, before it stops and reverses in the second half of our sample period.

Taken together, the results in Table 5 suggest that consumers in the treatment group respond strongly to the stimulus program upon announcement by increasing their spending via credit cards. There is a delay in spending response in their debit cards, which occurs only after the payment of the stimulus money and gradually plateaus over time. At the same time, consumers start to decrease their credit card debt as well as reduce their credit card spending in the early period after the disbursement. However, in the last few months of the 10 month treatment period, they stop paying down their credit card debt and at the same time increase their credit card spending significantly again.

### *6.6. Heterogeneity of spending and debt response across consumers*

We then study the dynamics of heterogeneous responses to the financial stimulus program across different consumers. The existing literature documents that liquidity constrained consumers respond more strongly in consumption to positive income shocks (e.g., Agarwal, Liu and Souleles, 2007). We have a rich array of account-holder information, including their demographics as well as financial health information, which allows us to study the heterogeneous response of consumers in greater depth.[9] Furthermore, with our data we are able to understand differences in the full path of the consumers' spending and debt response across different financial instruments. In the following subsections, we estimate Equation (4) by interacting for each group of comparison of consumers. To save space, we do not report the marginal effect coefficients. Instead, we plot the cumulative response coefficients, $b_s$, $s$ = 0-9, along with their corresponding 95% confidence intervals (figure 3).

[Insert Figure 3 About Here]

<u>A. Low Checking Account Balance vs. High Checking Account Balance</u>

We classify consumers in our sample as having low checking account balance, if their average monthly checking account balance in the four months before our analysis sample (i.e., 2010:04-2010:07) is below the 25$^{th}$ percentile of the distribution, or equivalently SGD 1,840 in the cross-section of consumers in that period. Consumers have high checking account balance if their average monthly checking account balance in that period is above the 75$^{th}$ percentile of the

9 Earlier studies use the demographics as proxies for liquidity constrained. For instance, the papers argue that young and old consumers are more likely to be liquidity constrained. Additionally, married consumers are less likely to be liquidity constrained.

distribution, or SGD 22,346. Consumers with low checking account balance are likely to be more liquidity constrained.

Panel A of Figure 3 shows the comparison in the path of spending and debt response between these two groups of consumers. Low balance consumers respond strongly in debit card spending: for each dollar of stimulus payment, $b_9$ = 50 cents for low balance consumers, and the effect is statistically significant at 1%. In particular, the low balance consumers start spending on debit cards from the second month of the announcement period, and continue to experience a significant increase until month 7, after which the debit card spending increase plateaus. There is also a strong cumulative increase in credit card spending among low balance consumers: $b_9$ = 76 cents for dollar received, and is statistically significant at 1%. On the other hand, the high balance consumers do not increase debit card spending, and their cumulative credit card spending increase by month 9 is equal to 47 cents per dollar received, which is smaller than the low balance consumers. We perform a formal test of the difference of total cumulative spending response between low balance and high balance consumers. We run an OLS regression of total spending and run an F-test of the difference of the cumulative coefficients $b_9$ between the two groups. The result is statistically significant at 1%, indicating that low balance consumers spend more using debit cards and credit cards than high balance consumers.

Low balance consumers start to pay down their credit card debt upon receipt of the stimulus money (month 2 after announcement), and by month 9 the cumulative debt decrease is 18 cents per dollar received and is statistically significant at 5%. On the contrary, there is no change in credit card debt for the high balance consumers. These results are consistent with the literature: liquidity constrained consumers react strongly to the stimulus in spending, and they also use the positive income shock to reduce their credit card debt.

B. High Credit Card Limit vs. Low Credit Card Limit

We classify consumers in our sample as with high credit card limit, if their maximum credit card limit in the four months before our analysis sample (i.e., 2010:04-2010:07) is above the 75 percentile of the distribution, or equivalently SGD 9,000 in the cross-section of consumers in that period. Consumers have low credit card limit if their maximum credit card limit between 2010:04-2010:07 is below the 25 percentile of the sample, or SGD 5,000. This is another measure to capture liquidity constrained consumers that is used in the previous literature.

Panel B of Figure 3 shows the comparison across these two groups of consumers. High credit card limit consumers have little spending response, regardless of the financial instruments. The cumulative spending coefficients for both credit cards and debit cards are statistically insignificant throughout the period. Low credit limit consumers react to the stimulus program by both increasing their debit card and credit card spending. However, the effect is stronger on the credit card spending. The cumulative debit card spending increase at month 9 after program announcement is $b_9$ = 19 cents per dollar received, and is statistically significant at 5%. Credit card spending has a cumulative increase of 87 cents per dollar received by month 9, and the effect is statistically significant at 1%. An F-test of the cumulative coefficients of the total spending suggests that low credit limit consumers' total spending response is greater than the high credit limit consumers' total spending response (difference = 79 cents and is statistically significant at 1%).

While low credit limit consumers see no credit card debt change during the 10-month period, high credit limit consumers' credit card debt experiences a strong decrease: by month 9, the cumulative credit card debt change is -27 cents per dollar received, and this effect is statistically significant at 1% level.

C. Low Income vs. High Income

We classify consumers in our sample as low income consumers, if their average monthly income in the year before the stimulus program (2010) is below the $25^{th}$ of the distribution, or equivalently SGD 3,049, in the cross-section of consumers in that period. High income consumers are those with an average monthly income in 2010 above the $75^{th}$ percentile of the distribution (or SGD 6,369). Panel C shows that low income consumers react strongly to the stimulus program in spending. For low income consumers, the cumulative coefficient by month 9 is 20 cents per dollar received (statistically significant at 5%) for debit card spending, and is 61 cents per dollar received (statistically significant at 1%) for credit card spending. For high income consumers, the cumulative coefficient for either debit card spending or credit card spending is statistically insignificant. However, the F-test shows that the cumulative total spending response is not statistically different between the low income consumers and the high income consumers. The weaker result for the low income consumers, although still broadly consistent with the findings of low bank balance and low credit card limit consumers, may be due to income being a noisier measure of liquidity-constraint.

D. Young vs. Old

We compare the spending and debt response pattern for young (2010 age <= $25^{th}$ percentile=32) and old consumers (2010 age >= $75^{th}$ percentile = 42) in Panel D. Young consumers have positive and significant cumulative spending responses: $b_9$ = 36 cents for every dollar received for debit card spending, and $b_9$ = 73 cents for credit card spending. Old consumers do not increase their debit card spending, but their cumulative credit card spending increase is significant: $b_9$ = 71 cents per dollar received, and is significant at 1%. The overall spending response is larger 39 cents per dollar received, and is statistically significant at 10% according to the F-test. In addition, we observe credit card debt decrease for old consumers. They start paying down their credit card debt from month 1 after program announcement, and by the end of month 9 the cumulative credit card debt decrease is 16 cents for every dollar received (statistically significant at 5%).

E. Married vs. Non-married

We compare the spending and debt response pattern for married and non-married consumers in Panel E. Overall, the total spending response is comparable between married and non-married consumers: the cumulative coefficients of total card spending are statistically indistinguishable between married and non-married consumers. Married consumers pay down their credit card debt upon receiving the stimulus money (month 2) and the cumulative credit card debt change is $b_9$ = -15 cents for every dollar received (statistically significant at 5%). Non-married consumers, on the other hand, do not reduce their credit card during the 10-month period.

F. Ethnicity: Chinese vs. Indian

Chinese, Malay and Indian are three major ethnic groups in Singapore, and we compare the difference in spending and debt response between Chinese Singaporeans and Indian Singaporeans in Panel F (Malays are dropped from the analysis due to their small sample size in our data). Chinese Singaporeans significantly increase their spending on both types of cards, more so on credit cards ($b_9$ = 67 cents for credit cards vs. $b_9$ = 22 cents for debit cards). Indian Singaporeans, on the other hand, have an insignificant cumulative spending response for both instruments. However, the F-test result shows that the difference in the cumulative response of total spending between the two groups is not statistically different from zero. Indians also save more on average. Compared to Chinese whose credit card debt remains flat during the 10-month period, Indians reduce their credit card debt significantly ($b_9$ = -43 cents for every dollar received, significant at 1%).

G. Male vs. Female

Lastly, we compare the gender difference in spending and debt response to the stimulus program (Panel G). The cumulative increase in debit card spending by month 9 after program announcement is strong for male consumers ($b_9$ = 26 cents for every dollar received, significant at 1%) but insignificant for female consumers ($b_9$ = 12 cents). Both groups respond strongly in credit card spending: $b_9$ = 74 cents for male consumers, significant at 1%, and $b_9$ = 50 cents for female consumers, significant at 1%). Overall, an F-test of the cumulative coefficients of total spending suggests that male consumers have a stronger response in total spending (by 38 cents per dollar received, statistically significant at 5%). Male consumers start to pay down debt upon receiving the money (month 2). Their cumulative credit card debt decrease amounts to 11 cents per dollar received by month 9, and is statistically significant at 10%.

### 6.7. Liquidity vs. credit constraint

The previous literature, due to data limitation, often uses credit card capacity (i.e., credit constraints) to proxy for liquidity constraints. In this section, we examine the differences in spending and debt response of liquidity-constrained consumers (*i.e.*, with low checking account balance) and credit-constrained consumers. We further classify consumers as both liquidity and credit constrained if they have low bank account balance and low credit limit. Consumers are liquidity constrained but less credit constrained if they have low bank account balance and high credit limit. Consumers are liquidity unconstrained but credit constrained if they have high bank account balance and low credit limit. Lastly, consumers are neither liquidity nor credit constrained if they have both a high bank account balance and high credit limit.

