Thy Neighbor's Misfortune: Peer Effect on Consumption*

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May 2016

Abstract

We study the credit and debit card spending response of individuals whose neighbors living in the same building experience bankruptcy. We document that the neighbors' monthly card consumption decreases by 3.4% over the one-year post-bankruptcy period—an annual decrease equivalent to 7% of monthly income. The absence of consumption response among individuals in immediately adjacent buildings provides validation of our identification. Consistent with a learning channel, the consumption response is more pronounced for consumers with greater peer awareness or financial sophistication, and is stronger in the non-conspicuous goods. Credit card debt and delinquency also decrease for the financially sophisticated consumers.

Keywords: Peer Effects, Social Learning, Consumption, Spending, Debt, Credit Cards, Household Finance, Banks, Loans, Durable Goods, Discretionary Spending

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

*We have benefited from the comments of Jessica Pan, Ivan Png, Nagpurnanand Prabhala, Tarun Ramadorai, David Reeb, Amit Seru, Nick Souleles, Bernard Yeung, and seminar participants at the National University of Singapore. All errors are our own. Please send correspondence to Wenlan Qian (Wenlan.qian@nus.edu.sg).

1. Introduction

Consumption constitutes the most important component of GDP in many countries, and consequently, understanding the determinants of consumption decisions is of first-order economic significance. Researchers have made substantial progress in studying how individuals' consumption responds to changes in (the expectation of) their own income or economic resources (Jappelli and Pistaferri, 2010). An equally interesting question is how consumption responds to changes in the resources and spending behaviour of their peers. Such a social multiplier effect on consumption bears aggregate implications. For example, incorporating peer responses would offer a more complete assessment of the total consumption response to an economic shock that has a direct impact on a selected population group. It also suggests that policymakers need to take into account the consumption externality when designing or evaluating stimulus or other income-transfer programs.

Despite its importance, we have limited success in understanding the scope and economic mechanism of the peer effect on consumption. Some studies find evidence suggestive of a strong peer influence on consumption patterns. For example, Charles, Hurst, and Roussanov (2009) show that relative status concerns in the community drive conspicuous consumption. Similarly, Bertrand and Morse (2015) find that middle-income households' consumption, especially of visible goods and services, trace the trajectory of consumption by top-income households. One major challenge in identifying the peer effect is the "reflection problem"—the difficulty of distinguishing peer influence from the role of correlated background factors that lead to similar individual choices (Manski, 1993). To get around the identification issues, previous studies rely on clever empirical designs with direct underpinnings of the peer effect on a specific (and non-routine) spending item such as restaurant dining, movie, or car purchase (Cai, Chen, and Fang, 2009; Moretti, 2011; Kuhn et al., 2011). However, it remains unclear how the insights from these findings generalize to total consumption implications.

In this paper, we exploit multiple novel datasets to study the effect of plausibly exogenous income shocks to peers on overall consumption behavior. We identify large, negative individual-specific income shocks by using the universe of all personal bankruptcy events in Singapore, obtained from the Supreme Court of Singapore. In our analysis, we focus on the creditor-filed bankruptcies, which likely capture liquidity-driven cases whereby individuals are forced into bankruptcy upon negative income shocks. The average bankruptcy amount in our sample is over SGD 100,000 (or equivalently USD 77,600). Upon bankruptcy, the debtor faces many restrictions on her choice of consumption (e.g., spending beyond necessities is prohibited). The debtor's assets will also be seized with a few notable exceptions such as her main residence in the public housing sector (a.k.a. HDB). Finally, after the bankruptcy order is issued, the Government Gazette publishes a notification so personal bankruptcy is effectively public information. In sum, our dataset captures the universe of individuals in Singapore who face large

negative income shocks that are salient to the public and upon such shocks will experience a significant spending decrease.

To measure individual consumption, we use a unique dataset of a large representative sample of consumers covering all credit card and debit card transactions between 2010:04 and 2012:03 from a leading bank in Singapore that has a market share of over 80 percent. Similar to the U.S., debit and credit cards are important mediums of disposable consumption in Singapore, with approximately 30 percent of aggregate personal consumption in the country being purchased via credit and debit cards (Agarwal and Qian, 2014).[1] Therefore, our data provide a more complete and accurate measure of individual-level consumption at a high frequency. In addition to the spending information, this dataset also contains a panel of other financial outcomes such as credit card debt and delinquency and a rich array of individual-specific demographic information including income, age, gender, nationality, address, and postal code.

We identify the treated individuals—those who live in the same building as the bankrupt individuals—by merging with the bankruptcy dataset using their postal code (excluding the bankrupt individuals). Relative to existing studies that use geographical proximity to classify peers, our data empower us with a finer measure of neighborhood within which individuals (more) closely observe and interact with each other. In Singapore, each (six-digit) postal code corresponds to a unique building; this means an average number of 220 people, or around 50 households living in one public housing building. In comparison, the same level of geographical unit in the United States—zip code—spans a much larger area and contains more than 30,000 households on average. What's also noteworthy is that the bankrupt individuals can keep their main residence in HDB and continue to interact with their neighbors, making it possible to study the influence on their neighbors' consumption behavior. The final sample contains 1,655 bankruptcy events and 17,326 treated individuals living in HDB flats during the two-year period (2010:04-2012:03) and we study their consumption responses following their neighboring peers' bankruptcy events.

One key identifying assumption is that the peer bankruptcy events are negative income shocks *specific* to these individuals, and are uncorrelated with unobserved common factors or characteristics that might affect all consumers living in the same neighborhood. At first glance, the personal bankruptcy events in Singapore exhibit no clustering pattern; they appear to be randomly distributed across both space and time (see Figure 1). In addition, our tight peer group, measured at the building level, also facilitates the empirical analysis to address the concern—individuals with common economic backgrounds or similar preferences are likely to sort into similar locations within a larger geographical vicinity rather than to precisely self-select into the same building. This is especially relevant in our context because Singaporeans have restricted

[1]The remaining 70 percent of consumption occurs through checks, direct transfers, and cash. Consumers with recurring payments including mortgage, rent, and auto loans payments typically use instruments such as checks and direct deposit.

ability to choose the precise building of their residence given the Ethnic Integration Policy in place that ensures similar distribution of ethnicities in every public housing building. Therefore, we can explicitly test the identifying assumption by studying the differential consumption response between the treated buildings and other neighboring buildings.

Our analysis is based on an event-study design that exploits the changes in consumption after peers in the same building experience personal bankruptcies. We find that, relative to the period of 12 months to two months prior to bankruptcy, individuals in our sample experience a large and statistically significant decrease of around 3.4 percent in monthly total debit and credit card spending in the year following their peers' bankruptcy events. The consumption response is economically sizable. Given the average pre-bankruptcy period monthly spending level, this result suggests a total annual decrease of SGD 274, or equivalently close to seven percent of the treated individuals' average monthly income. Moreover, credit card spending and debit card spending experience a decrease of similar magnitude.

In contrast, there is no discernible change in spending during the one-month pre-bankruptcy period; the effect is both statistically and economically insignificant. Turning to the individuals living within a close radius of the bankruptcy-hit buildings, we find no consumption change among those living in buildings within the 100-meter, or 100–300 meter ranges. As mentioned previously, individuals in the adjacent buildings are likely subject to similar background factors or preferences. Consequently, the collective evidence on the absence of consumption response among this group of consumers or during the one-month pre-bankruptcy period provides strong validation of our identifying assumption that the personal bankruptcy events are not confounded by common factors that may independently drive consumption behavior in the neighborhood.

We observe a great level of heterogeneity in the consumption response across individuals. The decrease in spending is concentrated among consumers who are presumably more aware of their peers' circumstances or behavior: women and consumers in an age group similar to that of the bankrupt individuals experience a greater decline by 7.3 and 6 percent per month respectively. In addition, using age, income as well as banking relationship variables as proxies of financial knowledge, we find that the consumption decrease following peers' bankruptcy events is stronger for consumers with greater financial sophistication.

We consider two main economic mechanisms that may explain the documented consumption response: (reduced) peer pressure for status competition and social learning. The status competition channel implies a visible or even greater reduction in conspicuous goods consumption (Charles, Hurst, and Roussanov, 2009). Exploiting the granularity of the spending type information in the credit and debit card transactions, we classify the total card spending into components that capture status-motivated conspicuous goods versus the rest. We observe no significant change in conspicuous spending while the non-conspicuous component of the total

card spending experiences a strong and significant reduction, which lends support to the social learning channel.

Finally, we study other financial outcomes for the treated individuals such as credit card debt and delinquency dynamics. If individuals learn from their peers' adverse economic conditions following the large negative income shocks, they may not only cut back on their spending but also make a conscious effort to change their credit card debt accumulating behavior to avoid similar financial situations. While we find no change in credit card debt and credit card delinquency for the average treated individual, financially more sophisticated consumers significantly reduce their credit card indebtedness following peers' bankruptcy events. The effect is economically large. A one-standard deviation increase in measures of financial sophistication is associated with 14 – 29 percent decrease in the amount of monthly credit card debt in the one-year period after peer bankruptcies. These consumers are also much less likely to become delinquent in making credit card payments in the same post-bankruptcy period. Relating to the previous finding that documents a broader scope of consumption response, these results suggest that peer bankruptcy events trigger learning in consumers' coping with credit card debt management but to a lesser extent.

To further alleviate the reflection problem, we perform several falsification tests. Specifically, we either hold the bankruptcy-hit buildings and treated individuals constant and randomly assign the timing of each bankruptcy event, or hold the bankruptcy-hit buildings as well as the event time fixed and randomly assign treated individuals in our sample. In both circumstances, we find no consumption responses. We also make use of the fact that bankrupt individuals cannot keep their private housing and thus those living in the private housing market most likely have to move out upon bankruptcy. We use the same procedure to identify non-bankrupt individuals living in bankruptcy-hit buildings in the private housing market, and repeat our analysis. Again, we find no consumption response, further validating the assumption that the personal bankruptcy shock is unlikely to be correlated with unobserved factors that simultaneously affect the financial well-being of other individuals living in the same location. It also underscores the importance of a continuous within-neighborhood interaction for the peer influence at work, given that the bankruptcy information is salient regardless of the neighborhood being in the public or private housing market segment.

