Online Appendix

Thy Neighbor's Misfortune: Peer Effect on Consumption

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Not Intended for Publication

1. More Information on Bankruptcy in Singapore

Similar to many developed economies such as the US, Singapore has strict laws governing bankruptcy, which are encompassed in the Bankruptcy Act (Chapter 20). According to Chapter 20, bankruptcy can be applied by the debtor herself or by the creditor with no less than SGD 10,000 debt involved (increased to S$15,000 in 2015). However, in Singapore, personal bankruptcy cases should be triggered by negative liquidity shocks rather than strategic incentives for the following reasons.

First, filing for bankruptcy will not erase one's debt. After the Bankruptcy Order, all assets under the bankrupt individual's name will be reported and controlled by an Official Assignee (OA) from the government, and the OA will be administering the bankrupt's affairs, including the selling of bankrupt's assets, verifying the creditor's claims and paying dividends to the creditors. Therefore even after bankruptcy, the debtor still has to pay for the debt claimed by creditors. The government-assigned OA will keep monitoring the debt repayment process. This largely reduces the financial benefits of strategic bankruptcy, as debt cannot be forgiven. On the other hand, debtors have alternative options before going through the bankruptcy procedure. Similar to Chapter 13 in the United States, there is a "Debt Repayment Scheme" (DRS) under Part VA of the Bankruptcy Act, which went into effect on 18 May 2009. Under DRS, debtors with unsecured debt not exceeding SGD 100,000 are allowed to enter into a "debt repayment plan" (DRP) with their creditors and avoid bankruptcy.[1] The debtors can commit to repay their debt over a fixed period of time, not more than five years (60 months).

Second, the bankrupt individuals face long-term multi-faceted repercussions in their lives. They cannot own any luxury items beyond subsistence needs, and cannot own car, private properties, credit cards, or mobile phone subscription. They also need permission from the High Court or the Official Assignee to travel or remain overseas, take a taxi, start and run their own businesses, or serve as directors of companies. Any interested party (such as employers) can search for one's bankruptcy record from the website of the Insolvency Office, leading to potential labor market externalities.[2] These impacts are long-lasting. The bankruptcy order and the corresponding restrictions will be discharged when most of the debt has been paid off, or upon agreement by most creditors, or when a minimum tenure has been served. Gauging the recent bankruptcy discharge cases, we find that the duration of the bankruptcy order takes 10 years on average.

Moreover, filing for personal bankruptcy is strongly discouraged by the Singapore government. As stated by the Singapore Ministry of Law, that "*the Official Assignee does not provide advice on the procedures for filing a self-petition*", and that "*You should not consider self-petition for bankruptcy as an option to relieve your financial problems. Bankruptcy should be considered as a last resort, as there are restrictions imposed on bankrupts*".

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[1] Information about DRS can be found on website of Singapore Ministry of Law (https://www.mlaw.gov.sg/content/io/en/bankruptcy-and-debt-repayment-scheme/debt-repayment-scheme.html.html)

[2] Website for Insolvency Office from the Ministry of Law is: https://www.mlaw.gov.sg/eservices/io/

Moreover, the government will publicly disclose the bankrupt individuals' information in the Gazette shortly after the bankruptcy order, which can be considered as another attempt to discourage bankruptcy filing.

There are three important dates in the bankruptcy procedure: 1) demand date, when creditor issues the Statutory Demand (requiring for repayment); 2) petition date, when the petition is filed to the court if the repayment requirement is not fulfilled within 21 days, or the debtor has not applied to the court to set aside the Statutory Demand; and 3) hearing date, when the court arranges a hearing and declares the bankruptcy order. Before the hearing date, the court may adjourn the application for up to six months, before which it determines the debtor's suitability for DRS.[3] In our data, the average lag between demand date and petition date is 2 months, and the lag between petition data and hearing data is 4 months on average. After the issuance of the bankruptcy order, the Government Gazette will publish a notification, which is observable by the public.

After the bankruptcy order, an Official Assignee will be appointed. The bankrupt individual needs to fill a Statement of Affairs form within 21 days to disclose everything truthfully and clearly, including her personal details, assets and liabilities, even her children's income (if any), and whether she gave away or sold any assets within the last five years before the Bankruptcy Order. Based on this filing, Official Assignee will take over the assets under the bankrupt's name and administrate the bankrupt's affairs.

The Official Assignee will seize a debtor's assets, with a few exceptions including her public housing flat (HDB), properties held in trust, CPF money, and basic everyday necessities for life and work.[4] This implies that if public housing flats are their main residence, individuals can keep the flats and live there after bankruptcy. In addition, family members' assets are also exempt, unless the family members are the co-borrowers, guarantors or sureties of the debt. The bankrupt shall distinguish the assets under his/her own name, and other family members' names very clearly in the Statement of Affairs form, and omitting information or providing false information could bring a fine of up to S$10,000 and/or up to two years' jail.

Individuals face many restrictions and inconveniences in their spending as well as career choices upon bankruptcy. For example, the bankrupt debtor has to pay a portion of her income to the creditor, cannot own any luxury items beyond subsistence needs, and cannot own car, private properties, credit cards, or mobile phone subscription. She also needs permission from the High Court or the Official Assignee to travel or remain overseas, take a taxi, start and run her own business, or serve as a director of a company.

The bankruptcy order and the corresponding restrictions can be discharged when most of the debt has been paid off, or upon agreement by most creditors, or when a minimum tenure has

[3] Please refer to the Bankruptcy Act available at: http://statutes.agc.gov.sg/aol/search/display/view.w3p;ident=9657b784-a989-4385-ac51-c4eed99205e6;page=0;query=DocId%3A%22c342424a-8867-494a-bbab-91b696d12bdc%22%20Status%3Ainforce%20Depth%3A0;rec=0#pr65-he-.

[4] Central Provident Fund (CPF), a compulsory comprehensive savings plan for working Singaporeans and permanent residents primarily to fund their retirement, healthcare, and housing needs.

been served.[5] Gauging the recent bankruptcy discharge cases published on the Government Gazette, we find that the duration of the bankruptcy order takes 10 years on average.

We plot the geographical distribution of the personal bankruptcies in Singapore in our sample period in Panel A of Figure A1. There is no clustering pattern in the geographical space—the events span all locations and all areas with housing establishments in the country. We also find that no bankruptcy-hit buildings are within the 300-meter radius of each other, lending further support to the graphical pattern of no clustering. In addition, the bankruptcy events are evenly distributed across months during the 2010:04-2012:03 period (Figure A1, Panel B). This provides assurance that personal bankruptcy events do not seem to correspond to or arise from systematic economic distress that simultaneously affects many people's economic well-being in the same neighborhood or time.

2. Public Transportation Trip Tests on Co-worker Sorting into Same Building

The ideal approach to examine sorting of co-workers into the same residential building is to collect granular information on work for each consumer in our sample, including his or her employer, work address, and job title, with which we can directly test the clustering hypothesis at the building level. While information of such granularity is generally unavailable, we exploit the unique institutional setting in Singapore and make use of an alternative strategy to examine residential clustering of co-workers.

Specifically, the idea is to measure work location based on the actual observation of individuals' work commute patterns. Using a dataset covering the universe of Singapore's public transportation trips via electronic cards, which represents 96% of the public transportation user population, we observe all public transportation trips (both subway and bus included) through around 4 million electronic travel cards (a.k.a. EZ Link cards). Since the data allow us to identify the boarding station, alighting station, as well as the precise time each card holder gets on and off the vehicle for all his or her trips, we can use the trip time, duration, information on the origin and destination location, and the EZ link card type (adult, senior or student/child) to infer work location.