Overall, the liquidity constrained group dominates the credit constrained group in the cumulative response of total card spending. The total card spending is statistically the same within the liquidity constrained category, whether consumers are credit constrained or non-constrained. They are equally strong, with cumulative responses of total spending equal to 120 cents per dollar received (statistically significant at 1%). On the other hand, the liquidity unconstrained group has statistically insignificant cumulative response in total spending, whether consumers are credit constrained or not. F-tests suggest that consumers in either of the subgroups of the liquidity constrained category have a greater cumulative response in total spending than either subgroup of the liquidity unconstrained category. In particular, low bank balance and high credit limit consumers experience a stronger cumulative response in total card spending than high bank balance and low credit limit consumers (at 10% level). This suggests that the spending response of the credit constrained consumers is dominated by that of the liquidity constrained consumers.

[Insert Figure 4 About here]

Figure 4 further shows the path of the spending across the two financial instruments for these four subgroups. Within the liquidity constrained group of consumers, even though they spend similar amount in total, the more credit constrained subgroup (low balance and low credit limit) of consumer use relatively more credit cards, whereas the less credit constrained subgroup (low balance and high credit limit) of consumers use relatively more debit cards. Similarly, the credit constrained consumers in the liquidity unconstrained group also increase their credit card spending ($b_9$ = 64 cents per dollar received, statistically significant at 5%), even though the cumulative effect of total spending is statistically insignificant. Taken together, these results imply that credit constrained consumers, conditional on being liquidity constrained, are more likely to use credit cards in their spending response to positive income shocks. In contrast, liquidity and credit unconstrained consumers do not increase debit card or credit card spending.

Lastly, the credit card debt decrease is strongest among liquidity constrained consumers that have credit capacity (i.e., low bank balance and high credit limit consumers). The cumulative credit card debt decrease by month 9 is 54 cents for each dollar received and is statistically significant at 5%. All three other subgroups of consumers do not reduce their credit card debt.

### *6.8. Robustness checks*

We perform the main analysis in the previous sections on a smaller sample, where the treatment group and control group are matched on several demographic variables. To ensure that the results can be generalized to the full sample, we repeat estimation in Equation (1) and (2) on the unmatched sample and report the results in Table 6.

[Insert Table 6 About Here]

The first column of Table 6, Panel A shows that consumers in the treatment group increase their card spending by a total of 46 cents for every dollar received during the 10-month period. Like before, over 2/3 of the total spending increase is attributable to the spending increase on credit cards (30 cents per dollar received, column 2 of Table 6, Panel A), and less than 1/3 is due to spending on debit cards (16 cents per dollar received, column 3 of Table 6, Panel A). Credit card debt experiences a statistically insignificant 3 cents decrease in total per dollar received during the 10-month period for the treatment group. Similarly, consumers in the treatment group increase their spending more on their credit cards during the announcement period, and switch to debit card use after disbursement. Overall, the results on the full, unmatched sample remain qualitatively the same. The somewhat smaller magnitude of the effect is expected, as the (unmatched) control group has higher income and wealth than the (unmatched) treatment group (Table 1, Panel A) and likely has a higher spending level and growth. Therefore, the estimated coefficients from the full sample are downward biased and should be viewed as a lower bound of the stimulus response.

In the main analysis, we dropped from our sample Singaporeans who also qualify for another cash stimulus program announced at the same time. To further isolate the response to the Growth Dividend program from other concurrent stimulus packages, we first note that there is a concurrent personal income tax rebate with a total worth of US$ 452.4 million, which is 1/3 of the size of the Growth Dividend program. Since the tax rebate applies to all working residents in Singapore based entirely on the income level, a foreigner is entitled to the same amount of tax rebate as another Singaporean with the same annual income in 2010. Since the control group and the treatment group in matched sample has comparable income levels (the difference is economically and statistically insignificant, as in Table 1 Panel B and Figure 1), the spending and debt response to the tax rebate are differenced out in our estimation and our coefficients are the incremental response beyond the tax rebate program. Lastly, the only other economically significant package (US$ 393.1 million) target older Singaporeans (age >= 45) by topping up their illiquid retirement medical accounts which can only be applied to hospitalization or certain out-patient care items and cannot be cashed out. To further validate our results, we carry out a separate analysis on a subsample of consumers younger than 45 years old who are entitled only to the Growth Dividend program. We do not report the results but they are qualitatively and quantitatively similar to those in the main analysis.

## 7. Conclusion

This paper uses a unique, new panel dataset of credit card, debit card, and checking accounts of 180,000 consumers in Singapore to analyze how consumers respond to a fiscal stimulus program announced on February 18th, 2011. The government distributed a one-time payout of Growth Dividends to all adult Singaporeans over 21 years old in 2011. The payments of the Growth Dividend program totaled US$ 1.17 billion, which corresponds to 12% of Singapore's monthly aggregate household consumption expenditure in 2011.We used a diff-in-diff identification to estimate the month-by-month response of credit card spending, debit card spending and debt to the program. We exploit the exclusion restriction of the program for identification as foreigners were not eligible for the growth dividend, this allows us to cleanly identify the causal effect of the program on spending.

Our findings are summarized as follows. First, consumers' consumption rose significantly after the fiscal policy announcement: for each dollar received, consumers on average spend 90 cents (aggregated across different financial accounts) during the ten months after announcement. On the other hand, consumers' credit card debt experienced a moderate decrease (so savings effectively increased). Second, we find strong announcement effect; consumers start to increase spending during the two-month announcement period before the cash payout. Third, consumption response is distributed across debit card (or 25% of the total response) and credit card (or 75% of the total response) spending. More importantly, consumers started spending using credit cards during the announcement period, and then switched to debit cards after disbursement, before finally increasing significantly the credit card use. Consistently, credit card debt dropped in the first months after disbursement and reverted back to the original level.

We also found other significant heterogeneity in the response to the fiscal stimulus across different types of consumers. Notably, spending rose most for consumers who were, according to various criteria, initially most likely to be liquidity constrained. Similarly, debt declined most (so saving rose most) for liquidity-constrained consumers. Comparing liquidity constraints with credit constraints, we find that the spending response of the credit constrained consumers is dominated by that of the liquidity constrained consumers. Liquidity-constrained consumers respond strongly to the stimulus, whether they are credit-constrained or not. Finally, consumption rose primarily in the non-food, discretionary category (consistent with Johnson et. al. 2006). These results suggest that liquidity constraints are important. More generally, the results suggest that there can be important dynamics in consumers' response to "lumpy" increases fiscal stimulus programs, working in part through balance sheet (liquidity) mechanisms.

As mentioned earlier, our main contribution, in relation to prior literature is three-fold. First, we are the first to document the announcement effect of the stimulus program. Second, we document the dynamics of consumption response across different spending instruments, rise in credit card spending subsequent to announcement, then switching to debit card spending subsequent to the disbursement of the stimulus, and finally, switching back to the credit card in the later months.

Finally we are also the first to document that liquidity constraints dominate credit constraints for the spending response to positive income shocks.

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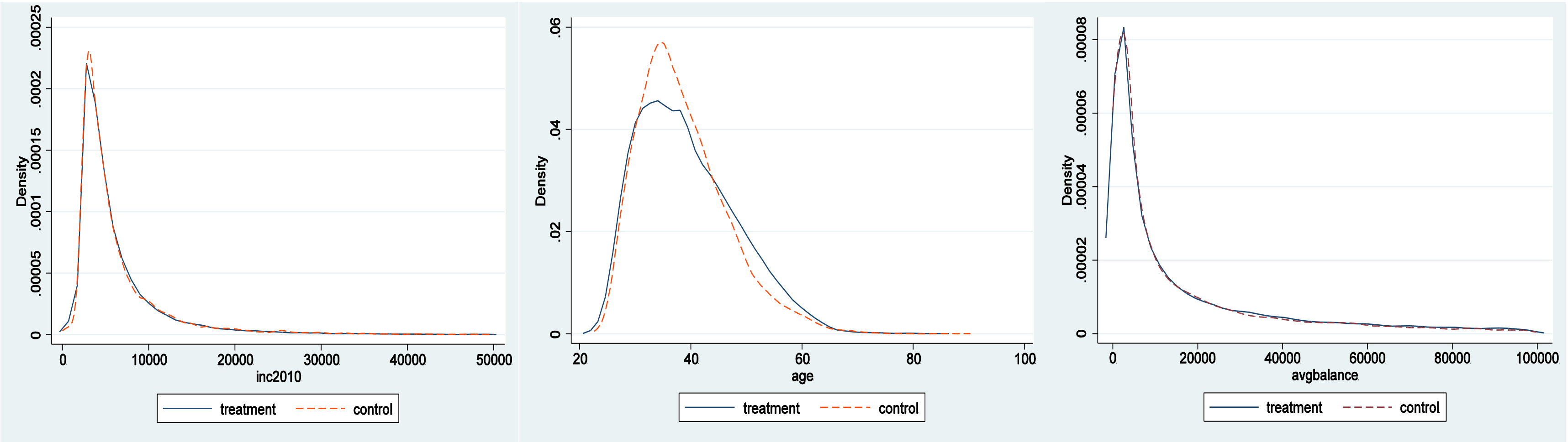
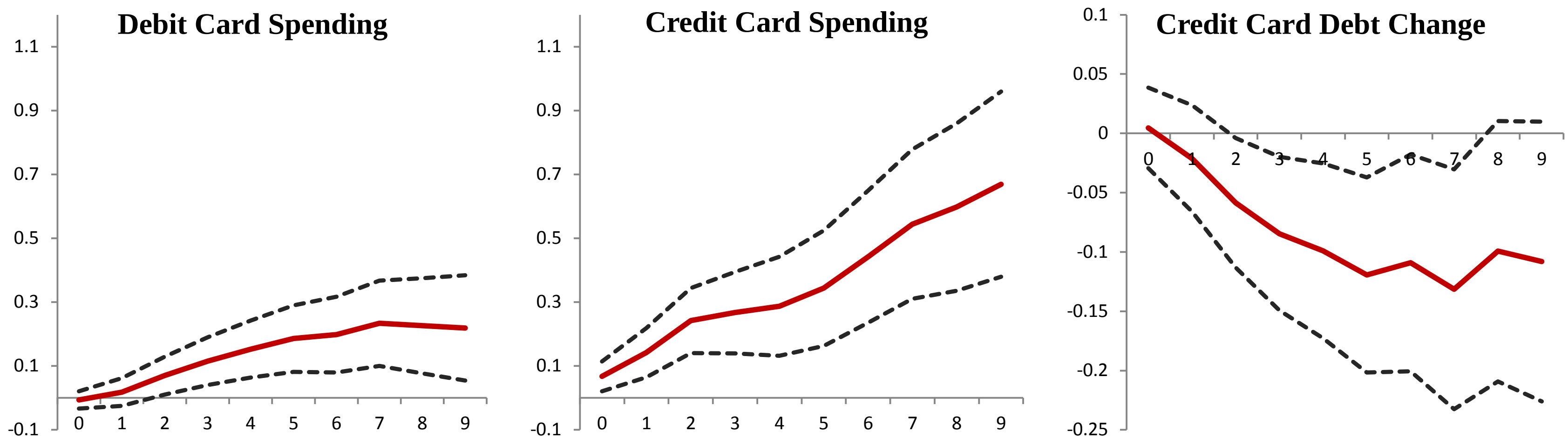
**Figure 1: Kernel Density Plots of the Matched Sample**

This figure shows the comparison of distributions, with kernel density plots, of average monthly income in 2010, age, and average bank checking account balance in the period of 2010:04-2010:07 between the treatment and control group, after the propensity score matching.



