Consumption and Debt Response to Unanticipated Income Shocks: Evidence from a Natural Experiment 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 an exogenous unanticipated income shock. We find that consumption rose significantly subsequent to the fiscal policy announcement: for each dollar received, consumers on average spent 90 cents during the ten months after the program's announcement. There was a moderate decrease in debt. We find a strong announcement effect—consumers increased spending via 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.

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

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1. Introduction

A central implication of the life-cycle/permanent income hypothesis (LCPIH) is that consumers should not respond to predictable and temporary changes in their income. Many studies, however, have rejected the LCPIH, noting declines in spending across time after a temporary change to income. Researchers have explained these declines across time primarily through liquidity constraints and precautionary savings (see, Souleles 1999, Carroll 1992, Johnson, Parker, and Souleles 2006, Agarwal, Liu, and Souleles 2007, Parker et al. 2013).

In this paper, we use a unique panel data set of consumer financial transactions to study how consumers respond to an exogenous unanticipated income shock.[1] Specifically, we use a representative sample of more than 180,000 consumers in Singapore and study how their credit card, debit card, and bank checking account spending behavior responded to a positive income shock, 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. The package is 0.5% of the annual GDP of Singapore in 2011, which is comparable to the size of the 2001 and 2008 US tax rebate. This payment represents a significant income bonus, corresponding to about 18 percent of monthly median income in Singapore in 2011. Our analysis is based on a difference-in-differences identification that exploits the program's qualification criteria—foreigners did not qualify for the program and thus comprise the control group in the study. In addition to allowing us to identify the causal impact of the fiscal policy on consumption, the richness of our data also lets us study the response in credit card spending and debit card spending, the change in credit card debt, and the change in banking transaction behavior in the 10 months following the policy announcement to help us understand different channels of the consumption response.

As discussed by Gross and Souleles (2002), credit cards play an important role in consumer finances, so they can be quite useful for studying consumer spending behavior. Half of consumers in the United States have a credit card, and total credit card debt was close to a trillion dollars in 2012 with 40 percent 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 in the country have a credit card, and the total credit card debt as a percentage of GDP was over 2 percent 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. However, Agarwal et al. (2007) point out the limitations of studying consumption dynamics using only credit card data, because credit cards potentially miss significant spending via other instruments (debit cards, cash, and checks).[2] For example,

[1] Although our objective is not to test any specific theoretical model, our results can be interpreted as a test of the LCPI model. If the LCPIH holds, we should not find significant increases in spending over a broad window after a temporary and unexpected change in income.

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

the purchase volume on debit cards was similar in magnitude to that on credit cards in the United States in 2012 (2.1 trillion vs. 2.3 trillion U.S. dollars) (U.S. Census Bureau, Statistical Abstract of the United States:2012). Similarly, in Singapore debit and credit cards are important mediums of disposable consumption. Virtually, everybody in Singapore has a debit card. Close to 30 percent of aggregate personal consumption in the country is already being purchased using credit and debit cards. The remaining 70 percent of consumption is transacted via checks, direct transfers, and cash. This study focuses on debt dynamics of households brought on by income changes and therefore we are particularly interested in credit card usage, because 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, recipients' consumption rose significantly after the fiscal policy announcement: for each dollar received, consumers on average spent 90 cents (aggregated across different financial accounts) during the ten months after the announcement. At the same time, consumers' credit card debt decreased moderately (so savings effectively increased). Second, we find a strong announcement effect: consumers started to increase spending during the two-month period after the announcement but before the cash payout. The magnitude of the response during the announcement period is comparable to that after disbusrment. The announcement effect is consistent with the life-cycle theory but inconsistent with past empirical evidence (Poterba, 1988 and Wilcox, 1989). One reason the past studies could not find any effect is because they had limited time series observations to pick up any announcement effect or the announcement was not a surprise. Third, consumption response was concentrated in debit card (25 percent of the total response) and credit card (75 percent of the total response) spending. Based on Agarwal et al. (2007), we expect the consumption response to show up in credit card spending. We find that consumers started spending via credit cards during the announcement period, then switched to debit cards after disbursement, before finally increasing their credit card use significantly. Consistent with Agarwal et al. (2007), credit card debt dropped in the first months after disbursement and then reverted back to its original level. Lastly, consumption response was heterogeneous across spending categories and across individuals. Consumption rose primarily in the non-food, discretionary category. Liquidity constrained consumers showed a strong consumption response, whether or not they were credit constrained.

We conduct a series of robustness tests to ensure that our results are not confounded by other policy changes in Singapore. For instance, during the sample period two other policy changes provided positive income shocks that could have affected consumption—all low-income Singaporeans and citizens above the age of 45 received these shocks. To be certain that these policies were not confounding our study, we dropped low-income households from our analysis

[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.

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 carried out a separate analysis on a subsample of consumers younger than 45 years old who were entitled only to the Growth Dividend Program. We also perform additional tests against other confounding events or alternative explanations. The results from these robustness tests are qualitatively and quantitatively similar to those in the main analysis.

A vast literature examines consumption responses to income shocks (e.g., Shapiro and Slemrod 1995, 2003a, 2003b, Souleles 1999, 2000, 2002, Parker 1999, Hsieh 2003, Stephens 2003, 2006, 2008, Johnson, Parker, and Souleles 2006, Parker et al. 2013). The literature finds mixed evidence: some studies find that consumption response is essentially zero, while others find that liquidity constrained consumers respond positively to fiscal stimulus programs. For a review of the literature see Browning and Collado (2003), and Jappelli and Pistaferri (2010).

Our paper is most closely related to Agarwal et al. (2007). Both our study and theirs look at the dynamics of consumption and debt as a function of an income shock. Like Agarwal et al., we find a significant spending response working through the balance sheets of the consumers, and we confirm that liquidity constraints matter. However, we document the dynamics of the consumption response across different spending instruments—a rise in credit card spending following the announcement, then a switch to debit card spending after disbursement of the stimulus, and finally, a switch back to the credit card in the later months. These dynamics imply that Agarwal et al. (2007) underestimate the spending response due to limitations in their data. Specifically, they are unable to measure spending via debit cards, which we show accounts for a significant portion of the marginal propensity to consume (MPC), especially in the initial months after disbursement.

We are also the first to document that the spending response of credit constrained consumers is dominated by that of the liquidity constrained consumers. Existing literature finds that consumption responds significantly to relaxation of the credit constraints (Gross and Souleles, 2002; Agarwal et al., 2007; Leth-Petersen, 2010). Our data allow us to differentiate liquidity constraints and credit constraints, and we find that 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 behavior. This implies that the MPC for the liquidity constrained consumers, estimated from the prior studies, might be a lower bound of their true consumption response.

More broadly, this study points out an important factor in understanding the consumption response to fiscal stimuli that no other study has been able to capture. Because the specific stimulus program we study has an unambiguous announcement date, we are able to show that consumption responds to the announcement. It provides new evidence consistent with the life-cycle theory predictions on the announcement effect. This also has a significant economic implication. In our study, 18 percent of the total consumption response occurs during the announcement period (prior to actual receipt of the payments), implying that 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

Several papers have studied consumers' responses to 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 accounts for seasonal fluctuations..

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

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 of nondurable goods but increase their spending in durable goods such as furniture and entertainment equipment. Stephens (2008), using the completion of vehicle loan payments, finds that a 10 percent increase in discretionary income leads to a 2 to 3 percent increase in nondurable consumption. Thus, the literature shows that using this identification strategy has led to mixed results related to the size and composition of the spending change. Other papers have looked at the consumption response to 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. They find that following a minimum wage hike, households with minimum wage workers often buy vehicles. On average, vehicle 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, dating back to just after the publication of Friedman's permanent income hypothesis (PIH). In 1959, Bodkin used insurance dividends paid to World War II veterans to reject the PIH, but Kreinen's 1961 study of restitution payments to certain Israelis was unable to reject the hypothesis. Among more recent studies, Browning and Collado (2003) and Hsieh (2003) fail to reject the PIH, but Shea (1995), Parker (1999), and Souleles (1999) all reject it.

Previous papers have also studied consumers' responses to tax cuts and other windfalls. Modigliani and Steindel (1977), Blinder (1981), and Poterba (1988) study the 1975 tax rebate. They all find that consumption responded to the rebate, but the authors come to somewhat different conclusions regarding the relative magnitude of the initial versus lagged response. All three studies use aggregate time-series data, but there are a number of advantages to using microlevel 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. Among more recent related studies, Souleles (1999) finds that consumption responds significantly to the federal income tax refunds that most taxpayers receive each spring. Gross and Souleles (2002) find that exogenous increases in credit card limits (i.e., windfall increases in liquidity) lead to significant increases in credit card spending and debt. Leth-Petersen (2010) also studies the spending response to an exogenous increase in the access to credit provided by a credit market reform that gave access for house owners to use housing equity as collateral for consumption. These papers all find evidence of liquidity constraints (as proxied by credit constraints).[5]

Four recent studies have used micro data to examine the 2001 tax rebates: Shapiro and Slemrod (2003a,b), Johnson, Parker, and Souleles (2006), and Agarwal et al. (2007). According to Shapiro and Slemrod (2003a), only 21.8% of their survey respondents reported they would mostly spend their rebate, consistent with an average MPC of about one third. They find no significant evidence of liquidity constraints. Shapiro and Slemrod (2003b) use a novel 2002 follow-up survey to try to determine whether there was a lagged response to the rebate. They find that among respondents

4 Blinder and Deaton (1985) find smaller consumption responses when they consider jointly the 1975 rebate and the 1968–1970 tax surcharges. Nonetheless, they find consumption to be too sensitive to the pre-announced changes in taxes in the later phases of the Reagan tax cuts. Overall, they conclude 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 (2003), Hsieh (2003), and Stephens (2003), among others.

who said they initially mostly used the rebate to pay down debt, most reported that they would "try to keep [down their] lower debt for at least a year." Johnson et al. (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 among illiquid households, which is indicative of liquidity constraints. Agarwal et al. (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-used credit card account was in the sample, spending on that account rose by more than $200 in the nine months after rebate receipt, which represents over 40 percent of the average household rebate. Finally, others have 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 in an attempt to share the nation's economic growth in 2010, the government would distribute a one-time pay out of Growth Dividends to all Singaporeans over 21 years old in 2011. While the amount each Singaporean received depended on his or her wealth, a typical qualified Singaporean received between US$428 and US$624 in Growth Dividends. This payment represented a significant income bonus, corresponding to about 18 percent of monthly median income in Singapore in 2011. The program's payments totaled US$1.17 billion, which corresponds to 12 percent of Singapore's monthly aggregate household consumption expenditure in 2011.