We conduct a battery of additional analyses for our findings' robustness. We exploit the bankruptcy amount information and conjecture that the consumption response should be increasing in the size of the peers' bankruptcies. We find consistent evidence that the responses in consumption, credit card debt, as well as delinquency are all stronger in buildings with a larger bankruptcy amount involved. In addition, we use different pre- and post-bankruptcy event windows in our empirical analysis and find qualitatively and quantitatively similar results. We perform further tests to dispel the concern that the consumption response may be driven by the behavior of immediate family members of the bankrupt individuals. Finally, our results are

robust to different definitions of the treatment sample as well as alternative measures of financial sophistication.

Our paper directly contributes to this literature by documenting an important social multiplier effect on consumption based on an accurate and more comprehensive measure of consumption. We do so by exploiting a plausibly exogenous (negative) income shock to address the reflection problem. Some extant research finds evidence suggestive of a strong peer influence on the general consumption pattern (Charles, Hurst, and Roussanov, 2009; Bertrand and Morse, 2015). Other studies use novel empirical settings that provide exogenous variation in a specific spending context, which calls for external validation (Grinblatt, Keloharju, and Ikaheimo, 2008; Cai, Chen, and Fang, 2009; Moretti, 2011; Kuhn et al., 2011). In addition, our findings offer new economic insight on the effect of social learning. In addition to the direct effect on consumption decisions, consumers may also learn from their peers' (adverse) economic circumstances and change their debt accumulating behavior; however, this learning behavior is much less pervasive across individuals than the consumption response.

This paper also contributes to the overall literature on peer effects or the social multiplier effect (Glaeser, Sacerdote, and Scheinkman, 2003). Existing literatures have shown the importance of peer effects in a variety of economic outcomes: education (Carrell, Fullerton, and West, 2009; Bobonis and Finan, 2009); risky behavior like sex, crime, drugs and smoking (Card and Giuliano, 2013; Glaeser, Sacerdote, and Scheinkman, 1996); program participation (Bertrand, Luttmer, and Mullainathan, 2000); Retirement savings (Duflo and Saez, 2003; Beshears, et al., 2015); Portfolio choice and asset prices (Abel, 1990; Hong, Kubik, and Stein, 2005; Bursztyn, et al., 2014).

Finally, our paper is broadly related to the vast literature on the determinants of consumption behavior at the micro-level. A large effort focuses on the consumption and savings responses of individuals who face expected and unexpected shocks to their own income; for example, see Shapiro and Slemrod (1995, 2003a, 2003b), Souleles (1999, 2000, 2002), Parker (1999), Hsieh (2003), Stephens (2003, 2006. 2008), Johnson, Parker and Souleles (2006), Agarwal, Liu and Souleles (2007), Stephens and Unayama (2011), Scholnick (2013), Parker et al. (2013), Agarwal and Qian (2014, 2016), and Agarwal, Pan, and Qian (2016). For a review of the literature, please refer to Browning and Collado (2003) and Jappelli and Pistaferri (2010).

The rest of the paper proceeds as follows: Section 2 introduces the institutional background of bankruptcy in Singapore. Section 3 describes the data and methodology. Results are presented in section 4 and 5, and Section 6 concludes.

2. Bankruptcy in Singapore

In general, there are mainly two types of personal bankruptcies: strategic bankruptcy, and liquidity-constrained bankruptcy. Strategic bankruptcy means that rational defaulters filing for

bankruptcy when the net financial benefits of discharged debt exceed non-exempt liquidated assets (Fay, Hurst, and White, 2002). Liquidity-constrained bankruptcy, on the contrary, is often triggered by negative income shocks. Events such as increases in medical expense and credit card debts (Domowitz and Sartain, 1999), divorce, and unemployment (Sullivan, Warren, and Westbrook, 2001; Warren and Tyagi, 2004) can severely affect the liquidity and the debt servicing ability of households, leading to bankruptcy filing.

Similar to many developed economies such as the US, Singapore has strict laws governing bankruptcy, which are encompassed in the Bankruptcy Act (Chapter 20) ("the Bankruptcy Act"). 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. Intuitively, debtors who voluntarily file for bankruptcy are more likely to be strategic defaulters, whereas those appealed by creditors are typically liquidity-constrained defaulters. In either case, debtors have alternative options before going through the bankruptcy procedures. 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[2]. The debtors can commit to repay their debt over a fixed period of time, not more than five years (60 months).

In the event the bankruptcy process is triggered by a creditor (or a group of creditors), a notice known as a Statutory Demand is first issued to demand payment against the debtor. If the payment is not met within 21 days, and the debtor has not applied to the court to set aside the Statutory Demand, then the creditor can file a petition in Court. If the debtor voluntarily files for bankruptcy, the case directly goes to court. In both cases, the court may adjourn the application for up to six months, before which it determines the debtor's suitability for DRS. If DRS is not applicable, a bankruptcy hearing will then be scheduled, followed by declaration of the bankruptcy order. In reality, a typical bankruptcy filing takes much less time--as stated by the Singapore Supreme Court, "the hearing of a Bankruptcy Application is fixed approximately four to six weeks from the date of filing of the Bankruptcy Application". After the issuance of the bankruptcy order, the Government Gazette will publish a notification, which is observable by the public, and the Official Assignee will be appointed to administrate the bankruptcy affairs.[3]

Upon bankruptcy, the Official Assignee will seize a debtor's assets with a few exceptions including her public housing flat (HDB), properties held in trust, CPF monies and basic everyday

[2]Information about DRS is 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)

[3] Information about bankruptcy proceedings is summarized from Singapore Supreme Court website (http://www.supremecourt.gov.sg/rules/court-processes/civil-proceedings/other-civil-proceedings-and processes/bankruptcy-proceedings) and online Bankrupt Act (http://statutes.agc.gov.sg/aol/search/display/view.w3p;ident=7adc4d85-27d7-4dbc-b723 6a65ecad824a;page=0;query=DocId%3A%22c342424a-8867-494a-bbab-91b696d12bdc%22%20Status%3Ainforce%20Depth%3A0;rec=0#pr65-he-.)

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. This unique institutional feature makes it possible for the bankrupt individuals to continue to interact with their neighbors in the same neighborhood, allowing us to test the peer effect.[5]

Individuals face many restrictions and inconveniences in their spending as well as career choices upon bankruptcy. For example, the bankrupted 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 severe and long-term bankruptcy consequences as well as the potentially high social stigma (as suggested by the government's decision to publicize each bankruptcy case) imply a strong incentive to avoid bankruptcy in Singapore.[6] Indeed, both the level and growth of the bankruptcy rate in Singapore are much smaller than that in the US during 1980-2012 (Agarwal et al, 2016). This also suggests that individuals who ultimately go into bankruptcy, especially those triggered by creditors, most likely incur large negative income shocks and face severe liquidity constraints that prevent them from arranging debt renegotiation under the DRS rule. Therefore, we will focus on the creditor-triggered bankruptcy events for our analysis and use the Statutory Demand date as the event time.

We first plot the geographical distribution of all personal bankruptcies in Singapore in our sample. There is no clustering pattern in the geographical space—the events span all locations and all areas with housing establishments in the country (Figure 1, Panel A). In addition, the bankruptcy events are evenly distributed across months in the 2010:04-2012:03 period (Figure 1, Panel B). This provides assurance that personal bankruptcy events do not seem to correspond to or arise from systematic economic distress that will simultaneous affect many people's economic well-being in the same neighborhood.

[Insert Figure 1 about here]

Bankrupted individuals, perhaps unsurprisingly, have different demographic characteristics than the full population. We report the summary statistics for gender, ethnicity, and age of the entire Singaporean population and the 2,806 individuals with creditor-filed bankruptcies between 2010:04 and 2012:03 in Table A1 in the Internet Appendix. Compared to the population, the

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

[5] Please refer to https://www.mlaw.gov.sg/content/io/en/bankruptcy-and-debt-repayment-scheme/bankruptcy/information-for-bankrupts/information-for-bankrupts1.html for more details on the impact of bankruptcy.

[6] Bloomberg News, Javier, Luzi Ann, "Singapore Amends Law to Help People Avoid Bankruptcy Amid Slump," January 19, 2009.

bankrupt individuals are less likely to be female, less likely to be Chinese, and tend to be younger than the average Singaporean.

3. Data

In this paper, we use multiple unique datasets, i.e., the universe of (creditor-filed) personal bankruptcies, demographic information of Singaporean citizens and permanent residents, and large panel datasets of financial transactions, to identify treated individuals—peers of bankrupt individuals—as well as to measure their consumption behavior.

3.1 Raw Data

A. Bankruptcy Data

We exploit the personal bankruptcy dataset obtained from the Supreme Court of Singapore to get the bankruptcy information. This dataset contains information of a total of 76,874 personal bankruptcies cases from year 1980 to year 2012, out of which 37,466 are creditor-triggered (i.e., those with Statutory Demand dates). For each creditor-filed bankruptcy case, we can obtain the personal information of related bankrupted individuals (a unique personal identifier), dollar amount related to the suit, and three sequential dates along the bankruptcy proceeding: Statutory Demand date, petition date, and hearing date. We use the month of Statutory Demand date as the event month for each bankruptcy cases, since it is the earliest time that the bankruptcy information may be disseminated. As mentioned, a bankruptcy application can be resolved approximately four to six weeks from the date of filing (i.e., the time lag between petition date and hearing date is usually four to six weeks).

B. Demographic Data

The second dataset we use is a unique proprietary dataset containing demographic information for more than two million Singaporean residents (citizens and permanent residents). As of 2012, the database covers over 60 percent of the Singapore resident population[7]. From this dataset, we are able to observe demographic information such as name, gender, ethnicity, and birthday. More important, we can also identify individual's unique personal identifier, residence type (public or private), and related postal code from this dataset, which allow us to merge all three datasets together. We merge the bankruptcy dataset with the demographic information dataset using the unique personal identifier, which leads to a merged dataset, augmented with demographics, of 31,920 creditor-filed bankruptcies between 1980 and 2012.[8]

[7] According to Department of Statistics Singapore, the total population of Singapore Residents is 3,818,205 by 2012. http://www.singstat.gov.sg/statistics/latest-data#16

[8] The merge success rate is 85.2%. We compare the bankruptcy amount of the 31,920 merged cases and the remaining 5,546 unmerged cases, and the difference is not statistically significant, indicating that there is no systematic bias in the merging process.