## Figure 2: Estimated Spending and Debt Response Dynamics

This figure plots the entire paths of cumulative coefficients $b_s$, $s$ = 0-9, along with their corresponding 95% confidence intervals, of debit card, credit card spending as well as credit card debt change response as estimated from Equation (3) (the marginal effect coefficients are reported in Table 5). The x-axis denotes the *i*th month after the announcement of the Growth Dividend program, and the y-axis shows the dollar response (for every dollar received).



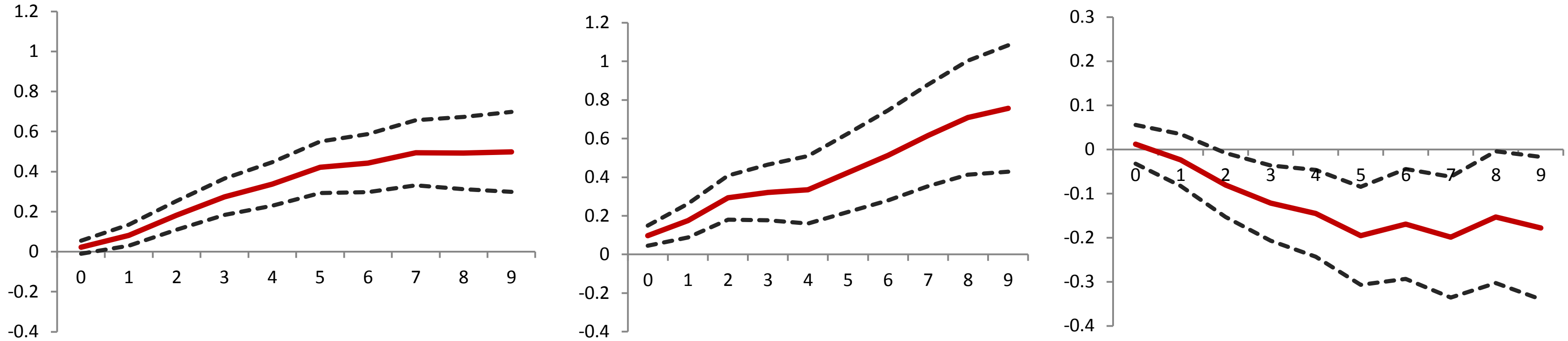
## Figure 3: Heterogeneity in Spending and Debt Response across Consumers

This figure plots the entire paths of cumulative coefficients $b_s$, $s$ = 0-9, along with their corresponding 95% confidence intervals, of spending and debt response across different consumers. For each comparison panel, column (a) shows the cumulative debit card spending response, column (b) shows the cumulative credit card spending response, and column (c) shows the cumulative credit card debt change response. The x-axis denotes the *i*th month after the announcement of the Growth Dividend program, and the y-axis shows the dollar response (for every dollar received). Panel A compares consumers with low bank checking account balance (i.e., average checking account balance between 2010:04-2010:07 <= SGD 1,840, or 25% of sample) with consumers with high bank checking account balance (i.e., average checking account balance between 2010:04-2010:07 >=SGD 22,346, or 75% of sample). Panel B compares consumers with high credit and limit (i.e., max credit card limit between 2010:04-2010:07 >= SGD 9,000, or 75% of sample) with consumers with low credit card limit (i.e., max credit card limit between 2010:04-2010:07 <= SGD 5,000). Panel C compares low income consumers (i.e., monthly income in the year before the Growth Dividend announcement <= SGD 3,049, or 25% of sample) with high income consumers (i.e., monthly income in the year before the Growth Dividend announcement >= SGD 6,360, or 755 of sample). Panel D compares young consumers (age <= 32, or 25% of sample) and old consumers (age >= 42, or 75% of sample). Panel E compares married and non-married consumers. Panel F compares different ethnicities within the treated consumers (Chinese vs. Indian). Panel G compares male and female consumers.