Public transportation is the dominant mode of work trip for Singapore workers across all industries and occupations. One important reason lies in the fact that Singapore is the most expensive country in the world to own a car. To accommodate the transportation needs, the government has developed a highly convenient public transportation system supporting all commercial and residential areas of Singapore: six out of ten households can access a subway station within 10 minutes' walk, and bus stops are within 300-400 meters away from each other. It is also reliable and affordable, ranking among the best public transport system in the

[5] The detailed requirements for bankruptcy discharge is available at the website for Ministry of Law: http://www.ifaq.gov.sg/MINLAW/apps/fcd_faqmain.aspx#FAQ_186523

world.[6] According to the 2015 Singapore Household Survey, 63 percent of Singapore adult workers living in public houses (i.e., HDB) use public transport daily to commute to work.

The dataset covers the universe of Singapore's public transportation trips via electronic cards during the whole month of 2013:08 (see Agarwal, et al., 2020) for a more detailed description of the data). We exclude trips from child/student and senior citizen cards and focus on adult workers starting their trips from (public transport stations near) their HDB home buildings. For each of the adult cards that have made morning trips (during 6 to 10 a.m., when work trips most likely to take place), we identify its most frequently visited origin-destination pair (OD pair afterward), and the number of days in the month that this OD pair trip has happened in the morning. Following Agarwal, et al. (2019), we identify the most frequently visited OD pair as the card holder's work trip, if its morning commute during 6-10 am took place for at least 14 days in the month. Then the origin station of the most frequently visited OD pair is defined as the home station, and the destination station is defined as the work station. For each HDB postal code, we use the public transport information from the nearest home station to proxy for the residents' work trip information in the building.

First, we test whether HDB residents work closely from home, by studying their work commute duration. Since *all* HDB buildings are within close reach of public transport stations by design, we use the station closest to a postal code to proxy for workers' home building and the station-average work trip time to measure the average work commute duration for the matched HDB building. Specifically, for each adult cardholder (i.e., worker), we compute his or her work commute time as the time difference between the boarding time on the public transport vehicle at the home station, and the alighting time at the work station during morning work hours (6-10 am) for each workday in our sample period. For each worker, we compute his or her average work commute time during 2013:08. Then for each HDB building, we calculate the mean of the average work commute time for all the workers from the mapped home station.

As shown in the first row of Panel A, Table A2, among the population of HDB buildings in the entire Singapore, the average and median commute time for work trips are both 33 minutes. Since the Singapore Island is only 42 km long and 23 km wide, a 33-minute public transport can travel around 11 km. As a comparison, it only takes about 40 minutes to drive through the island (between east and west).[7] Therefore, the stats in the table suggest that on average Singaporeans do not live close to their work locations. Note that this is likely an underestimate of the distance to work because our calculation does not consider the distance from home to the public transport stations, nor from the stations to employers.[8] Furthermore, comparing the bankruptcy-hit buildings in our sample versus other HDB buildings, the average commute time stays around 33 minutes for both groups, and the difference is

[6] Channel NewsAsia. 21 Aug., 2018. "Singapore's Public Transportation System among Best in the World: McKinsey Report."

[7] According to Google map, the driving distance (time) from Tuas Checkpoint (the West) to Changi Airport (the East) starting at 7:00 a.m. is around 46 km (35-45 min). As a comparison, the commute time by subway for a 11-km trip starting at 7:00 a.m. takes around 30 minutes.

[8] While our sample does not include car commuters, their distance to work is unlikely shorter since the benefit of driving plausibly is higher on average for those who live farther from work.

economically negligible (and statistically insignificant). It suggests that the bankruptcy-hit buildings do not differ from the other HDB buildings in residents' average work commute time, alleviating the concern of a closer distance between home and work for the bankruptcy-hit building residents.

Next, we show that within each bankruptcy buildings in our sample, there is considerable variation in the travel time to work. We compute the within-building standard deviation, together with the difference between 75^{th} percentile and 25^{th} percentile of the work commute time for residents in each bankruptcy-hit building (this exercise is restricted to buildings with at least 5 workers). As shown in the first row of Panel B, Table A2, the mean and median of the standard deviation in commute time for the bankruptcy-hit buildings are both over 16 minutes, which is equivalent to half of the average commute time (i.e., 33 minutes as reported in Panel A). In addition, three quarters of the buildings have within building commute time standard deviation of over 14 minutes. A slightly different metric—the distribution of the difference between the 75^{th} and 25^{th} percentile of the within-building work commute time—reveals a similar pattern. The mean and median for the within-building inter-quartile range are both around 20 minutes. The large variation of the commute time to work within each bankruptcy-hit building in our sample again suggests that residents in the same building are unlikely to work for the same employers or work at the same locations.

Finally, we test whether co-workers cluster their residential choice within one building using work trip origin-destination station information. If we observe two workers regularly depart for work from the same public transport station and get off at the same station, then they are likely same-building neighbors working for the same employer. Thus, we proxy for the building-level co-worker fraction as the number of workers in each HDB building who share the same origin and destination station for work trips, divided by the total number of workers in the same building. Specifically, for day t of a home station s, if there are M workers boarding at this station for their work trips, and N of them alight at the same work station, then the co-worker fraction for home station s on day t is N/M. Note that it is possible for a home station-day to have more than one group of co-workers; for example, 2 workers alight at work station A, and 8 workers alight at work station B. If such case happened, we just use the largest number of co-workers—8 co-workers in the last example—as N to compute the fraction of co-workers. We restrict this exercise to station-days with more than 1 worker, and to the home stations with at least averagely 5 workers per workday in the month. Then for each HDB building, we calculate the mean co-worker fraction during our sample period from the mapped home station.

In the full sample, the average (median) co-worker fraction is 15.5 percent (12.8 percent) as reported in Panel C of Table A2. Even at the 75^{th} percentile, we observe less than 19% of the workers who commute from the same origin station to the same destination station. It is worth mentioning that the computed ratio is an upper bound of the true co-worker fraction because it includes people working in different companies with shared destination stations. In addition, the average co-worker fraction is very similar among HDB buildings in our sample (15.8 percent) and other HDB buildings (15.4 percent), with the difference indistinguishable from zero both economically and statistically. This again confirms that the extent of co-worker clustering is equally low in the bankruptcy-hit buildings in our sample and other HDB buildings.

To summarize, while we cannot provide direct evidence on co-workers' residential choice, our work commute evidence suggests that it is quite unlikely to have sorting of co-workers into the same residential building in Singapore. Workers tend to travel long distances to work and commute to different work locations. This pattern holds in the full sample as well as in subsample of bankruptcy-hit buildings. It is consistent with our existing evidence that shows a low concentration of occupations within an HDB building and lends further support to the notion that residential choice (at the building level) is close to a random assignment due to Singapore's public housing policy.

3. Definition of Trend-adjusted and Income-scaled Spending Change

We compute the consumption change for each peer consumer (in Section 4.3.1 and Figure 1 of the main body) in the following steps (by properly controlling for time trend and scaling income differences across individuals).

A. For each event building in our sample, we calculate the average total card spending for each month from other non-event buildings in the same postal sector. The purpose of this step is to create a counterfactual consumption level using spending from consumers living in the nearby, unaffected buildings.[9] This is meant, similar to the fixed effects in the regression framework, to control for common trends in consumption (in a time frame when Singapore experienced strong economic growth in general).
B. Then we adjust the monthly spending for consumers living in bankruptcy-hit buildings by subtracting the postal-sector-average spending in the same month.
C. For each peer consumer, we calculate the average of the adjusted monthly spending during the pre-event period and the average of the adjusted monthly spending during the post-event period. We scale both the pre-event and post-event average adjusted spending by the pre-event period average monthly income.
D. Finally, the spending change is defined by subtracting the pre-event period average adjusted spending (scaled by income) from the post-event period equivalence.