Eligible Singaporeans received the payment by the end of April 2011, typically via direct bank transfer. The amount of Growth Dividend an individual received was jointly determined by income and annual home value. The annual value is the estimated annual rental revenues if the property 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. We do not have data on the exact annual home value for each individual in our data set, but we take advantage of the fact that the government uses the annual value of home criteria to identify less well-off Singaporeans living in 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 were serving or who had served in the army received an additional Growth Dividend of $100 in recognition of their contributions to the nation. The average Growth Dividend amount that each qualified individual in our sample received was SG$522 (US$407). See Table 1A for the exact pay out schedule.

Other stimulus programs were announced at the same time in February 2011, but we focus on the Growth Dividend for several reasons. The Growth Dividend Program was significantly larger than the other stimulus packages. The program was unprecedented and unanticipated by the population. It also has features that allow better identification of the consumption response: it is the only one with a cash payment (as opposed to, for example, illiquid retirement account) and a targeted population, adult Singaporeans, which allows us to use foreigners as the control group. To control for the confounding effects of other stimulus packages, we drop from our analysis individuals who qualify for another cash stimulus package, the Workfare Special Bonus.[6] We also perform other robustness checks to verify our results.

4. Data

We use in our analysis a unique, proprietary data set obtained from the leading bank in Singapore that has more than 4 million customers, or 80 percent of the entire population in Singapore. Our sample contains consumer financial transactions data of more than 180,000 individuals, which is a random representative sample of the bank's customers, in the 24-month period between 2010:04 and 2012:03. For each individual in our sample period, we have monthly statement information about 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); and credit limit, payments, and debt (for credit cards). At the disaggregate level, the data contain transaction-level information about the individual's credit card and debit card spending, including the transaction amount, transaction date, merchant name, and merchant category for each transaction. The data set also contains a rich set of demographic information about each individual, including age, gender, income, property type (HDB or private), property address zip code, nationality, ethnicity, and occupation.[7]

This data set offers several advantages. Relative to traditional household spending data sets in the United States such as the Survey of Consumer Finance, our sample is larger with little measurement error, and it allows high frequency analysis. Compared to studies that use microlevel credit card data (e.g., Gross and Souleles 2002, Agarwal et al. 2007, Aaronson et. al. 2012), we have more complete information on the 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 account that the individual holds with the bank. Although we do not have information about 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 three credit cards, which is also the number of credit cards an average consumer has in our data set. In other words, we believe we are picking up the entire consumption of these households through the spending information on the credit and debit cards

[6] The qualification criteria for the Workfare Special Bonus were as follows: Singaporean citizens who were age 35 or older by December 2010 and who worked for at least three months out of any six-month period in 2010 with a monthly income lower than SG$1700.

[7] Unlike the United States, where a zip code represents a wide area with a large population, a zip code in Singapore represents a building. A unique zip code is assigned to a single family house or for, say, a building with 10 apartment units.

at this bank. In addition, the richness of the transaction-level information as well as the individual demographics allows us to better understand heterogeneity in consumers' consumption responses to the positive income shock.

For our purposes, 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 as 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 remained inactive (i.e., with no transactions) throughout 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 groups in our sample. Panel A shows the demographics of the treatment and control groups. 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 wealth level; thus, to reliably identify the policy effect, individuals in the treatment and control groups should have comparable levels of wealth. Therefore, we perform propensity score matching based on the wealth variables as well as other determinants of spending, including income in 2010, property type, as well as age, gender, ethnicity, and occupation (see Table 2A in the Appendix for the propensity score matching result). After matching, the difference between the treatment and control groups in income and property type becomes statistically and economically indistinguishable from zero (Panel A, Table 1). Differences in 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 1a). In sum, the matched treatment and control group are homogeneous in wealth and demographics, hence the difference of the two groups' change in spending (and debt) after the stimulus program should reflect the causal impact of the policy. For this reason, we report the results of our main analysis using the matched sample of the control and treatment groups. It is important to note that with the unmatched sample, the bias should go in the opposite direction: the control group is wealthier and so their spending will be higher, which implies a likely underestimation of the response.

[Insert Figure 1]

We also plot, in Figure 1b, the unconditional mean total spending of the treatment and control group in the matched sample during the period of 2010:04 to 2011:11. On average, the treatment group has a higher total spending than the control group. Moreover, the difference in total spending between the treatment group and the control group before the announcement of the Growth Dividend program remains constant, which confirms the underlying identifying assumption of a parallel trend. Note that the gap between the treatment group and the control group visibly increases after the program, which provides the first suggestive evidence of consumer spending response to the income shock.

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 by 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. Spending is a flow variable and is therefore analyzed in levels.

$\$benefit_i$ is the amount of the Growth Dividend that individual *i* received, and is equal to zero for the control group. 1_{post} is a binary variable equal to one for the months after the announcement of the Growth Dividend Program (i.e., later than 2011:01). α_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 α_i is the individual dummy included to absorb differences in consumption preferences at the individual level. The β 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 the months during the announcement window (2011:02–2011:03), and $1_{disburse}$ is a binary variable equal to one for the months after the disbursement of the Growth Dividends (i.e., later than 2011:04). Therefore, the coefficients β_a and β_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 the following distributed lag model:

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

Following Agarwal et al. (2007), the results can be interpreted as an event study. The coefficient β_0 measures the immediate dollar response per dollar dividend received. The *marginal* coefficients β_1, …, β_9 measure the *additional* responses one 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 β_0 = 6 cents on a dollar of Growth Dividend in the announcement month and after one month spending rises by β_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.

We also study how 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:

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

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

Unless indicated otherwise, Equations (1) – (4) are estimated by ordinary least squares (OLS), and the standard errors are adjusted for heteroscedasticity across accounts as well as serial correlation within accounts.

6. Results

We begin by estimating the average response of spending (in various financial accounts) and debt to the Growth Dividend Program. To sharpen the results, we later analyze dynamics using a distributed lag model and heterogeneity in response across different spending categories and different types of individuals. In the main analysis, we focus on the matched sample in the period from six months before to ten 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 had a bank account, debit card, and credit card account with the bank at the same time.[9]

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

Panel A of Table 2 shows the average response from applying Equation (1) to spending and the change in credit card debt. The first column shows the average response of 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 Growth Dividend received. The effect is both statistically and economically significant, and it corresponds to a total increase of 89 cents per dollar received. More than two thirds 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 3 of Table 2, Panel A), and less than one third is due to spending on debit cards (22 cents per dollar received, column 2 of Table 2, Panel A). Credit card debt experiences a 1.1 cents decrease per month or an 11-cent decrease in total per dollar received for the treatment group after the announcement, but the effect is only statistically significant at the 10 percent level.

[Insert Table 2 About Here]

6.2. Announcement vs. disbursement effect

The Growth Dividend Program was a one-time stimulus program that was unprecedented and *unanticipated* by the population in Singapore. In addition, the program was announced with full information on the eligibility, timing, and size of the pay out in February 2011, two months before qualified Singaporeans received the payments in April 2011. As a result, we can investigate the announcement effect separately from the disbursement effect. The prior literature has not been unsuccessful at estimating the announcement effect because the announcement was anticipated. This weakened the identification of the announcement effect. However, the life-cycle theory has a clear prediction that consumers should respond to the announcement. Our setting is the first to cleanly test this theory: the two prior papers (Poterba 1988 and Wilcok 1989) that look at this effect had weaker identification between announcement and disbursement. We thus estimate Equation (2) by decomposing the post-policy window into the announcement period and the disbursement period (Table 2, Panel B).

We find a significant increase in total card spending in both windows: individuals spent 8 cents per month for every dollar received in the two-month announcement period and 9.2 cents per

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

[9] We include individuals with fewer than three accounts with the bank in the analysis as a robustness check, and our results remain qualitatively the same.

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 during 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 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 et al. 2007).

In summary, consumers started spending the stimulus money upon announcement of the program, before the actual receipt of the dividend. Compared to the disbursement window, they increased spending in the announcement period by a similar amount, primarily through credit card use. After receiving the dividend, they used their debit cards along with credit cards to increase spending. Consumers also started to pay down debt after receiving the money.

6.3. Response in bank checking accounts

We next study debit transactions in consumers' bank checking accounts before and after the announcement of the Growth Dividend Program. Because 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 increased 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 account debit transactions after the stimulus program for the treatment group. We also decompose debit transactions into ATM, in-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 increased their spending through card spending, either with debit or credit cards.[10]

[Insert Table 3 About Here]

6.4. Heterogeneity in spending response: by spending category

The extant literature documents heterogeneity in the type of spending response to positive income shocks (e.g., Parker et al. 2013). We select several major spending categories into which we decompose the total monthly card spending for each individual. Table 4 shows the estimation results of the average spending response by spending category. As in Tables 2 and 3, we use the

[10] We perform an additional test by inferring the amount of monthly cash/check spending for each individual. By assuming that individuals deposit their monthly income into and pay their credit card balance from this particular bank's account, we estimate (a noisy measure of) the monthly cash/check spending as bank balance at the start of the month+ income – total card spending – bank balance at the end of the month. In an unreported regression, we find that there is no difference in the change of cash/check spending between the treatment group and the control group, which is consistent with the finding on the number of bank transactions in Table 3.

dollar amount of spending as the dependent variable in Panel A of Table 4, so the coefficient captures the spending response in dollars for every dividend dollar received. Discretionary spending categories, 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 in other categories such as supermarket, dining, entertainment, and transportation, but the economic and statistical effect is weaker than the increases in apparel and travel spending.

[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 captures the percentage change in spending after the stimulus program relative to the pre-stimulus spending level in that category. Overall, consumer spending increases in the treatment group by 13.5% in apparel, 8.8% in travel, 7.6% in transportation, and 11.1% in entertainment. These results are statistically significant (at the 1 percent or 5 percent level) and economically large. In particular, although consumers do not appear to spend a significant amount (in absolute terms) on entertainment, the spending increase is large as a proportion of their pre-stimulus spending in entertainment. In sum, spending responds to the stimulus program across spending categories, but the effect is strongest in the discretionary spending categories (entertainment, apparel, and travel).