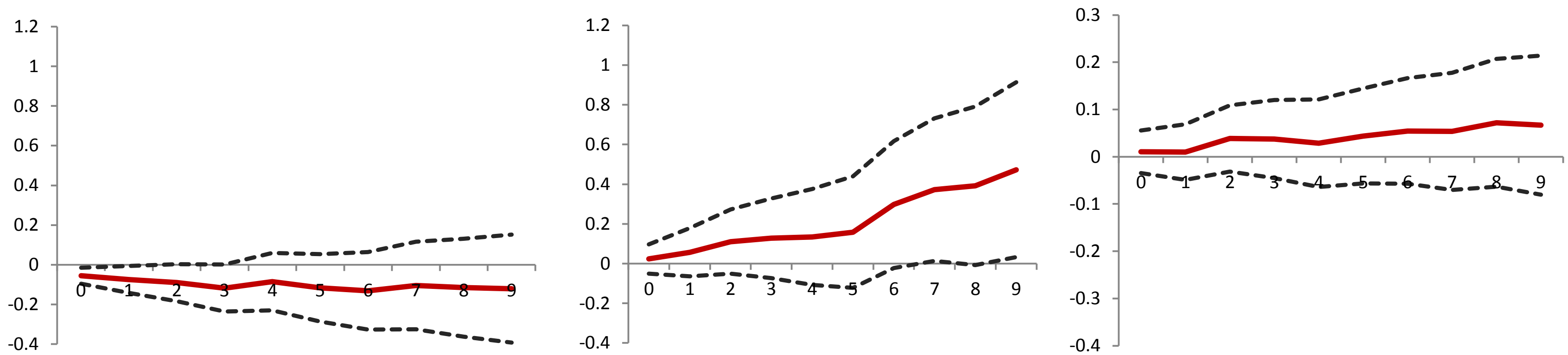
**Panel A:**

**(a)** **(b)** **(c)**

**<u>Low Bank Balance</u>**



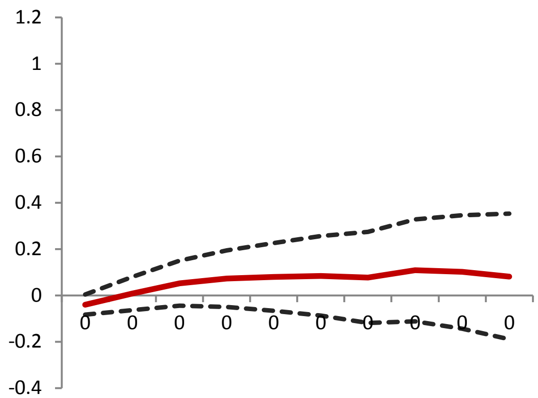

**<u>High Bank Balance</u>**

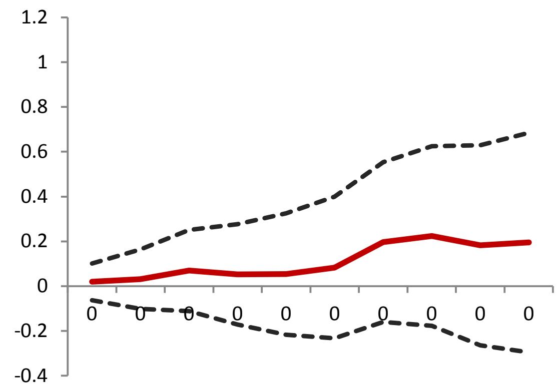


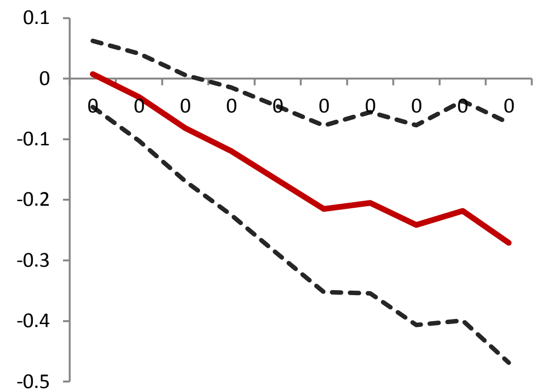
**Panel B:**

**(a)** **(b)** **(c)**

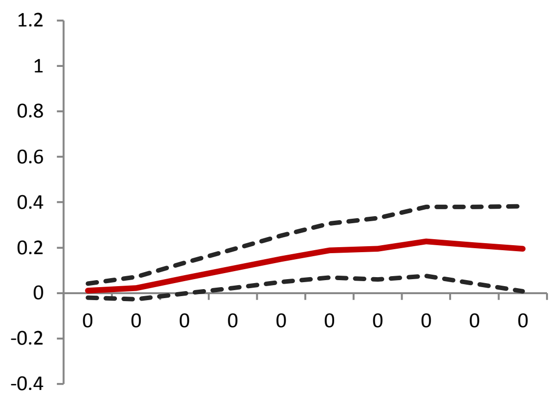
**<u>High Credit Card Limit</u>**

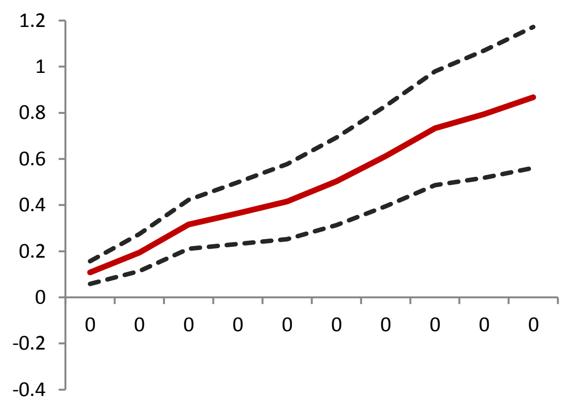


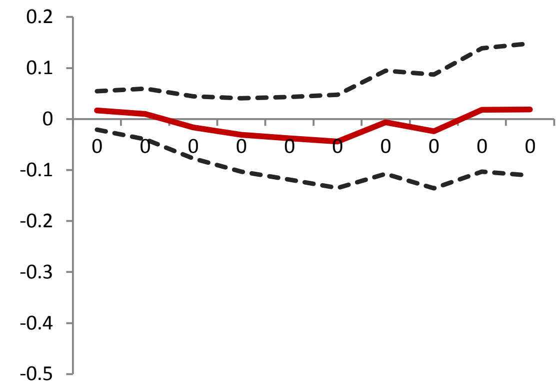




**<u>Low Credit Card Limit</u>**



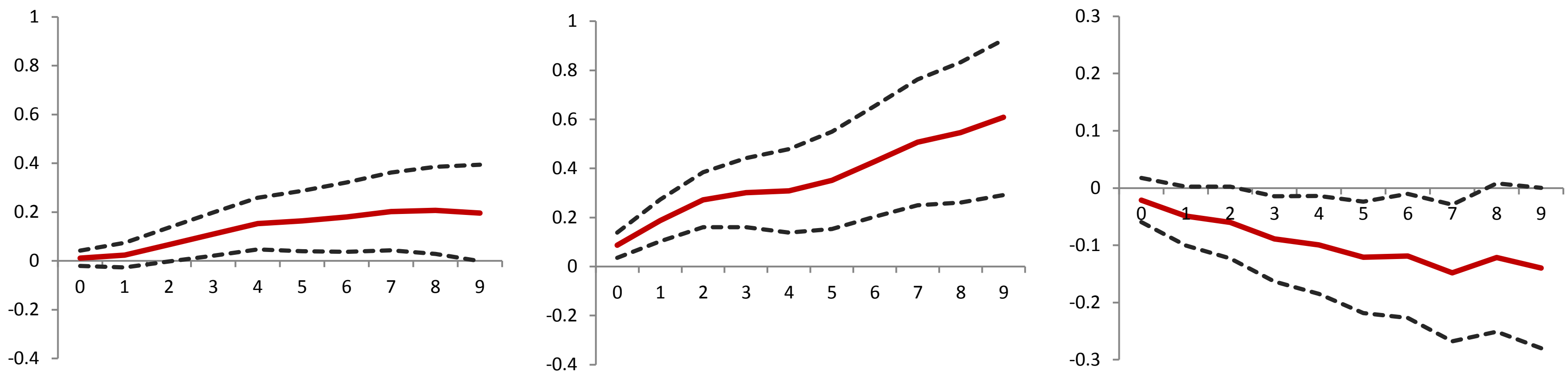



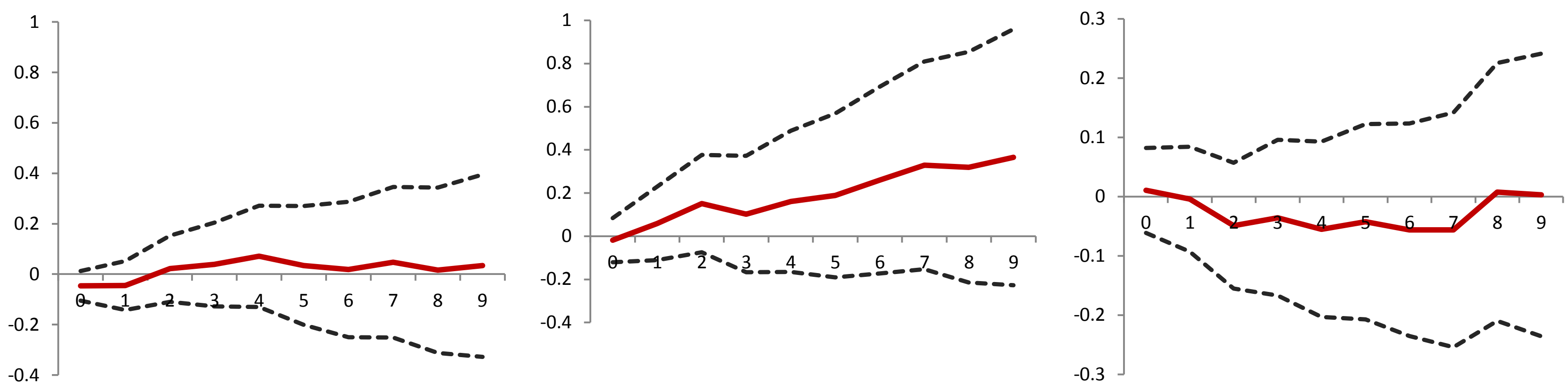
**Panel C:**

**(a)** **(b)** **(c)**

**<u>Low Income</u>**



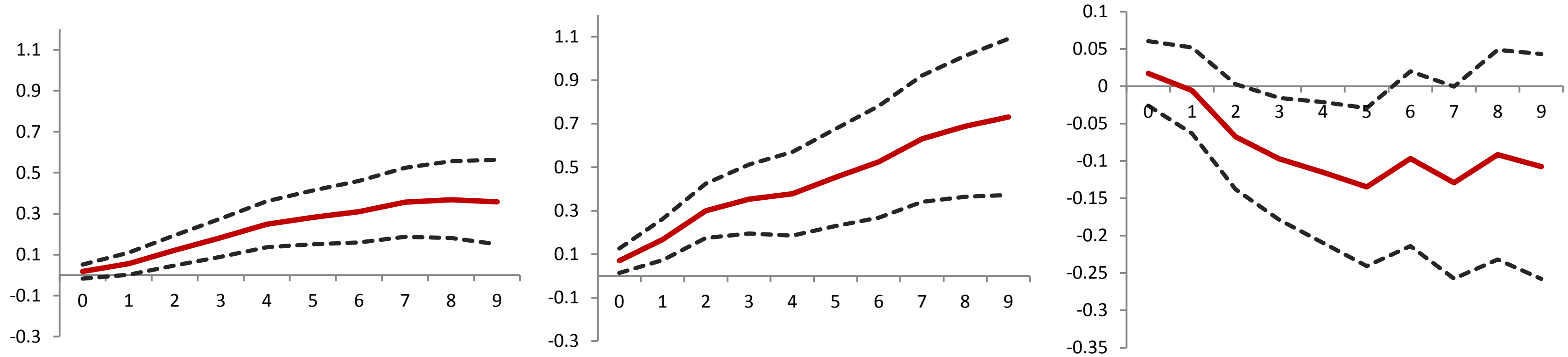

**<u>High Income</u>**



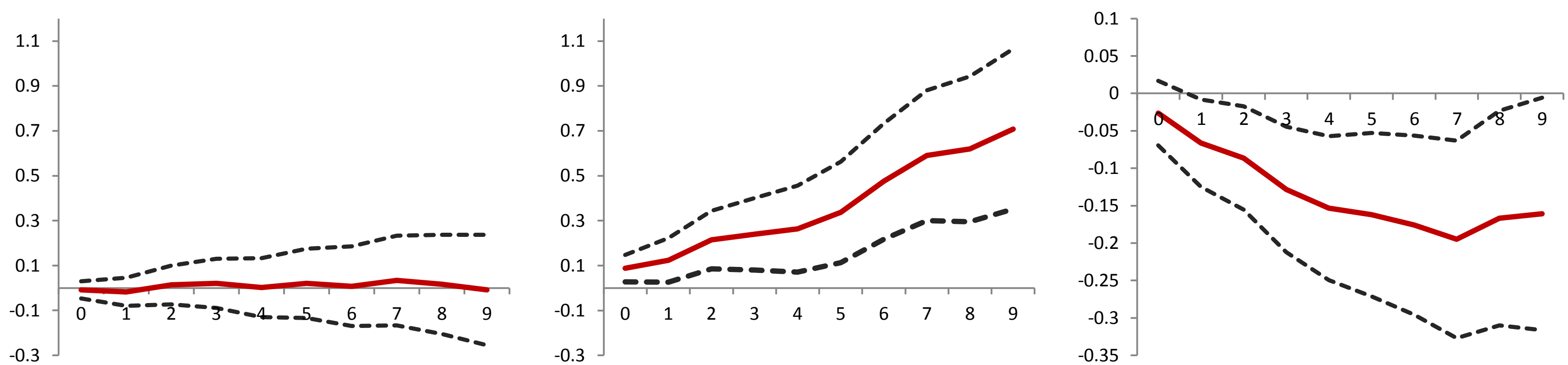
**Panel D:**

**(a)** **(b)** **(c)**

**Young**



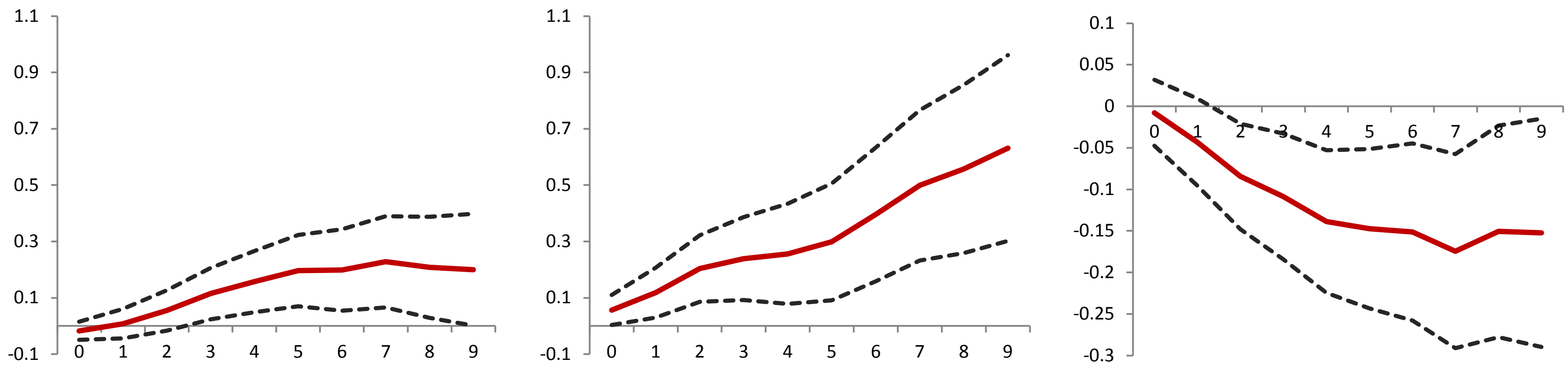

**Old**



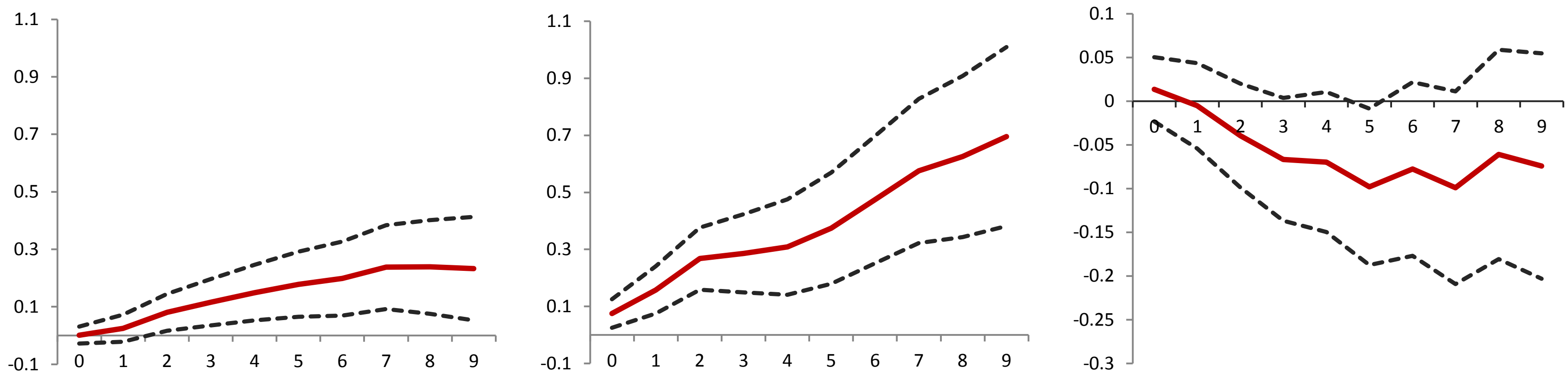