4. Economic Mechanisms

4.1 Keeping Up with the Joneses and Status Signaling

We consider two major competing mechanisms through which consumption externalities could take place. Both channels incorporate peers' consumption into an individual's utility function, thereby allowing the peers' consumption decisions to influence her own. The "keep up with the Joneses" mechanism models an individual's utility as a function of the average

[9] In Singapore, the first 2 digits of zip code represent the sector where a building locates. There are 28 postal sectors in Singapore. The reason why we use the average spending among consumers in a broader region (i.e., sectors) instead of nearby buildings is to increase the sample size and estimation precision of the counterfactual.

consumption level of her peers, and thus peers' consumption shall affect the intertemporal substitution of her consumption decision (e.g., Gali, 1994). On the other hand, the status signaling mechanism creates distortions in the intra-temporal consumption decision of peers, whereby the allocation of consumption is tilted towards more visible or conspicuous goods (Veblen, 1899; Bagwell, Simon, and Bernheim, 1996).

If the peer effect works through the status signaling mechanism which mainly affects peers' intra-temporal consumption decision, then we should expect to see a disproportionate decrease in conspicuous compared to non-conspicuous consumption. One possibility is that peers become relatively richer after their same-building neighbor went bankrupt, leading to a reduced incentive to signal. Under this hypothesis, they would allocate a lower proportion of spending on conspicuous goods and reduce disproportionately more of their conspicuous consumption. Alternatively, neighbor's bankruptcy lowers the overall peer group income which increases the benefit of signaling. This will predict a smaller reduction in peers' conspicuous consumption. Both arguments point to unequal changes in the conspicuous and non-conspicuous consumption. On the other hand, if the "keep up with the Joneses" mechanism plays a more prominent role, then we should expect to see an equal decrease in both conspicuous and non-conspicuous consumption. Since that mechanism affects peers' inter-temporal consumption decision, they will decrease their overall consumption but keep the proportion of conspicuous consumption unchanged.

Next, we exploit the detailed transaction-level information from our consumption dataset and construct a finer test to differentiate the two mechanisms.

4.1.1 Visible and Non-Visible Consumption

First, we exploit the granular information on the merchant types from the credit and debit card transactions in our consumption dataset. Transactions are grouped into the visible and non-visible categories following the definitions in Charles, Hurst, and Roussanov (2009) (CHR thereafter) and Heffetz (2011).

By conducting an anonymous online survey of 320 students at the University of Chicago's Harris School and Graduate School of Business, CHR (2009) define "visible goods" as expenditures on apparel (including accessories such as jewelry), personal care, and vehicles (excluding maintenance). Similarly, Heffetz (2011) conducted a randomized survey among a sample from the above-18 US population. Based on 480 completed interviews, he constructed a "visibility index" (VI thereafter) for all the 31 categories of goods included in the paper. Visibility index varies from 0 to 1, and a higher value means higher perceived visibility from the interviewees. We compare the two papers, and find that all categories of "visible goods" defined in CHR (2009) have "visibility index" no lower than 0.6 in Heffetz (2011).

Specifically, there are 10 categories of goods out of 31 categories in Heffetz (2011) that have VI≥0.6, including cigarettes (VI=0.76), cars (VI=0.73), clothing (VI=0.71), furniture (VI=0.68), jewelry (VI=0.67), recreation 1 (VI=0.66), food out (VI=0.62), alcohol home (VI=0.61), barbers, etc. (VI=0.60), and alcohol out (VI=0.60). There is another category of recreation goods in Heffetz (2011)—"recreation 2"—with a VI of 0.58, which ranks next to the visibility of "barters, etc." and "alcohol out". Because the merchant categories provided in our card transaction data do not clearly distinguish between the two types of recreational activities/goods, we classify all goods/services in "recreation 1" and "recreation 2" defined in Heffetz (2011), together with the other 9 categories of goods that with VI≥0.6 as "visible goods". We report how we correspond the merchant categories in card transaction data to the visible goods categories defined in CHR (2009) and Heffetz (2011) in Table A6. Note that if any categories of goods among the above-mentioned 11 types in Heffetz (2011) are not reported in Table A6, it means that there is no corresponding expenditure category in our debit card or credit card transaction.

In columns 1-2 of Table 5, we find a similar extent of consumption responses for both visible-goods and non-visible goods (the Chi-statistic suggests two regression coefficients for the $1_{[0,+12]}$ dummy are not statistically different—*p* value=0.949).

4.1.2 By the Value in a Single Purchase

The second pattern we exploit from the disaggregated spending transactions is to detect luxury spending on merchandise or services by the spending amount in a single purchase. Specifically, we study the entire (credit and debit) transaction dataset during the full sample period (2010:04-2012:03) to find the single-purchase amount cutoff as the top five percentile of the distribution, which is equal to SGD 370. Then we aggregate all spending transactions above (below) that threshold at the individual-month level as *total card spending on high-value single purchase* (*total card spending on normal-value single purchase*). During our two-year sample period for the peer consumers, the average dollar amount for *total card spending on high-value single purchase* is SGD 335, and the average dollar amount for *total card spending on normal-value single purchase* is SGD 520.

We repeat the consumption response specification with these two spending measures as dependent variables and report the results in columns 3-4 of Table 5. The monthly spending response on high-value purchases is statistically insignificant. However, we cannot reject the hypothesis that the spending decrease on high-value purchase is equal to the spending decrease on normal-value purchase (the Chi-statistic suggests two regression coefficients for the $1_{[0,+12]}$ dummy are not statistically different—*p* value=0.757).

Taken together, the results with different proxies of conspicuous consumption or status-driven spending provide consistent evidence that peer consumers do not disproportionately change their conspicuous or status-driven spending after their neighbor's bankruptcy event. Therefore, these findings are more supportive of the "keep up with the Joneses" channel.

4.2 Bankruptcy Event as an Information or Salience Shock

Bankruptcy is a salient event in Singapore. As described earlier, the bankruptcy order is made publicly available through Government Gazette. In addition, neighbors in the same building likely observe the distress experienced by the bankrupt individual. As a result, peer consumers may obtain information about the severe consequences associated with bankruptcy that they would otherwise be unaware of or inattentive to. This implies an alternative channel to explain the consumption decrease among peer consumers, as they cut their spending to avoid potential financial distress in the future. Following this argument, we should observe a stronger decrease in credit card spending if peer consumers aimed to cut their (credit card) debt in order to reduce the risk of financial distress. However, the previous result finds equal consumption decrease using debit cards and credit cards (columns 2-3 of Panel B, Table 2).

We further investigate the information story by examining the differential consumption response among the subsample of peer consumers for whom the information is more relevant. We use three proxies to measure the level of economic resources: age, income, and length of bank relationship. The information channel would predict a stronger consumption decrease for younger, lower-income (or wealth) peer consumers, as the probability of experiencing financial distress is higher for them. On the other hand, the peer effect channel could imply a stronger impact on the less economically constrained consumers, who are more likely to be close peers given the bankrupts' high level of credit access prior to bankruptcy (e.g., the average amount of debt at the time of bankruptcy is SGD 100K, see Table 1).

To formally test the hypothesis, we normalize the three continuous measures (age, income, and length of bank relationship) in the following way. For each of the continuous measure X, we take its average during the three-month pre-bankruptcy period and construct the standardized measure for X as the difference between an individual's average pre-bankruptcy X and its cross-sectional mean among all individuals, divided by the standard deviation of average pre-bankruptcy X from the same cross-sectional distribution. Then the coefficient for the interaction term between the post-bankruptcy dummy and this standardized measure can be interpreted as the incremental effect associated with one standard deviation change in the continuous variable X, relative to its cross-sectional mean.

In contrast to the prediction of the information channel, we find evidence of a much stronger consumption response among older, higher-income, or longer banking relationship peers (Table A7). We also construct dummy indicators based on the value of these measures, and continue to find the same results.

Perhaps the bankruptcy event does not provide new information to consumers but instead triggered the behavioral change purely due to its salience (Han, Hirshleifer, and Walden, 2018). However, the salience-based explanation is also difficult to reconcile with our existing finding on the private market effect. The salience of the event holds equally for bankrupt individuals living in the public housing market and those living in the private housing market. However, we do not find any consumption decrease among peer consumers living in the private bankruptcy-hit buildings (Table 3, column 3).

5. Further Analysis

In this section, we carry out a series of additional analyses to strengthen the identification and provide robustness checks for the main results presented earlier.