C. Consumption Data

We use a proprietary dataset obtained from one of Singapore's leading banks to measure individual consumption. This bank has more than four million customers, or over 80 percent of the entire population of Singapore[9]. The entire data set contains consumer financial transactions of a large, representative sample of more than 180,000 bank customers between 2010:04 and 2012:03. For individuals in our sample, we have monthly statement information about each of their checking accounts, credit cards and debit cards with the bank. We observe the monthly spending (for credit and debit cards), credit card debt, credit card delinquency status, and fees (for credit cards).[10] The data also include disaggregated transaction-level information about the individual's credit card and debit cards spending, including the transaction amount, transaction date, merchant name, and merchant category. Moreover, the data contains a rich set of demographics and other financial information, including age, gender, ethnicity, income, property type (public or private housing), property address (postal code), as well as the type of their checking accounts (e.g., premium account), and length of relationship with the bank.

Credit cards play an important role in consumer finances and can be useful for studying consumer-spending behaviour (Japelli, Pischke and Souleles, 1998; Gross and Souleles, 2002). As discussed in Agrawal and Qian (2014), consumer credit also plays an important role in Singapore – more than a third of consumers have a credit card, and the total credit card debt in the end of 2014 was over 2.6 percent of GDP in that year. Moreover, debit and credit cards combined are important mediums of disposable consumption in Singapore, with approximately 30 percent of aggregate consumption in the country being purchased via credit and debit cards.[11]

This dataset offers several key advantages. First, relative to the tradition survey-based datasets in the United States such as the Survey of Consumer Finance (SCF) or Consumer Expenditure

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[9] According to Department of Statistics Singapore, the total population of Singapore is around 5.54 million by 2015. http://www.singstat.gov.sg/statistics/latest-data#16

[10] The specific banking products that we study (credit card, debit card, and bank checking account) are similar to those used in the United States. Consumers are typically eligible to obtain a bank checking account, and they can conduct banking transactions using branches, Automatic Teller Machines (for cash withdrawals, transfers, or bill payment), checks, or online methods. The typical banking fees and other costs are quite standard, similar to those of a typical US bank, and moreover they are comparable with banking costs at other major banks in Singapore. Debit cards are linked to the bank account, and debit card transactions are drawn on the bank account balance. Similarly, credit cards are granted upon application to consumers who have met the bank's criteria (e.g., income, age, and credit profile). One interesting difference for credit cards is that all credit card holders with the bank have the same prevailing interest rate of 24 percent per annum, regardless of the credit card limit. The other important observation is that savings in bank accounts in Singapore typically accrue at close to zero interest rates. For example, various types of accounts in our bank have a maximum of 0.1 percent annual interest rate, and thus we aggregate the balance across all bank accounts for the same individual.

[11] The remaining 70 percent of consumption is transacted via checks, direct transfers, and cash. Consumers with recurring (and thus less discretionary) payments like mortgages payment, rent payments, and auto loans payments use instruments such as checks and direct deposit. We confirm this using our credit and debit transaction-level data; looking through the transaction category codes, merchant names, transaction types, we do not find a *single* transaction for mortgage, rent, and auto loan payments in over 18 million debit card and credit card transactions. Hence, we conclude that these reoccurring payments are through checks and direct deposits.

Survey (CEX), our administrative dataset covers captures consumption with little measurement error and allows high frequency analysis on a large representative sample of consumers. Compared to existing studies that use micro-level credit card data (e.g. Gross and Souleles 2002, Agarwal, Liu, and Souleles, 2007, Aaronson, Agarwal, and French, 2012), this data set has more complete consumption information. For example, rather than observing a single credit card account, we have information on every credit card, debit card, and bank account that each individual has with the bank. One important limitation of our data is that we do not have information about accounts individuals have with other banks in Singapore. Nevertheless, it is likely that the measurement error is minimal given the market share of the bank. For example, an average Singaporean consumer has three cards, which is also the number of cards an average consumer has in our data set. Hence, we are confident that we are picking up practically the entire (discretionary) consumption of these households through the spending information on the various accounts at this bank. Furthermore, the richness of the individual demographic and transaction-level information allows us to better disaggregate heterogeneity in consumers' consumption response.

Following Agarwal and Qian (2014), we aggregate the data at the individual month level. Credit card spending is computed by adding monthly spending over all credit card accounts for each individual. Similarly, debit card spending is computed by adding monthly spending over all debit card accounts for each individual.

For our analysis, we restrict the main sample to those who live in the public housing (HDB) segment. We exclude dormant/closed accounts that remained inactive (i.e. with no transactions in at least six months in our 24-month sample period). We further require the individuals in sample to have all three types of accounts with the bank—checking account, debit card, and credit card—to capture consumers who are more likely to have an exclusive relationship with the bank.[12] With these restrictions, the resulting sample size is 86,846 individuals.

3.2 Merged Final Sample and Summary Statistics

Since our consumption data is from 2010:04 to 2012:03, we restrict the creditor-triggered bankruptcies filed during this period (N = 2,806). Due to the fact that bankrupt individuals can only keep their main residence if it is in the public housing market, we will focus on the bankruptcy cases for individuals living in HDB, giving us 2,454 such cases. We use personal bankruptcies in the private housing market later to perform a falsification test.

We further restrict the sample to postal codes with only one bankruptcy event during the whole sample period. In other words, only postal codes affected by bankruptcy in one month between 2010:04 and 2012:03 are included in our study, whereas buildings with bankruptcy cases in multiple months during the two-year window are excluded. Additionally, we exclude bankruptcy-hit postal codes that are preceded, within a 12-month period, by another bankruptcy

[12] However, our results are insensitive to the three-account restriction.

case that occurred before 2010:04.[13] These restrictions help isolate the consumption response from other confounding events and facilitate interpretation. The final bankruptcy sample contains 1,655 bankruptcy cases. Consistent with the frequency of our consumption data, we aggregate the bankruptcy cases into monthly frequency within each postal code, and define bankruptcy events at the monthly level.[14]

We then merge the final bankruptcy event sample with our consumption dataset using postal code to identify the treated individuals—those who live in the same postal code as the bankrupt individuals. To assess the peer effect, we need to exclude the bankrupt individuals. Although the consumption dataset does not have the unique personal identifier, we note that our cleaned consumption dataset unlikely captures the bankrupt individuals. By law, bankrupt people are not allowed to have credit cards in Singapore, and our final consumption dataset excludes those individuals who have closed or inactive credit card accounts for an extended time during the two-year period. This makes it highly unlikely for us to (incorrectly) include the bankrupt individuals in the treatment sample.

To further alleviate the concern that the credit card accounts of bankrupt individuals may be closed much later (i.e., after the end of our sample period), due to the unknown date of bank enforcement, we address this issue in the following way. From both the bankruptcy and consumption datasets, we observe the demographics including gender, age and ethnicity. Then we identify 250 individuals, from the consumption dataset, who live in the treatment postal sector with the same gender, ethnicity, and age as the bankrupt individual. We exclude these 250 individuals from our sample. Given the administrative nature of both datasets, there is little measurement error in the recorded demographics data, and such filtering will be able to accurately identify all potential bankruptcy candidates. Furthermore, this is a conservative strategy since we may exclude from the analysis close peers of the bankrupt individuals (given the similar demographics), rendering a likely underestimate of the true peer effect on consumption. In section 5.3, we will also perform several additional tests using alternative approaches to identify the treated individuals.

Relative to existing studies that use geographical proximity to classify peers, our data empower us with a finer measure of neighborhood within which individuals (more) closely observe and interact with each other. In Singapore, each (six-digit) postal code corresponds to a unique building; this means an average size of 220 people, or around 50 households living in one public housing building. In comparison, the same level of the geographical unit in the United States—zip code—spans a much larger area and contains more than 30,000 households on average. In

[13] For example, if a postal code only has one bankruptcy event month between 2010:04 and 2012:03, say in 2010:07, then we also require no other bankruptcy cases in the same postal code between 2009:07 and 2010:03.

[14] Out of the 1,655 bankruptcy cases, 83 correspond to more than one bankruptcy in the same building-month pair, or equivalently 5.29 percent. In the main analysis, for the building-month pairs with more than one bankruptcy case, we treat that month as one event month, and use the sum of the bankruptcy amount of involved cases as the amount for this bankruptcy event. We also perform a robustness check of our main result by excluding those buildings with more than one bankruptcy case in the same month in the later robustness section.

addition, Singaporeans have restricted ability to choose the precise building of their residence given the Ethnic Integration Policy in place that ensures similar distribution of ethnicities in every public housing building.[15] This further alleviates the concern of self-selection of individuals with a common background into the same building.

Our final matched sample includes 1,655 bankruptcy cases and 17,326 treated individuals. Panel A of Table 1 provides the summary statistics of information for all HDB bankruptcy cases during our sample period, as well as for the (sub) sample of bankruptcy cases included in our main sample. Demographics are fairly comparable between the two samples, with 24 percent of the bankrupt individuals being female, 63 percent of them being Chinese, and an average age of around 42. In addition, the average dollar amount of a bankruptcy case is around SGD 100,000 for the full sample and the final sample in our analysis. Differences in means of all characteristics are economically small and statistically insignificant.

[Insert Table 1 about here]

In Panel B of Table 1, we report and compare the demographic and spending characteristics for individuals in the consumption dataset before and after merge. In the original before-merge sample (N = 86,646), 42.6 percent are female, 78.2 percent have Chinese ethnicity, the average age is 38.7, and the mean monthly income is SGD 4,354. In addition, 1.6 percent of the sample has a premium bank account, and the average length of relationship with the bank is 14.2 months. In comparison, the after-merge sample of treated individuals exhibits similar demographics. Even though the t-test statistics appear significant, the difference is economically small. Overall, the subsample of treated individuals appears to be largely representative of the original sample.