**Panel E:**

**(a)** **(b)** **(c)**

**<u>Married</u>**



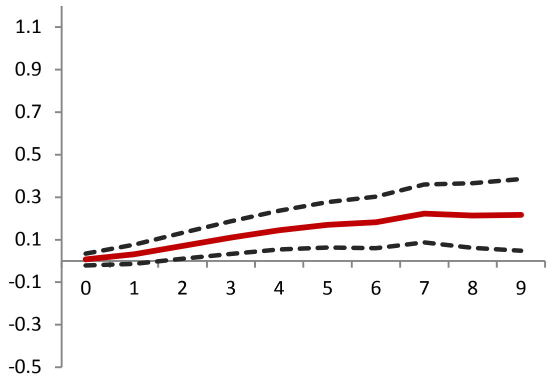

**<u>Non-married</u>**

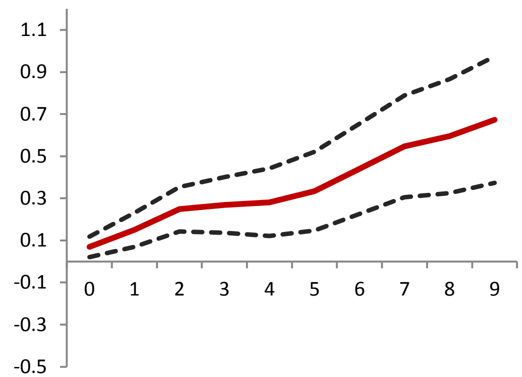


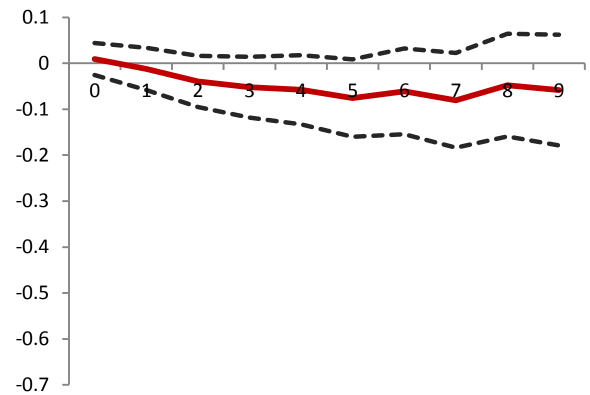
**Panel F:**

**(a)** **(b)** **(c)**

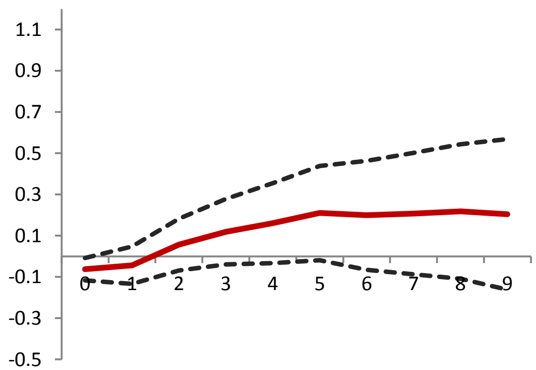
**<u>Chinese</u>**

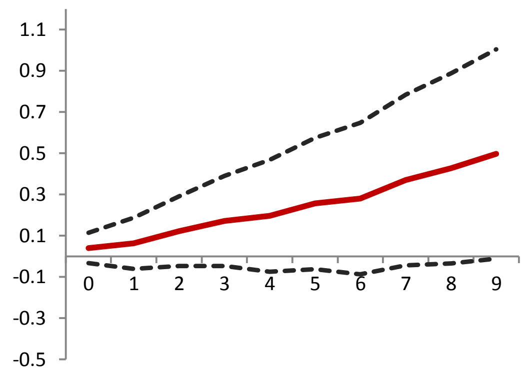


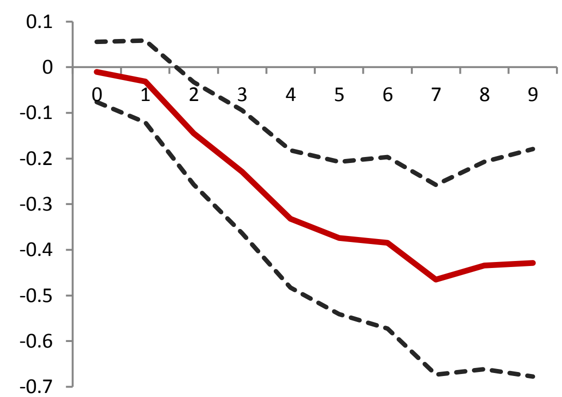




**<u>Indian</u>**



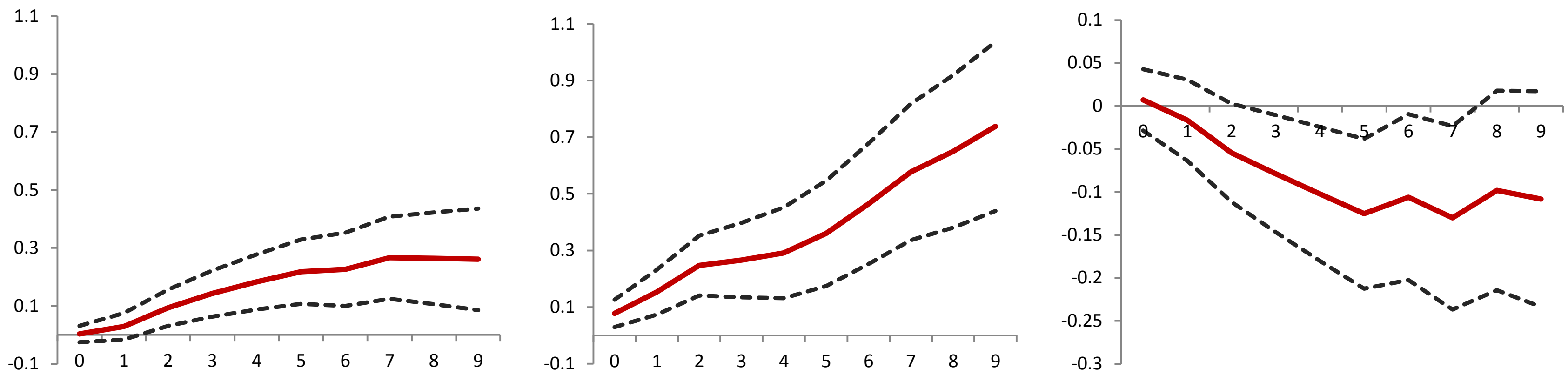



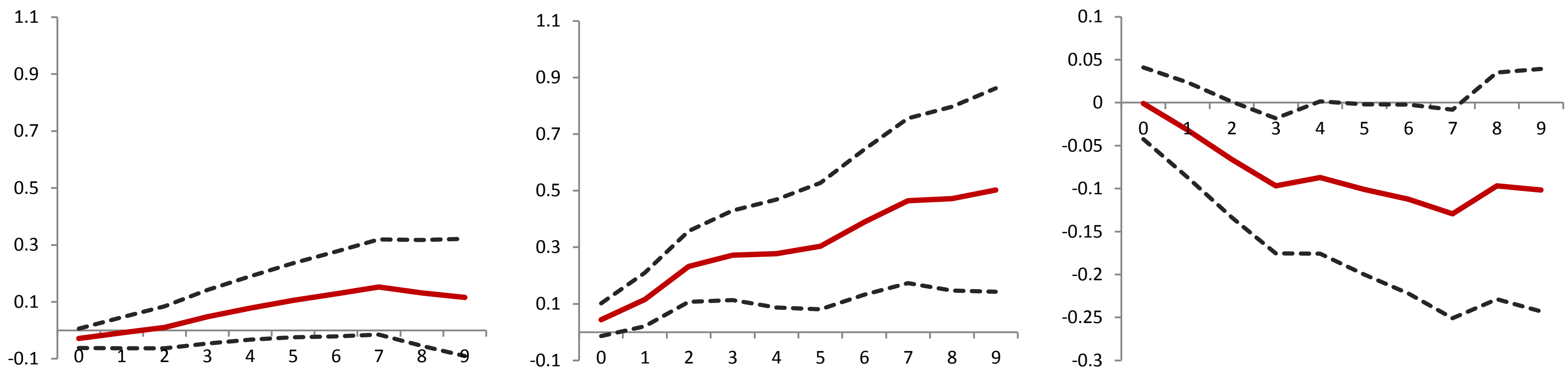
**Panel G:**

**(a)** **(b)** **(c)**

**Male**




**Female**

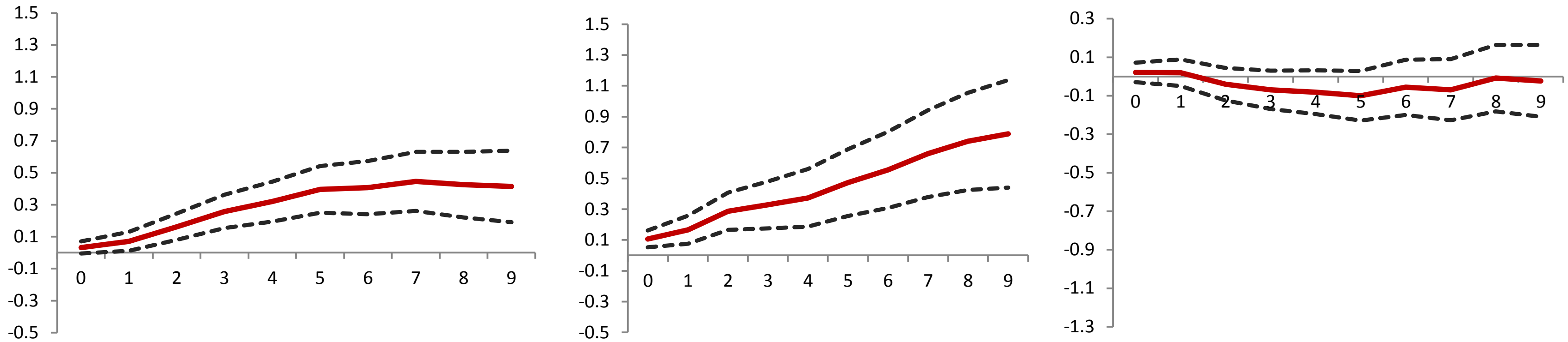


## Figure 4: Liquidity Constraints vs. Credit Constraints

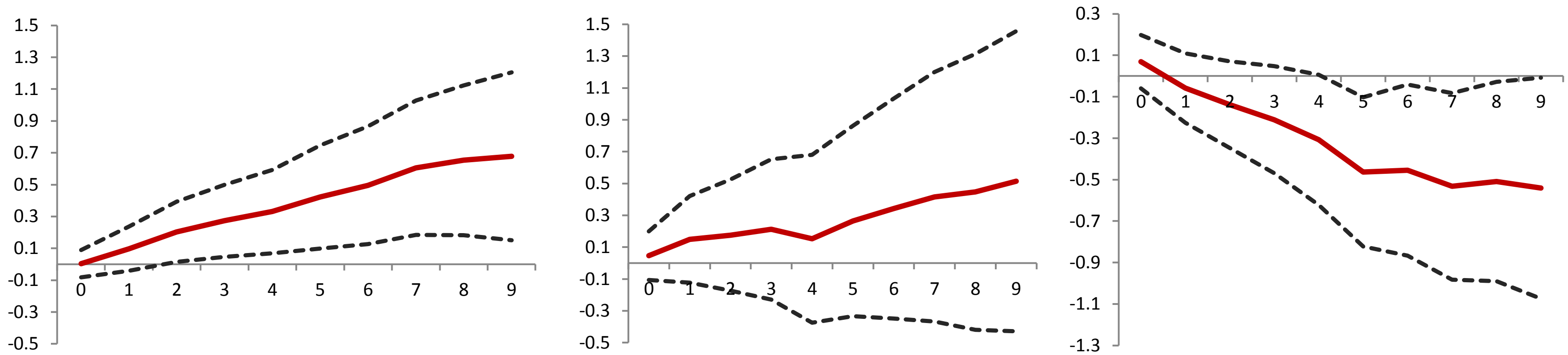
This figure plots the entire paths of cumulative coefficients $b_s$, $s$ = 0-9, along with their corresponding 95% confidence intervals, of spending and debt response across the following four groups of consumers: low