Consumption and Debt Response to Unanticipated Income Shocks: Evidence from a Natural Experiment in Singapore

Sumit Agarwal and Wenlan Qian

National University of Singapore

Online Appendix
(Not Intended for Publication)

1. Additional Heterogeneity Analyses

1.1. Heterogeneity response across spending categories in the matched sample

In our data, merchant type descriptions are provided in the debit and credit card transactions, from which we group them into the following eight categories: supermarket, service, dining, entertainment, apparel, travel, small durable goods, and online.[1] We decompose the total monthly card spending for each individual in those eight categories. Table A4 shows the estimation results of the average spending response by spending category. As in Tables 2 and 3 in the main text, we use the dollar amount of spending as the dependent variable in Table A4, so the coefficient captures the spending response in dollars for every dividend dollar received. Since we have shown that there is no pre-treatment effect in Table 2 and 3, we absorb the pre-treatment variable ($\$D_i \times 1_{pre}$) in the heterogeneity analysis for the purpose of easier interpretation. In Table A4, the coefficient on $\$D_i \times 1_{post}$ measures the total card spending response, for each dollar received and in each spending category, of the Singaporeans in the post-announcement period compared to the entire six month pre-announcement period.

[Insert Table A4 About Here]

Discretionary spending categories, such as apparel and travel, responded strongly to the stimulus program. For each dollar of the Growth Dividend received, consumers spent 2.0 (1.6) cents per month, or 20 (16) cents in total in our 10-month post-announcement sample period, on travel (apparel) purchases. Consistent with the existing literature (Parker et al., 2013), consumption also responded significantly in the small durable goods category. Although consumers are unlikely to increase car or housing consumption after the Growth Dividend program, they increased spending in the less costly durable goods such as electronics, computers, home or office furnishings and appliances. For each dollar received, consumers spent 1.2 cents per month on small durable categories, which is economically large and statistically significant. Consumers increased their spending in other categories such as supermarket, dining, entertainment, and transportation, but the economic and statistical effect is weaker.

1.2. Heterogeneous response across consumers in the matched sample

In addition to the analysis in section 5.1, we perform additional regressions, in the matched sample, based on consumers' income and demographics information. We plot the cumulative response coefficients (starting from month 0, or the announcement month) during the 10 month period upon announcement (Figure A1).

[Insert Figure A1 about here]

[1] A small portion of transactions remain unclassified by the bank, which we label them as "Unclassified" which are also reported in Table 4 (column 9).

A. Income: low vs. high

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 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 A shows that low-income consumers reacted strongly to the stimulus program in spending. For low-income consumers, the cumulative coefficient by month 9 is 20 cents per dollar received (p value=0.049) for debit card spending, and is 57 cents per dollar received (p value < 0.001) for credit card spending. For high-income consumers, the cumulative coefficient for debit card spending is statistically insignificant, but the 10-month cumulative increase for credit card spending is 70 cents and is significant (p value = 0.014). The F-test shows that the cumulative total spending response is higher for the low-income consumers but the difference is not statistically significant (p value=0.916). The weaker result for the low-income consumers may be due to income being a noisier measure of liquidity constraint.

B. Young vs. Old

We compare the spending and debt response pattern for younger (2010 age ≤ 25th percentile = 32) and older consumers (2010 age ≥ 75th percentile = 42) in Panel B. Younger consumers had positive and significant cumulative spending responses: b_9 = 36 cents for every dollar received for debit card spending, and b_9 = 70 cents for credit card spending. Older consumers did not increase their debit card spending, but their cumulative credit card spending increase is significant: b_9 = 69 cents per dollar received, which is significant at the 1 percent level. The overall spending response of the young is larger—31 cents per dollar received—but is not statistically significant (p value = 0.166). In addition, we observe a credit card debt decrease among the older consumers. They started 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 (p value = 0.050).

C. Married vs. Non-married

We compare the spending and debt response pattern for married and non-married consumers in Panel C. 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 (p value = 0.510). Married consumers paid down their credit card debt upon receiving the stimulus money (month 2), and the cumulative credit card debt change is b_9 = -14 cents for every dollar received (p value = 0.040). Non-married consumers, on the other hand, did not reduce their credit card debt during the 10-month period.

D. Ethnicity: Chinese vs. Indian

Chinese, Malay, and Indian are three major ethnic groups in Singapore, and we compare the differences in spending and debt response between Chinese Singaporeans and Indian Singaporeans in Panel D. (Malays are dropped from the analysis due to their small sample size in our data.) Chinese Singaporeans significantly increased their spending on both types of cards, though more so on credit cards (b_9 = 59 cents for credit cards vs. b_9 = 22 cents for debit cards). A similar pattern holds for Indian Singaporeans, and 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 (p value = 0.919). In addition, Indians saved more on average. Compared to Chinese Singaporeans, whose credit card debt remained flat during the 10-month period, Indian Singaporeans reduced their credit card debt significantly (b_9 = -42 cents for every dollar received, with p value = 0.001).

Our analysis uncovers a new finding on the heterogeneous response along the ethnicity gradient (Panel D, Figure A1). For example, Indian Singaporeans decreased significantly their credit card debt in the 10-month post-announcement period, whereas Chinese Singaporeans did not. We further study whether the difference can be explained by socioeconomic factors: Indians in Singapore could be economically less advantaged and are thus more likely to pay down their debt in the presence of higher precautionary saving motive. To proceed, we create subsamples of consumers based on wealth indicators such as credit card limit, bank balance and income. Then we run regressions within each subgroup of consumers (e.g., high credit card limit vs. low credit card limit consumers) and interact the key variable of interest $\$D_i \times 1_{post}$ with Indian ethnicity dummy variable. Results in Table A5 suggest that conditional on the level of credit card limit (or bank account balance or income), Indian Singaporeans decreased their debt significantly more than Chinese Singaporeans. In particular, in the same subpopulation for which precautionary saving motive is similarly strong (i.e., low income, low bank balance, or low credit card limit), Indian Singaporeans reduced their credit card debt significantly more than Chinese Singaporeans. These results suggest that economic differences between the ethnic groups are unlikely the answer to explain the significant difference in their debt behavior after the income shock. Given that Indian Singaporeans are a minority of the Singaporean population (less than 10 percent of the citizen population, while Chinese constitute 74 percent and Malay constitute 13 percent of the citizen population), it is plausible that their saving behavior is related to their minority status in the population (e.g., lack of trust in the government (Puri and Iyer (2012)). Another possibility is, as the referee pointed out, that the results could be less accurate given their sample size.

[Insert Table A5 about here]

<u>E. Male vs. Female</u>

Lastly, we compare the gender differences in spending and debt response to the stimulus program (Panel E). The cumulative increase in debit card spending 10 months after the program announcement is strong for male consumers (b_9 = 26 cents for every dollar received with a p

value = 0.004) but is insignificant for female consumers (b_9 = 12 cents with a p value = 0.270). Both groups responded strongly in credit card spending: b_9 = 67 cents for male consumers (p value < 0.001), and b_9 = 43 cents for female consumers (p value = 0.014). Overall, the F-test of the cumulative coefficients of total spending suggests that male consumers have a stronger response in total spending (by 39 cents per dollar received, with a p value = 0.018). Both male and female consumers started to pay down debt upon receiving the money (month 2), but their 10-month cumulative credit card debt decreases are statistically insignificant.

1.3. Identifying the effect of precautionary saving motives

The comparison between low bank balance and high bank balance consumers (Section 5.1 in the paper) shows that low bank balance consumers, likely those with low liquid assets and are constrained, responded strongly in consumption. High balance consumers, on the other hand, did not seem to react to the stimulus program. In this section, we investigate further into high balance consumers as they are likely individuals with precautionary saving motives. According to buffer stock models, consumers who face income uncertainty and incomplete insurance (or credit) markets choose to delay consumption and save to prepare for negative income shocks in the future. Upon an unanticipated income increase, these consumers should respond by increasing their spending because the (unanticipated) positive income shock reduces their income uncertainty. Given the unanticipated nature of our policy experiment, it would be interesting to identify consumers with precautionary saving motive and study their consumption response. High balance is suggestive of the presence of precautionary saving motive, but the measure may also reflect other offsetting factors (such as large wealth). Therefore, we study, within the high balance subsample, consumers that have a low spending history during the out-of-sample months (i.e., 2010:04-2010:07). These consumers are more likely to have precautionary saving motive since they have high savings but low usage of their credit card limit. Similarly as before, we plot the cumulative response coefficients (starting from month 0, or the announcement month) during the 10 month period upon announcement (Figure A2).

[Insert Figure A2 about here]

First, consistent with predictions of buffer stock models, there is a strong consumption response (and no credit card debt response) among these high balance and low credit usage consumers during the 10 month period upon announcement. The 10-month cumulative total card spending response is 106 cents for each dollar received (p value < 0.001). Second, there is a strong announcement effect: during the two announcement months, the cumulative card spending increased by 23 cents (p value = 0.002). This lends strong support to the precautionary saving model, which predicts an immediate response as income uncertainty decreases upon the surprise announcement of the unanticipated stimulus program. The evidence also implies that the market is less than complete to the extent that precautionary savers cannot smooth out the transitory (unanticipated) income shock, which is consistent with our other findings that in general liquidity constraints matter for consumption response in our data. Lastly, the strong consumption response concentrates in credit card spending, which is an inexpensive consumption smoothing mechanism for these consumers that have high savings and presumably no or low credit card debt (given their very low credit card usage).

1.4. Bank balance vs. credit card limit

Due to data limitations, previous studies often use credit card limit to proxy for financial constraints.[2] Our data identifies various proxies that allow a better understanding of constraints (e.g., bank account balance, credit limit, and income level). In this and the next sub-section, we examine the differences in the spending and debt responses of consumers using different constraints proxies. First, we study consumers with low checking account balances and consumers with low credit card limit. To increase power of the test, we use the tercile cutoffs (based on the average bank balance or credit card limit in the four out-of-sample months, 2010:04-2010:07) instead of the quartile thresholds as in section 5.1. We classify consumers into four groups using the top and bottom terciles of their level of liquid assets and credit access. We plot the cumulative response in debit card spending, credit card spending, and credit card debt change (starting from month 0, or the announcement month) for the four subgroups of consumers in Figure A3.

[Insert Figure A3 About here]

Overall, low bank account balance consumers had a stronger spending response than the low credit card limit consumers. The total card spending response is statistically the same within the low bank balance category, whether consumers have low or high credit limits. They are equally strong, with the cumulative response of total spending equal to 105 cents per dollar received for consumers with low bank balance and low credit limit, and 136 cents per dollar received for consumers with low bank balance and high credit limit. Both effects are statistically significant at the 1 percent and are not different from each other *(p* value = 0.398 for the F-test).

On the other hand, the high bank account balance group had a statistically insignificant cumulative response in total card spending, whether consumers have easy access to credit or not. F-tests suggest that consumers in either subgroup within the low bank balance category had a greater cumulative response in total spending than either subgroup within the high bank balance category. In particular, low bank balance and high credit limit consumers experienced a stronger cumulative response in total card spending than high bank balance and low credit limit consumers (*p* value = 0.059).