5.1 Alternative Event Windows

Our spending behavior results are robust to the pre-bankruptcy control period (for parallel trends verification) and event window choice. We study the average spending response by using the three-month pre-bankruptcy period to test the parallel trends assumption, extending the event window to [-12, +18] month range, and shortening the event window to [-6, +12] month range. The results remain qualitatively and quantitatively similar (Table A8).

5.2 Additional Falsification Tests

We present additional falsification tests. First, we hold the bankruptcy-hit buildings and peer consumers constant and randomly assign the timing of each bankruptcy event from our bankruptcy sample. Then we repeat our main specification on the total card spending response as in column 1 of Table 2. Next, we hold the bankruptcy-hit buildings as well as the event time fixed, and randomly assign peer consumers into the building from our treatment sample. For each building, we ensure the number of "pseudo" treated consumers randomly assigned equals to the number of true peer consumers. We repeat our main specification as in column 1 of Table 2. Both exercises find no significant consumption response (Table A9).

5.3 Additional Tests on Outliers

We remove individuals with the most extreme changes in spending during the post-event period from our sample. We find a similar spending decrease of around 3.6 percent per month as in the full sample, and the effect is statistically significant at the 1 percent level (Column 1, Table A10).

To further dispel the notion that outlier individuals drive the consumption response, we randomly pick and remove one treated individual from our sample and repeat the analysis in Table 2, column 1. We iterate this analysis 100 times and obtain 100 coefficient estimates for the post- and pre-bankruptcy dummies. The average coefficient for the post-bankruptcy dummy is -0.033 with an average *p* value of 0.019. In contrast, the average of the pre-bankruptcy dummy estimates is small and insignificant (average *p* value=0.425) (Figure A3).

We also study whether the consumption decrease is driven by a few HDB buildings that have large bankruptcy shocks. We create a dummy variable equal to one if the building's bankruptcy event amount is among the top 10 percentile of the cross-sectional distribution of all bankruptcy cases in our sample. Peer consumers living in buildings associated with a greater bankruptcy amount did exhibit a greater reduction of total card spending, consistent with the implication of a stronger financial distress affecting their bankrupt neighbors. On the other hand, peers living in buildings with lower than 90 percentile of the bankruptcy amount distribution also reduce their monthly spending after the event by 2.9 percent, and the effect is statistically significant at the 5 percent level (Column 2, Table A10). Taken together, our evidence suggests that the consumption decrease is not driven by outlier individuals or buildings.

5.4 Sample Selection Concerns

In our main analysis, we restrict the sample to buildings with only one bankruptcy event during the whole sample period, and we exclude bankruptcy-hit buildings that are preceded, within a 12-month period, by another bankruptcy case that occurred before 2010:04. As briefly explained in the main text, we impose these restrictions for two reasons. The first reason is that multiple bankruptcies in the same building during the two-year period might reflect some common shocks to all residents in the building. The second reason is more of an econometric concern. For buildings with multiple bankruptcy events during our sample period, the average (median) difference between two bankruptcy events is 7.5 (6) months. As a result, a month can fall in *both* the pre-event period *and* the post-event period. For example, if building B has two bankruptcy cases in 2011:01 and 2011:07 respectively, then 2011:02-2011:06 are the post-event months for the first bankruptcy case, in which we are likely to observe a decrease in peer consumer's consumption (as we show in our main result). However, they will also be used as pre-event months to measure the baseline period consumption level for the second bankruptcy case. This makes it econometrically challenging to identify the true change in consumption, due to a poor measurement of the baseline (i.e., pre-event) period for the multiple bankruptcy events. Specifically, the possible consumption decrease in the baseline period (in response to the previous bankruptcy event) will lead to an underestimation of the true consumption response for the later bankruptcy event in the multiple-bankruptcy-events building.

Excluding the multiple bankruptcy event buildings may, however, raise sample selection concerns. We check and verify that there are no significant differences between the single-bankruptcy-event and multiple-bankruptcy-events buildings in terms of both the bankrupt individuals' characteristics and the peer consumers' observable characteristics (Table A11). Moreover, despite the poor measurement of the pre-event period and the associated estimation bias, we conduct a robustness check by including the multiple-bankruptcy-events buildings in our sample and continue to find a significant consumption decrease (Column 1, Table A12).

On the other hand, some bankruptcy-hit buildings in our sample contain multiple bankruptcy cases (and individuals). Even though it is a small subsample, we conduct a robustness check by removing all those multiple bankruptcy case events (N=82). We continue to find a similar response, both in statistical significance and economic magnitude (Column 2, Table A12).

Another potential concern regarding our treatment sample is the higher number of bankruptcy events in the last two months of our sample period. One question remains is whether this represents an aggregate (upward) trend or a temporary spike. In unreported results, we tabulate the number of bankruptcy cases until 2012:09 (end of our raw bankruptcy data), and find that the number of bankruptcy cases went back to the average level by August of 2012. In addition, we remove the bankruptcy events during these two months and repeat the main analysis. Our results remain robust: the estimated average reduction in total card spending is 3.5 percent per month and the effect is statistically significant at the 1 percent level (Column 3, Table A12).

5.5 Alternative Measures

We use an alternative approach to exclude bankrupt individuals from our sample. Specifically, we identify, from individuals living in the bankruptcy-hit HDB buildings, those who happened to close their credit card accounts during the one-year period after the peer bankruptcy event (i.e., between month 0 and month 12). Given the Singapore bankruptcy law, these are potential bankruptcy candidates (though not all of them closed their accounts due to bankruptcy). We drop these individuals from our sample and repeat our analysis in Column 1 of Table 2. The coefficient on the post-bankruptcy dummy becomes -0.033, which is very similar to that in Table 2, and is statistically significant at the 5 percent.

Finally, we use the number of purchases as alternative measures of consumption and continue to find a significant decrease in the number of transactions for total card spending, credit card, and debit card spending. We also perform an analysis using the number of bank transactions (such as via ATM, branch, or online) that offer a coarse measure of cash and check transactions, and find no change around peer bankruptcy events (Table A13).