bank balance and high credit limit consumers, low bank balance and low credit limit consumers, high bank balance and high credit limit consumers, and high bank balance and low credit limit consumers. Please refer to Figure 3 for definitions of high/low bank balance consumers and high/low credit limit consumers. For each comparison panel, column (a) shows the cumulative debit card spending response, column (b) shows the cumulative credit card spending response, and column (c) shows the cumulative credit card debt change response. The x-axis denotes the *i*th month after the announcement of the Growth Dividend program, and the y-axis shows the dollar response (for every dollar received).

**(a)** **(b)** **(c)**

**<u>Low Bank Balance and Low Credit Limit</u>**

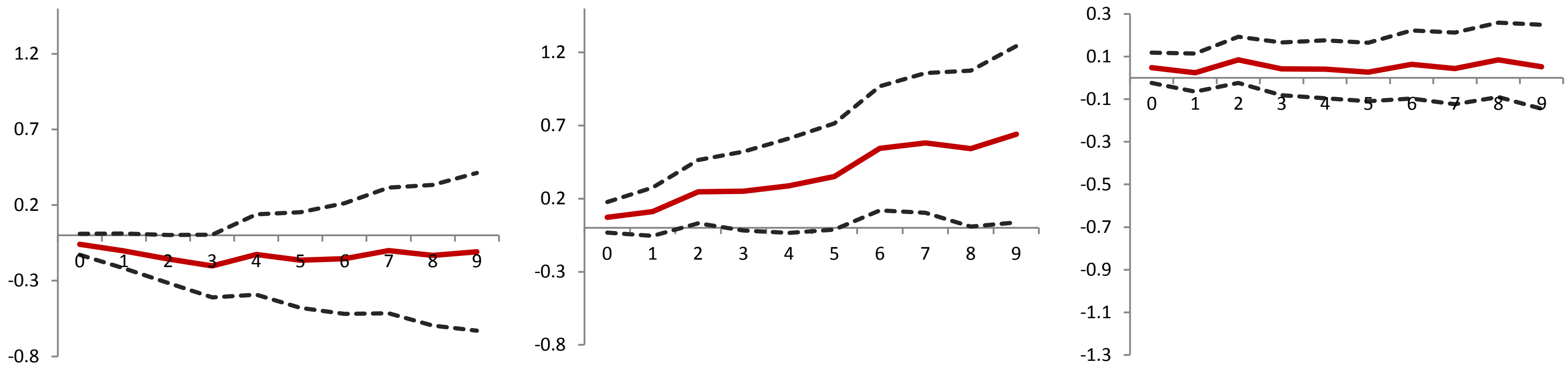



**<u>Low Bank Balance and High Credit Limit</u>**

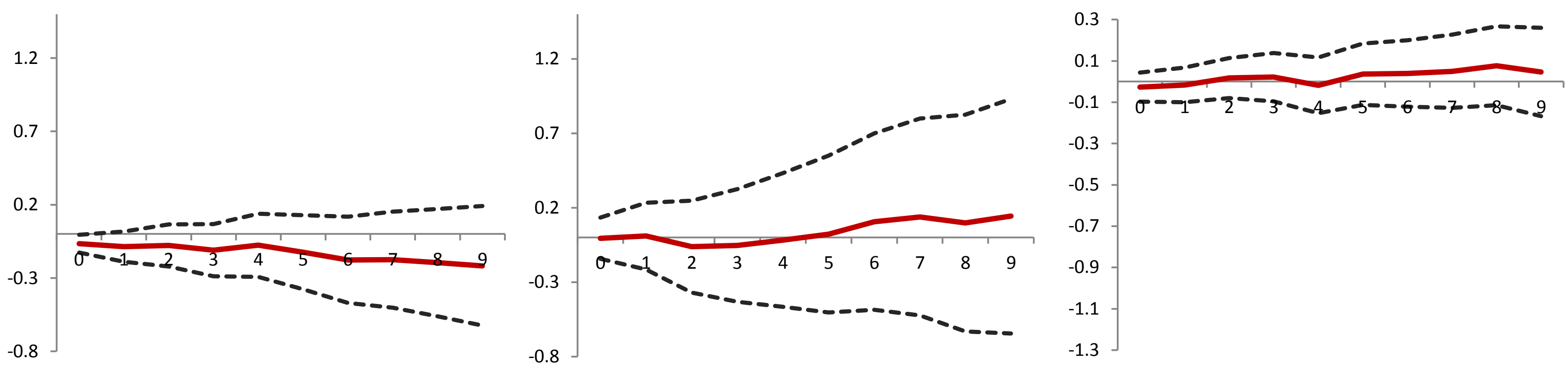


(a) (b) (c)