Furthermore, consumers in both samples share similar average spending levels during the two-year period (2010:04-2012:03). Take the treated individuals as an example: the average monthly card spending is SGD 841, with SGD 491.8 and 349.2 on credit cards and debit cards respectively. The average monthly credit card debt for the treated individuals is SGD 597.2.[16] Credit card delinquency has a frequency of 0.6 percent in our sample period.

3.3 Empirical Strategy

We examine the response of consumption (as well as other financial variables) by the treated individuals to their peers' bankruptcy events. Our empirical strategy exploits monthly individual-level data and the unique bankruptcy-hit building and event timing pair during the two-year period (Figure 1, Panel B). Similar to Agarwal, Pan, and Qian (2016), we use the following model to estimate the average spending response:

[15] https://en.wikipedia.org/wiki/Public_housing_in_Singapore#Physical_organisation_and_design

[16] For all spending and debt variables, we winsorize them at 1 percent and 99 percent level to eliminate the possible influence of outliers.

$$Y_{i,t} = \delta_t + \alpha_i + \gamma W_{i,-1m} + \beta W_{i,(0m,12m)} + \epsilon_{i,t} \quad (1)$$

In our main analysis, we include observations of the treated individuals in the [-12, +12 month] period around each bankruptcy event, where month 0 is the bankruptcy month. The dependent variable $Y_{i,t}$ represents the log of spending amount (total card spending, credit card spending, or debit card spending), log of credit card debt, or credit card delinquency by individual *i* at month *t*.[17] δ_t represents a vector of year-month fixed effects, and α_i represents a vector of individual fixed effects. $W_{i,-1m}$ is an indicator variable for the one month *before* the bankruptcy event (i.e., month -1) that hits the building where *i* lives, and $W_{i,(0m,12m)}$ is an indicator variable for the 13 months *on and after* the bankruptcy event (i.e., month 0 to month 12) that hits the building where *i* lives. The absorbed period is from 12 months to 2 months before the bankruptcy event month (i.e., month -12 to month -2), and is the benchmark period against which our estimated response is measured. We cluster the standard errors of our estimates at the individual level.

The results can be interpreted as an event study. Specifically, estimated coefficients γ and β approximate, relative to the baseline period, the average monthly percentage change in the outcome variables in the month before the bankruptcy event and during the 13-month period starting from the bankruptcy event month respectively. If the consumption response truly reflects the peer influence, treated individuals should only change their spending behavior *upon* the peer bankruptcy event, implying that γ should not be different from zero.

4 Main Results

4.1 The Average Spending Response

We begin by examining the average spending response of the treated individuals to peer bankruptcy. Specifically, we study the change in total card spending, credit card spending, and debit card spending, and report the results in Columns 1-3 of Table 2.

The first column shows the average response of monthly total card spending (i.e., debit card spending + credit card spending) by the treated individuals. Overall, treated individuals decrease their total card spending by 3.4 percent per month, relative to the average during the 12th – 2nd month period before the peer bankruptcy event.[18] The effect is both statistically and economically significant. Given the average pre-bankruptcy period monthly spending of SGD 801 for the treated individuals, this result suggests a total decrease of SGD 274 during the one year (12 months) following the bankruptcy event, or equivalently close to seven percent of the treated individual's monthly income. We decompose total card spending into credit card

[17] For each dollar amount variable X, we calculate the log of X as log (X + 1) to include 0 values for X.
[18] The estimated coefficient for log of total card spending in column 1 of Table 2 is 0.035, which is equivalent to a percentage decline of 3.4 percent (= exp(-0.035) – 1). All subsequent percentage effect interpretations for log dependent variables follow the same formula.

spending and debit card spending and find the spending response with similar magnitudes in the two instruments (columns 2-3).[19]

[Insert Table 2 about Here]

In contrast, there is little difference in the change in total card spending in the one-month period before peer bankruptcy, as the coefficient for $1_{[-1,-1]}$ is economically small and statistically indistinguishable from zero. This shows that consumption responds only after the bankruptcy event, suggesting the documented decrease in spending more likely works through the peer influence channel instead of being driven by other confounding factors that affect all consumers in the same building.

To better isolate the peer effect from correlated background factors that influence individual choices (i.e., the reflection problem), we exploit our unique setting of the tight peer group measured at the building level. Individuals with common economic backgrounds or similar preferences are also likely to sort into similar locations within a larger geographical vicinity rather than to precisely self-select into the same building. This is especially relevant in our context where Singaporeans have restricted ability to choose the precise location of their residence given the Ethnic Integration Policy in place that ensures a similar distribution of ethnicities in every public housing building. The institutional restriction further alleviates the concern of self-selection of individuals with a common background into the (exact) same building.

Therefore, we can explicitly test the identifying assumption by studying the differential consumption response between the treated buildings and other neighboring buildings. If the consumption response is due to correlated background factors, then we should expect to see a similar decrease in consumption among individuals in neighboring buildings. On the contrary, if the response is local with very weak or insignificant consumption decrease for consumers even in the adjacent buildings, then the documented finding is attributable to the influence by peers who live and interact closely in a tight neighborhood.

We define neighboring buildings as those within a 100-meter radius and in a 100-meter to 300-meter range respectively. This includes 34,045 and 13,741 individuals in 1,129 and 461 HDB buildings accordingly.[20] Columns 4-5 of Table 2 report average responses of total spending for consumers living in those adjacent non-bankruptcy-hit HDB buildings. In column 4, we find no change in the total card spending for consumers living in the adjacent buildings within the 0-100m radius around the bankruptcy-hit building. Though the coefficient for $1_{[0,+12]}$ is still

[19] Ideally we also want to test the spending responses through other instruments, such as cash and checks, but our data do not provide transaction-level information on cash and check spending. We 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 transaction, and find no change around peer bankruptcy events. This is likely due to the non-discretionary nature of spending with cash and checks (Agarwal and Qian, 2014, 2016).

[20] Including non-bankruptcy-hit neighbouring buildings in the private housing market won't change our results.

negative, it is very small (-0.008) in magnitude, and statistically insignificant. Moreover, a formal F-test indicates that it is not distinguishable from the effect associated with the one-month pre-bankruptcy window (-0.006). Looking at buildings a bit farther away, again we find no response in total card spending for individuals living in buildings within the 100-300m radius—if anything, the estimated coefficient (0.006) suggests an increase in total card spending during the post-bankruptcy period. In addition, coefficients on the one-month pre-bankruptcy period dummy are both insignificant statistically and economically. The overall results suggest no change in the spending pattern among individuals whose nearby building is hit by a bankruptcy event.

To summarize, results from Table 2 collectively provide strong evidence in support of the peer effect—when individuals experience large negative income shocks (and plausible negative consumption changes), their neighbors, who observe and/or interact closely with the affected individuals, also start to change their consumption behavior by reducing their spending. Such an effect is unlikely to be explained by other confounding factors that drive consumption behavior orthogonal to the peer effect—we observe no spending changes in adjacent neighborhoods that also are subject to the same economic factors.

4.2 Heterogeneity in the Spending Response

An interesting follow-up question relates to the distributive effect of the documented consumption response. Does the peer influence affect all treated individuals in the same way? In this section, we test the heterogeneity in the consumption response among the treated individuals.

Even though the bankruptcy event is salient public information (as disclosed by the Government Gazette), we conjecture that the peer influence works more strongly for the treated individuals who are more sensitive to their neighbor's bankruptcies. By sensitive, we mean those who may be more active in the social interaction and thus are more aware of the peer bankruptcies and the associated implications.

We use two individual traits to proxy for (greater) peer awareness. Females are usually keener observers of neighborhood news and tend to have more interaction with neighbors. Alternatively, treated individuals in the same age group (specifically within [-4, +4] years) as the bankrupt are also more aware of peers' bankruptcy events due to plausibly closer social ties or stronger peer pressure.[21] We interact the post-bankruptcy dummy with the two proxies and report the results in columns 1-2 of Table 3.

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[21] For buildings with bankruptcy events that related to more than one bankruptcy case in the same month, the *Close in age* dummy is undefined and those observations are not included in this particular analysis. We also considered alternative close peer proxies such as treated individuals sharing the same ethnicity as the bankrupted individuals. However, for the ethnicity, our sample of peers and bankruptcy cases is dominated by Chinese, and the lack of variation makes it difficult to isolate the same-ethnicity effect.

Compared to their male counterparts, female treated individuals decrease their monthly card spending by 7.3 percent (= exp(-0.076)-1) more, and this difference is highly statistically significant (*p*value < 0.001). In fact, male treated individuals do not experience any change in their card spending, as the estimated coefficient is very small (-0.002) and insignificant. Similarly, the total card spending is concentrated among treated individuals who are within [-4, +4] year range as their bankrupt neighbors. Their total card spending experiences a monthly decrease of seven percent (=exp(-0.011-0.062)-1), which is six percent more than other treated individuals outside this age bracket (=exp(-0.062)-1). Both the total effect and the incremental effect are statistically significant at the one percent level. In unreported results, we also find a similar effect by using alternative age brackets including [-3,+3] and [-5,+5] year ranges.

[Insert Table 3 about Here]

In addition, those treated individuals who have a better financial knowledge and greater capacity to fully understand the nature and implications of bankruptcy events are also likely more responsive to their peers' bankruptcies. We use four proxies to measure financial sophistication: age, income, length of bank relationship, and whether one has a premium bank account (that is offered, at the bank's discretion, to a select set of individuals with a more customized account service). We first test the correlations among the four measures—they are positively correlated but the correlation coefficients are generally lower than 0.25, suggesting that each of four proxies independently captures different aspects of financial sophistication.[22] To facilitate interpretation, we normalize the three continuous measures (age, income, and length of bank relationship) in the following way. Specifically, for each of the continuous measure X, we take the difference between X and its cross sectional mean, measured by the average of the three-month pre-bankruptcy period, and divide by the standard deviation of X from the same cross-sectional distribution. Then the coefficient for the interaction term of the post-bankruptcy dummy and this normalized measure can be interpreted as the incremental effect associated with one standard deviation change in the continuous variable X, relative to the cross sectional mean.