6.5. The dynamics of the spending and debt response

Results in Tables 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 beginning with the program announcement (Equation (3)). Table 5 reports the marginal coefficients, β_s, s = 0-9. Figure 2 graph the entire paths of cumulative coefficients b_s, s = 0-9, along with their corresponding 95 percent confidence intervals. The results can be interpreted as an event study, with month 0 being the time of pay out 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 percent level. By the end of 9 months after the announcement, the cumulative increase in total card spending is b_9 = 89 cents per dollar received. However, the increase in total card spending between month 3 and month 9 (after the announcement) is not evenly distributed. In months 3 and 4 after the announcement, the marginal increase in total card spending continues but by a smaller amount and is less statistically significant (only at the 10 percent level). In months 5, 6, and 7, total card spending increases by a significant amount, ranging from 9.0 to 13.7 cents per dollar received, before tapering off in months 8 to 9 after the announcement.

Decomposing the debit card and credit card spending gives more insight into the spending response dynamics. We find 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 was announced. In the first month after the announcement, debit card spending starts to rise but by a considerably smaller amount compared to the 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 months 3 and 4 after the announcement. In the later period, the debit card spending increase gradually plateaus by month 8, but the credit card spending increase picks up again, and there is still evidence of a marginal increase in credit card spending in months 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 card 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 the 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 the 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 percent level. After month 5, the credit card debt stops decreasing and experiences a significant increase in month 8 after the announcement. By month 9, the cumulative credit card debt has decreased by b_9 = 10.8 cents per dollar received, and it is only marginally statistically significant (p = 10 percent). We also perform an additional statistical test: the difference between the cumulative credit card debt changes in the first five months compared to that in the last five months is -0.09 cents (per dollar) and is statistically significant at the 5 percent level. This suggests that the credit card debt decrease is concentrated 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 responded strongly to the stimulus program upon announcement by increasing their spending via credit cards. We find a delayed spending response via debit cards, which occurred only after the payment of the stimulus money and then gradually plateaued over time. At the same time, consumers started 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 ten-month treatment period, they stopped paying down their credit card debt and increased their credit card spending significantly again.

6.6. Heterogeneity of spending and debt response across consumers

We next study the dynamics of heterogeneous responses to the financial stimulus program across different consumers. Previous literature has shown that the consumption of liquidity constrained consumers responds more strongly to positive income shocks (e.g., Agarwal et al. 2007). We have a rich array of account-holder information, including their demographics and financial health information, which allows us to study the heterogeneous response of consumers in greater depth.[11] Furthermore, our data allow us to understand differences in the full path of the consumers' spending and debt responses 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 percent confidence intervals (Figure 3).

[Insert Figure 3 About Here]

A. Low Checking Account Balance vs. High Checking Account Balance

We classify consumers in our sample as having a 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 25th percentile of the distribution, or equivalently SGD 1,840 in the cross-section of consumers in that period. Consumers have a high checking account balance if their average monthly balance in that period is above the 75th percentile of the distribution, or SGD 22,346. Consumers with low checking account balances 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 via debit card spending: for each dollar of stimulus payment, b_9 = 50 cents for low-balance consumers, and the effect is statistically significant at the 1 percent level. In particular, 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

[11] Earlier studies use demographics as proxies for liquidity constrained consumers. 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.

plateaus. There is also a strong cumulative increase in credit card spending among low-balance consumers: b_9 = 76 cents for each dollar received, which is statistically significant at the 1 percent level. On the other hand, 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 that of the low-balance consumers. We perform a formal test of the difference in 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 in the cumulative coefficients b_9 between the two groups. The result is statistically significant at the 1 percent level, indicating that low-balance consumers spend more via 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 the announcement), and by month 9, the cumulative debt decrease is 18 cents per dollar received and is statistically significant at the 5 percent level. In contrast, there is no change in credit card debt among 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 having a 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 75th percentile of the distribution, or equivalently SGD 9,000 in the cross-section of consumers during that period. Consumers have a low credit card limit if their maximum credit card limit between 2010:04 and 2010:07 is below the 25th percentile of the sample, or SGD 5,000. This is another measure to capture liquidity constrained consumers that has been used in previous studies.

Panel B of Figure 3 shows the comparison across these two groups of consumers. High credit card limit consumers show 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 increasing both their debit card and credit card spending. However, the effect is stronger on credit card spending. The cumulative debit card spending increase at month 9 after the program announcement is b_9 = 19 cents per dollar received and is statistically significant at the 5 percent level. Credit card spending has a cumulative increase of 87 cents per dollar received by month 9, and the effect is statistically significant at the 1 percent level. An F-test of the cumulative coefficients of total spending suggests that low credit limit consumers' total spending response is greater than that of high credit limit consumers (difference = 79 cents and is statistically significant at the 1 percent level).

While low credit limit consumers see no credit card debt change during the 10-month period, high credit limit consumers' credit card debt decreases strongly: by month 9, the cumulative credit card debt change is -27 cents per dollar received, and this effect is statistically significant at the 1 percent 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) was below the 25th percentile of the distribution, or equivalent to 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 75th 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 the 5 percent level) for debit card spending, and is 61 cents per dollar received (statistically significant at the 1 percent level) for credit card spending. For high-income consumers, the cumulative coefficients for both debit card spending and credit card spending are 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 younger (2010 age $\leq$ 25th percentile = 32) and older consumers (2010 age $\geq$ 75th percentile = 42) in Panel D. Younger 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. Older consumers do not increase their debit card spending, but their cumulative credit card spending increase is significant: b_9 = 71 cents per dollar received, which is significant at the 1 percent level. The overall spending response of the young is larger—39 cents per dollar received—and is statistically significant at the 10 percent level according to the F-test. In addition, we observe a credit card debt decrease among the older consumers. They start paying down their credit card debt from month 1 after the program announcement, and by the end of month 9, their cumulative credit card debt decrease is 16 cents for every dollar received (statistically significant at the 5 percent level).

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 the two groups: 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 the 5 percent level). Non-married consumers, on the other hand, do not reduce their credit card debt 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, though more so on credit cards (b_9 = 67 cents for credit cards vs. b_9 = 22 cents for debit cards). Indian Singaporeans, in comparison, 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. In addition, Indians save more on average. Compared to Chinese Singaporeans, whose credit card debt remains flat during the 10-month period, Indian Singaporeans reduce their credit card debt significantly (b_9 = -43 cents for every dollar received, significant at the 1 percent level).

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 the program announcement is strong for male consumers (b_9 = 26 cents for every dollar received, significant at the 1 percent level) but insignificant for female consumers (b_9 = 12 cents). Both groups respond strongly in credit card spending: b_9 = 74 cents for male consumers, and b_9 = 50 cents for female consumers, both significant at the 1 percent level). 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 the 5 percent level). Male consumers start to pay down debt upon receiving the money (month 2). Their cumulative credit card debt decrease is 11 cents per dollar received by month 9 and is statistically significant at the 10 percent level.

6.7. Liquidity vs. credit constraint

Due to data limitations, previous studies often use credit card capacity (i.e., credit constraints) to proxy for liquidity constraints.[12] In this section, we examine the differences in the spending and debt responses of liquidity constrained consumers (i.e., those with low checking account balances) and credit constrained consumers. We further classify consumers as both liquidity and

[12] The existing literature focuses on the credit card capacity as the main measure of credit constraints since it is arguably more exogenous than credit card balance and credit card utilization (balance divided by credit card limit) , which are measures based on (endogenous) spending choice of individuals (see Agarwal, Liu, and Souleles, 2007).

credit constrained if they have a low bank account balance and a low credit limit. Consumers are liquidity constrained but less credit constrained if they have a low bank account balance but a high credit limit. Consumers are liquidity unconstrained but credit constrained if they have a high bank account balance but a low credit limit. Lastly, consumers are neither liquidity nor credit constrained if they have both a high bank account balance and a 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 nonconstrained. They are equally strong, with cumulative responses of total spending equal to 120 cents per dollar received (statistically significant at the 1 percent level). On the other hand, the liquidity unconstrained group has a 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 (significant at the 10 percent level). This suggests that the spending response of credit constrained consumers is dominated by that of liquidity constrained consumers.

[Insert Figure 4 About here]

Figure 4 further shows the path of spending across the two financial instruments for these four subgroups. Within the liquidity constrained group of consumers, even though they spend similar amounts in total, the more credit constrained subgroup (low balance and low credit limit) spend relatively more via credit cards, whereas the less credit constrained subgroup (low balance and high credit limit) of consumers spend relatively more via 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 the 5 percent level), 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 who 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 the 5 percent level. The other three subgroups of consumers do not reduce their credit card debt.

6.8. Full Sample Analysis

We perform the main analysis in the previous sections on a smaller sample in which 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 the estimation in Equations (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 two thirds of the total spending increase is attributable to the spending increase via credit cards (30 cents per dollar received, column 3 of Table 6, Panel A), and less than one third is due to spending on debit cards (16 cents per dollar received, column 2 of Table 6, Panel A). Credit card debt experiences a statistically insignificant 3-cent 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 then 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.

6.9. Robustness checks

In this section, we perform and discuss a series of tests to study the robustness of our results. For brevity, we do not report the tables which are available upon request.

About 40% of the population of Singappore are foreigners. While a majority of them are from China, India, Malaysia, and Indonesia, there are quite a large proportion from Australia, Europe and Ameirca. It is possible that foreigners (as our control group) in general may differ from Singaporeans (our treatment group) in their consumption preferences and habits, which will confound our interpretation of the difference-in-difference analysis. We address the potential concern by restricting the control group to consumers with the following nationalities: Malaysia, China, India, and Indonesia. These foreigners either come from neighboring countries or have similar ethnic and cultural backgrounds as Singaporeans. As a result, they have a tighter bond with the country and likely share the same consumption preferences or/and habits as consumers in our treatment group. Using the smaller control group with these restricted foreigners, we repeat the difference-in-difference analysis and our results are both qualitatively and quantitatively very similar.

It is still possible that foreigners are different in unobservable ways, so we perform an additional robustness analysis by completely dropping the foreigners from the sample. Instead, we exploit the heterogeneity in the payout amount within the treated group and use the Singaporeans with the smallest amount of the Growth Dividend, i.e., those with an annual income greater than SGD 100,000, as the control group. We continue to find a very significant increase in the total spending after the dividend program.

In the main analysis, we dropped from our sample Singaporeans who also qualified 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 worth a total of US$452.4 million, which is one third of the size of the Growth Dividend Program. Because the tax rebate applies to all working residents in Singapore based entirely on income level, a foreigner is entitled to the same amount of tax rebate as another Singaporean with the same annual income in 2010. Because the control group and the treatment group in the matched sample have 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) targeted older Singaporeans (age $\geq$ 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. We verify our results in a separate analysis on a subsample of consumers younger than 45 years old who are entitled only to the Growth Dividend Program.