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

Lastly, the credit card debt decrease is stronger among low bank balance consumers who have high credit limit consumers. The cumulative credit card debt decrease by month 9 is 46 cents for each dollar received (p value = 0.009). The other three subgroups of consumers did not reduce their credit card debt. Collectively, these results suggest that constraints in liquid assets such as measured by the bank account balance add incremental value in understanding liquidity constraints and its role in consumers' response to income shocks.

1.5. Income level vs. credit access

In this subsection, we further investigate the relationship between different indicators of constraints. Previously we find that low income consumers had a (weakly) stronger spending response than high income consumers. In addition, low income consumers tended to reduce debt. In a similar spirit as in section 1.4 in the Appendix, we perform the subsample analysis by dividing consumers into four groups using the top and bottom terciles of income level and credit card limit. We plot the cumulative response in debit card spending, credit card spending, and credit card debt change (starting from month 0, or the announcement month) for the four subgroups of consumers in Figure A4.

[Insert Figure A4 about here]

Low income consumers responded to the stimulus in spending, especially those with a lower level of credit limit. At the same time, high income consumers with low credit limit also responded strongly to the policy. Interestingly, the subsample of low income consumers with high credit card limit decreased their credit card debt, consistent with the interpretation that these (credit) constrained consumers used the stimulus money to pay off their debt.

1.6. Heterogeneity analysis in the full, unmatched sample

We further perform external validity tests for the heterogeneity analysis. Specifically, we replicate the estimation in section 5.1 in the main text and section 1.2 in Appendix on the full, unmatched sample. Similar as in section 4.5 in the main text, we perform the weighted regression by using the estimated propensity scores as the regression weights. We plot the cumulative responses for debit card spending, credit card spending, and credit card debt change (starting from month 0, or the announcement month) in Figure A5. The results are qualitatively very similar.

[Insert Figure A5 about here]

2. Robustness Checks

2.1. Foreigners as the control group

About 40 percent of the population of Singapore is foreigners. While a majority of them are from China, India, Malaysia, and Indonesia, there are quite a large proportion from Australia, Europe and America. 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. Even though there are no pre-treatment differences in spending and credit card debt between the matched Singaporeans and foreigners, we perform an additional test. We completely drop 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. A better identification would be to use regression discontinuity approach to compare Singaporeans just above and below the eligibility threshold. However, we note that the treatment status is imperfectly observed in our data (especially around the different payout thresholds), since we cannot pin down their assessed property value needed to precisely identify the benefit amount. As a result, regression discontinuity approach cannot be applied. Instead, we continue to use diff-in-diff analysis by assigning Singaporeans with income < 100K as the treated (as they receive more benefits) and Singaporeans with income > 100K as the control. By construction, the treatment and control groups are unbalanced: they are differentiated by income which is an important determinant of spending. As a result, the pre-treatment-period comparison is not very informative. Moreover, since the research design is validated in both the matched (Table 2 or Figure 2 Panel A) and full sample analysis (Figure 2 Panel B), we decide to plot the dynamics of the spending and debt response starting from the treatment months which shows consistent post-treatment response pattern (Figure A6).

[Insert Figure A6 about here]

We also address the concern regarding inherent differences between Singaporeans and foreigners in an alternative test. Specifically, we restrict 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 of these restricted foreigners, we repeat the difference-in-differences analysis (still using the matched sample) and our results are both qualitatively and quantitatively very similar (Panel A, Table A6). [3]

[Insert Table A6 about here]

2.2. Concurrent government programs

[3] For easier interpretation, we omit the pre-treatment variable in robustness tests in Table A6 and regress spending and credit card debt change variables on $\$D_i \times 1_{post}$ (but our results are otherwise qualitatively the same).

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 responses to the tax rebate are differenced out in our estimation, and our coefficients measure the incremental response beyond the tax rebate program.

The only other economically significant package (US$393.1 million) 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 therefore 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 (Panel B, Table A6). To further address the possibility that the Singapore government gives additional benefits to women (e.g., subsidy for raising children), we replicate our analysis in the men-only subsample. Results in Table A6 Panel C show a strong spending response (with similar response mechanism) among men. We also note that heterogeneity results in Figure A1 Panel E indicate that men have a stronger spending response than women, further alleviating this concern.

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.[4] In unreported results, we find that consumers in the treatment group spent 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.

2.3. Other confounding treatments: bonus season

The stimulus program may coincide with the timing of the annual bonus distribution, and Singaporeans (treatment) and foreigners (control) may receive different bonus amounts. From the reported occupation fields in the data, we identify consumers who are self-employed, housewives, retirees, non-workers, or students as non-salaried. We restrict our sample to non-

[4] 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.

salaried consumers who did not receive bonuses and our results remain robust (Panel D, Table A6).

3. Alternative Specification Checks

Our inference is based on panel difference-in-differences regressions (with standard errors clustered at the individual level) on a matched sample, since we can combine accuracy from the matched sample approach and efficiency from the regression approach (Imbens, 2004). In addition, by exploiting the panel feature of the data, we are able to gain insight on the dynamic response which is of great interest to the literature. In this section, we discuss two potential statistical inference concerns regarding our specification.

Bertrand, Duflo, and Mullainathan (2004) discuss the consistency issues of standard errors in the difference-in-differences estimates due to serially correlated outcome variables. To investigate the robustness of our inference, we follow Bertrand Duflo, and Mullainathan (2004) and collapse the time series information, for each individual, into a "pre-announcement" and a "post-announcement" period (by taking the average of the outcome variables in the pre- and post-period). Then we regress, in the cross-section of consumers, the difference in outcome variables (i.e., spending or credit card debt change) between the pre- and the post- period on a dummy variable for the treatment group indicator multiplied by the amount of the stimulus. We have performed this exercise both on the matched sample (Panel A, Table A7) and on the full, unmatched sample (Panel B, Table A7). Both tests produce very similar results as in the original panel setting.[5]

[Insert Table A7 about here]

Our main analysis is carried out on the matched sample based on the nearest neighbour propensity score matching, and the recent literature shows that standard errors for (nearest-neighbor) matching estimators are inconsistent (Abadie and Imbens, 2006). First we have replicated the analysis using the full, unmatched sample, with very similar results (Figure 2 Panel B). To further alleviate the concern, we use the correction procedure proposed by Abadie and Imbens (2006). Similar as before, we collapse the panel into one cross section and use the difference in outcome variables (i.e., spending or credit card debt change) between the pre- and the post- period as the dependent variables.[6] Following the literature on non-parametric matching estimators, we estimate the treatment effect based on the binary treatment status (instead of MPC

[5] Due to the cross-sectional nature of these additional specification tests in Table A7, we do not decompose total spending response into debit vs. credit card response, which are primarily informative on the dynamics of the response.

[6] The correction procedure outlined in Abadie and Imbens (2006) applies to the cross-section, and to the best of our knowledge no standard adjustment exists for matched panels such as ours. As a result, we apply the correction procedure on the cross-section of matched sample.

as in the panel diff-in-diff regressions). We study three different specifications of the matching estimators: nearest neighbour (N=1), radius (with caliper = 0.01), and the bias-corrected and heteroscedasticity-consistent nearest neighbour (as proposed by Abadie and Imbens (2006)). Results in Panel C-E of Table A7 show that Singaporeans (the treatment group) respond strongly to the stimulus program with a monthly spending increase of around S$26 relative to the foreigners. In particular, differences in t-statistics between the uncorrected (Panel C) and corrected (Panel E) matching estimators are very small, which further suggest that our main findings are unlikely contaminated by the (im)precision in estimating standard errors in the matched sample.

4. 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 have an increase in credit limit, they find that debt levels rise by as much as $350. Their results are consistent with models of liquidity constraint and buffer-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 micro level data. First, it is difficult to analyze infrequent events like tax cuts using time-series data.[7] 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 credit constraints.[8]

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, Liu, and Souleles (2007). According to Shapiro and Slemrod (2003a), only 21.8 percent of their survey respondents reported they would mostly spend their rebate, consistent with an average MPC of about one

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[7] 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.”

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

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 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, Parker, and Souleles (2006) find that consumers spent only about a third of the rebate initially, within a quarter. But they also find evidence of a substantial lagged consumption response in the next two quarters. The consumption response is greatest among illiquid households, which is indicative of liquidity constraints. Agarwal, Liu, and Souleles (2007) find that consumers initially saved much of the rebates, on average, by increasing their credit card payments and thereby paying down debt. But soon afterwards, spending temporarily increased, offsetting the initial extra payments, so that debt eventually rose back near its original level. For people whose most-used credit card account is 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)). More recent papers look study the consumption response to the recent financial crisis (Baker (2014)).

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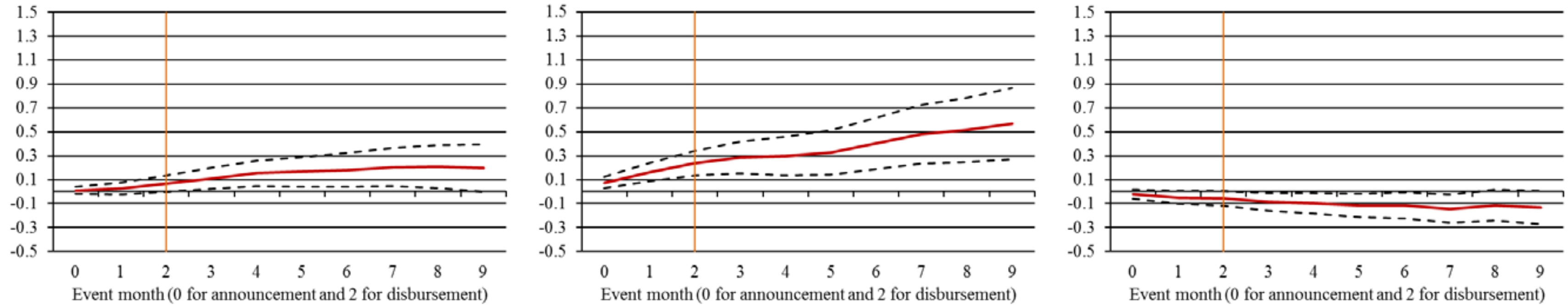
Figure A1: Further Results on Heterogeneity in Spending and Debt Response across Consumers

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. The sample includes the matched treatment and control groups during the period of 2010:08 – 2011:11. 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. Panel A 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 6,369, or 75 of sample). Panel B compares younger consumers (age <= 32, or 25 percent of the sample) and older consumers (age >= 42, or 75 percent of the sample). Panel C compares married and non-married consumers. Panel D compares different ethnicities within the treated consumers (Chinese vs. Indian). Panel E compares male and female consumers. The x-axis denotes the *s*th month after the announcement of the Growth Dividend Program, and the y-axis shows the dollar response (for every dollar received).