We find evidence of a much stronger consumption response among the subgroup of treated individuals with greater financial sophistication. For example, older treated individuals tend to decrease by a greater amount (column 3 of Table 3). Individuals with an average age in the treatment sample reduce 3.1 percent (= exp(-0.032)-1) of their total spending per month during the [0, +12m] post-bankruptcy period. A one standard deviation increase in age is associated with an additional 7.6 percent (=exp(-0.079)-1) decrease in monthly card spending, and the difference is highly statistically significant (*p*value < 0.001).

Using income and length of bank relationship tells a similar story (columns 4-5, Table 3). The average income (or average bank relationship length) individuals reduce their monthly card spending by 3.1 percent (=exp(-0.032)-1) during the post-bankruptcy period. However,

[22] The one exception is the correlation between age and length of relationship with the bank measure is 0.5 (and to some degree is expected).

individuals with a higher income or longer bank relationship experience a much greater decrease in their monthly card spending. A one standard deviation increase in income (months of bank relationship) is associated with 4.5 (4.5) percent (=exp(-0.046)-1) decrease in total monthly card spending, relative to those with an average income (bank relationship length). In addition, the treated individuals with a premium bank account also experience a greater decline in their total monthly card spending—even though the interaction term is not statistically significant, the effect is negative and economically large, providing consistent evidence.

Overall, the findings show a great deal of heterogeneity in the post-peer-bankruptcy consumption response across the treated individuals. Treated individuals with a higher sensitivity to neighbors' bankruptcy events, either due to their greater awareness of the neighborhood happenings or due to a higher level of financial sophistication, respond more with a larger decrease in spending. Granted that each of the proxies is a rather indirect way to capture sensitivity to peer bankruptcies, but the collection of consistent evidence provides confidence to our interpretation of the results.

4.3 Economic Mechanism: Status Competition or Social Learning?

We consider two potential economic channels that can explain the pattern of the consumption response: status competition (as a result of peer pressure or social norm for example) or social learning (e.g., Bikhchandani, Hirshleifer, and Welch, 1998; Bursztyn, et al., 2014). The status competition channel arises from the fact the treated individuals face less peer pressure to catch up with the Joneses, when their peers experience large negative income shocks and restrictions in their spending choices. Alternatively, it may work through an independent channel whereby treated individuals learn, either through observing or interaction, about the severe financial circumstances and consequences facing the bankrupt peers. As a result, treated individuals become more prudent and change their spending behavior to avoid the possibility of such adverse economic situations. The average spending response, as well as the heterogeneous effect, is broadly consistent with both economic channels. While the greater consumption decrease for the subgroup of financial sophistication is strongly indicate of the social learning channel, the fact that female and close-age peers reduce spending more than male and non-close-age counterparts suggests that the (reduced) status competition may also be in effect.

In this section, we exploit the detailed transaction-level information from our consumption dataset and construct a finer test to identify the primary economic mechanism. Previous research suggests that status or relative income concerns particularly influence spending in luxury goods or conspicuous items that are more visible to others (Charles, Hurst, and Roussanov, 2009; Bertrand and Morse, 2015). Therefore, if individuals face reduced pressure to compete for status as a result of peers' bankruptcies, we should observe their spending decline to be concentrated in the area of visible items or luxury goods. On the other hand, if the social learning is the more dominant channel, their spending decrease should be more even across different types of

spending without a prominent tilt towards visible or luxury goods. Below we adopt two strategies to identify status-driven spending.

A. 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 following categories according to the merchant type information provided by the bank: apparel, car accessories, electronics, home furnishings or decorations, entertainment, service, dining, supermarket, travel, online, and others. We classify apparel, car accessories, electronics, home furnishings or decorations as visible consumption categories; and entertainment, service, dining, supermarket, and travel as non-visible goods categories.[23] During our two-year sample period for the treated individuals, the average dollar amount for visible goods consumption is SGD 170, and the average dollar amount for non-visible goods consumption is SGD 538 (Panel B, Table 1).

Then we study the consumption response separately for the visible goods and non-visible goods card spending (columns 1-2, Table 4). Spending on both visible goods and non-visible goods experiences a monthly decrease of 3.2 percent (= exp(-0.033)-1) during the post-bankruptcy event window. However, the post-bankruptcy dummy coefficient is marginally significant for the visible good scenario with a *p* value of 0.09. On the other hand, the total card spending decrease in non-visible goods is statistically significant with a *p* value of 0.021.

[Insert Table 4 about Here]

B. By the Value in a Single Purchase

The second spending pattern we exploit is the spending amount in a single purchase to detect luxury spending on merchandise or services. 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 for 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 treated individuals, 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 (Panel B, Table 1).

We repeat the consumption response specification with these two spending measures and report the results in columns 3-4 of Table 4. The monthly spending on high-value purchases does not

[23] For spending in "online" and "others" categories, we do not have enough information to tell whether the related goods are visible or non-visible, and we omit them in this part. These two categories of spending take relatively small portions in total spending: "online" spending takes up around 1.6 percent of the total spending, and "others" spending takes up around 13.4 percent of total spending. Ignoring them will not influence our results in a significant way.

experience a meaningful change; the estimated coefficient is -0.032 but is statistically insignificant (*p*value = 0.155). On the contrary, the monthly spending on normal-value purchases exhibits a significant decline of 2.5 percent (=exp(-0.025)-1) during the (0, +12m) post-bankruptcy period (*p*value = 0.041).

Taken together, the results with different proxies of status-driven spending measures provide consistent evidence: the treated individuals do not appear to reduce their spending (more) in the area of luxury or visible items, and most of the spending response arises from their reduction in their normal daily consumption.

Furthermore, we also study the heterogeneity effect for the status-driven and non-status-driven spending, using the same measures of peer awareness and financial sophistication as in Table 3. We find a similar result; even within the group of treated individuals who are presumably subject to greater status concerns (e.g., female or close age peers), we do not find any evidence of a more significant decrease in status-driven spending relative to their less status-driven counterparts. Instead they experienced a much greater decrease in spending on the non-status-driven items relative to male and non-close-age peers. Financially sophisticated consumers significantly reduce their spending on both types.[24] Taken together, the evidence in this section lends support to the social learning interpretation of the observed consumption response upon their peers' bankruptcies.

4.4 Other Financial Outcomes: Credit Card Debt and Delinquency

To further investigate the implications of the social learning channel, we study the response in the other financial behavior by the treated individuals. Specifically, we are interested in understanding how they change their behavior regarding the (credit card) debt management. The large negative income shocks to their peers, as well as the severe consequences, may encourage the treated individuals to reassess their own financial health and prompt them to become more prudent and attentive in financial matters especially with respect to their debt. To test this hypothesis, we will focus on two financial variables: credit card debt and credit card delinquency.

A. <u>Credit Card Debt Response</u>

We observe the monthly debt accumulated on all the credit cards each individual has with the bank. During our two-year sample period, the average monthly credit card debt is SGD 597 for the treated individuals. We study the change in the credit card debt upon peer bankruptcy events and report the results in Table 5.

The average treated individual does not appear to change their credit card debt accumulating behavior (column 1, Table 5). The coefficient on the post-bankruptcy dummy is small (-0.016)

[24] For brevity, we leave the detailed results in Table A2 in the Internet Appendix.

and statistically insignificant (*p*value = 0.417). Given the great heterogeneity of the spending response within the treated group, we then test whether the subgroups of treated individuals with a stronger consumption response experience changes in credit card debt. Interestingly, even though female or close-age consumers significantly reduce their spending, they do not reduce their credit card debt (columns 2-3, Table 5). The estimated reduction of credit card debt for female or close-age treated individuals is 0.2 and 4.4 percent respectively, and neither coefficient is statistically significant (*p*value = 0.919 and 0.176 respectively).

[Insert Table 5 about Here]

On the other hand, financially sophisticated treated individuals do respond, significantly, in their credit card debt (columns 4-7, Table 5). Compared to the treated individuals with a mean age, income or length of bank relationship, a one standard deviation increase in those variables is associated with a large decline in the monthly credit card debt by 14.2-20.1 percent, and all three coefficients are statistically significant at the one percent level. Similarly, the treated individuals with a premium bank account experience an additional decrease of 29.4 percent in their monthly credit card debt during the post-bankruptcy period.

B. Credit Card Delinquency

The other financial variable we study is the instance of credit card delinquency. Specifically, we replace the dependent variable with an indicator variable of whether the individual is at least 30 days late in (one of the) credit card(s) at the bank (multiplied by 100). Results are reported in Table 6.

Similar to the results on the credit card debt response, the credit card delinquency rate does not change for the treated individuals on average (column 1, Table 6). In addition, female or close-age treated individuals do not respond in their credit card delinquency rates (columns 2-3, Table 6). The combined effects (i.e., the sum of coefficients on $1_{[0,+12]}$ and the interaction term) in both cases are statistically insignificant (*p*value = 0.655 and 0.445 respectively).

[Insert Table 6 about Here]

Consistent with findings in Table 5, the treated individuals with greater financial sophistication reduce their credit card delinquency rates and the effects are economically large (columns 4-7, Table 6). Compared to the treated individuals with a mean age, income or length of bank relationship, a one standard deviation increase in those variables is associated with a large decline in the credit card delinquency rates equivalent to 22.2-33.2 percent of the mean delinquency rate in sample (0.6 percent). In addition, the treated individuals with a premium bank account experience an additional decrease in credit card delinquency that amounts to 95.5 percent of the mean delinquency rate.

What is also noteworthy is that these financially sophisticated consumers are also wealthier and more resourceful on average—among the treated individuals, those with age, income and bank relationship length that are one or more than one standard deviation above than the cross-sectional mean have a checking account balance (i.e., liquid savings) greater than SGD 32,000 during the three-month pre-bankruptcy period. In other words, relaxation of liquidity constraints (due to their decreased spending) are less likely to account for their change in credit card debt and delinquency behavior, lending further support to the learning interpretation.