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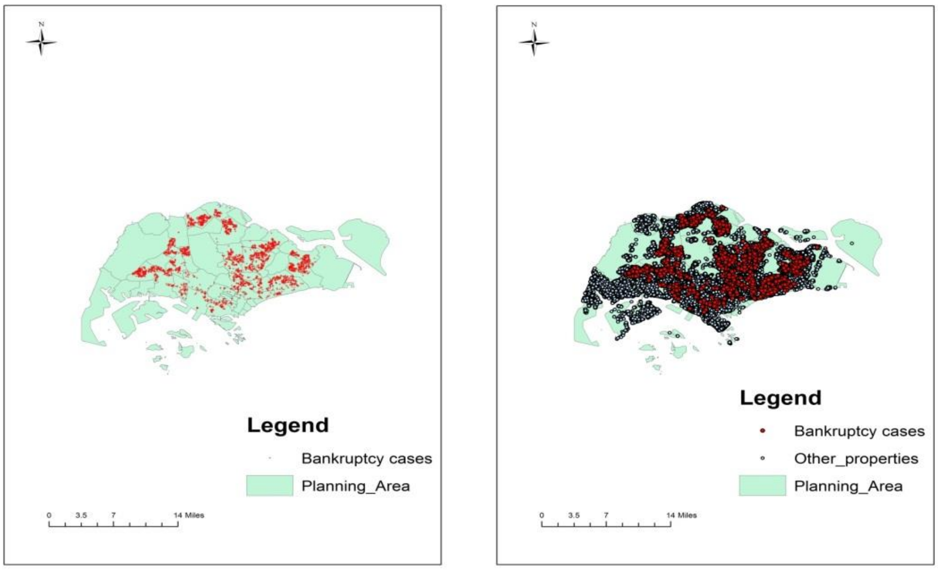
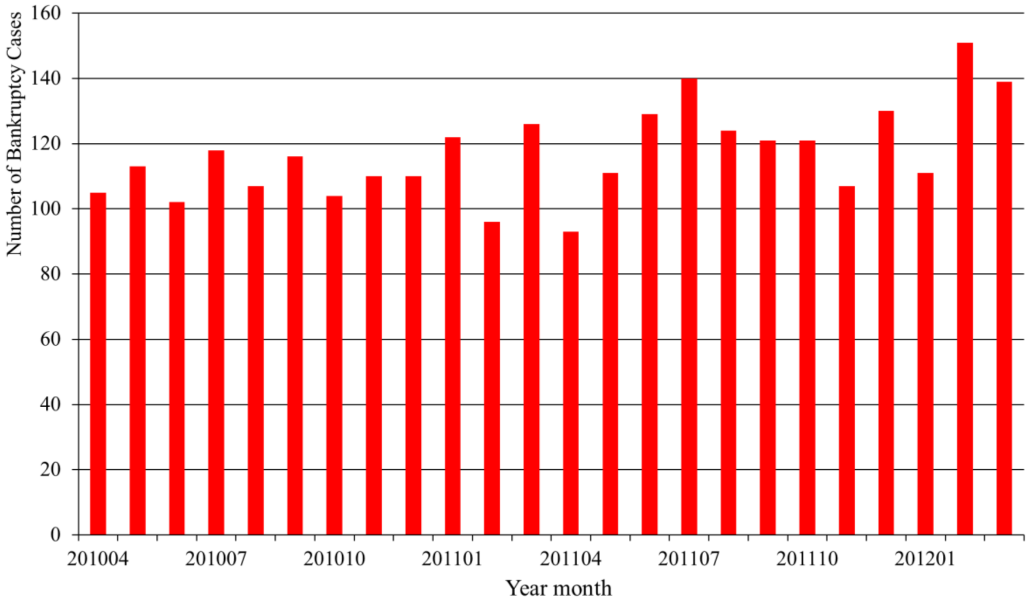
Veblen, Thorstein. 1899. "The Theory of the Leisure Class: An Economic Study in the Evolution of Institutions." Macmillan.

Figure A1. Distribution of Personal Bankruptcy Events

Panel A: By location

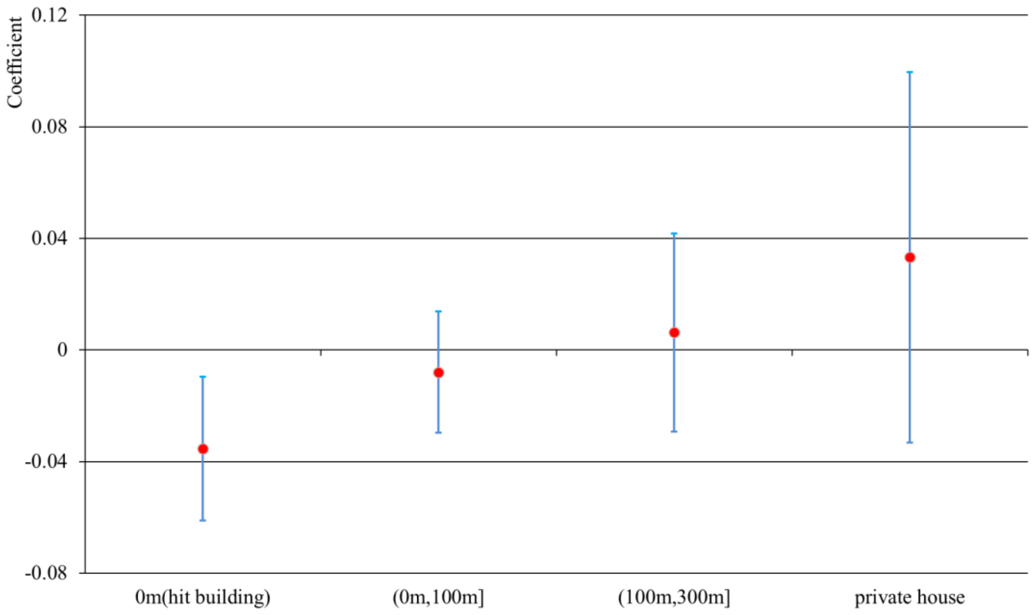


Panel B: By calendar time



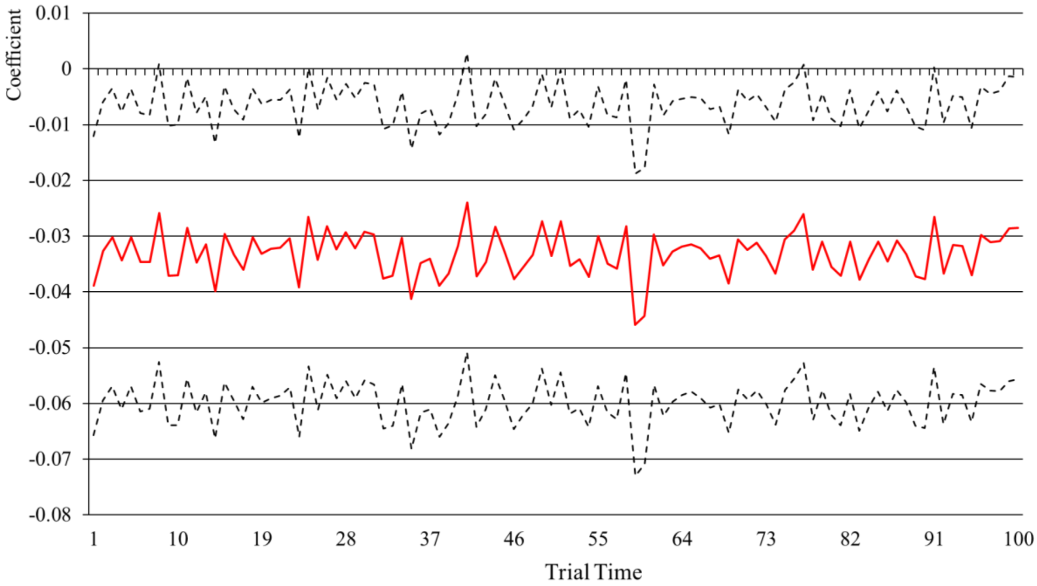
Note. Panel A plots the location distribution of all bankruptcy cases during our sample period (2010:04-2012:03). Panel B plots the time distribution of all bankruptcy cases during our sample period.

Figure A2. Spending Response in Nearby HDB Buildings and Private Housing Market



Note. This figure plots the estimated spending response and 95 percent confidence intervals for different groups of consumers. The first data point presents the average response of peer consumers living in bankruptcy-hit HDB buildings (i.e., the peers included in our main analysis), and the regression result is reported in column 1 of Table 2. The second data point represents the average consumption change of bank consumers living in the buildings within 100-meter radius of the bankruptcy-hit building. The regression coefficient is taken from column 1 of Table 3. The third data point represents the average consumption change of bank consumers living in the buildings within 100-meter to 300-meter radius of the bankruptcy-hit building. The regression coefficient is taken from column 2 of Table 3. And the last data point represents the average consumption change of peer consumers in the private housing market. The regression coefficient is taken from Column 3 of Table 3.

Figure A3. Distribution of Spending Response Coefficients after Randomly Dropping One Peer in Each Building



Note. This figure plots the estimated coefficient and 95 percent confidence intervals from the regression equation (1) after one random peer consumer is dropped from each building in our sample. We repeat the random drop trial for 100 times.

Table A1. Demographics of the Bankrupt Individuals

	Bankrupt individuals			Singapore residents			
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	Difference in means (1) – (4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female (%)	24.2	42.8	0	51.0	50.0	100	-26.9***
Chinese (%)	65.8	47.5	100	82.3	38.1	100	-16.6***
Age	43.2	10.5	43.0	46.9	14.8	47.0	-3.7***
Number of individuals	2,806			2,353,550			

Note. This table provides summary statistics of demographic information for the bankrupt individuals during our sample period (2010:04-2012:03), compared to the population of Singaporean citizens and permanent residents from our demographics data. *Age* measures the age of an individual in the year 2011. Please refer to Table 1 for other variable definitions. Differences in means of each variable are reported in column 7. *** indicates significant at the 1 percent, ** indicates significant at the 5 percent, and * indicates significant at the 10 percent respectively.