We further study whether the documented consumption response is due to the Growth Dividend program or attributable to general government subsidies that usually occur in the month of April. We compare the total spending difference between the treatment group and the control group in April of 2011 (our event year) with the difference in April of 2010.[13] We find that consumers in the treatment group spend significantly more than those in the control group in April of 2011, but their total spending is smaller than that of the same control group in April 2010 and the difference is statistically indistinguishable from zero. This result suggests that our findings on the consumption (and debt) response are unlikely to be explained by other government subsidies or an April effect.

We also perform falsification tests by carrying out the difference-in-differences analysis on the treatment and control groups using randomly picked dates for the stimulus program. Specifically, we choose June, 2011 (i.e., 4 months after the stimulus program) and October, 2010 (i.e., 4 months before the stimulus program), and study whether the treatment group's spending and debt change, relative to the control group, in the two month period after the chosen month compared to the previous two months. Our results show that there are no spending (and debt) responses after both (random) dates, which suggests that our estimates in the main analysis capture the response to the specific stimulus program announced in February, 2011.

[13] Ideally we want to perform a similar difference-in-difference analysis around April in other years. However, we only have two years of data which begins in April 2010 and hence our data does not allow such analysis.

Lastly, to address the possibility that the stimulus program coinsides with the timing of the annual bonus disbtribution and that Singaporeans (treatment) and foreigners (control) may receive different bonus amounts, we restrict our sample to non-salaried consumers who do not receive bonuses and our results remain robust.[14]

7. Conclusion

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

We find that consumption rose significantly after the fiscal policy announcement: for each dollar received, consumers on average spent 90 cents (aggregated across different financial accounts) during the ten months after the announcement. Consumers' credit card debt moderately decreased during this period (so savings effectively increased). We also identify a strong announcement effect: consumers started to increase spending during the two-month announcement period before the cash payout. We also find that consumption response is distributed across debit card (25 percent of the total response) and credit card (75 percent of the total response) spending. More importantly, consumers started spending via credit cards during the announcement period, then switched to debit cards after disbursement, before finally significantly increasing their credit card usage. Consistent with previous research, credit card debt dropped in the first months after disbursement and then reverted back to pre-announcement levels.

We also found other significant heterogeneity in the response to the fiscal stimulus across different types of consumers. Notably, spending rose most among consumers who were, according to various criteria, initially most likely to be liquidity constrained. Similarly, debt declined most (so savings rose most) among 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

[14] From the reported occupation, we identify consumers who are self-employed, housewives, retirees, non-workers, or students as non-salaried.

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' responses to "lumpy" increases via fiscal stimulus programs, working in part through balance sheet (liquidity) mechanisms.

Our main contribution in relation to prior literature is three-fold. First, we are the first to document the announcement effect of this stimulus program, which is of comparable magnitude of the consumption response after disbursement. It also provides new evidence consistent with theory predictions. Second, we document the dynamics of consumption response across different spending instruments—a rise in credit card spending following the program's announcement, then the switch to debit card spending after the disbursement of the stimulus, and finally the switch back to credit card spending in the later months. Finally, we are also the first to document that liquidity constraints dominate credit constraints in regard to the spending response to positive income shocks. Our paper can also help inform the design of fiscal policy. Our results suggest that the announcement of a fiscal stimulus program can cause a consumption response, even before the disbursement of the stimulus funds. Typically, policy makers announce fiscal programs over a long time horizon, dampening the announcement effect of the stimulus program. Finally, in the context of Singapore, our results provide support for the 2013 fiscal budget released by the Ministry of Finance in Singapore, which allocates future stimulus to liquidity constrained consumers.

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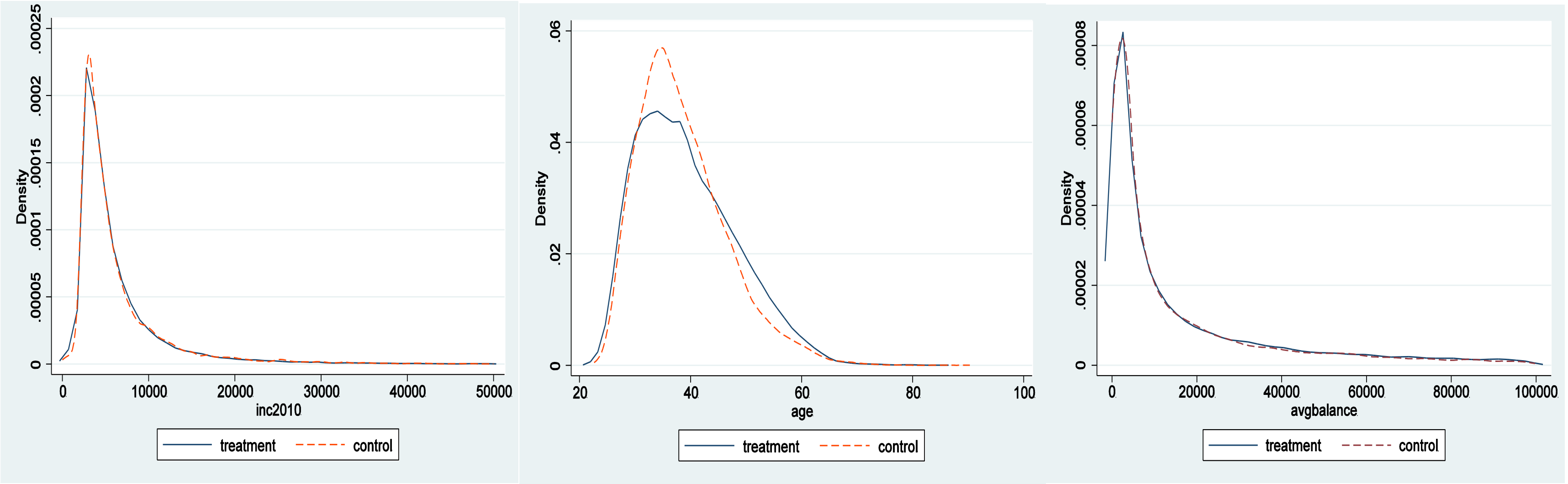
Figure 1: Summary Statistics of the Matched Sample

Figure 1a. shows the comparison of distributions of average monthly income in 2010, age, and average bank checking account balance during the period 2010:04–2010:07 between the treatment and control group, after the propensity score matching. Figure 1b. shows (logarithm of) the unconditional mean of total spending of the treatment and control group during the period of 2010:04 to 2012:03.

1a. Kernel Density Plots of the Matched Sample



1b. Unconditional Total (Log) Spending of the Matched Sample

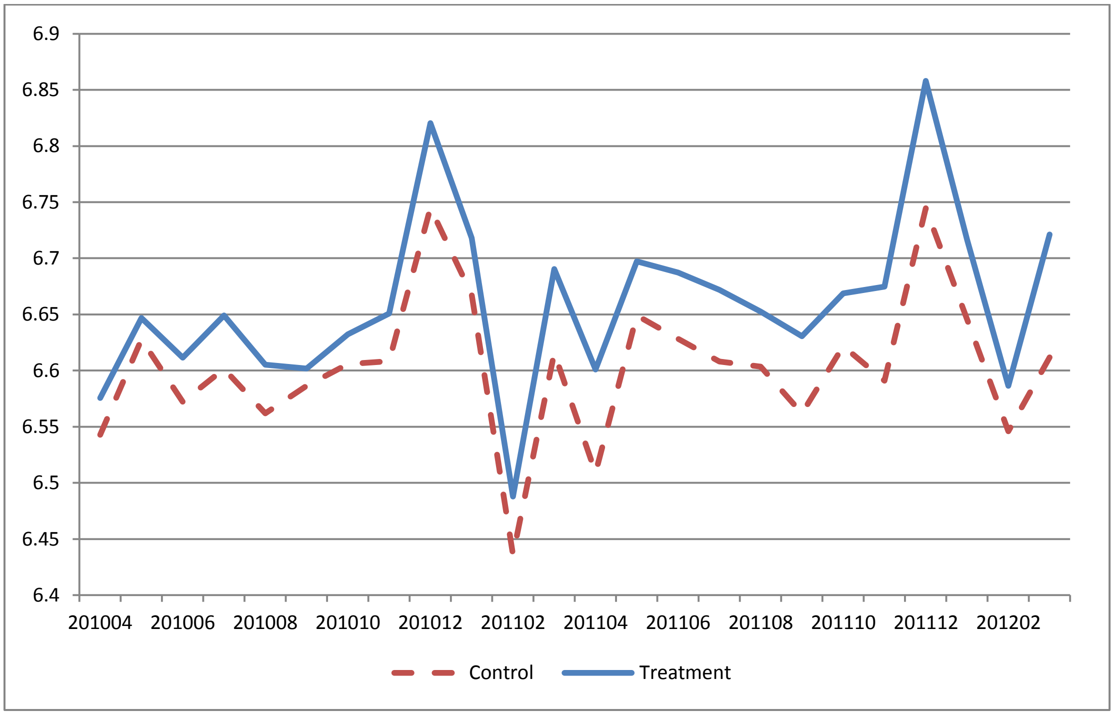


Figure 2: Estimated Spending and Debt Response Dynamics

This figure plots the entire paths of cumulative coefficients b_s, s = 0-9, along with their corresponding 95 percent confidence intervals, of debit card and 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).