To provide further validation of our results, we also study whether treated individuals are more attentive to the use of other forms of credit card debt. For example, one can withdraw cash from the credit card within the offered credit limit, and such cash withdrawals are treated as debt since interest plus a fee will be charged on the advanced amount, calculated from the day of the advance. Our bank dataset records the (administrative) fees charged per month on the cash advance transactions from each consumer's credit cards, which allows us to observe the use of this alternative form of debt. We do find evidence consistent with a reduction in the amount of cash advance fees, which is again more discernible among the financially sophisticated group of treated individuals. Because the variable is sparsely populated (many zeros in the data), it restricts the power of the test and statistical significance is weak for most of the results, even though they are all directionally consistent (see Table A3 in the Internet Appendix). Nevertheless, this suggestive evidence joins the findings on credit card debt and delinquency in providing a coherent interpretation.

The findings in this section have two major implications. First, the fact the credit card debt and delinquency rate decrease after the peers' bankruptcies suggests that the scope of learning among treated individuals extends beyond what we capture through the consumption response. Second, the learning of debt management is less pervasive. Compared to the consumption response reflected in a wider group of treated individuals, we find that the credit card debt and delinquency rate decreases are restricted to financially sophisticated consumers. Other consumers exhibit no behavioral changes in their credit card debt management. One potential explanation is due to the visibility bias in the transmission of information (from peers), i.e., consumption increase due to positive income shocks is more salient than consumption decrease due to negative income shocks (Han and Hirshleifer, 2015). As a result, the general public (except the more financially savvy group) exhibits a limited response to peers' negative income shocks.

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 in the last section.

5.1 Falsification Tests

We present several falsification tests. First, we hold the bankruptcy-hit buildings and treated individuals 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. The result in Table 7, column 1 shows no consumption response. In particular, the coefficient on the post-bankruptcy dummy is statistically insignificant ($p$value = 0.511) and even positive (0.009).

[Insert Table 7 about Here]

Next, we hold the bankruptcy-hit buildings as well as the event time fixed, and randomly assign treated individuals from our treatment sample. For each building, we ensure the number of "pseudo" treated consumers randomly assigned equals or approximates the actual number of treated individuals. Again we repeat our main specification as in column 1 of Table 2 and find no consumption response. The coefficient estimate is small, insignificant and moreover positive in sign (column 2, Table 7).

Last, we make use of the fact that bankrupt individuals cannot keep their private housing and thus those living in the private housing market are most likely obliged to move out upon bankruptcy. We use the same procedure to identify non-bankrupt individuals living in bankruptcy-hit buildings in the private housing market, and repeat our analysis. Again, we find no consumption response, further validating the assumption that the personal bankruptcy shock is unlikely to be correlated with unobserved factors that simultaneously affect the financial well-being of other individuals living in the same location (column 3, Table 7). It also suggests that a continuous within-neighborhood interaction is crucial for the peer influence at work, given that the bankruptcy information is salient regardless of the neighborhood being in the public or private housing market segment.

5.2 The Effect of the Bankruptcy Amount

Bankruptcy events associated with a larger amount serve as a stronger negative shock to the bankrupt individuals, which, as a result, will have a greater impact on their neighbors. We study this hypothesis by interacting the post-bankruptcy dummy with a dummy variable $Large\ amount_k$ in the regression. The dummy variable is equal to one if the peer's bankruptcy event amount is in the top 10 percentile of the cross-sectional distribution of all bankruptcy cases in our sample. Regression results are reported in Table 8.

Consistent with our hypothesis, treated individuals living in buildings associated with a greater bankruptcy amount experience a greater response in total card spending, credit card debt and delinquency rate. Specifically, relative to the treatment group living in buildings with a bankruptcy amount in the bottom 90 percentile, they reduce their total card spending by an additional 5.8 percent (=exp(-0.060)-1) per month. Moreover, their credit card delinquency rate decreases by 0.25 percentage points more, or equivalently 41.7 percent of the mean delinquency

rate in sample. The incremental reduction in credit card debt is not statistically significant. However, the magnitude of the effect is large—treated consumers living in large-bankruptcy-amount buildings experience an additional 6.6 percent (=exp(-0.068)-1) per month.

[Insert Table 8 about Here]

5.3 Additional Robustness Checks

Our results on spending behavior are robust to the pre-bankruptcy control period (for parallel trends verification) and event window choice. In Table A4 of the Internet Appendix, we report 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.

We also perform tests to alleviate the concern that the consumption response is potentially driven by family members of the bankrupt individuals (such as spouses and/or relatives living in the same building), due to the fact that we do not observe the complete information on consumers' background and family relationships in our data. Such an argument implies that the consumption response is restricted to a small set of consumers living in the bankruptcy-hit building, and, in turn, our identified response will be much muted, especially in buildings with more treated individuals. We study the consumption response separately for buildings with greater or fewer than 11 peer consumers (the median number of treated individuals in one HDB building in our sample). Contrary to the family member explanation, we find a strong spending response in buildings with a larger number of treated individuals. By contrast, the buildings with a smaller number of treated individuals experience a spending decrease that is statistically insignificant. In addition, we find that the consumption response is stronger among treated individuals *without* a joint bank account with others, further alleviating the concern that spouses of bankrupt individuals drive the spending decrease observed in the data. Please refer to Table A5 in the Internet Appendix for detailed regression results.

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 statistically significance and economic magnitude, in the average response in total card spending, credit card debt and delinquency rate (see Table A6 of the Internet Appendix).

We conduct further tests on the validity of our treatment sample. 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 happen to close their credit card accounts during the one year period after the peer bankruptcy event (i.e., between month 0 and month 112). Given the bankruptcy law in Singapore, these are also 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 Table 2, column 1. 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 five percent. To further dispel the notion that the (incorrectly included) bankrupt 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 0.017. In contrast, the average of the pre-bankruptcy dummy estimates is small and insignificant (average *p*value=0.425). This suggests that the documented strong spending decrease cannot be explained by the behavorial change of a single person.

Another potential concern regarding our treatment sample is the higher number of bankruptcy events in the last two months of our sample period. 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.

In the main analysis, we use continuous variables of age, income, and length of bank relationship to measure the degree of financial sophistication. We also construct dummy indicators based on the value of these measures, and continue to find the same strong(er) response in total card spending, credit card debt as well as delinquency rate (see Table A7 in the Internet Appendix).

6. Conclusion

This paper exploits a plausibly exogenous (negative) income shock and documents an important social multiplier effect on overall consumption behavior. We identify large, negative individual-specific income shocks by using the universe of all creditor-triggered personal bankruptcy events in Singapore, and merge by location with a proprietary dataset of credit card and debit card spending transactions of a large representative sample of consumers from a leading bank in Singapore.

Relative to existing studies that use geographical proximity to classify peers, our data allow for a finer measure of the neighborhoods within which individuals (more) closely observe and interact with each other. In Singapore, each (six-digit) postal code corresponds to a unique building; in comparison, the same level of geographical unit in the United States—zip code—spans a much larger area and contains more than 30,000 households on average.

Our analysis is based on an event-study design that exploits the changes in consumption after peers in the same building experience personal bankruptcies. We find that, relative to the period of 12 months to two months prior to peer bankruptcy, individuals in our sample experience a large and statistically significant decrease of around 3.4 percent in the monthly total debit and credit card spending in the year following their peers' bankruptcy events.

To investigate the reflection problem that these personal bankruptcy events are correlated with other common background factors that independently influence individuals' behavior, we first find no change in behavior by the treated individuals in the months immediately before their peers' bankruptcy events. More important, we exploit our tight peer neighborhood measurement—individuals with common economic backgrounds or similar preferences are also likely to sort into similar locations within a larger geographical vicinity rather than to precisely self-select into the same building. This is especially relevant in our context because Singaporeans have restricted ability to choose the precise location of their residence given the Ethnic Integration Policy in place that ensures similar distribution of ethnicities in every public housing building. Indeed, we find no consumption change among those living in the adjacent buildings within the 100-meter, or 100–300 meter range.

We observe a great level of heterogeneity in the consumption response across individuals. The negative consumption response is more pronounced for consumers with greater peer awareness or financial sophistication. Moreover, it is stronger in the non-conspicuous goods, consistent with a social learning channel. Credit card debt and delinquency rate also experience a decrease, but the effect is restricted to financially sophisticated consumers.

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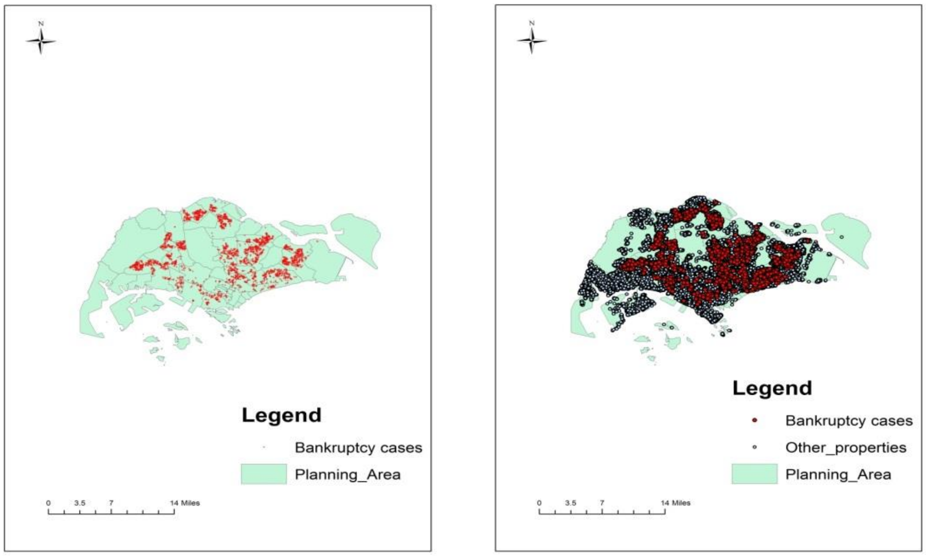
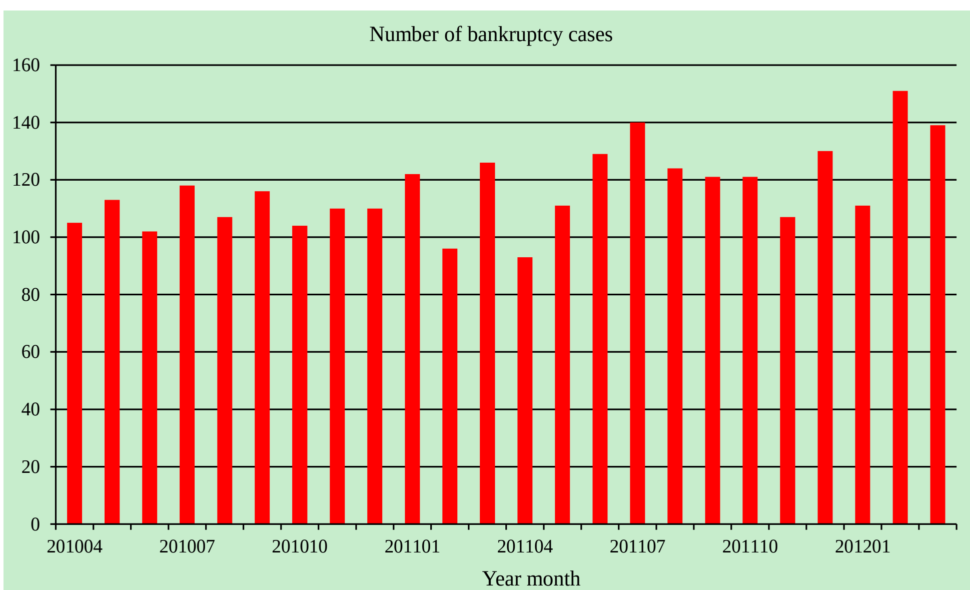
Figure 1: Distribution of Personal Bankruptcy Events