Table A2. Work Commute Time and Co-worker Fraction

Panel A: Building-level commute time

	Mean	25th percentile	Median	75th percentile
	(1)	(2)	(3)	(4)
All HDB buildings (in minutes)	33.01	25.06	33.43	40.74
Buildings in sample	33.37	26.05	34.17	40.96
Other HDB buildings	32.93	25.00	33.34	40.72
Difference in mean (=HDB in sample - other HDB)	0.44			

Panel B: Within-building variation of commute time

	Mean	25th percentile	Median	75th percentile
	(1)	(2)	(3)	(4)
Standard deviation (in minutes)	16.71	13.89	16.72	19.60
75th percentile – 25th percentile	21.07	14.70	19.67	26.76

Panel C: Building-level co-worker fraction

	Mean	25th percentile	Median	75th percentile
	(1)	(2)	(3)	(4)
All HDB buildings (in percentage)	15.51	9.03	12.80	18.54
Buildings in sample	15.82	9.14	13.19	18.62
Other HDB buildings	15.45	9.03	12.78	18.54
Difference in mean (=HDB in sample - other HDB)	0.37			

Note. This table reports the distribution of work trip commute time and co-worker fraction for HDB buildings from the public transport trips. Panel A reports the distributions of building-level average work trip commute time for all HDB buildings in Singapore, bankruptcy-hit HDB buildings in the sample, and other HDB buildings respectively. Panel B reports the within-building variation in work trip commute time for bankruptcy-hit HDB buildings in the sample. The within-building variation is proxy by within-building standard deviation and inter-quartile difference in individual work trip commute time. Panel C reports the distributions of building-level co-worker fraction for all HDB buildings in Singapore, bankruptcy-hit HDB buildings in the sample, and other HDB buildings respectively. *** indicates significant at the 1 percent, ** indicates significant at the 5 percent, and * indicates significant at the 10 percent respectively.

Table A3. Heterogeneity by Neighborhood Size and Sampling Rate

	Neighborhood size	Sampling rate
	Log(Total card spending)	
	(1)	(2)
$1_{[-1,-1]}$	-0.011	-0.011
	[0.013]	[0.013]
$1_{[0,+12]}$	-0.025	-0.037**
	[0.018]	[0.015]
$1_{[0,+12]}$×High # of peers	-0.016	
	[0.020]	
$1_{[0,+12]}$×Low sampling rate		0.005
		[0.019]
Constant	5.574***	5.574***
	[0.020]	[0.020]
Individual FE	Y	Y
Year-month FE	Y	Y
Observations	278,054	278,054
R-squared	0.47	0.47

Note. This table investigates the possibility that family members of bankrupt individuals are driving the consumption response. Column 1 reports the heterogeneity of average consumption responses from large versus small neighbourhoods. *High # of peers* is a dummy variable equal to one if the number of peers in a building is higher than the median (around 11). Column 2 reports the heterogeneity of average consumption response in low sampling rate buildings versus high sampling rate buildings. *Low sampling rate* is a dummy variable equal to one if the sampling rate of a building is lower than the median. For each bankruptcy-hit HDB building, the sampling rate $= \frac{\text{number of peer consumers in sample}}{\text{total number of residents in a building}} \times 100\%$, and the median sampling rate is around 4.3 percent. The dependent variables are log of total card spending. Individual and year-month fixed effects are included. Standard errors clustered at the building level are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table A4. Post-Bankruptcy Credit Limit Change

Panel A: Univariate comparison: pre-event vs. post-event credit limit

	Pre-event period			Post-event period			Difference in means
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	(1)-(4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Credit limit (SGD)	8,540	5,369	7,000	12,523	8,317	10,500	-3,983***
Number of individuals	940			973			

Panel B: Regression analysis

	Log (Credit limit)
	(1)
$1_{[-1,-1]}$	-0.000
	[0.002]
$1_{[0,+12]}$	-0.001
	[0.002]
Constant	8.646***
	[0.002]
Individual FE	Y
Year-month FE	Y
Observations	236,941
R-squared	0.98

Note. This table reports the change of credit limit among peer consumers after their neighbors' bankruptcy event. Panel A compares the average monthly credit limit for peer consumers in our sample during the pre-event period (i.e., event month -12 to event month -1) and post-event period (i.e., event month 0 to event month +12). Panel B presents the regression result when the log of credit limit is used as the dependent variable. We calculate the log of the credit limit as log (credit limit + 1). Individual and year-month fixed effects are included. Standard errors clustered at the building level are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table A5. Checking Account Inflow Response

	Log(Checking account inflow)
	(1)
$1_{[-1,-1]}$	-0.002
	[0.017]
$1_{[0,+12]}$	0.001
	[0.016]
Constant	7.260***
	[0.026]
Individual FE	Y
Year-month FE	Y
Observations	277,528
R-squared	0.63

Note. This table reports peer consumers' response in monthly checking account inflow during 2010:04-2012:03. We calculate log of checking account inflow as log (checking account inflow + 1) to include 0 cash flow cases. Individual and year-month fixed effects are included. Standard errors clustered at the building level are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table A6. Visible Goods Classification

Transaction category name (1)	Category name: CHR (2009) (2)	Visible goods: CHR (2009) (3)	Category name: Heffetz (2011) (4)	Visibility Index: Heffetz (2011) (5)
Panel A. Debit card				
Driving centers	Vehicle (expanded)	Yes	Cars	0.73
departmental stores	Clothing/jewelry	Yes	Clothing	0.71
fashion accessories & apparel	Clothing/jewelry	Yes	Clothing	0.71
jewelry	Clothing/jewelry	Yes	Jewelry	0.67
electronic & computer		No	Recreation 1	0.66
sports merchandise		No	Recreation 1	0.66
entertainment & recreational		No	Recreation 1/ recreation 2	0.66/0.58
restaurants, cafe, bars		No	Food out/alcohol out	0.62/0.60
beauty salons & cosmetics & spa	Personal care	Yes	Barbers, etc.	0.60
child & mother care	Personal care	Yes	Barbers, etc.	0.60
Panel B. Credit card				
specialty retail	Clothing/jewelry	Yes	Cigarettes/jewelry/alcohol home	0.76/0.67/0.61
automotive related	Vehicle (expanded)	Yes	Cars	0.73
rental	Vehicle (expanded)	Yes	Cars	0.73
apparel	Clothing/jewelry	Yes	Clothing	0.71
departmental stores	Clothing/jewelry	Yes	Clothing	0.71
watches & jewelry	Clothing/jewelry	Yes	Clothing	0.71
home/office furnishing & appliances		No	Furniture	0.68
electronic and computer		No	Recreation 1	0.66
music		No	Recreation 1	0.66
entertainment & recreational		No	Recreation 1/ recreation 2	0.66/0.58
dining		No	Food out/alcohol out	0.62/0.60
associations/ memberships	Personal care	Yes	Barbers, etc./ recreation 2	0.60/0.58
pets		No	Recreation 2	0.58

Note. This table gives the merchant categories defined as visible goods for debit card spending (Panel A) and credit card spending (Panel B). If any categories of goods among the 11 categories with VI≥0.58 in Heffetz (2011) are not reported here, it means that there is no corresponding expenditure category in our debit card or credit card data.