**High Bank Balance and Low Credit Limit**




**High Bank Balance and High Credit Limit**



## Table 1: Summary Statistics

This table reports the summary statistics of our treatment and control sample, both before and after propensity score matching. The treatment sample consists of individuals who qualify for the Growth Dividend program (but not for the other stimulus package such as Workfare Special Bonus), and the control sample consists of all non-Singaporeans as they do not qualify for the Growth Dividend program. We also exclude individuals/accounts that are dormant or closed, or have no transaction activity during the six months period before the policy announcement. Panel A shows the comparison of demographics between the treatment and control group, both before and after propensity score matching. Panel B shows the comparison of credit card and debit card spending, credit card debt, bank checking account balance information between the treatment and control group in the 24 month period (2010:04-2012:03), both before and after propensity score matching. *$benefit* is the Growth Dividend amount individuals receive in the treatment group. *Credit card spending* is computed by adding monthly spending over all debit card accounts for each individual. *Credit card debt* is computed to be the difference between the current month's credit card payment and the previous month's credit card balance. *Credit card cycle payment* is the payment to the most recent credit card statement. *Debit card spending* is computed by adding monthly spending over all debit card accounts for each individual. For the checking account, we compute *# debit transactions* to be the aggregate number of debit (outflow) transactions for each individual every month. *# ATM debit transactions/# branch debit transactions/# online debit transactions* are the number of debit transactions at ATM, or in branches or via online transaction. *Total card spending* is the sum of debit card spending and credit card spending for each individual in a month. All the dollar amounts are in the local currency (SG$), and 1SGD = 0.78 USD in February 2011.

**Panel A: Demographics of Treatment and Control Group**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | **Mean** | **Std.** | **Mean** | **Std.** | |
| | **Treatment Group** | | **Control Group** | | **Diff** |
| **Age** | 44.09 | 10.57 | 40.31 | 8.45 | -3.78*** |
| **Monthly Income in 2010** | 6,053 | 8,861 | 7,795 | 11,395 | 1,742*** |
| **Female** | 0.42 | 0.49 | 0.30 | 0.46 | -0.13*** |
| **Ethnicity** | | | | | |
| **Chinese** | 0.89 | 0.31 | 0.49 | 0.50 | -0.40*** |
| **Malay** | 0.05 | 0.22 | 0.01 | 0.07 | -0.04*** |
| **Indian** | 0.03 | 0.18 | 0.17 | 0.38 | 0.14*** |
| **Married** | 0.47 | 0.50 | 0.49 | 0.50 | 0.02*** |
| **Property Type = HDB** | 0.70 | 0.46 | 0.55 | 0.50 | -0.14*** |
| **$benefit** | 522 | 213 | 0 | 0 | |
| **N** | 82,533 | | 23,268 | | |
| | **Matched Treatment Group** | | **Matched Control Group** | | **Diff** |
| **Age** | 40.37 | 8.87 | 39.57 | 8.00 | -0.79*** |
| **Monthly Income in 2010** | 6,644 | 9,618 | 6,684 | 9,893 | 40 |
| **Female** | 0.38 | 0.49 | 0.35 | 0.48 | -0.04*** |
| **Ethnicity** | | | | | |
| **Chinese** | 0.88 | 0.33 | 0.76 | 0.43 | -0.12*** |
| **Malay** | 0.003 | 0.06 | 0.003 | 0.06 | 0.00 |
| **Indian** | 0.07 | 0.26 | 0.13 | 0.34 | 0.06*** |
| **Married** | 0.45 | 0.50 | 0.45 | 0.50 | -0.00 |
| **Property Type = HDB** | 0.66 | 0.47 | 0.65 | 0.48 | -0.01 |
| **$benefit** | 511 | 214 | 0 | 0 | |
| **N** | 36,989 | | 10,567 | | |

**Panel B: Financial Account Information of Treatment and Control Group**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Treatment Group | | Control Group | | Matched Treatment Group | | Matched Control Group | |
| | **Mean** | **Std.** | **Mean** | **Std.** | **Mean** | **Std.** | **Mean** | **Std.** |
| **Credit Card** | | | | | | | | |
| **spending** | 721 | 1,183 | 1,047 | 1,644 | 763 | 1,229 | 824 | 1,343 |
| **cycle payment** | 701 | 17,193 | 1,043 | 2,485 | 736 | 6,258 | 798 | 1,843 |
| **debt** | 719 | 1,958 | 843 | 2,268 | 667 | 1,921 | 655 | 1,945 |
| **change in debt** | 6 | 490 | 7 | 652 | 6 | 514 | 4 | 551 |
| **Debit Card** | | | | | | | | |
| **spending** | 216 | 507 | 235 | 542 | 225 | 519 | 190 | 476 |
| **Bank Checking Account** | | | | | | | | |
| **# debit transactions** | 15 | 12 | 16 | 11 | 15 | 12 | 12 | 10 |
| **# ATM debit transactions** | 0.68 | 3.08 | 0.63 | 2.58 | 0.55 | 2.68 | 0.44 | 2.19 |
| **# branch debit transactions** | 0.32 | 0.88 | 0.27 | 0.74 | 0.28 | 0.81 | 0.24 | 0.71 |
| **# online debit transactions** | 0.26 | 0.71 | 0.29 | 0.72 | 0.32 | 0.78 | 0.30 | 0.73 |
| **month-end balance** | 16,036 | 21,823 | 14,320 | 20,531 | 15,513 | 21,391 | 14,083 | 20,076 |
| **Total (card) spending** | 937 | 1,290 | 1,282 | 1,770 | 988 | 1,341 | 1,014 | 1,443 |
| **total spending on transportation** | 77 | 130 | 44 | 89 | 78 | 129 | 44 | 91 |
| **total spending on dining** | 66 | 194 | 113 | 292 | 74 | 206 | 79 | 230 |
| **total spending on supermarket** | 56 | 119 | 95 | 181 | 59 | 122 | 67 | 144 |
| **total spending on apparel** | 86 | 246 | 131 | 316 | 93 | 256 | 100 | 270 |
| **total spending on travel** | 56 | 306 | 142 | 482 | 60 | 317 | 95 | 384 |
| **total spending on entertainment** | 38 | 154 | 37 | 120 | 36 | 142 | 28 | 106 |
| **N** | 1,893,217 | | 512,213 | | 845,339 | | 233,197 | |

## Table 2: The Average Spending and Debt Response to Stimulus Program

This table shows the results of average spending and debt response (Equation (1) and (2)) of the matched sample in the period of 2010:08-2011:11. Panel A presents the estimation results of Equation (1), and Panel B shows the estimation results of Equation (2). $\$benefit$ is the amount of the Growth Dividend received for the treatment group, and is equal to zero for the control group. $1_{post}$ is a binary variable equal to one for months after the announcement of the Growth Dividend program (i.e., later than 2011:01). $1_{announce}$ is a binary variable equal to one for months during the announcement window (2011:02-2011:03), and $1_{disburse}$ is a binary variable equal to one for months after the disbursement of the Growth Dividends (i.e., later than 2011:04). Please refer to Table 1 for definitions of other variables. Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. T-statistics are reported in parentheses under the coefficient estimates and ***, **, and * denote statistical significance at the 1%, 5% and 10% level respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A** | | | | |
| | **Total card spending** | **Debit card spending** | **Credit card spending** | **Credit debt change** |
| **\$ Benefit x $\mathbf{1}_{>post}$** | 0.089*** | 0.022*** | 0.067*** | -0.011* |
| | (5.16) | (2.65) | (4.54) | (-1.85) |
| **Constant** | 1,204.544*** | 490.356*** | 714.188*** | 16.206*** |
| | (164.56) | (144.22) | (111.65) | (4.10) |
| **R-squared** | 0.506 | 0.499 | 0.481 | 0.032 |
| **Panel B** | | | | |
| **\$ Benefit x $\mathbf{1}_{>announce}$** | 0.080*** | 0.009 | 0.071*** | -0.011 |
| | (3.47) | (0.82) | (3.62) | (-0.92) |
| **\$ Benefit x $\mathbf{1}_{>disburse}$** | 0.092*** | 0.026*** | 0.066*** | -0.011* |
| | (4.93) | (2.83) | (4.15) | (-1.85) |
| **Constant** | 1,204.545*** | 490.357*** | 714.188*** | 16.206*** |
| | (164.55) | (144.22) | (111.65) | (4.10) |
| **Fixed Effects** | | Individual, year-month | | |
| **R-squared** | 0.506 | 0.499 | 0.481 | 0.032 |

## Table 3: Spending Response: The Number of Checking Account Debit transactions

This table studies whether the number of checking account debit transactions change for the treatment group after the announcement of the stimulus program in the matched sample in the period of 2010:08-2011:11. The dependent variables are the log of the number of debit, ATM debit, online debit, and branch debit transactions (equal to ln(0.01) for zero values). Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. T-statistics are reported in parentheses under the coefficient estimates and ***, **, and * denote statistical significance at the 1%, 5% and 10% level respectively.

| | (1)<br>**# of debit transactions** | (2)<br>**# of ATM transactions** | (3)<br>**# of online transactions** | (4)<br>**# of branch transactions** |
|---|---|---|---|---|
| $\mathbf{1}_{treatment} \times \mathbf{1}_{>post}$ | -0.000 | -0.002 | -0.013 | 0.006 |
| | (-0.04) | (-0.28) | (-0.85) | (0.39) |
| **Constant** | 2.660*** | -4.224*** | -3.803*** | -4.026*** |
| | (914.29) | (-1,228.81) | (-441.63) | (-385.52) |
| **Fixed Effects** | | Individual, year-month | | |