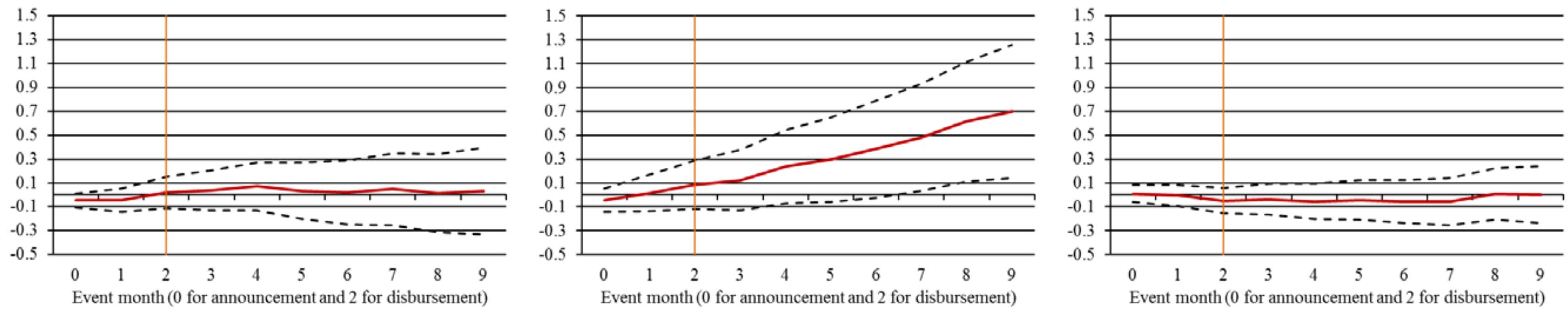
Panel A:

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

<u>Low income</u>



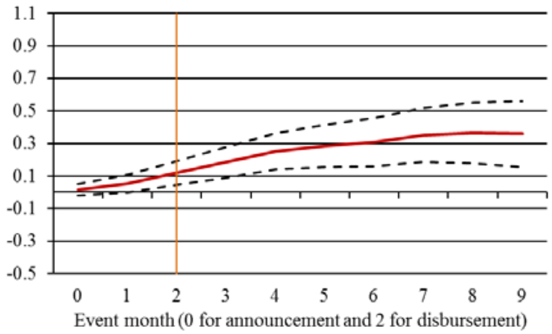
<u>High income</u>

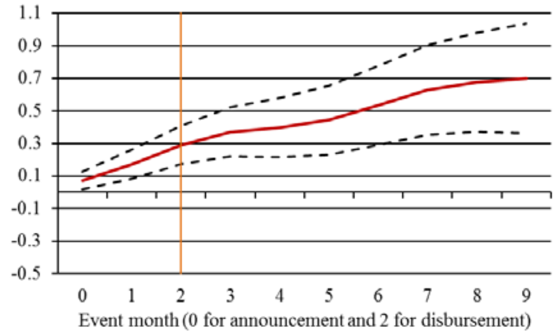


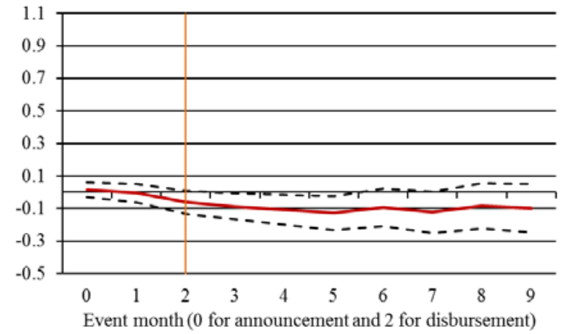
Panel B:

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

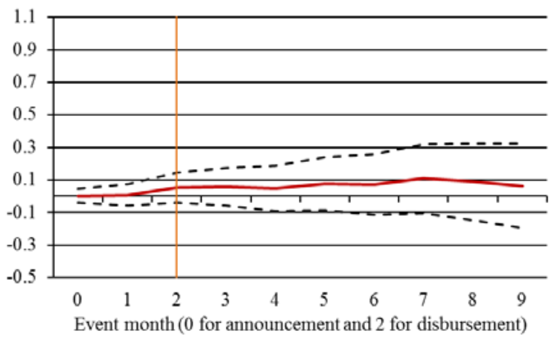
Young

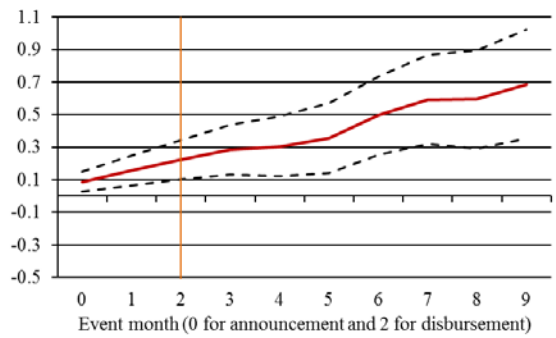


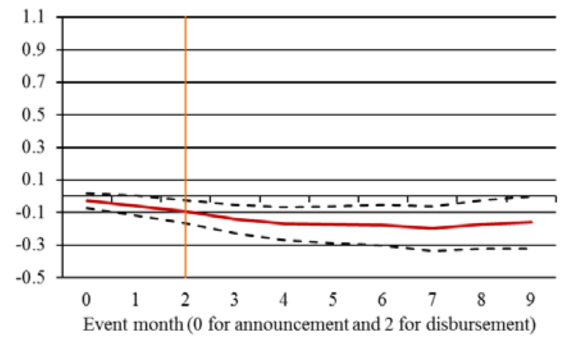




Old



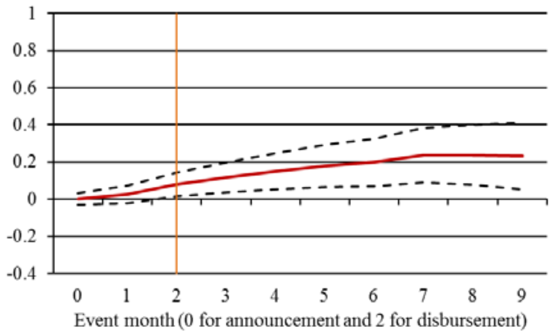


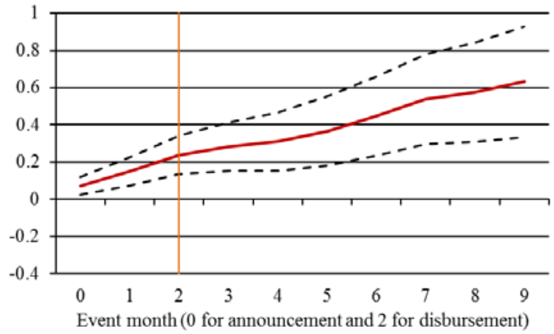


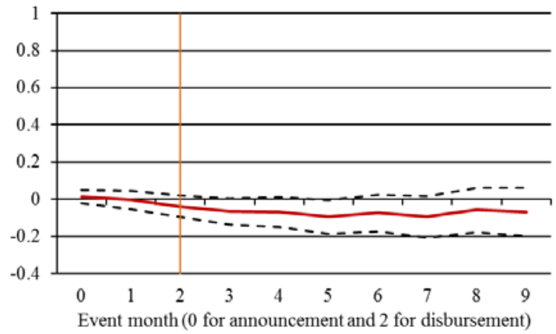
Panel C:

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

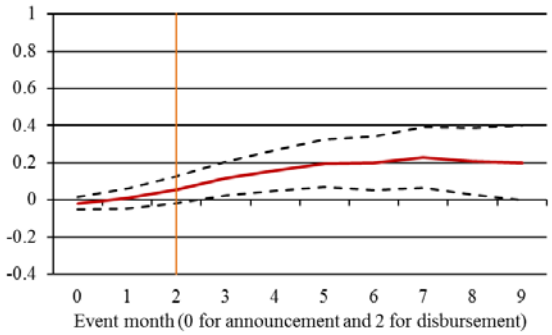
<u>Single</u>

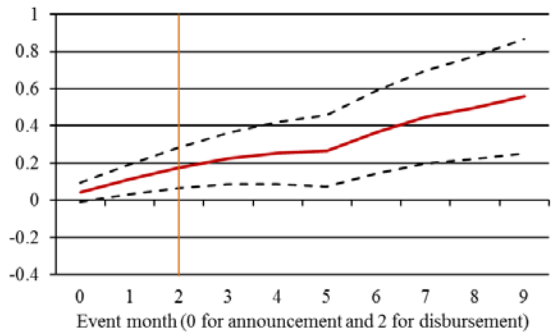


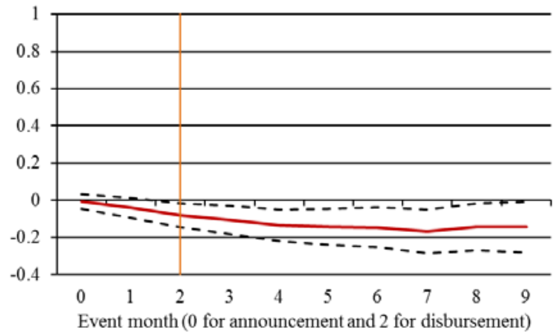




<u>Married</u>



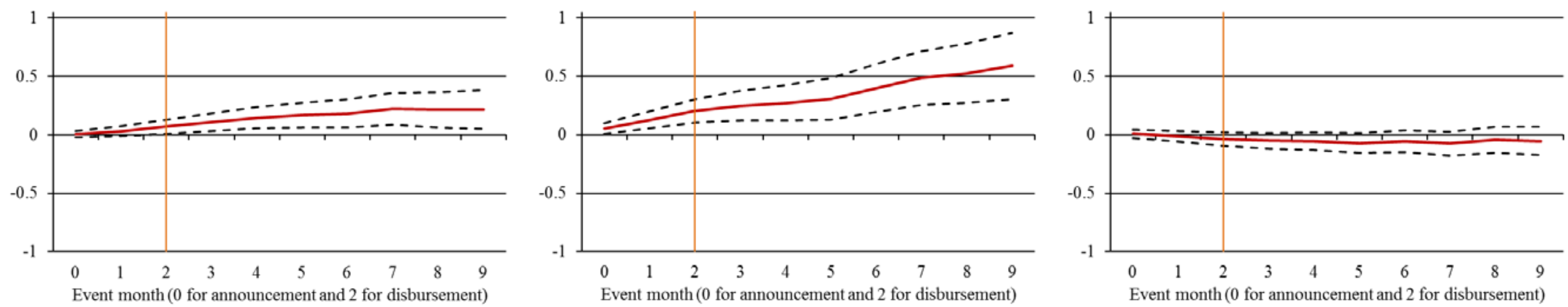




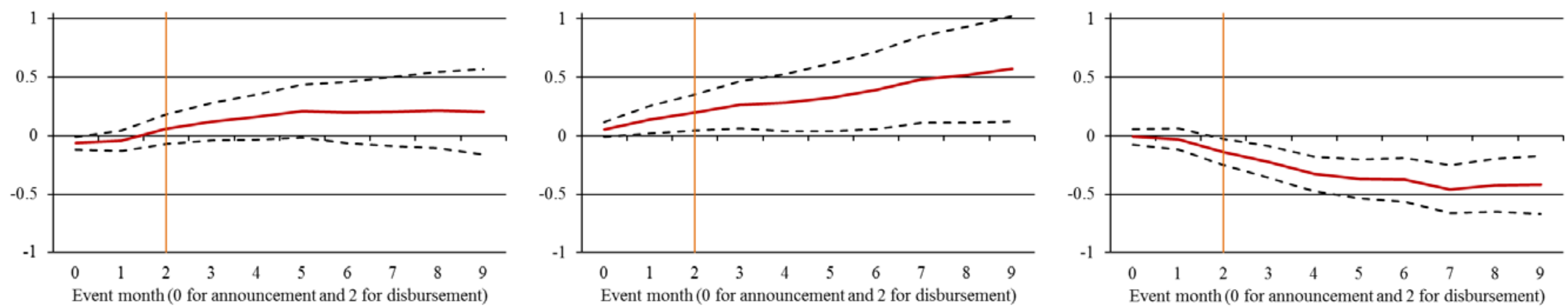
Panel D:

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

<u>Chinese</u>



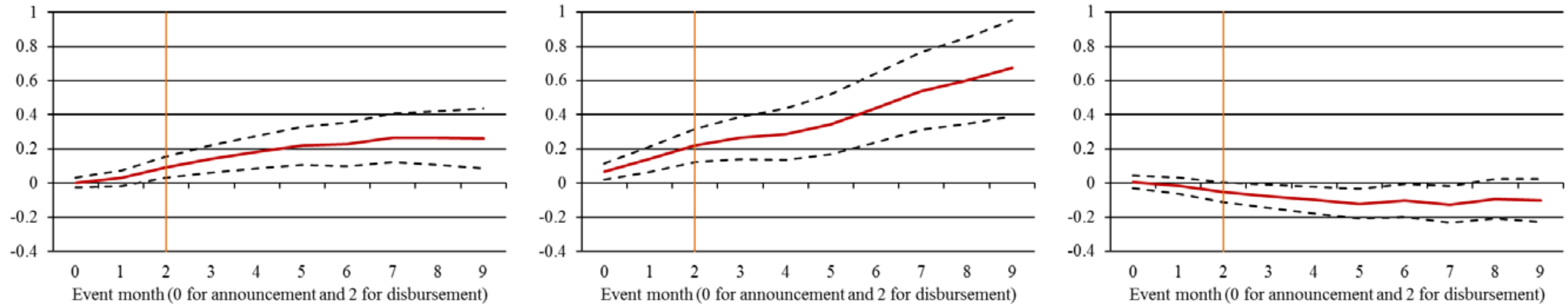
<u>Indian</u>



Panel E:

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

<u>Male</u>



<u>Female</u>

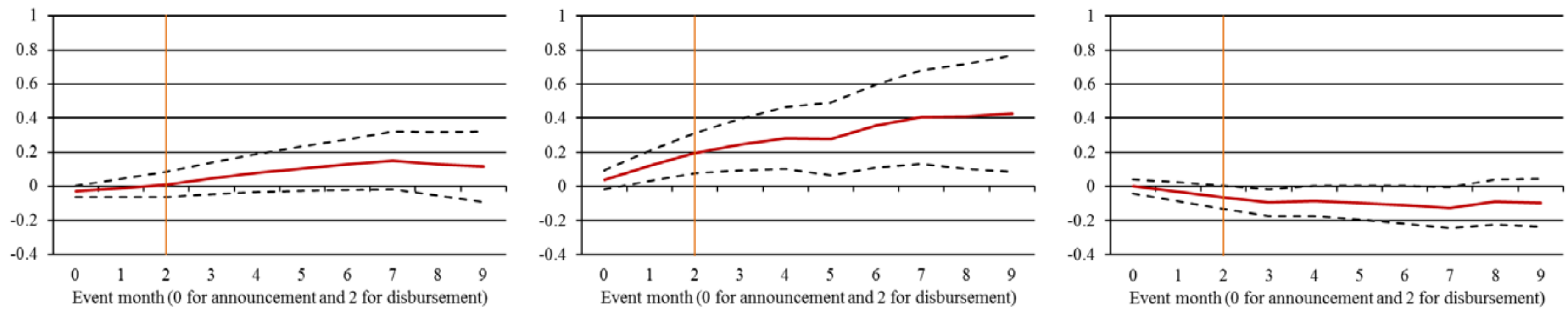


Figure A2: Response of High Bank Balance and Low Credit Card Usage Consumers

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 change response of the high bank balance and low credit card usage consumers. The sample includes the matched treatment and control groups during the period of 2010:08 – 2011:11. A consumer is considered to have low bank balance and low credit card usage if his average monthly checking account balance in the four months before our analysis sample (i.e., 2010:04–2010:07) is above the top tercile of the distribution (SGD 13,148) and his average monthly usage of the credit card limit in those four months is below the bottom tercile of the distribution (=3.4 percent). 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 *s*th month after the announcement of the Growth Dividend Program, and the y-axis shows the dollar response (for every dollar received).

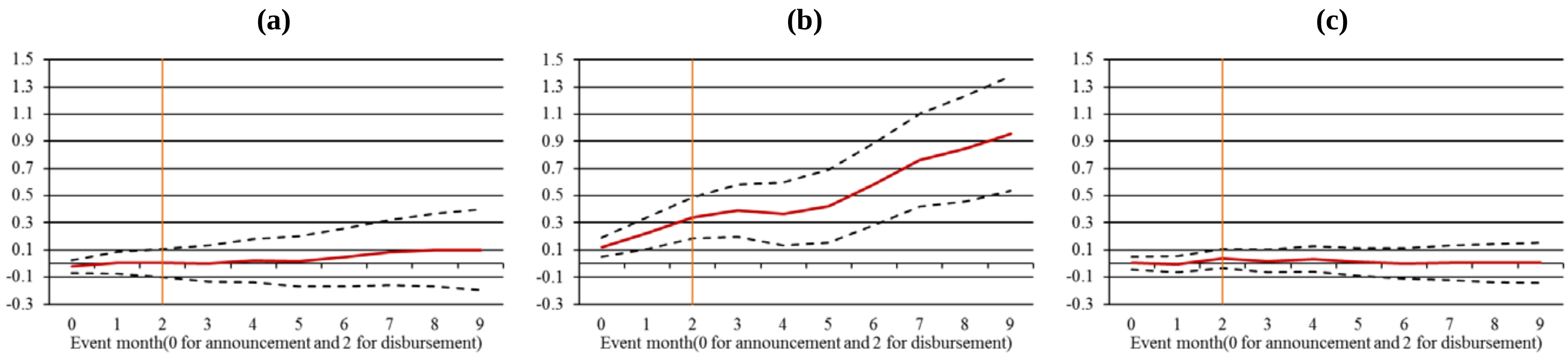
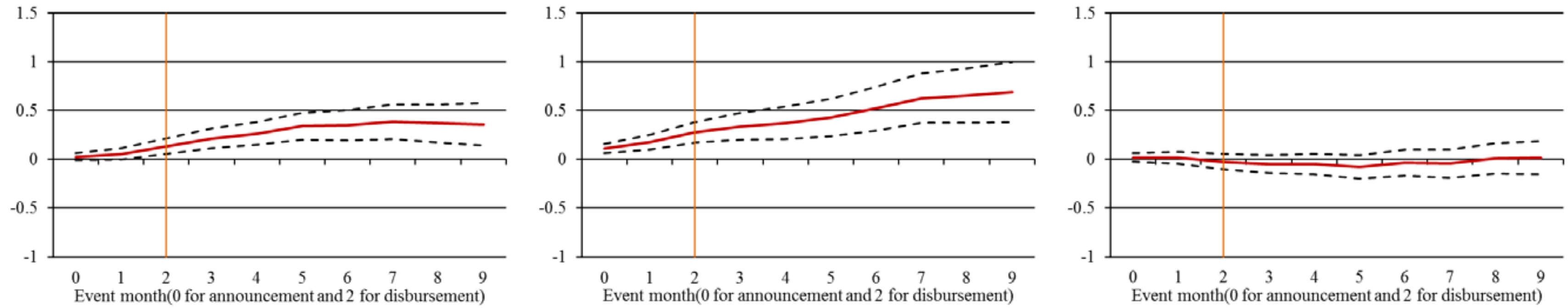


Figure A3: Bank balance vs. Credit Access

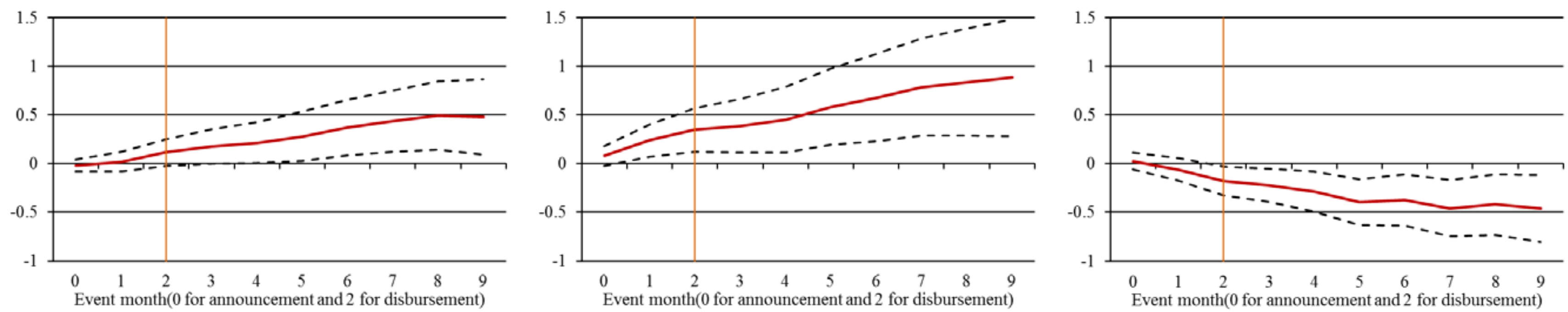
This figure plots the entire paths of cumulative coefficients b_s, s = 0-9, along with their corresponding 95 percent confidence intervals, of spending and debt change response across the following four groups of consumers: low bank balance and low credit limit consumers, low bank balance and high credit limit consumers, high bank balance and low credit limit consumers, and high bank balance and high credit limit consumers. The sample includes the matched treatment and control groups during the period of 2010:08 – 2011:11. For this figure, we use the tercile cutoffs (i.e., 33 or 66 percentiles) rather than quartile cutoffs (as used in Figure 3 in the main text) for bank balance and credit card limit. 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 *s*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)