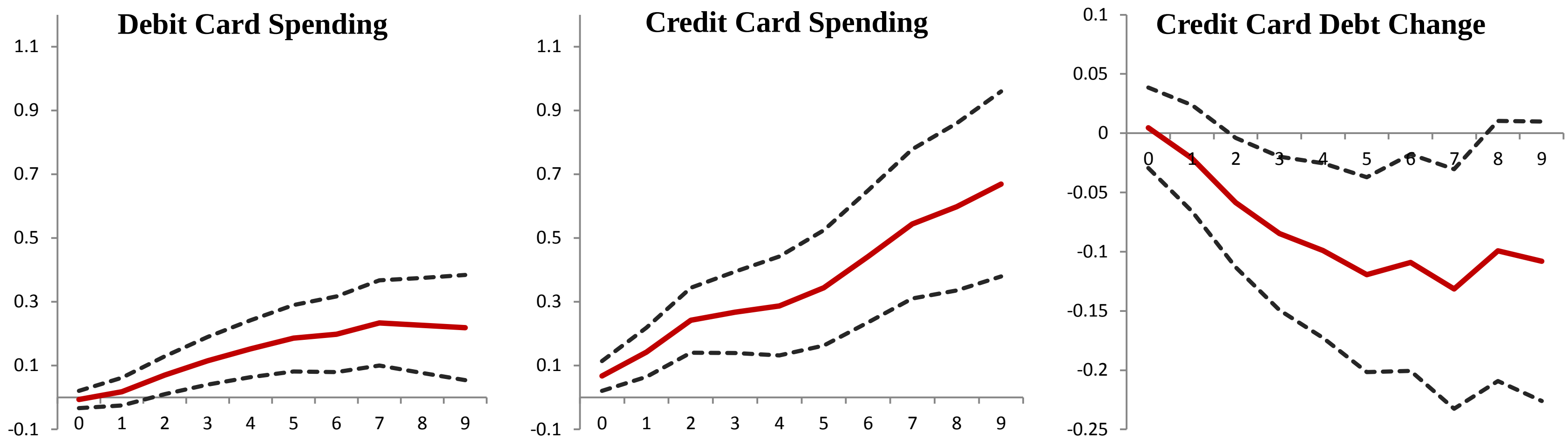


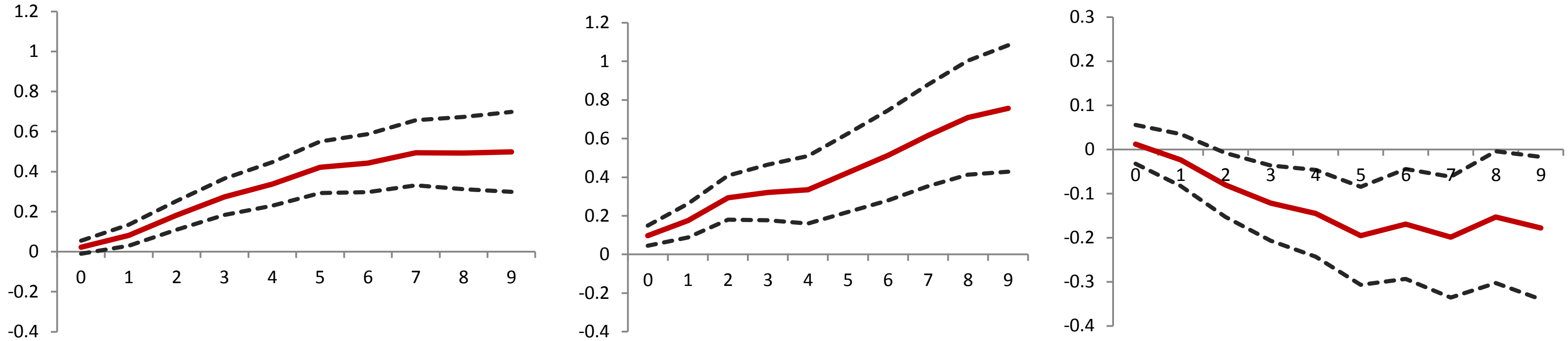
Figure 3: Heterogeneity in Spending and Debt Response across Consumers

This figure plots the entire paths of cumulative coefficients b_s, s = 0-9, along with their corresponding 95 percent 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 balances (i.e., average checking account balance between 2010:04 and 2010:07 <= SGD 1,840, or 25% of sample) with consumers with high bank checking account balances (i.e., average checking account balance between 2010:04 and 2010:07 >=SGD 22,346, or 75 percent of the sample). Panel B compares consumers with high credit card limit (i.e., max credit card limit between 2010:04 and 2010:07 >= SGD 9,000, or 75 percent of the sample) with consumers with low credit card limits (i.e., max credit card limit between 2010:04 and 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 percent of the sample) with high-income consumers (i.e., monthly income in the year before the Growth Dividend announcement >= SGD 6,360, or 75 of sample). Panel D compares younger consumers (age <= 32, or 25 percent of the sample) and older consumers (age >= 42, or 75 percent of the 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.

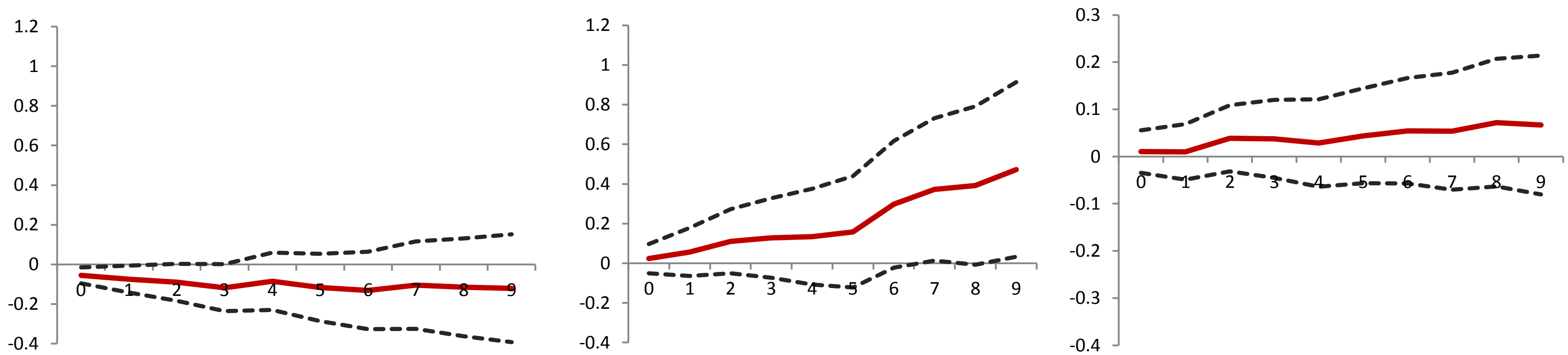
Panel A:

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

Low Bank Balance



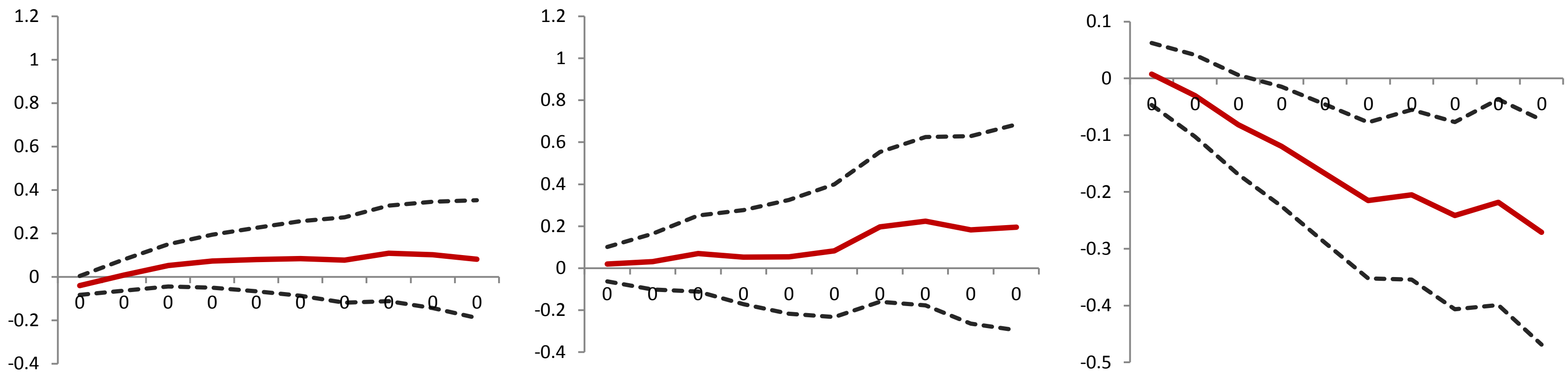
High Bank Balance



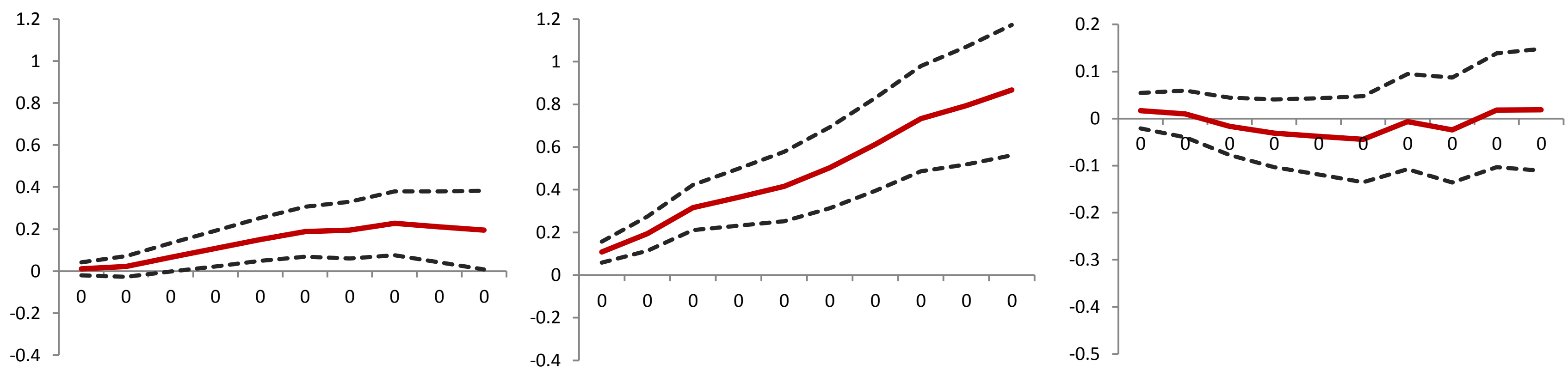
Panel B:

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

<u>High Credit Card Limit</u>



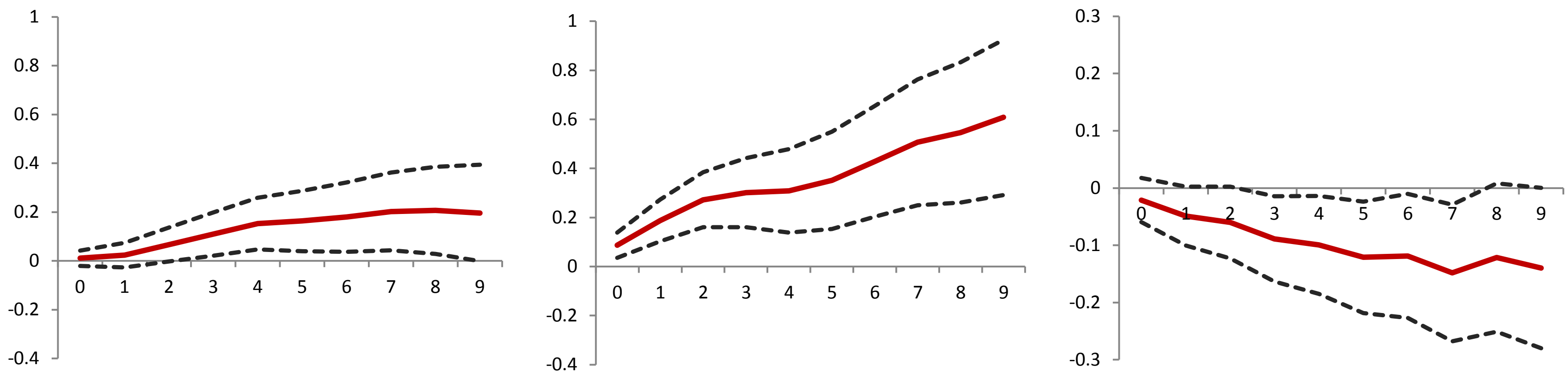
<u>Low Credit Card Limit</u>



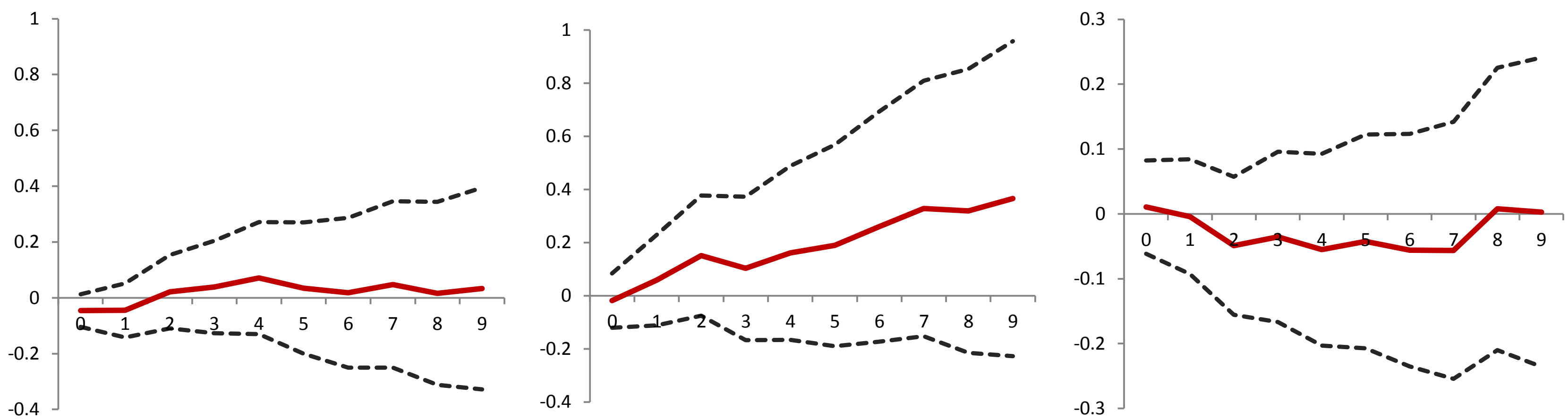
Panel C:

(a) (b) (c)

<u>Low Income</u>



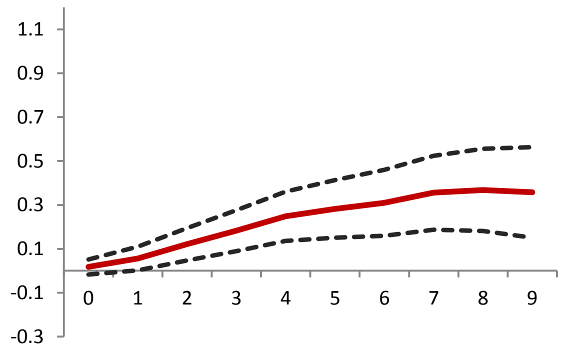
<u>High Income</u>

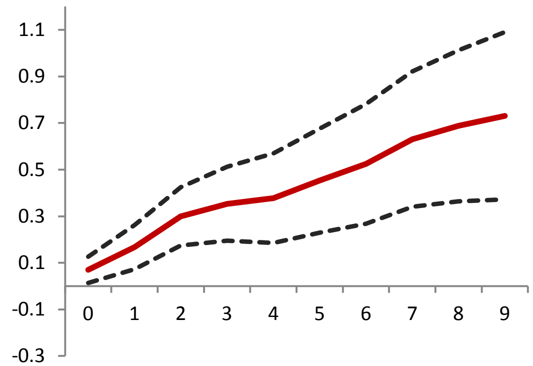


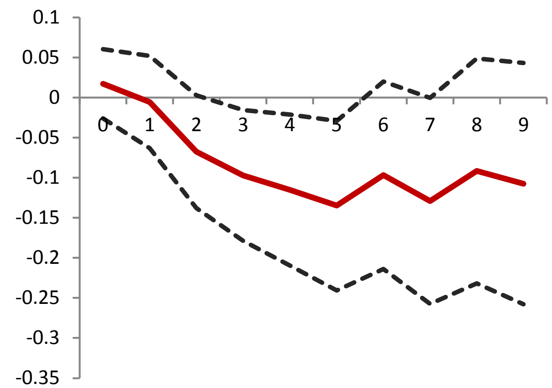
Panel D:

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

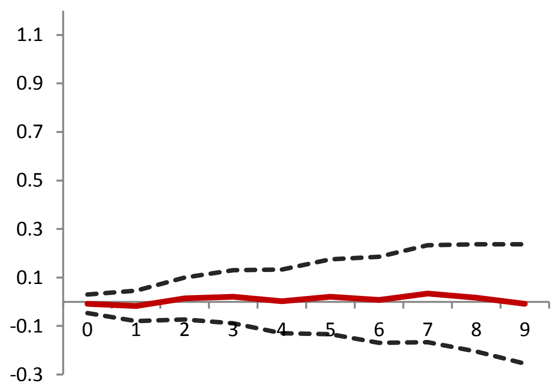
<u>Young</u>

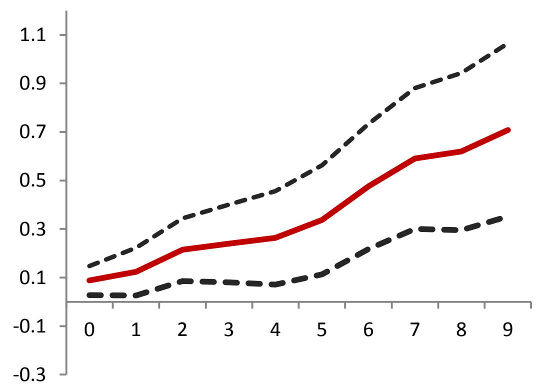


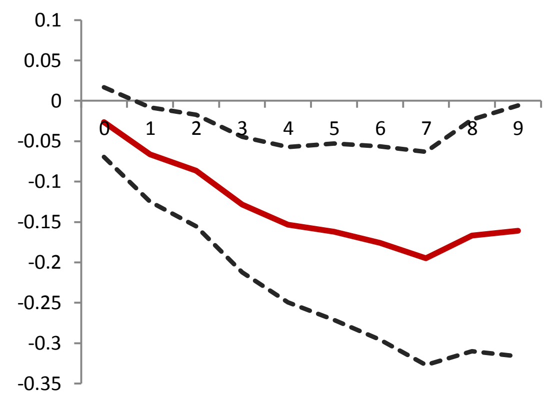




<u>Old</u>



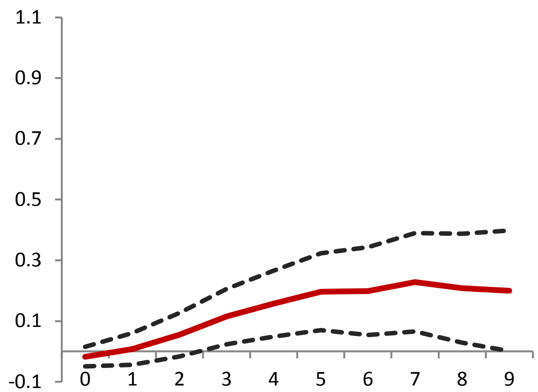


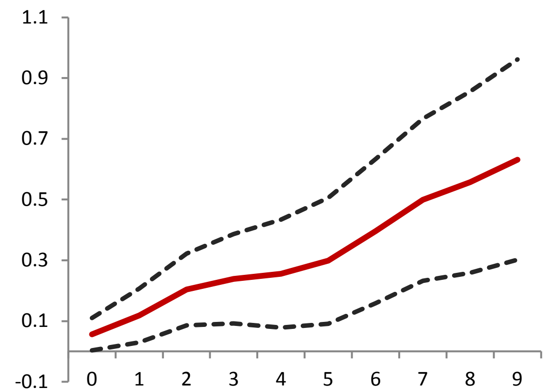


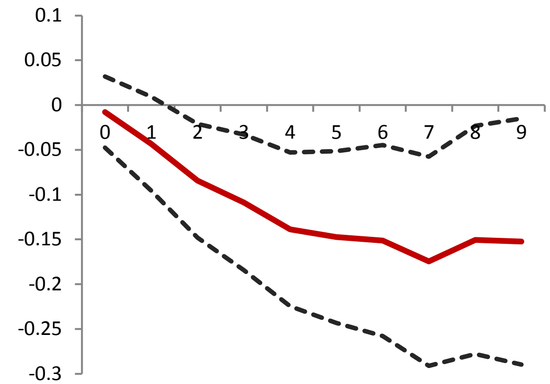
Panel E:

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

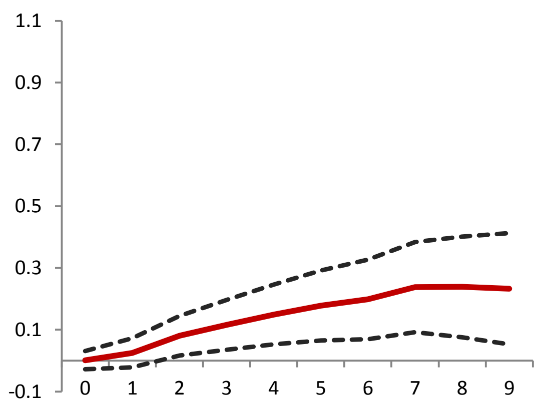
<u>Married</u>

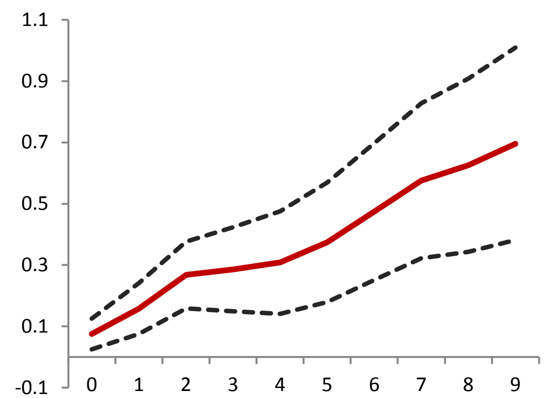


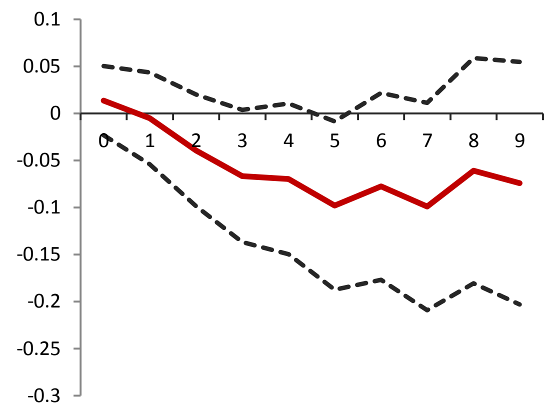




<u>Non-married</u>



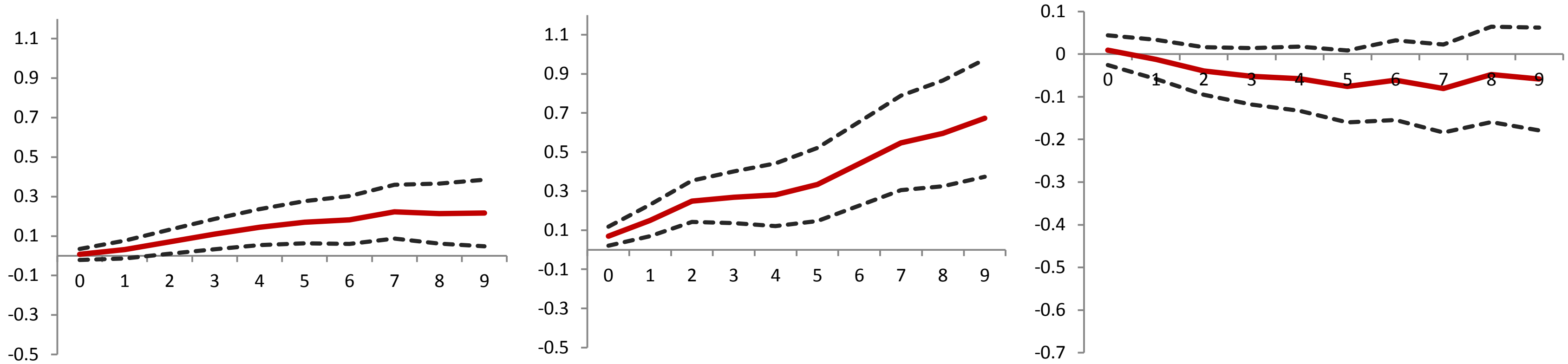




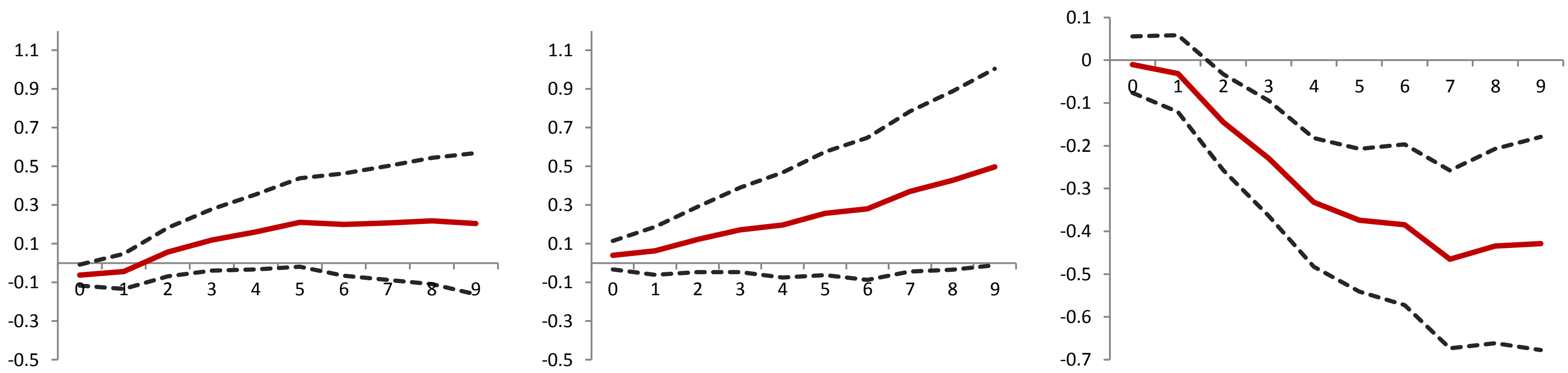
Panel F:

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

<u>Chinese</u>



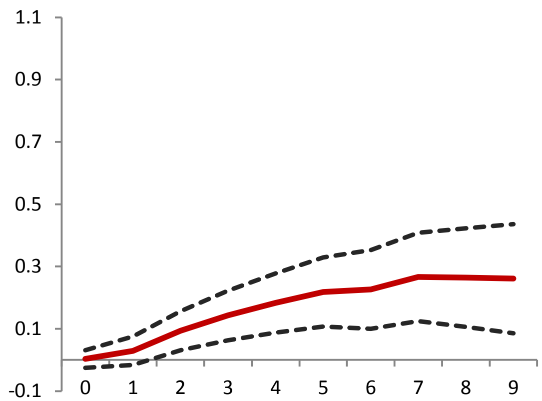
<u>Indian</u>

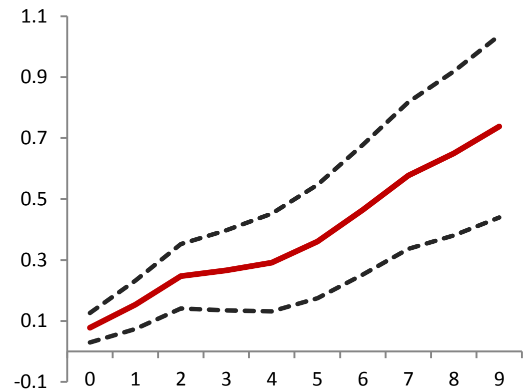


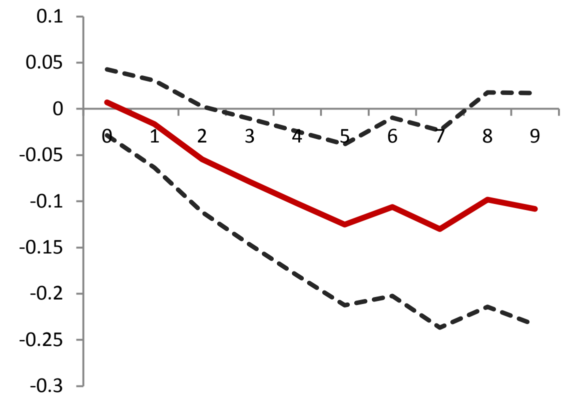
Panel G:

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

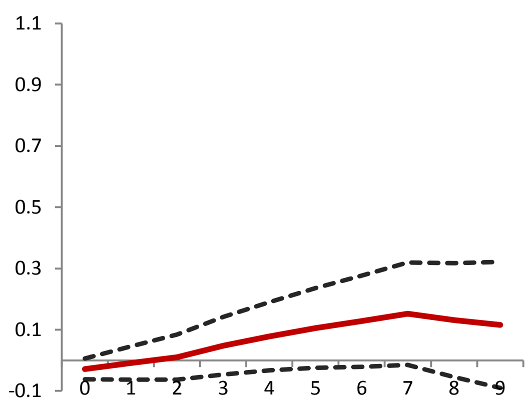
<u>Male</u>

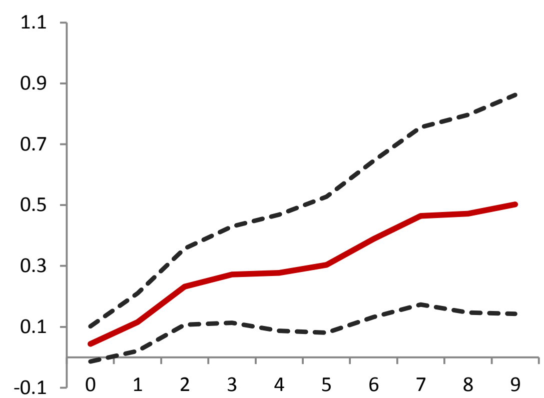






<u>Female</u>





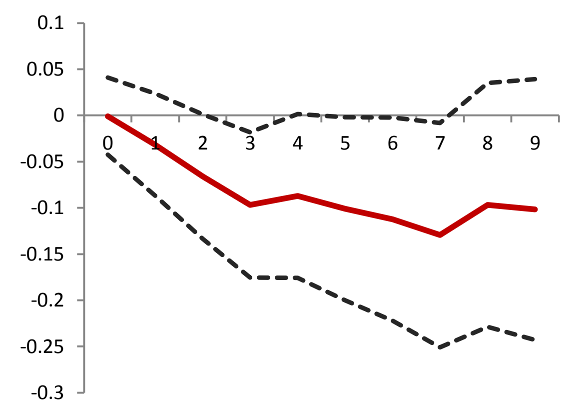
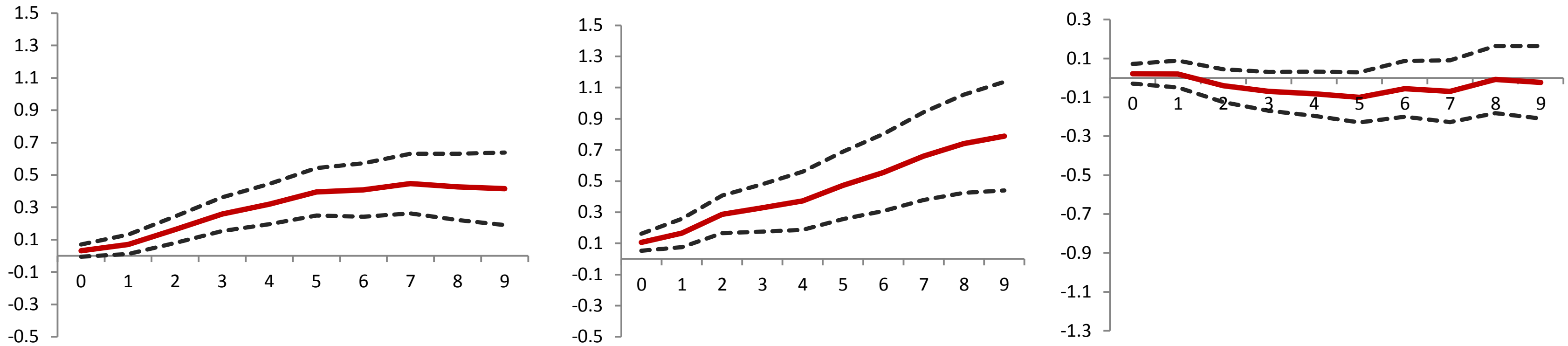