## Table 4: The Average Spending Response: by Category of Spending

This table shows the results of average spending response (Equation (1) and (2)) by spending categories of the matched sample in the period of 2010:08-2011:11.. The dependent variable is the monthly total card spending on supermarket, dining, entertainment, transportation, apparel, and travel for each individual in our sample. Panel A uses the dollar total spending as the dependent variable, and Panel B uses the log of total card spending as the dependent variable. Please refer to Table 1 and 2 for definitions of other variables. Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. T-statistics are reported in parentheses under the coefficient estimates and ***, **, and * denote statistical significance at the 1%, 5% and 10% level respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | **Supermarket** | **Dining** | **Entertainment** | **Transportation** | **Apparel** | **Travel** |
| **Panel A** | | | | | | |
| **\$ benefit x** $\mathbf{1}_{>post}$ | 0.004** | 0.002 | 0.002 | 0.003** | 0.016*** | 0.017*** |
| | (2.08) | (0.68) | (0.99) | (2.40) | (4.52) | (3.66) |
| **Constant** | 99.988*** | 69.271*** | 55.687*** | 71.265*** | 112.633*** | 81.803*** |
| | (140.91) | (67.45) | (70.96) | (178.79) | (77.25) | (33.59) |
| **R-squared** | 0.588 | 0.479 | 0.699 | 0.797 | 0.407 | 0.253 |
| **Panel B** | | | | | | |
| $\mathbf{1}_{treatment} \times \mathbf{1}_{>post}$ | 0.015 | 0.000 | 0.111*** | 0.076** | 0.135*** | 0.088*** |
| | (0.41) | (0.01) | (3.09) | (2.18) | (3.32) | (2.68) |
| **Constant** | 1.512*** | -1.346*** | -1.982*** | 1.056*** | 0.339*** | -3.498*** |
| | (64.20) | (-56.64) | (-91.78) | (53.30) | (12.54) | (-173.16) |
| **R-squared** | 0.588 | 0.479 | 0.699 | 0.797 | 0.407 | 0.253 |
| **Fixed Effects** | Individual, year-month | | | | | |

## Table 5: Dynamics of Spending and Debt Response

This table reports the result of the estimation of the distributed lag model as in Equation (3) in the matched sample in the period of 2010:08-2011:11. $1_{post\ mj}$ is a binary variable that is equal to one for the month that is the $j$th month after the announcement of the Growth Dividend program. For example, $1_{post\ m0}$ is equal to one for the announcement month (2011:02), and $1_{post\ m9}$ is equal to one for the 9th month after the announcement (2011:11). Please refer to Table 1 and 2 for definitions of other variables. Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. T-statistics are reported in parentheses under the coefficient estimates and ***, **, and * denote statistical significance at the 1%, 5% and 10% level respectively.

| | (1)<br>**Total card spending** | (2)<br>**Debit card spending** | (3)<br>**Credit card spending** | (4)<br>**Credit debt change** |
|---|---|---|---|---|
| **$ Benefit x $\mathbf{1}_{post\ m0}$** | 0.062** | -0.006 | 0.068*** | 0.005 |
| | (2.19) | (-0.44) | (2.84) | (0.26) |
| **$ Benefit x $\mathbf{1}_{post\ m1}$** | 0.099*** | 0.024* | 0.074*** | -0.026 |
| | (3.30) | (1.68) | (2.92) | (-1.64) |
| **$ Benefit x $\mathbf{1}_{post\ m2}$** | 0.152*** | 0.052*** | 0.100*** | -0.037** |
| | (5.19) | (3.44) | (4.10) | (-2.32) |
| **$ Benefit x $\mathbf{1}_{post\ m3}$** | 0.071** | 0.046*** | 0.025 | -0.026* |
| | (2.28) | (2.90) | (0.96) | (-1.69) |
| **$ Benefit x $\mathbf{1}_{post\ m4}$** | 0.057* | 0.037** | 0.020 | -0.014 |
| | (1.83) | (2.40) | (0.74) | (-0.94) |
| **$ Benefit x $\mathbf{1}_{post\ m5}$** | 0.090*** | 0.033** | 0.057** | -0.020 |
| | (2.87) | (2.08) | (2.12) | (-1.28) |
| **$ Benefit x $\mathbf{1}_{post\ m6}$** | 0.111*** | 0.012 | 0.099*** | 0.010 |
| | (3.52) | (0.81) | (3.65) | (0.65) |
| **$ Benefit x $\mathbf{1}_{post\ m7}$** | 0.137*** | 0.035** | 0.102*** | -0.022 |
| | (4.31) | (2.24) | (3.74) | (-1.43) |
| **$ Benefit x $\mathbf{1}_{post\ m8}$** | 0.046 | -0.007 | 0.053* | 0.032** |
| | (1.42) | (-0.46) | (1.93) | (2.02) |
| **$ Benefit x $\mathbf{1}_{post\ m9}$** | 0.065* | -0.007 | 0.072** | -0.009 |
| | (1.89) | (-0.40) | (2.46) | (-0.54) |
| **Constant** | 1,204.544*** | 490.357*** | 714.187*** | 16.206*** |
| | (164.55) | (144.22) | (111.65) | (4.10) |
| **Fixed Effects** | | Individual, year-month | | |
| **R-squared** | 0.506 | 0.499 | 0.481 | 0.032 |

## Table 6: Average Spending and Debt Response: Entire Sample, without Propensity Score Matching

This table shows the results of average spending and debt response (Equation (1) and (2)) of the full sample (without propensity score matching) in the period of 2010:08-2011:11. Panel A presents the estimation results of Equation (1), and Panel B shows the estimation results of Equation (2). Please refer to Table 1 and 2 for definitions of other variables. Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. T-statistics are reported in parentheses under the coefficient estimates and ***, **, and * denote statistical significance at the 1%, 5% and 10% level respectively.

| **Panel A** | (1) **Total card spending** | (2) **Debit card spending** | (3) **Credit card spending** | (4) **Credit debt change** |
|---|---|---|---|---|
| **$ Benefit x $\mathbf{1}_{>post}$** | 0.046*** | 0.016*** | 0.030*** | -0.003 |
| | (3.80) | (2.73) | (2.92) | (-0.76) |
| **Constant** | 1,228.324*** | 507.068*** | 721.257*** | 17.729*** |
| | (249.32) | (219.85) | (168.50) | (6.73) |
| **R-squared** | 0.546 | 0.513 | 0.524 | 0.035 |
| **Panel B** | | | | |
| **$ Benefit x $\mathbf{1}_{>announce}$** | 0.085*** | 0.014* | 0.071*** | 0.003 |
| | (5.33) | (1.88) | (5.16) | (0.42) |
| **$ Benefit x $\mathbf{1}_{>disburse}$** | 0.035*** | 0.016** | 0.019* | -0.005 |
| | (2.71) | (2.57) | (1.72) | (-1.17) |
| **Constant** | 1,228.318*** | 507.068*** | 721.250*** | 17.727*** |
| | (249.32) | (219.85) | (168.50) | (6.73) |
| **R-squared** | 0.546 | 0.513 | 0.524 | 0.035 |
| **Fixed Effects** | Individual, year-month | | | |

## APPENDIX

### Table A1 Payout Schedule of the Growth Dividend Program in 2011

This table summarizes the payout schedule of the Growth Dividend program by income and annual value of residence. We do not directly observe the annual value of residence, which is determined by IRAS, Singapore's tax authority, but we make use of the fact that the SG$13,000 cutoff is chosen to identify Singaporeans who live in the government subsidized housing (HDB). Singaporeans living in HDB can have different growth dividends, especially for the lower income individuals. For our purpose, we use the average of the two dividend values for individuals living in HDB within the same income category. For example, for Singaporeans with an annual income no greater than SG$30,000, if they live in HDB, we assign them with a growth dividend of SG$700. The exchange rate in February 2011 is 1 SGD = 0.78 USD.

| **Assessable Annual Income in 2010** | Annual Value of Residence (as of December 2010) | | |
|---|---|---|---|
| | <= SG$7,000 | SG$7,001 to SG$13,000 | > SG$13,000 |
| | HDB | | Non-HDB |
| **<= SG$30,000** | SG$800 | SG$600 | SG$300 |
| **SG$30,001 to SG$100,000** | SG$600 | SG$600 | SG$300 |
| **>SG$100,000** | | SG$100 | |
| **National Service Men** | | +SG$100 | |

## Table A2 Propensity Score Matching Logistic Regression

This table presents the result of the propensity score matching logistic regression. The dependent variable, *eligible*, is equal to one for individuals in the treatment group, and zero for those in the control group. The treatment sample consists of individuals who qualify for the Growth Dividend program (but not for the other stimulus package such as Workfare Special Bonus), and the control sample consists of all non-Singaporeans as they do not qualify for the Growth Dividend program. We also exclude individuals/accounts that are dormant or closed, or have no transaction activity during the six months period before the policy announcement. In addition to the explanatory variables below, we include 16 occupation categories as fixed effects. T-statistics are presented in parenthesis below the coefficient estimates, and ***, **, * represent statistical significance at the 1%, 5% and 10% level respectively.

| | (1)<br>**Eligible** |
|---|---|
| **ln(age)** | -2.106*** |
| | (-4.48) |
| **ln(monthly income in 2010** | -2.322*** |
| | (-11.24) |
| **ln(age) x ln(monthly income in 2010)** | 0.550*** |
| | (9.91) |
| **property type dummy (HDB=1)** | 0.350*** |
| | (16.66) |
| **Chinese** | 3.106*** |
| | (104.28) |
| **Malay** | 4.718*** |
| | (48.00) |
| **Indian** | 1.090*** |
| | (28.30) |
| **married** | -0.066*** |
| | (-3.28) |
| **female** | 0.357*** |
| | (17.72) |
| **Fixed Effects** | Occupation |
| **Constant** | 8.795*** |
| | (5.04) |
| **Observations** | 103,985 |
| **Pseudo R-squared** | 0.265 |