Low bank balance and low credit card limit

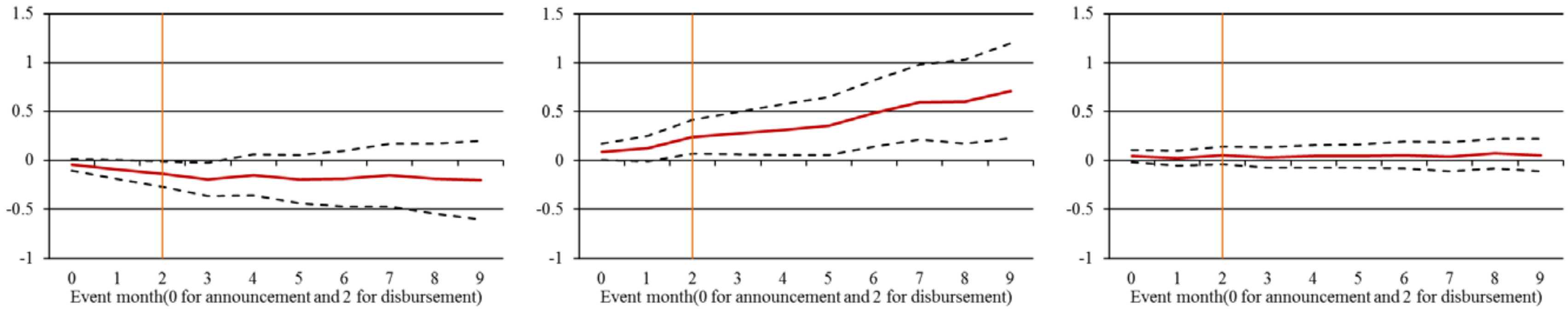


Low bank balance and high credit card limit



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

High bank balance and low credit card limit



High bank balance and high credit card limit

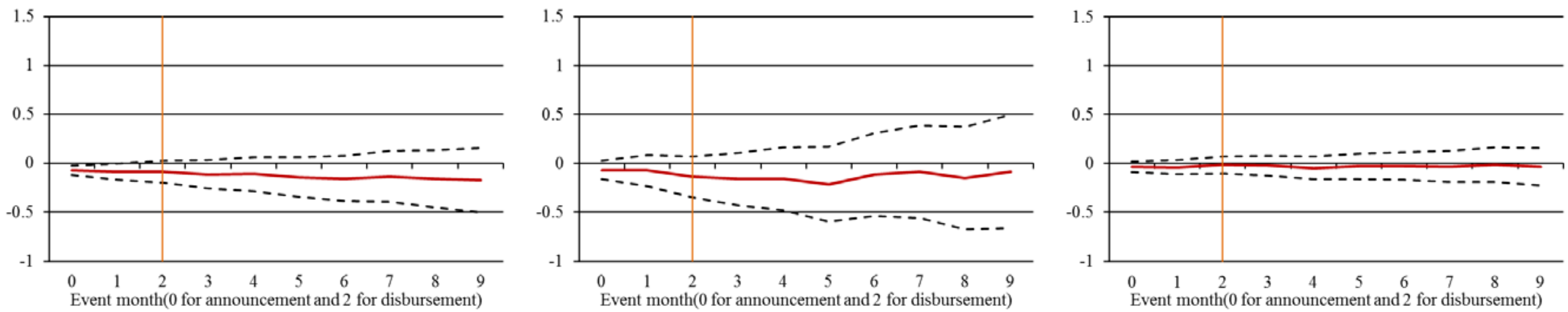
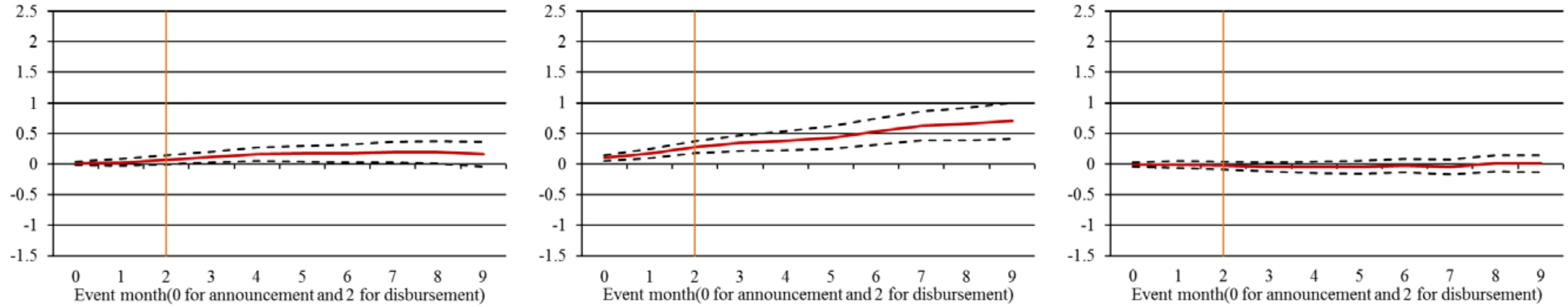


Figure A4: Income Level vs. Credit Access

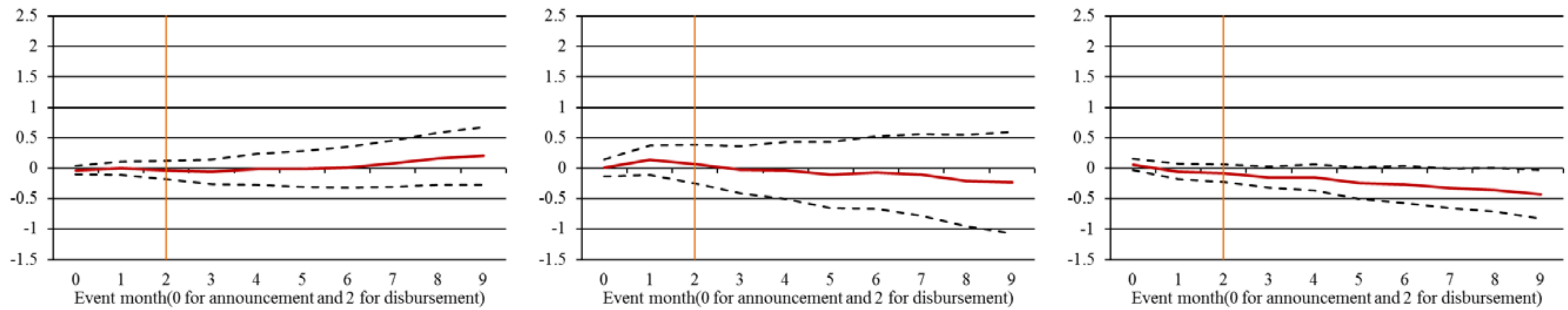
This figure plots the entire paths of cumulative coefficients b_s, s = 0-9, along with their corresponding 95 percent confidence intervals, of spending and debt change response across the following four groups of consumers: low income and low credit limit consumers, low income and high credit limit consumers, high income and low credit limit consumers, and high income and high credit limit consumers. The sample includes the matched treatment and control groups during the period of 2010:08 – 2011:11. For this figure, we use the tercile cutoffs for income and credit card limit. 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 *s*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)

Low income and low credit card limit

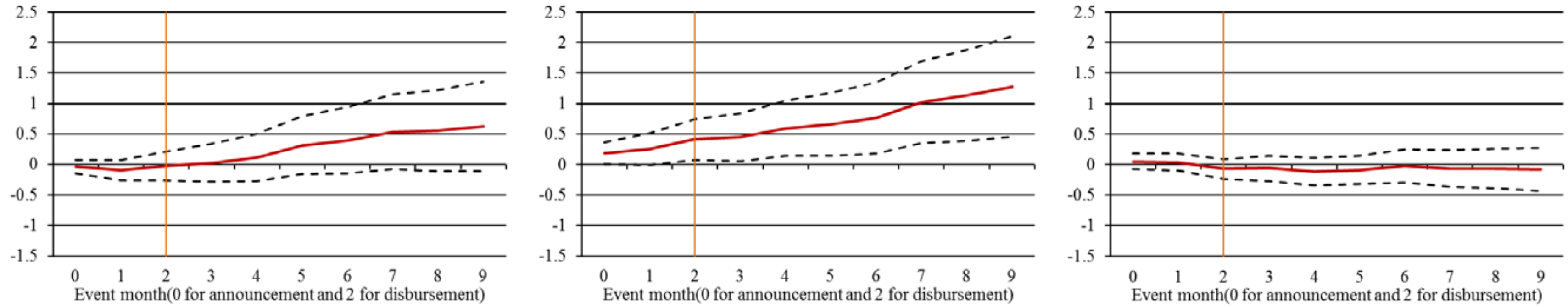


Low income and high credit card limit



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

High income and low credit card limit



High income and high credit card limit

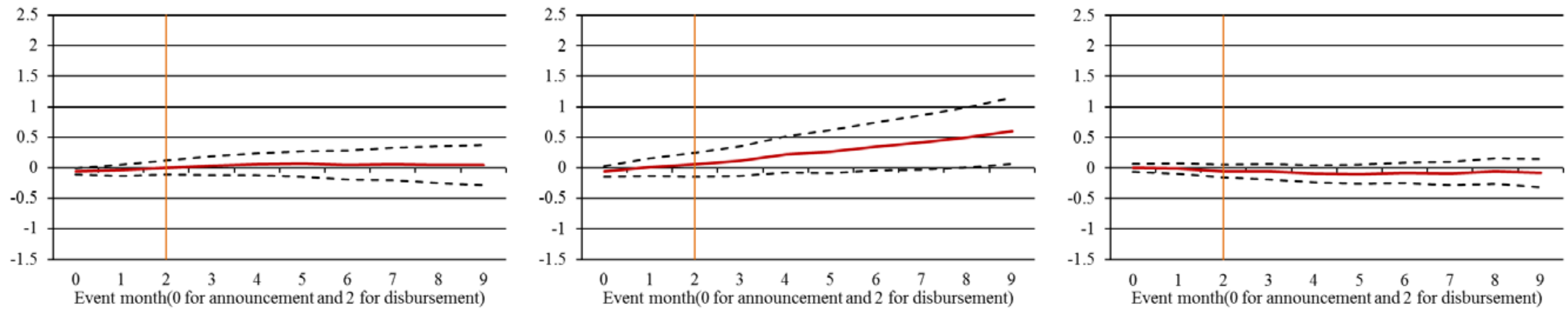


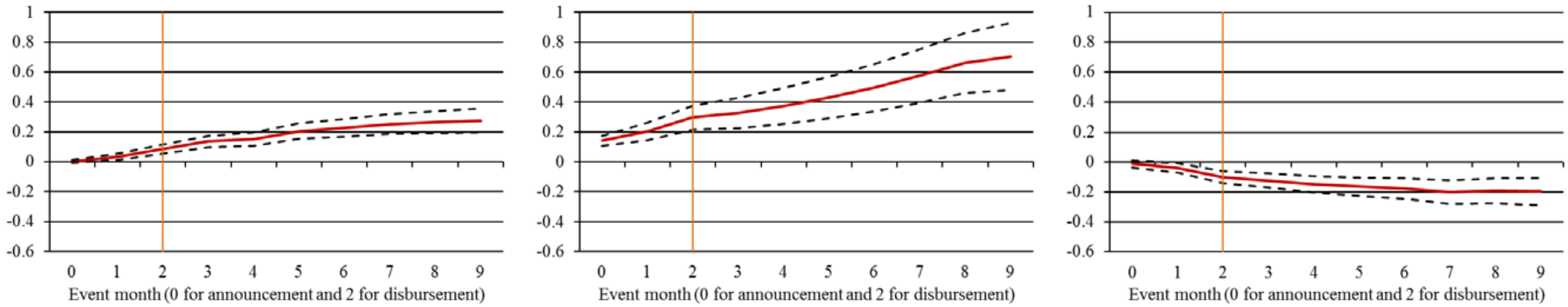
Figure A5: Heterogeneity in Spending and Debt Response in the Full Unmatched Sample

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 change response across different consumers in the full unmatched sample (and without 3 account restrictions) during the period of 2010:08 to 2011:11. We estimate the full sample results with weighted least square regressions, using the propensity scores (from Table A3) as weights. As in Figure 3 and Figure A1, we use the quartile cutoffs to define heterogeneity. 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 *s*th month after the announcement of the Growth Dividend Program, and the y-axis shows the dollar response (for every dollar received).