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 with identifiable timing of the bankruptcy event.

Table 1: Summary Statistics: HDB

	(1) Mean	(2) Std. dev.	(3) Median	(4) Mean	(5) Std. dev.	(6) Median	(7) Difference in means (1) – (4)
Panel A: Bankruptcy cases							
	All bankruptcy cases			Bankruptcy cases in sample			
Female (%)	24.4	NA	NA	23.8	NA	NA	0.01
Chinese (%)	63.9	NA	NA	63.4	NA	NA	0.01
Age	42.3	10.2	42	42.2	10.3	42	0.09
Bankruptcy amount (SGD)	95,179	492,524	24,267	103,064	573,134	23,631	7,884.96
Number of cases	2,454			1,655			

(continued on next page)

Note. This table provides summary statistics of demographics and spending information for individuals living in HDB. Panel A reports information related with all bankruptcy cases that happen within our sample period (i.e., 2010:04-2012:03) and bankruptcy cases included in our main sample. Panel B reports demographic and spending information of the full sample of consumers from the bank data who live in HDB and have all three accounts (credit card account, debit card account, and checking account), as well as the subsample living in bankruptcy-hit HDB buildings. *Female* is a dummy variable equal to one if the individual is female. *Chinese* is a dummy variable equal to one if the individual is ethnic Chinese. For bankruptcy cases in Panel A, *age* measures the individual's age at bankruptcy year. For consumers in Panel B, *age* measures the age of a consumer during our sample period. *Bankruptcy amount* is the dollar amount associated with the bankruptcy event in Singapore dollars. *Premium bank account* is a dummy variable equal to one if the individual's bank account is a premium account for at least one month within our sample period. *Income* is the consumer's (verified) monthly income during our sample period in Singapore dollars. *Bank relationship* is the consumer's length of relationship with the bank measured in months. *Total card spending* is consumer's total monthly credit and debit cards spending in Singapore dollars. *Total card spending on visible goods* is consumer's total monthly spending on apparel, car accessories, electronics as well as home furnishings or decorations. *Total card spending on non-visible goods* is consumer' total monthly spending on entertainment, service, dining, supermarket, and travel. *Total card spending on high-value single purchase* is consumer's total monthly spending on items where each single purchase value is greater than or equal to 370 SGD (i.e., 95th percentile of all card transaction amounts in the full sample). *Total card spending on normal-value single purchase* is consumer's total monthly normal spending on items where each single purchase value is lower than 370 SGD. *Credit card spending* is consumer's monthly credit card spending amount in Singapore dollars. *Debit card spending* stands for the total monthly spending amount of debit card and checking account in Singapore dollars. *Credit card debt* is the consumer's total monthly debt on credit cards with the bank. *Credit card delinquency* is a dummy variable equal to one when the individual is at least 30 days late in payment on (one of) the credit card(s) with the bank in that month. *Cash advance fee* is consumer's monthly cash advance fee amount in Singapore dollars. In Panel B, the age, income, spending, debt, delinquency, and fee variables are reported at individual level in our sample period (obtained from the monthly averages during 2010:04-2012:03 period). Average exchange rate between Singapore dollars and US dollars during our sample period is about 0.776 USD per SGD (source: Monetary Authority of Singapore, https://secure.mas.gov.sg/msb/ExchangeRates.aspx). 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 1 (continued): Summary Statistics: HDB

Panel B: Consumers

	Full sample			Treated individuals			Difference in means
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	(1)-(4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Demographics and financial characteristics							
Female (%)	42.6	NA	NA	43.0	NA	NA	-0.45
Chinese (%)	78.2	NA	NA	76.0	NA	NA	2.18***
Age	38.7	10.0	37.2	38.0	9.8	36.4	-0.67***
Income (SGD)	4,354	3,273	3,606	4,165	2,997	3,498	188.89***
Premium bank account (%)	1.6	NA	NA	1.3	NA	NA	0.28**
Bank relationship (in mos)	14.2	5.5	12.4	13.8	5.6	12.4	0.42***
Spending and debt (monthly)							
Total card spending (SGD)	841.9	703.2	655.6	841.0	708.8	647.3	0.87
Total card spending on visible goods	165.0	219.5	97.8	170.2	241.7	96.91	-5.25***
Total card spending on non-visible goods	544.2	487.0	416.3	538.0	481.5	407.7	6.21
Total card spending on high-value single purchase	335.0	513.4	183.4	334.8	521.6	175.5	0.20
Total card spending on normal-value single purchase	520.5	369.5	431.1	520.2	368.2	426.6	0.32
Credit card spending (SGD)	496.2	582.2	319.9	491.8	584.9	309.8	4.38
Debit card spending (SGD)	345.7	358.2	239.3	349.2	361.5	240.0	-3.51
Credit card debt (SGD)	583.3	1,530	13.5	597.2	1,555	13.1	-13.89
Credit card delinquency (%)	0.6	NA	NA	0.6	NA	NA	-0.06*
Number of individuals	86,646			17,326			

Table 2: Average Spending Response to Peer Bankruptcy

	Bankruptcy-hit Buildings			Neighboring Buildings	
				(0m,100m]	(100m,300m]
	Log(Total card spending)	Log(Credit card spending)	Log(Debit card spending)	Log(Total card spending)	Log(Total card spending)
	(1)	(2)	(3)	(4)	(5)
$1_{[-1,-1]}$	-0.011	-0.016	-0.005	-0.006	0.019
	(-0.87)	(-0.87)	(-0.28)	(-0.55)	(1.08)
$1_{[0,+12]}$	-0.035***	-0.036*	-0.039**	-0.008	0.006
	(-2.74)	(-1.76)	(-2.41)	(-0.70)	(0.35)
Constant	5.574***	3.623***	4.239***	5.614***	5.613***
	(290.02)	(134.93)	(176.55)	(327.49)	(204.94)
Individual FE	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y
Observations	278,054	278,054	278,054	347,221	136,440
R-squared	0.47	0.55	0.50	0.48	0.48

Note. This table shows the average spending response of the peer consumers living in the same building with bankrupted individuals, and living in buildings close to the bankruptcy-hit buildings during our sample period (2010:04-2012:03). Bankruptcy month is defined as month 0. $1_{[-1,-1]}$ is a binary variable equal to one for the one months before bankruptcy (i.e., month -1). $1_{[0,+12]}$ is a binary variable equal to one for the 13 months on and after the bankruptcy (i.e., ≥month 0). Our sample includes individuals living in the HDB buildings during the [-12, +12 month] window. Dependent variables in columns (1) – (3) are logs of monthly total card spending, credit card spending, and debit card spending respectively. Both dependent variables in columns (4) – (5) are log of total card spending. Column (4) presents the average response of neighbors living in 0m-100m radius of the bankruptcy-hit building (the bankruptcy-hit building itself excluded). Column (5) presents the average response of neighbors living in 100m-300m radius of the bankruptcy-hit building. All neighboring buildings are also required not to contain bankruptcy events during the sample period (2010:04-2012:03). We calculate logs 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 individual level. T-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table 3: Total Spending Response: Cross-sectional Heterogeneity

	Peer awareness		Financial sophistication			
	(1)	(2)	(3)	(4)	(5)	(6)
$1_{[-1,-1]}$	-0.011	-0.007	-0.009	-0.006	-0.009	-0.011
	(-0.87)	(-0.54)	(-0.71)	(-0.48)	(-0.70)	(-0.87)
$1_{[0,+12]}$	-0.002	-0.011	-0.032**	-0.032**	-0.032**	-0.034***
	(-0.15)	(-0.71)	(-2.47)	(-2.47)	(-2.45)	(-2.66)
$1_{[0,+12]}$×Female	-0.076***					
	(-4.03)					
$1_{[0,+12]}$×Close in age		-0.062***				
		(-2.88)				
$1_{[0,+12]}$×Standardized age			-0.079***			
			(-8.18)			
$1_{[0,+12]}$×Standardized income				-0.046***		
				(-4.12)		
$1_{[0,+12]}$×Standardized bank relationship (in mos.)					-0.046***	
					(-4.50)	
$1_{[0,+12]}$×Premium bank account						-0.073
						(-0.79)
Constant	5.573***	5.573***	5.579***	5.585***	5.579***	5.574***
	(290.04)	(279.16)	(276.18)	(275.73)	(275.93)	(290.02)
Individual FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Observations	278,054	261,764	261,413	258,759	261,413	278,054
R-squared	0.47	0.47	0.47	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] window. *Close in age* is a dummy variable equal to one if the peer is within the age range of four years older or younger than the bankrupted people living in the same building. This variable is assigned as missing when more than one neighbor is bankrupted in the same event month. *Standardized* age_i = (age_i*-mean age)/sd age*, where age_i is the age for individual i one month period before the bankruptcy event in the building; *mean age* is the mean age in the cross section, and *sd age* is the cross-sectional standard deviation of 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 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 clustered at the individual level. T-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table 4: Identifying the Economic Mechanism: by Spending Patterns