Table A7. Bankruptcy Event as an Information Shock

	Log(Total card spending)		
	(1)	(2)	(3)
$1_{[-1,-1]}$	-0.009	-0.006	-0.009
	[0.013]	[0.013]	[0.013]
$1_{[0,+12]}$	-0.032**	-0.032**	-0.032**
	[0.013]	[0.013]	[0.013]
$1_{[0,+12]}$×Standardized age	-0.079***		
	[0.010]		
$1_{[0,+12]}$×Standardized income		-0.046***	
		[0.011]	
$1_{[0,+12]}$×Standardized bank relationship (in mos.)			-0.046***
			[0.011]
Constant	5.579***	5.585***	5.579***
	[0.021]	[0.021]	[0.021]
Individual FE	Y	Y	Y
Year-month FE	Y	Y	Y
Observations	261,413	258,759	261,413
R-squared	0.47	0.47	0.47

Note. This table reports the heterogeneity across individuals in their total card spending responses. Our sample includes individuals living in the bankruptcy-hit HDB buildings during the [-12, +12 month] event window. *Standardized age$_i$ = (average age$_i$-mean age)/sd age*, where *average age$_i$* is the average age for individual *i* during the three-month period before the bankruptcy event in the building; *mean age* is the cross-sectional mean of all *age$_i$* , and *sd age* is the cross-sectional standard deviation of all *average age$_i$*. *Standardized income$_i$ = (average income$_i$-mean income)/sd income*, where *average income$_i$* is the mean of monthly income for individual *i* during the three-month period before the bankruptcy event in building; *mean income* is the cross-sectional mean of all *average income$_i$*.; and *sd income* is the cross-sectional standard deviation of all *average income$_i$*, *Standardized bank relationship$_i$ = (average bank relationship$_i$ - mean bank relationship)/sd bank relationship*, where *average bank relationship$_i$* is the mean of individual *i*'s length of relation with the bank during the three-month period before the bankruptcy event in building measured by month, *mean bank relationship* is the cross-sectional mean of all *average bank relationship$_i$*., and *sd bank relationship* is the cross-sectional standard deviation of all *average bank relationship$_i$*. Please refer to Table 1 and Table 2 for more detailed variable definitions. We calculate the log of total spending as log (total card spending + 1) to include 0 spending cases. Individual and year-month fixed effects are included. Standard errors are clustered at the building level, and are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table A8. Alternative Pre- and Post-bankruptcy Windows

	Log (Total card spending)		
	Event window [-12,+12]	Event window [-6,+12]	Event window [-12,+18]
	(1)	(2)	(3)
$1_{[-3,-1]}$	0.002		
	[0.011]		
$1_{[-1,-1]}$		-0.011	-0.010
		[0.012]	[0.013]
$1_{[0,+12]}$	-0.030*	-0.038***	
	[0.016]	[0.014]	
$1_{[0,+18]}$			-0.032**
			[0.013]
Constant	5.574***	5.553***	5.577***
	[0.020]	[0.029]	[0.020]
Individual FE	Y	Y	Y
Year-month FE	Y	Y	Y
Observations	278,054	219,080	305,325
R-squared	0.47	0.50	0.46

Note. This table provides three sets of robustness checks for the average response of total card spending (i.e., result in Table 2, column 1 by using different event windows or alternative pre-bankruptcy window control. All three specifications include treated individuals in the HDB buildings only. In column 1, we use 3 months before the bankruptcy event to test the pre-event trend. In column 2, we employ a shorter event window (i.e., [-6, +12 month]) in the analysis. In column 3, we adopt an extended event window (i.e. [-12, +18 month]) in our analysis. $1_{pre[-3,-1]}$ is a binary variable equal to one for the three months before bankruptcy (i.e., month -3 to -1). Please refer to Table 1 and Table 2 for more detailed variable definitions. We calculate log of spending as log (Total card spending + 1) to include 0 spending cases. Individual and year-month fixed effects are included. Standard errors are clustered at the building level, and are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table A9. Additional Falsification Tests

	Log (Total card spending)	
	Randomly assigned bankruptcy time	Randomly assigned peer consumers
	(1)	(2)
$1_{[-1,-1]}$	0.021	0.017
	[0.013]	[0.013]
$1_{[0,+12]}$	0.009	0.012
	[0.013]	[0.012]
Constant	5.614***	5.570***
	[0.019]	[0.019]
Individual FE	Y	Y
Year-month FE	Y	Y
Observations	276,503	277,182
R-squared	0.47	0.47

Note. This table presents three sets of falsification tests for the average response of total card spending. In column 1, we randomly assign the timing of each in-sample bankruptcy event to the peer consumers in bankruptcy-hit buildings. In column 2, we assign the peer consumers in our sample to a randomly chosen bankruptcy-hit building and event time pair. Please refer to Table 1 and Table 2 for more detailed variable definitions. The samples in all three specifications include the observations in the [-12, +12 month]. We calculate the log of total card spending as log (total card spending + 1) to include 0 spending cases. Individual and year-month fixed effects are included. Standard errors are clustered at the building level, and are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table A10. Influence of Outlier Bankruptcy Buildings or Outlier Peers

	Log (Total card spending)	
	Exclude outlier consumers	Interact with the high bankruptcy amount dummy
	(2)	(1)
$1_{[-1,-1]}$	0.003	-0.011
	[0.013]	[0.013]
$1_{[0,+12]}$	-0.037***	-0.029**
	[0.013]	[0.014]
$1_{[0,+12]}\times$ Large amount		-0.060*
		[0.031]
Constant	5.703***	5.573***
	[0.021]	[0.020]
Individual FE	Y	Y
Year-month FE	Y	Y
Observations	227,418	278,054
R-squared	0.49	0.47

Note. This table reports the effect of the Outliers. In column 1, we exclude the individuals with the most extreme consumption change after the bankruptcy event in each building, and estimate the average consumption response for the remaining peer consumers. For each bankruptcy-hit building in our sample, we get the average monthly spending from each peer consumers during the pre-event period (i.e., from event month -12 to event month -1) and post-event period (i.e., from event month 0 to event month +12). Then we construct the percentage change in total card spending for each peer consumer as (post-event average monthly spending – pre-event average monthly spending)/pre event average monthly spending$\times$100%. Then for each building, we drop the peer consumers with the most extreme change in total card spending. Note that buildings with less than 3 peer consumers identified are automatically dropped in this test. In column 2, we check the possible effect of bankruptcy events with extremely high bankruptcy amount. *Large amount* is a dummy variable equal to one if the related bankruptcy event amount is greater than the 90th percentile among all bankruptcy events in our sample (i.e., S$ 110,139). Please refer to Table 1 and Table 2 for more detailed variable definitions. We calculate log of spending as log (spending + 1) to include 0 spending cases. Individual and year-month fixed effects are included. Standard errors are clustered at the building level, and are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table A11. Single Bankruptcy Event Buildings vs. Multiple Bankruptcy Event Buildings

Panel A: Bankrupt individuals in single-event buildings vs. multiple-event buildings

	Single-event buildings			Multiple-events buildings			Difference in means
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	(1)-(4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female (%)	23.8	42.6	0	25.5	43.6	0	-1.7
Chinese (%)	63.4	48.2	100	64.7	47.8	100	-1.3
Age	42.2	10.3	42.0	42.5	10.2	42.0	-0.3
Number of cases	1,655			733			

Panel B: Bank consumers in single-event buildings vs. multiple-events buildings

	Single-event buildings			Multiple-events buildings			Difference in means
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	(1)-(4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female (%)	42.9	20.0	42.9	43.3	20.1	42.9	-0.3
Chinese (%)	77.1	18.8	80.0	77.3	18.1	81.8	-0.2
Age	38.2	4.6	38.1	37.5	4.7	37.7	0.7**
Income (SGD)	4,004	1,264	3,833	3,997	1,276	3,966	7.4
Bank relationship (in mos)	14.0	2.3	14.0	14.0	2.2	14.0	0.0
Number of buildings	1,485			313			

Note. This table provides comparisons between single-bankruptcy-event buildings and multiple-bankruptcy-event buildings. In Panel A, we compare the demographic characteristics of bankrupt individuals between the two types of buildings. In Panel B, we compare the pre-event building-level demographic and financial characteristics of the bank consumers living in two types of buildings. Specifically, for each building, we get the monthly average value of the characteristics for each bank consumers during the three-month pre-event period (i.e., month -3 to month -1), then we take the average value at the building level. Differences in means of each variable are reported in column 7. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table A12. Choice of Bankruptcy Events