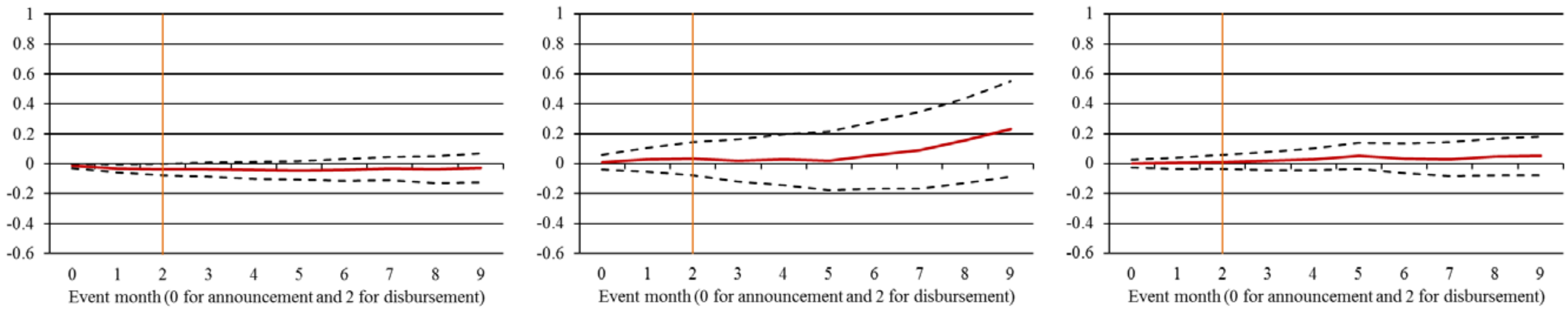
Panel A:

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

<u>Low bank balance</u>



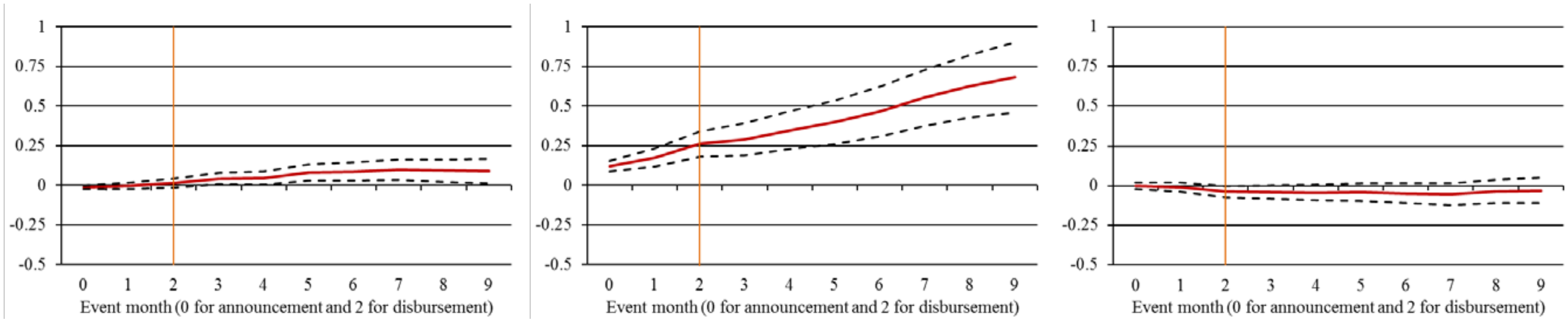
<u>High bank balance</u>



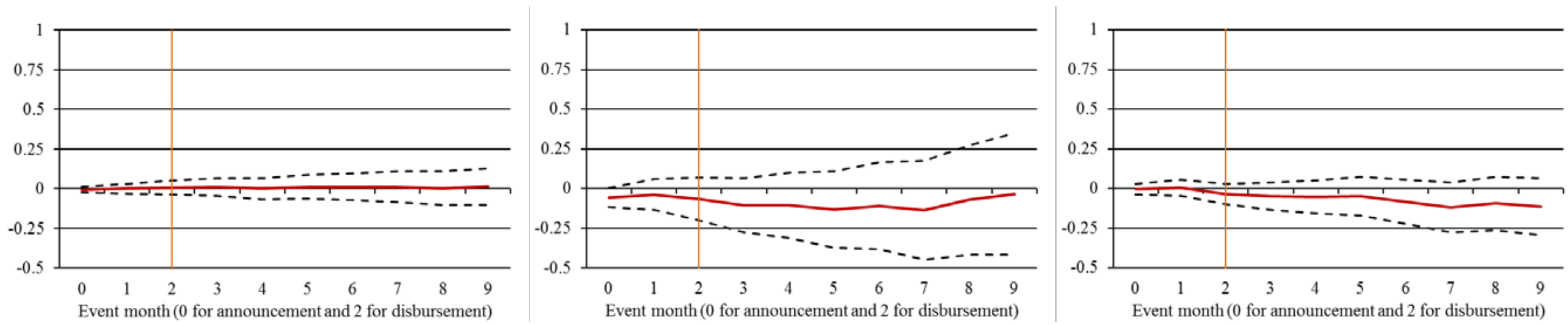
Panel B:

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

<u>Low credit card limit</u>



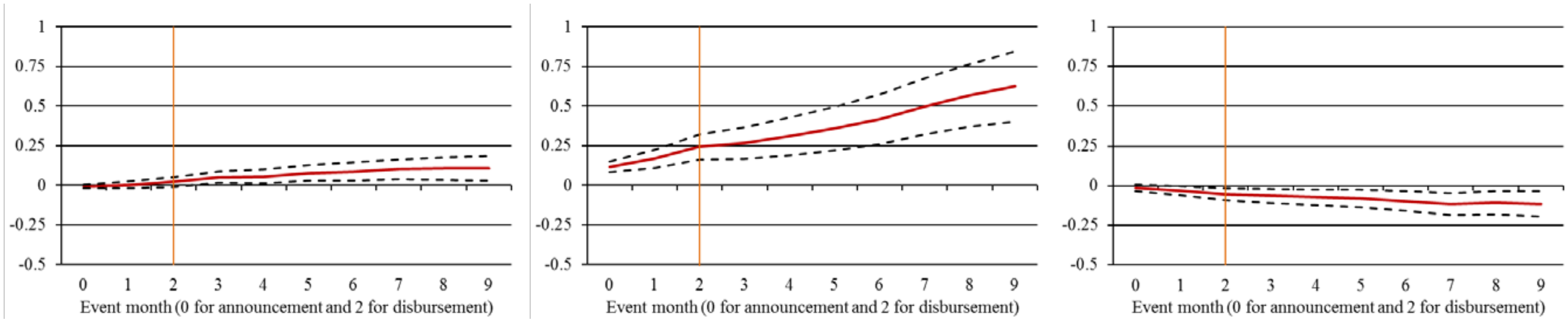
<u>High credit card limit</u>



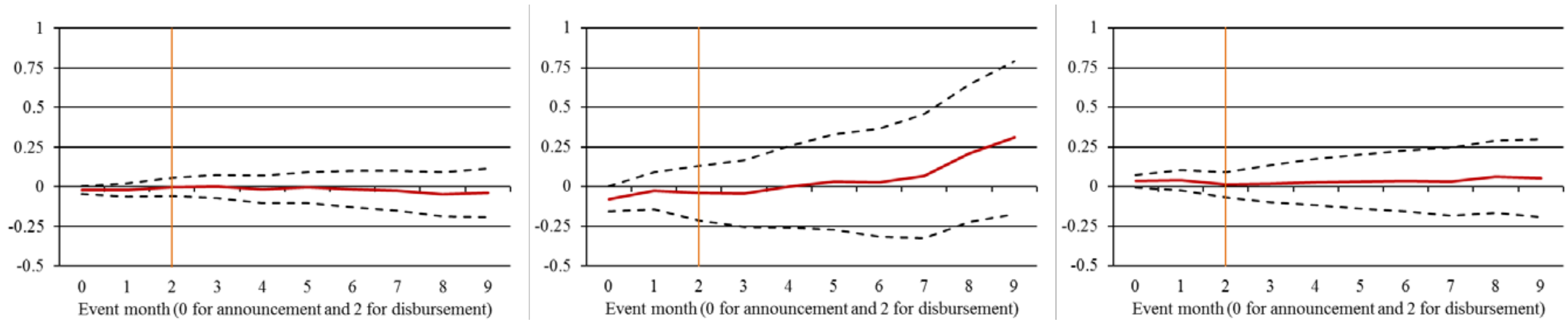
Panel C:

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

<u>Low income</u>



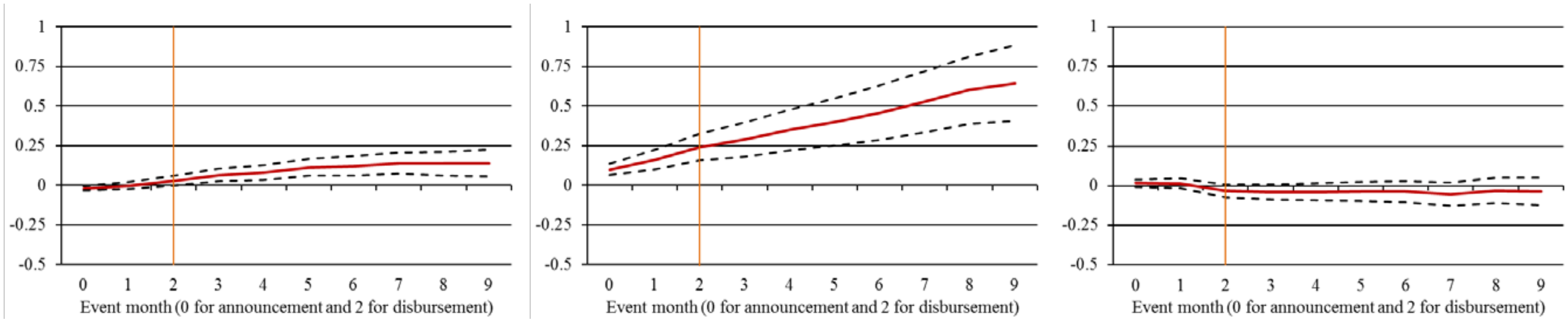
<u>High income</u>



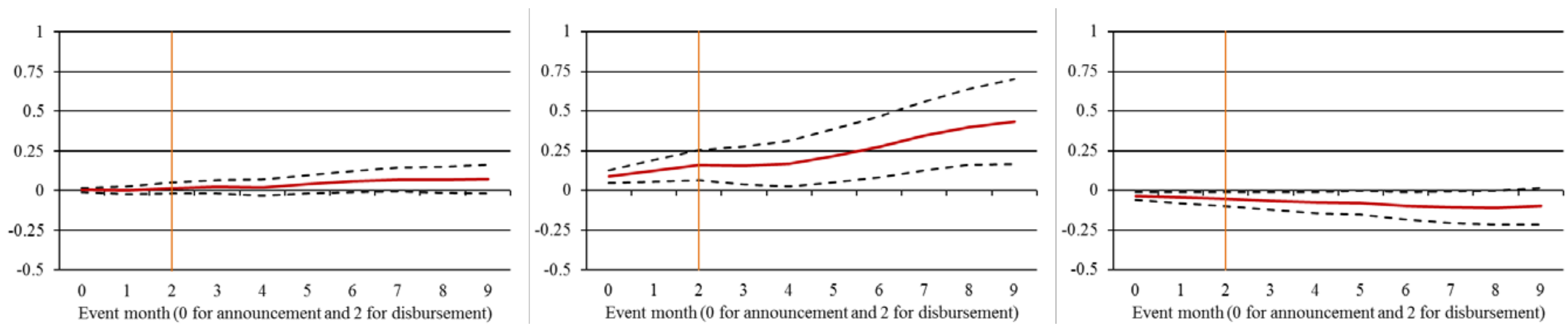
Panel D:

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

Young



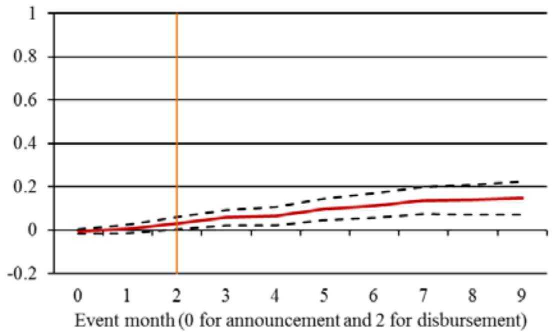
Old

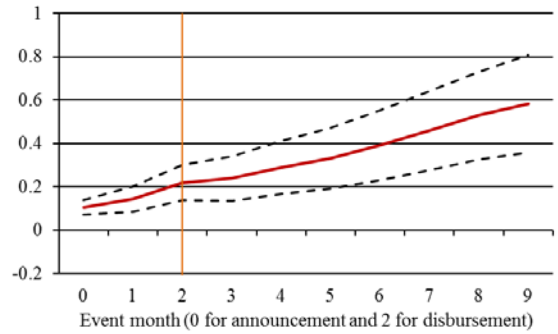


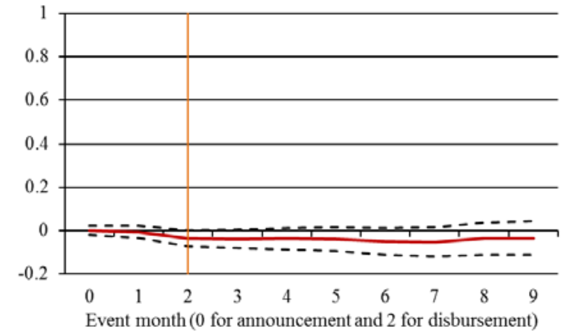
Panel E:

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

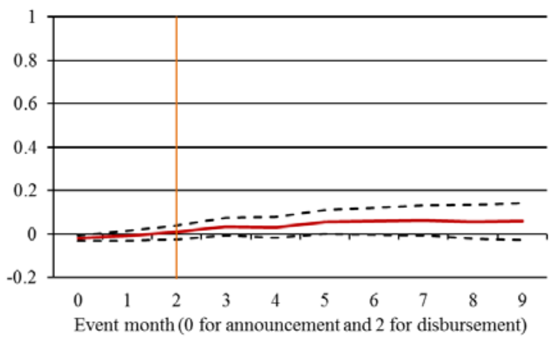
Single

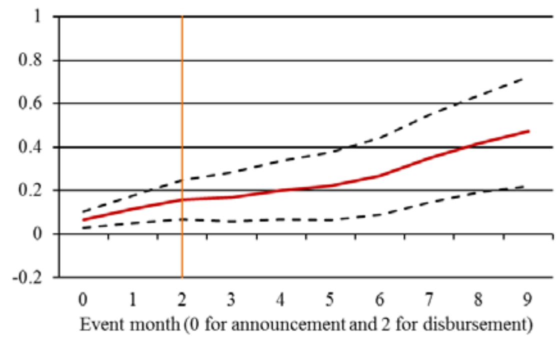


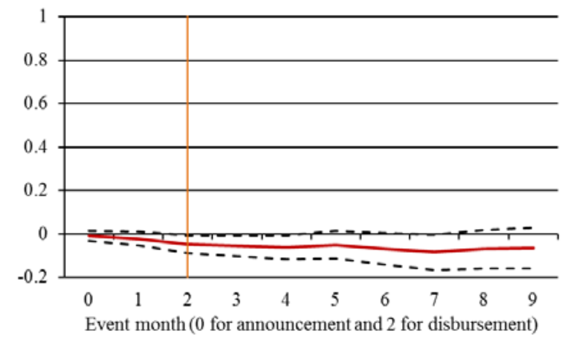




Married



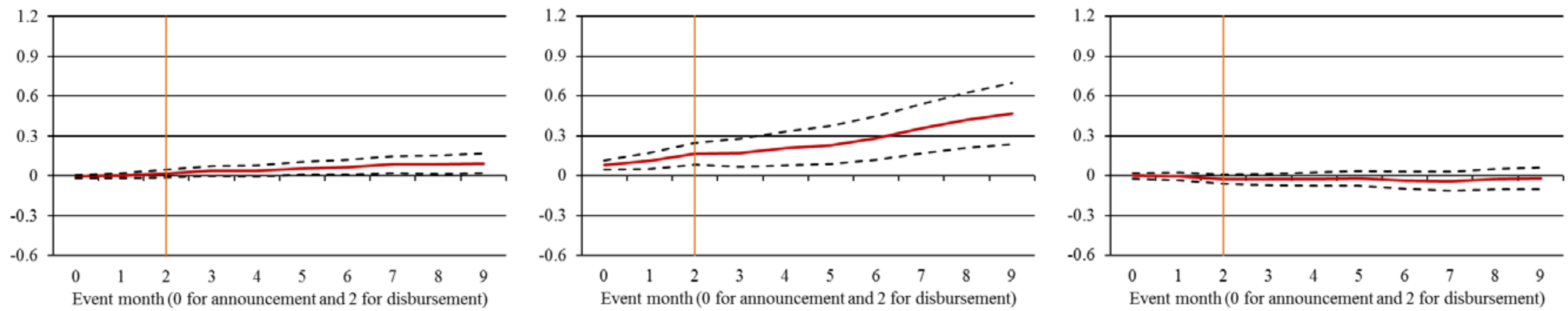




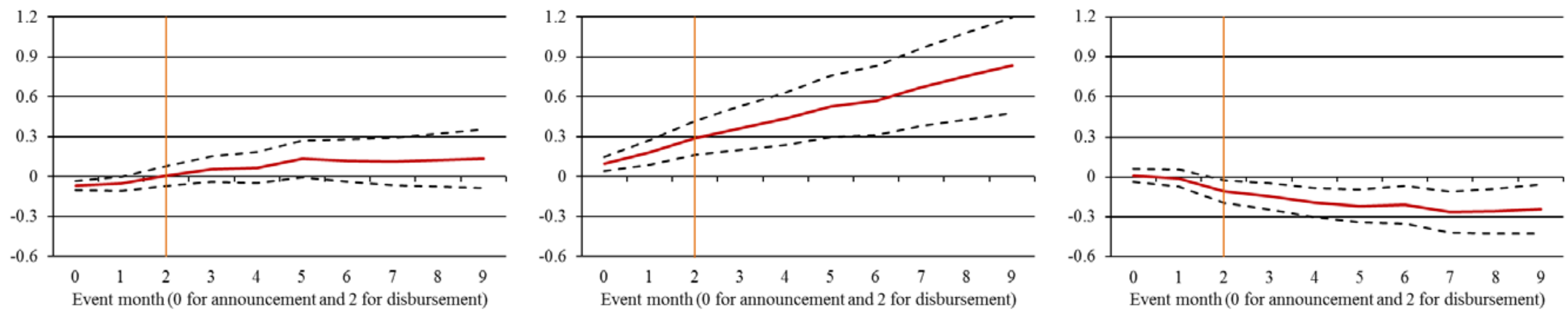
Panel F:

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

<u>Chinese</u>



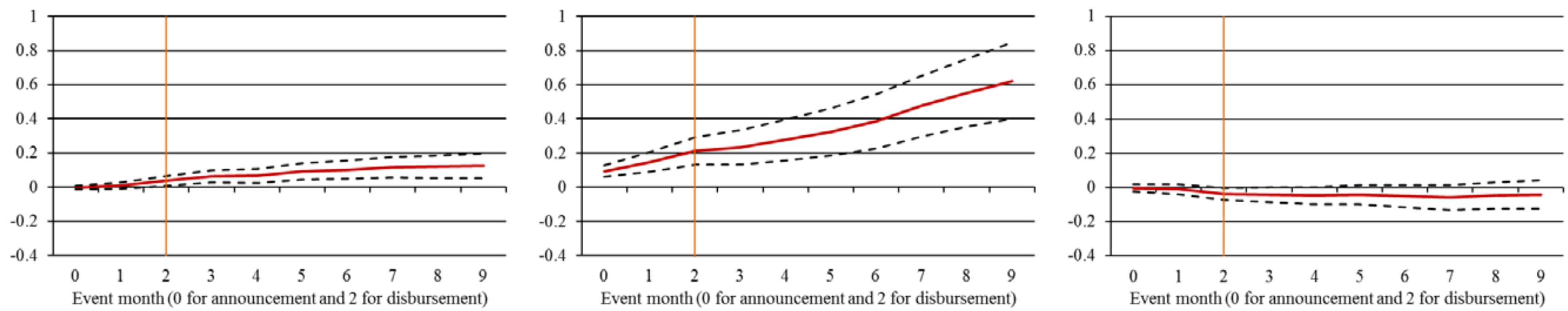
<u>Indian</u>



Panel G:

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

<u>Male</u>



<u>Female</u>

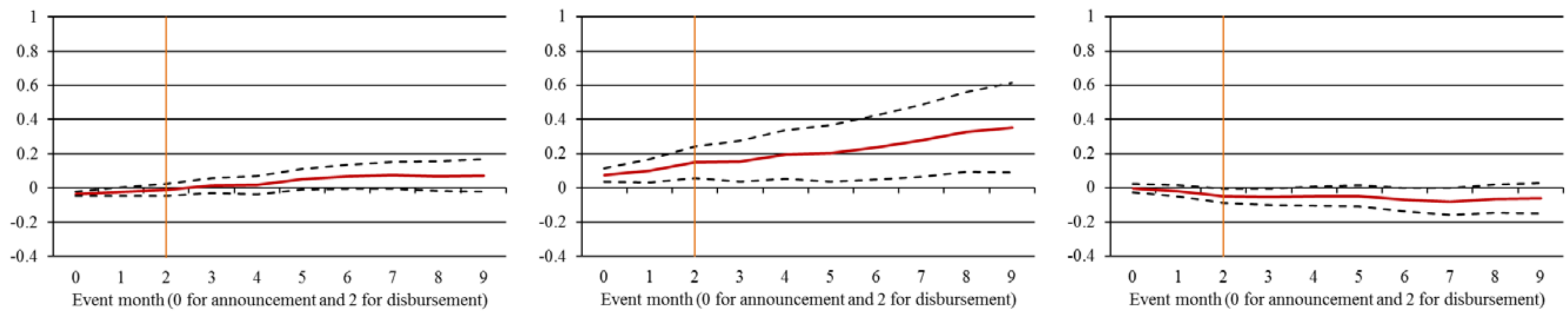


Figure A6: Estimated Spending and Debt Response Dynamics in the Subsample with Singaporeans Only

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 sample includes all Singaporeans who are eligible for the Growth Dividend program (but not the other cash package) during the period of 2010:08-2011:11. In this robustness, we exploit the variation in the different amount received by different subpopulations. We define the treatment group consists of all Singaporeans with annual incomes in 2010 < S$100,000, and the control group includes Singaporeans with annual income >= S$100,000 in 2010. The x-axis denotes the *s*th month after the announcement of the Growth Dividend Program, and the y-axis shows the dollar response (for every dollar received).