Figure 4: Liquidity Constraints vs. Credit Constraints

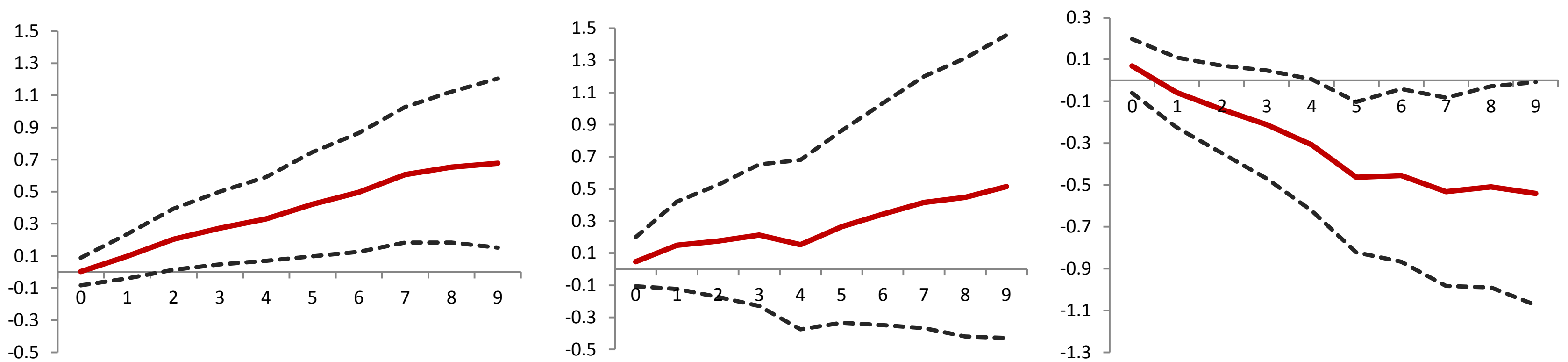
This figure plots the entire paths of cumulative coefficients b_s, s = 0-9, along with their corresponding 95 percent confidence intervals, of spending and debt response across the following four groups of consumers: low bank balance and high credit limit consumers, low bank balance and low credit limit consumers, high bank balance and high credit limit consumers, and high bank balance and low credit limit consumers. See 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>

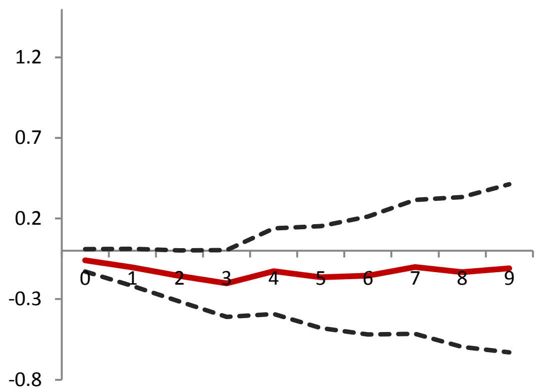


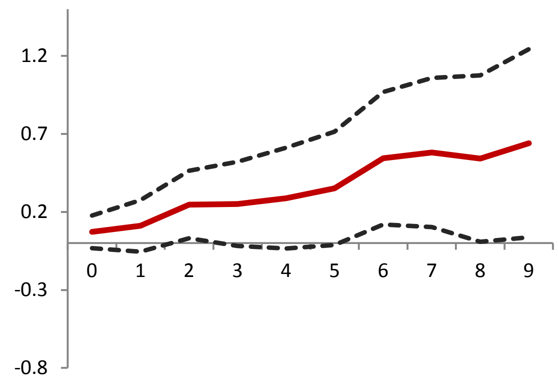
<u>Low Bank Balance and High Credit Limit</u>

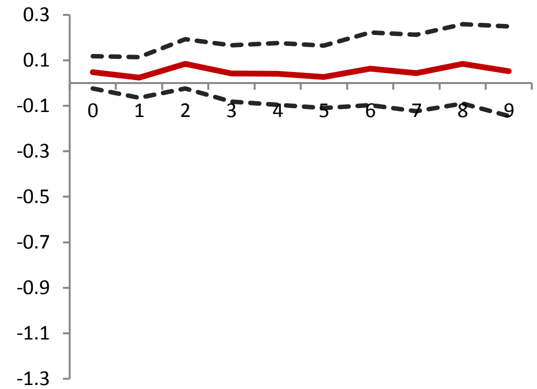


(a) **(b)** **(c)**

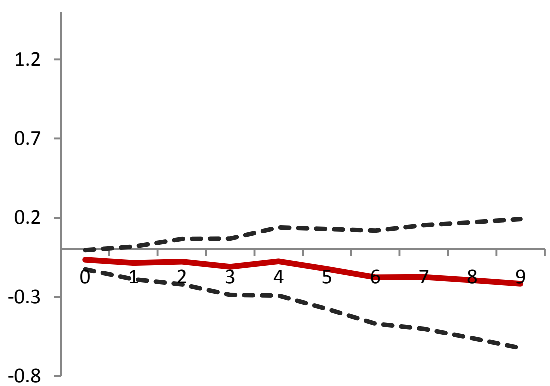
<u>High Bank Balance and Low Credit Limit</u>

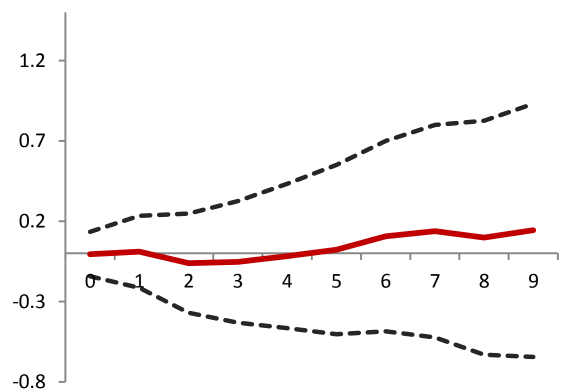






<u>High Bank Balance and High Credit Limit</u>





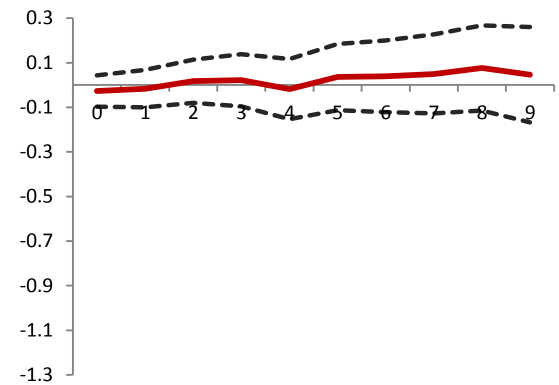


Table 1: Summary Statistics

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 other stimulus packages such as the 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 that had no transaction activity during the six-month period before the policy announcement. Panel A shows the comparison of demographics between the treatment and control groups, both before and after propensity score matching. Panel B shows the comparison of credit card and debit card spending, credit card debt, and bank checking account balance information between the treatment and control groups in the 24-month sample period (2010:04–2012:03), both before and after propensity score matching. *$benefit* is the Growth Dividend amount individuals received in the treatment group. *Credit card spending* is computed by adding monthly spending over all credit card accounts for each individual. *Credit card debt* is computed as the difference between the current month's credit card payment and the previous month's credit card balance. *Credit card cycle payment* is the payment to the most recent credit card statement. *Debit card spending* is computed by adding monthly spending over all debit card accounts for each individual. For the checking account, we compute *# debit transactions* as the aggregate number of debit (outflow) transactions for each individual every month. *# ATM debit transactions/# branch debit transactions/# online debit transactions* are the number of debit transactions at ATMs, in branches, or via online transactions, respectively. *Total card spending* is the sum of debit card spending and credit card spending for each individual in a month. All the dollar amounts are in the local currency (SG$), and 1SGD = 0.78 USD as of February 2011.

Panel A: Demographics of Treatment and Control Group

	(1) Mean	(2) Std.	(3) Mean	(4) Std.	(5)
	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 Groups

	(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 the Stimulus Program

This table shows the average spending and debt response (Equations (1) and (2)) of the matched sample in the period from 2010:08 to 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 the 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 the months during the announcement window (2011:02–2011:03), and $1_{disburse}$ is a binary variable equal to one for the 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.

Panel A	(1) **Total card spending**	(2) **Debit card spending**	(3) **Credit card spending**	(4) **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 during 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) **# of debit transactions**	(2) **# of ATM transactions**	(3) **# of online transactions**	(4) **# 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: Selected Categories of Spending

This table shows the average spending response (Equations (1) and (2)) by spending categories for 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 Tables 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) Supermarket	(2) Dining	(3) Entertainment	(4) Transportation	(5) Apparel	(6) 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 *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 Tables 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) **Total card spending**	(2) **Debit card spending**	(3) **Credit card spending**	(4) **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 (Equations (1) and (2)) for 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 government subsidized housing (HDB). Singaporeans living in HDB can have different Growth Dividends, especially among the lower income individuals. For our purposes, 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 a Growth Dividend of SG$700. The exchange rate in February 2011 was 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 results 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 other stimulus packages such as the 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 were dormant or closed or that had had no transaction activity during the six-month 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 parentheses below the coefficient estimates, and ***, **, * represent statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) **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