	Include multiple bankruptcy event buildings (1)	Exclude multiple-case events (2)	Exclude events in last 2 months (3)
$1_{[-1,-1]}$	-0.010	-0.006	-0.013
	[0.010]	[0.013]	[0.013]
$1_{[0,+12]}$	-0.020**	-0.027**	-0.036***
	[0.010]	[0.013]	[0.014]
Constant	5.584***	5.576***	5.576***
	[0.017]	[0.020]	[0.020]
Individual FE	Y	Y	Y
Year-month FE	Y	Y	Y
Observations	418,825	262,391	256,390
R-squared	0.48	0.47	0.47

Note. This table presents the average spending response among peer consumers under different choices of bankruptcy events. In column 1, we allow the buildings to have multiple bankruptcy events within our two-year sample period, and also allow them to be preceded by other bankruptcy case(s) that occurred before 2010:04. In column 2, we exclude the buildings with multiple bankruptcy-cases happened within one month. In column 3, we drop all buildings with bankruptcy events happening in the last two months of our sample period (i.e., 2012:02 and 2012:03). All dependent variables are log of total card spending. We calculate the log of total card spending as log (Total card spending + 1) to include 0 spending cases. Please refer to Table 1 and Table 2 for more detailed variable definitions. Individual and year-month fixed effects are included. Standard errors are clustered at the building level, and are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table A13. Alternative Consumption Measures: Number of Purchases

Panel A: Number of transaction count

	Log(Total card # of purchase)	Log(Credit card # of purchase)	Log(Debit card # of purchase)
	(1)	(2)	(3)
$1_{[-1,-1]}$	-0.002	-0.006	0.001
	[0.005]	[0.006]	[0.006]
$1_{[0,+12]}$	-0.012**	-0.010*	-0.010*
	[0.005]	[0.006]	[0.005]
Constant	1.892***	0.993***	1.367***
	[0.008]	[0.008]	[0.008]
Individual FE	Y	Y	Y
Year-month FE	Y	Y	Y
Observations	278,054	278,054	278,054
R-squared	0.64	0.65	0.67

Panel B: Count of ATM, branch, online transaction

	Log(ATM transaction cnt)	Log(Branch transaction cnt)	Log(Online transaction cnt)
	(1)	(2)	(3)
$1_{[-1,-1]}$	-0.002	0.003	0.000
	[0.001]	[0.003]	[0.002]
$1_{[0,+12]}$	-0.001	-0.001	0.002
	[0.001]	[0.003]	[0.002]
Constant	0.068***	0.119***	0.122***
	[0.002]	[0.004]	[0.003]
Individual FE	Y	Y	Y
Year-month FE	Y	Y	Y
Observations	277,528	277,528	277,528
R-squared	0.89	0.28	0.65

Note. This table shows the response of the number of purchases from peer consumers living in the same building with bankrupt individuals during our sample period (2010:04-2012:03). Panel A shows the response of card spending numbers, and dependent variables in columns 1 – 3 are logs of monthly total card swipe count, credit card swipe count, and debit card swipe count respectively. Panel B shows the response of ATM, branch, and online transaction counts, and dependent variables in columns 1 – 3 are logs of monthly ATM, branch, and online transaction count respectively. We calculate log of card swipe time as log (card swipe time + 1) to include 0 swipe cases. Please refer to Table 1 and Table 2 for more detailed variable definitions. Individual and year-month fixed effects are included. Standard errors are clustered at the building level, and are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table A14. Response of Other Financial Outcomes among Peer Consumers

Panel A: Credit card debt amount

	Log (Credit card debt)					
	(1)	(2)	(3)	(4)	(5)	(6)
$1_{[-1,-1]}$	-0.004	-0.004	-0.003	0.004	0.007	0.005
	[0.018]	[0.018]	[0.019]	[0.018]	[0.018]	[0.018]
$1_{[0,+12]}$	-0.016	-0.026	-0.008	-0.004	-0.004	-0.003
	[0.020]	[0.024]	[0.023]	[0.020]	[0.020]	[0.020]
$1_{[0,+12]}$×Female		0.024				
		[0.031]				
$1_{[0,+12]}$×Close in age			-0.037			
			[0.036]			
$1_{[0,+12]}$×Standardized age				-0.234***		
				[0.015]		
$1_{[0,+12]}$×Standardized income					-0.178***	
					[0.016]	
$1_{[0,+12]}$×Standardized bank relationship (in mos)						-0.153***
						[0.016]
Constant	1.275***	1.275***	1.276***	1.266***	1.279***	1.266***
	[0.023]	[0.023]	[0.025]	[0.025]	[0.025]	[0.025]
Individual FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Observations	278,054	278,054	261,764	261,413	258,759	261,413
R-squared	0.68	0.68	0.68	0.68	0.68	0.68

Panel B: Incidence of delinquency on credit cards

	Credit card delinquency (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
$1_{[-1,-1]}$	0.040	0.040	0.040	0.038	0.030	0.040
	[0.078]	[0.078]	[0.081]	[0.078]	[0.078]	[0.078]
$1_{[0,+12]}$	-0.056	-0.066	-0.054	-0.049	-0.065	-0.050
	[0.072]	[0.078]	[0.081]	[0.075]	[0.075]	[0.074]
$1_{[0,+12]}$×Female		0.023				
		[0.090]				
$1_{[0,+12]}$×Close in age			-0.021			
			[0.093]			
$1_{[0,+12]}$×Standardized age				-0.184^{***}		
				[0.045]		
$1_{[0,+12]}$×Standardized income					-0.133^{***}	
					[0.041]	
$1_{[0,+12]}$×Standardized bank relationship (in mos)						-0.199^{***}
						[0.044]
Constant	0.248^{**}	0.248^{**}	0.260^{**}	0.230^{**}	0.246^{**}	0.238^{**}
	[0.103]	[0.103]	[0.109]	[0.109]	[0.109]	[0.109]
Individual FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Observations	236,941	236,941	223,217	223,229	221,227	223,229
R-squared	0.22	0.22	0.22	0.21	0.21	0.21

Panel C: Cash advance fee amount on credit cards

	Log (credit card cash advance fee)					
	(1)	(2)	(3)	(4)	(5)	(6)
$1_{[-1,-1]}$	0.001	0.001	-0.001	0.001	0.001	0.001
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
$1_{[0,+12]}$	-0.001	0.002	-0.002	-0.002	-0.002	-0.002
	[0.003]	[0.004]	[0.004]	[0.003]	[0.003]	[0.003]
$1_{[0,+12]}$×Female		-0.007*				
		[0.004]				
$1_{[0,+12]}$×Close in age			0.000			
			[0.005]			
$1_{[0,+12]}$×Standardized age				-0.002		
				[0.002]		
$1_{[0,+12]}$×Standardized income					-0.004*	
					[0.002]	
$1_{[0,+12]}$×Standardized bank relationship (in mos)						-0.002
						[0.002]
Constant	0.034***	0.034***	0.034***	0.032***	0.032***	0.032***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Individual FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Observations	278,054	278,054	261,764	261,413	258,759	261,413
R-squared	0.34	0.34	0.35	0.34	0.34	0.34

Note. This table shows the response of other financial outcomes from peer consumers after their same-building neighbors' bankruptcy. In Panel A, we report the response of peer consumers' credit card debt, and the dependent variables are log (credit card debt+1). In Panel B, we report the response of peer consumers' credit card delinquency status. For each individual-month, we assign a dummy variable equal to 1 if the individual is at least 30 days late in payment on (one of) the credit card(s) with the bank in that month. The dependent variables are credit card delinquency dummy × 100%. In Panel C, we report the response of peer consumers' credit card cash advance fee, and the dependent variables are log(credit card cash advance fee+1). Please refer to Table 1 for more detailed variable definitions. Individual and year-month fixed effects are included. Standard errors are clustered at the building level, and are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.