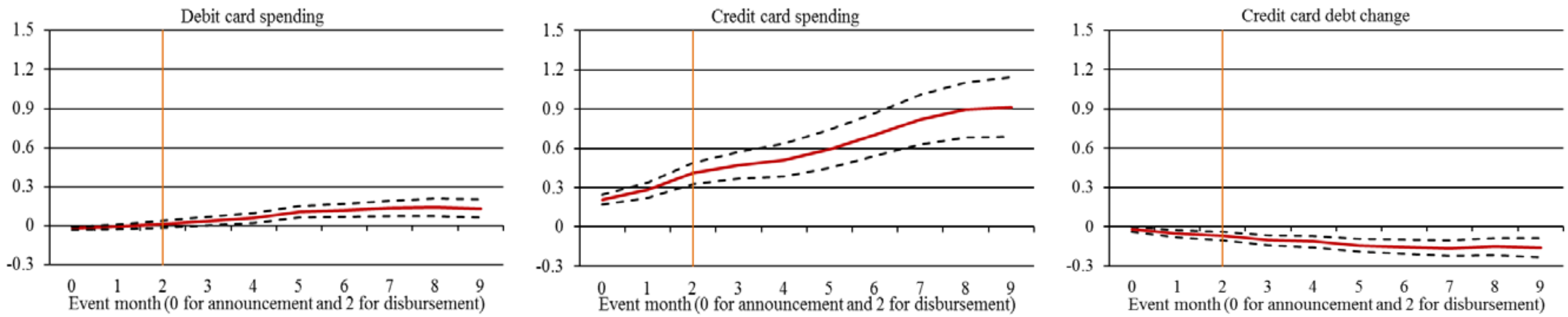


Table A1: Payout Schedule of the Growth Dividend Program in 2011

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. Comparison of Our Bank with other Banks in Singapore

This table presents a comparison on the basic features of banking facilities and account characteristics between the bank in our sample and other players in Singapore. The other banks include two Singaporean banks and four foreign banks, and the statistics in the table are computed based on the average across these six banks. ATM stands for automatic teller machines, which are mainly for cash withdrawals, transfers, or bill payments.

	# of ATM	# of Branches	Minimum initial deposit	Monthly account fee	Average daily minimum deposit	Fall-blow fee	Early account closure fee (<6 months)
Bank in our sample	746	84	S$0	S$0-S$2	S$1,000-S$5,000	S$2-S$7.5	S$0-S$20
Other banks in Singapore	186	30	S$0-S$5,000	S$0-S$2	S$500-S$5,000	S$0-S$7.5	S$0-S$50

Table A3: 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 cash 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 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 percent, 5 percent, and 10 percent 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

Table A4: The Average Spending Response in the Matched Sample: Selected Categories of Spending

This table shows the average total card spending response by spending categories for the matched sample in the period of 2010:08–2011:11. The dependent variables are the monthly total card spending on supermarket, service, dining, entertainment, apparel, travel, small durable goods, and online for each individual in our sample. Merchant type descriptions are provided in the debit and credit card transactions, from which we group them into the above eight categories. A small portion of transactions remain unclassified by the bank, which we label them as "Unclassified" (reported in column 9). 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 percent, 5 percent, and 10 percent level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Supermarket	**Service**	**Dining**	**Entertainment**	**Apparel**	**Travel**	**Small Durable Goods**	**Online**	**Unclassified**
\$ D x $\mathbf{1}_{>post}$	0.004**	0.003	0.002	0.004*	0.016***	0.020***	0.012***	0.001	0.007*
	(2.08)	(0.44)	(0.68)	(1.80)	(4.25)	(4.12)	(3.18)	(0.92)	(1.78)
Constant	99.988***	290.751***	69.271***	69.099***	109.948***	161.611***	73.096***	17.084***	146.243***
	(140.91)	(102.99)	(67.45)	(79.87)	(70.07)	(63.08)	(48.32)	(39.87)	(90.71)
Fixed Effects	Individual, year-month								
R-squared	0.588	0.385	0.479	0.658	0.393	0.335	0.256	0.470	0.344

Table A5: Understanding the Response Heterogeneity in Ethnicity

This table shows ethnicity heterogeneity in the average spending and debt response (Equation (2)) of the matched sample in the period from 2010:08 to 2011:11. We remove the Malay ethnic group from this analysis (due to their small sample size), and study the difference in response between Chinese and Indian ethnic groups in subsamples divided by credit card limit, bank balance and income, with the same cutoff thresholds as in Figure 3. To facilitate interpretation, we do not include the pre-treatment variables in the regressions. Please refer to Table 1 and 2 for definitions of 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 percent, 5 percent, and 10 percent level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Total card spending		**Credit card debt change**		**Total card spending**		**Credit card debt change**		**Total card spending**		**Credit card debt change**	
	Low CC limit	**High CC limit**	**Low CC limit**	**High CC limit**	**Low balance**	**High balance**	**Low balance**	**High Balance**	**Low Income**	**High income**	**Low income**	**High income**
\$ D x $\mathbf{1}_{>post}$	0.047**	0.130***	-0.002	-0.008	0.065**	0.128***	-0.005	0.002	0.016	0.153***	-0.002	-0.001
	(2.27)	(2.84)	(-0.16)	(-0.51)	(2.43)	(3.16)	(-0.35)	(0.26)	(0.66)	(3.21)	(-0.16)	(-0.05)
\$ D x $\mathbf{1}_{>post}$ x Indian	0.009	-0.132	-0.055***	-0.019	-0.040	0.015	-0.050**	-0.008	0.024	0.055	-0.049***	0.012
	(0.26)	(-1.24)	(-3.40)	(-0.54)	(-1.13)	(0.16)	(-2.37)	(-0.28)	(0.55)	(0.50)	(-2.59)	(0.33)
Fixed Effects	Individual, year-month											
R-squared	0.469	0.561	0.027	0.040	0.469	0.578	0.041	0.020	0.479	0.559	0.032	0.032

Table A6: The Average Spending and Debt Response: Robustness Checks

This table presents robustness checks of the results in the matched sample shown in Table 2. Panel A reports the results by restricting the control sample to those with Chinese, Malaysian, Indian and Indonesian nationalities. Panel B shows results by restricting the sample of consumers < 45 (above which Singaporeans are eligible for some other non-cash benefits from the government). Panel C reports results in the men-only subsample. Panel D shows the results in the subsample of non-salary employees (due to power issue, we use all the non-salary employees in the full, unmatched sample). Please refer to Table 1 and 2 for definitions of 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 percent, 5 percent, and 10 percent level, respectively.

Panel A: restrict to Chinese, Malaysian, Indian, and Indonesian in the control sample				
	(1)	(2)	(3)	(4)
	Total card spending	**Debit card spending**	**Credit card spending**	**Credit card debt change**
$ D x $\mathbf{1}_{>post}$	0.080***	0.018**	0.062***	-0.015**
	(4.76)	(2.14)	(4.37)	(-2.38)
Constant	1,103.926***	486.497***	617.429***	17.508***
	(158.28)	(141.83)	(103.39)	(4.41)
R-squared	0.528	0.497	0.521	0.032
Panel B: age < 45				
$ D x $\mathbf{1}_{>post}$	0.073***	0.023**	0.050***	-0.014**
	(4.12)	(2.53)	(3.36)	(-2.10)
Constant	1,072.312***	462.131***	610.181***	18.429***
	(143.51)	(125.09)	(95.27)	(4.16)
R-squared	0.526	0.470	0.523	0.031
Panel C: restrict to men				
$ D x $\mathbf{1}_{>post}$	0.064***	0.023**	0.041**	-0.012
	(3.01)	(2.13)	(2.29)	(-1.48)
Constant	1,171.845***	499.036***	672.810***	13.448**
	(121.85)	(105.96)	(81.59)	(2.43)
R-squared	0.547	0.493	0.545	0.034

Panel D: restrict to non-salary-employees				
	(1)	(2)	(3)	(4)
	Total card spending	**Debit card spending**	**Credit card spending**	**Credit card debt change**
$ D x 1$_{>post}$	0.069***	0.016***	0.052***	-0.017**
	(3.49)	(2.74)	(2.78)	(-2.45)
Constant	839.214***	159.154***	680.060***	13.854***
	(111.89)	(70.67)	(96.01)	(3.34)
R-squared	0.585	0.657	0.573	0.037

Table A7 Alternative specifications

This table presents robustness checks of the results shown in Table 2 Panel A using alternative specifications. We compute the average monthly total card spending (or credit card debt change) during the six months before treatment (2010:08-2011:01), and during the ten months after treatment (2011:02-2011:11) respectively. Then we compute, as our dependent variable, the difference between the after-treatment average and before-treatment average for each individual. In Panel A and B, we following Bertrand, et al. (2004) and regress the dependent variables on the amount of the Growth Dividend received, *$D,* in the cross section tests**.** In Panel C-E, we use the non-parametric matching estimators to identify the average treatment effect (Imbens, 2004). In Panel C, we use the nearest neighbor matching based on the estimated propensity score (estimation see Table A3). In Panel D, we modify the matching algorithm by using radius matching with a 0.01 caliper. In Panel E, we use the bias-corrected and heteroscedasticity-consistent nearest neighbor matching algorithm (Abadie and Imbens, 2002, 2006). Please refer to Table 1 and 2 for definitions of variables. T-statistics are reported in parentheses under the coefficient estimates, and ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively.

	(1) **Change in monthly average total card spending**	(2) **Change in monthly average credit debt change**
Panel A: cross sectional test in the matched sample		
$ D	0.079***	-0.011*
	(4.97)	(-1.89)
Panel B: cross sectional test in the full sample		
$ D	0.066***	-0.003
	(10.53)	(-1.50)
Panel C: matching estimator: nearest neighbor		
$\mathbf{1}_{treatment}$	25.817***	2.298
	(2.52)	(0.62)
Panel D: matching estimator: radius, with caliper (= 0.01)		
$\mathbf{1}_{treatment}$	26.847***	0.595
	(2.87)	(0.17)
Panel E: matching estimator: nearest neighbor, bias-corrected and heteroscedasticity-consistent		
$\mathbf{1}_{treatment}$	25.953***	2.295
	(2.66)	(0.72)