	Total card spending on			
	visible goods	non-visible goods	high-value single purchase	normal-value single purchase
	(1)	(2)	(3)	(4)
$1_{[-1,-1]}$	-0.034	-0.021	-0.008	-0.000
	(-1.63)	(-1.47)	(-0.32)	(-0.01)
$1_{[0,+12]}$	-0.033*	-0.033**	-0.032	-0.025**
	(-1.69)	(-2.32)	(-1.42)	(-2.05)
Constant	2.248***	4.990***	1.309***	5.331***
	(80.79)	(243.62)	(41.17)	(296.32)
Individual FE	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
Observations	278,054	278,054	278,054	278,054
R-squared	0.41	0.49	0.27	0.50

Note. This table reports the average consumption response by spending types. Our sample includes individuals living in the bankruptcy-hit HDB buildings during the [-12, +12 month] window. The dependent variables are the log of monthly total card spending on visible goods (column 1), the log of monthly total card spending on non-visible goods (column 2), log of monthly total card spending on items where each single purchase value is greater than or equal to 370 SGD, or equivalently the 95th percentile of all card transactions in the full sample (column 3); and log of monthly total card spending on items where each single purchase value is lower than 370 SGD (column 4). Please refer to Table 1 and Table 2 for more detailed variable definitions. We calculate logs of spending as log (spending + 1) to include 0 spending cases. Individual and year-month fixed effects are included. Standard errors clustered at the individual level. T-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table 5: Credit Card Debt Response to Peer Bankruptcy

	Log (Credit card debt)						
	Full	Peer Awareness		Financial Sophistication			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$1_{[-1,-1]}$	-0.004	-0.004	-0.003	0.004	0.007	0.005	-0.004
	(-0.22)	(-0.22)	(-0.18)	(0.22)	(0.38)	(0.28)	(-0.21)
$1_{[0,+12]}$	-0.016	-0.026	-0.008	-0.004	-0.004	-0.003	-0.012
	(-0.81)	(-1.08)	(-0.35)	(-0.20)	(-0.21)	(-0.14)	(-0.58)
$1_{[0,+12]}$×Female		0.024					
		(0.76)					
$1_{[0,+12]}$×Close in age			-0.037				
			(-1.04)				
$1_{[0,+12]}$×Standardized age				-0.234***			
				(-15.83)			
$1_{[0,+12]}$×Standardized income					-0.178***		
					(-11.21)		
$1_{[0,+12]}$×Standardized bank relationship (in mos)						-0.153***	
						(-9.47)	
$1_{[0,+12]}$×Premium bank account							-0.348***
							(-4.36)
Constant	1.275***	1.275***	1.276***	1.266***	1.279***	1.266***	1.275***
	(53.70)	(53.69)	(51.04)	(50.93)	(51.20)	(50.86)	(53.71)
Individual FE	Y	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y
Observations	278,054	278,054	261,764	261,413	258,759	261,413	278,054
R-squared	0.68	0.68	0.68	0.68	0.68	0.68	0.68

Note. This table shows the credit card debt response to peer bankruptcy events. Our sample includes individuals living in the bankruptcy-hit HDB buildings during the [-12, +12 month] window. Please refer to Table 1, Table 2, and Table 3 for more detailed variable definitions. We calculate log of Credit card debt as log (Credit card debt + 1) to include 0 debt cases. Individual and year-month fixed effects are included. Standard errors clustered at the individual level. T-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table 6: Credit Card Delinquency Response to Peer Bankruptcy

	Credit card delinquency (%)						
	Full	Peer Awareness		Financial Sophistication			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$1_{[-1,-1]}$	0.040	0.040	0.040	0.038	0.030	0.040	0.041
	(0.52)	(0.52)	(0.50)	(0.49)	(0.38)	(0.52)	(0.52)
$1_{[0,+12]}$	-0.056	-0.066	-0.054	-0.049	-0.065	-0.050	-0.048
	(-0.75)	(-0.83)	(-0.65)	(-0.63)	(-0.85)	(-0.66)	(-0.64)
$1_{[0,+12]}$×Female		0.023					
		(0.25)					
$1_{[0,+12]}$×Close in age			-0.021				
			(-0.23)				
$1_{[0,+12]}$×Standardized age				-0.184***			
				(-4.13)			
$1_{[0,+12]}$×Standardized income					-0.133***		
					(-3.25)		
$1_{[0,+12]}$×Standardized bank relationship (in mos)						-0.199***	
						(-4.58)	
$1_{[0,+12]}$×Premium bank account							-0.575**
							(-2.54)
Constant	0.248**	0.248**	0.260**	0.230**	0.246**	0.238**	0.247**
	(2.48)	(2.48)	(2.46)	(2.18)	(2.33)	(2.26)	(2.47)
Individual FE	Y	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y
Observations	236,941	236,941	223,217	223,229	221,227	223,229	236,941
R-squared	0.22	0.22	0.22	0.21	0.21	0.21	0.22

Note. This table shows the credit card delinquency response to peer bankruptcy events. Our sample includes individuals living in the bankruptcy-hit HDB buildings during the [-12, +12 month] window. Please refer to Table 1, Table 2, and Table 3 for more detailed variable definitions. Individual and year-month fixed effects are included. Standard errors clustered at the individual level. T-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table 7: Falsification Tests

	Log (Total card spending)		
	Randomly assigned bankruptcy time	Randomly assigned treated individual	Private housing
	(1)	(2)	(3)
$1_{[-1,-1]}$	0.021	0.017	0.029
	(1.60)	(1.35)	(0.60)
$1_{[0,+12]}$	0.009	0.012	0.072
	(0.66)	(1.00)	(1.61)
Constant	5.614***	5.570***	6.199***
	(296.21)	(291.47)	(69.26)
Individual FE	Y	Y	Y
Year-month FE	Y	Y	Y
Observations	276,503	277,182	21,271
R-squared	0.47	0.47	0.53

Note. This table presents three sets of falsification tests for average response of total card spending. In column (1), we randomly assign the timing of each in-sample bankruptcy event to the treated individuals in bankruptcy-hit buildings. In column (2), we assign the treated individuals in our sample to a randomly chosen bankruptcy-hit building and event time pair. In column (3), we use the same procedure to identify bankruptcy-hit buildings and treated individuals in the private housing market and repeat the analysis on the average total card spending response in Table 2 (column 1). 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 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 clustered at the individual level. T-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table 8: The Effect of Bankruptcy Amount

	Log (Total card spending)	Log (Credit card debt)	Credit card delinquency (%)
	(1)	(2)	(3)
$1_{[-1,-1]}$	-0.011	-0.004	0.041
	(-0.87)	(-0.21)	(0.52)
$1_{[0,+12]}$	-0.029**	-0.008	-0.027
	(-2.15)	(-0.41)	(-0.36)
$1_{[0,+12]}\times$ Large amount	-0.060**	-0.068	-0.250**
	(-2.01)	(-1.38)	(-2.09)
Constant	5.573***	1.275***	0.246**
	(289.93)	(53.69)	(2.46)
Individual FE	Y	Y	Y
Year-month FE	Y	Y	Y
Observations	278,054	278,054	236,941
R-squared	0.47	0.68	0.22

Note. This table reports the effect of the bankruptcy amount. Our sample includes individuals living in the bankruptcy-hit HDB buildings during the [-12, +12 month] window. *Large amount* is a dummy variable equal to one if the related bankruptcy event amount is greater than 90th percentile among all bankruptcy events in our sample. Please refer to Table 1 and Table 2 for more detailed variable definitions. We calculate log of spending and debt as log (spending + 1) and log (debt + 1) respectively to include 0 spending and debt. Individual and year-month fixed effects are included. Standard errors clustered at the individual level. T-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Internet Appendix

Thy Neighbor's Misfortune: Peer Effect on Consumption

Not Intended for Publication

Sumit Agarwal, Wenlan Qian, and Xin Zou

Table A1: Demographics of the Bankruptcy Sample

	Singapore residents			Bankrupted individuals			
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	Difference in means (1) – (4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female (%)	51.0	NA	NA	24.2	NA	NA	26.9***
Chinese (%)	82.3	NA	NA	69.9	NA	NA	12.4***
Age	46.9	14.7	46	43.2	9.1	38	3.72***
Number of individuals	2,353,550			2,806			

Note. This table provides summary statistics of demographic information for the bankruptcy sample 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: Heterogeneity for Spending Patterns

	Peer awareness		Financial sophistication			
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Log of total card spending on visible goods						
$1_{[-1,-1]}$	-0.034	-0.039*	-0.034	-0.032	-0.034	-0.034
	(-1.63)	(-1.81)	(-1.64)	(-1.54)	(-1.64)	(-1.62)
$1_{[0,+12]}$	-0.011	-0.034	-0.036*	-0.036*	-0.035*	-0.031
	(-0.50)	(-1.54)	(-1.81)	(-1.83)	(-1.80)	(-1.60)
$1_{[0,+12]}$×Female	-0.050*					
	(-1.82)					
$1_{[0,+12]}$×Close in age		-0.015				
		(-0.47)				
$1_{[0,+12]}$×Standardized age			-0.085***			
			(-6.43)			
$1_{[0,+12]}$×Standardized income				-0.053***		
				(-3.58)		
$1_{[0,+12]}$×Standardized bank relationship (in mos.)					-0.044***	
					(-3.16)	
$1_{[0,+12]}$×Premium bank account						-0.014
						(-1.08)
Individual FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Observations	278,054	261,764	261,413	258,759	261,413	278,054
R-squared	0.41	0.41	0.41	0.41	0.41	0.41

Note: We repeat the analysis in Table 4 by studying the heterogeneity following the same measures in Table 3. Our sample includes individuals living in the bankruptcy-hit HDB buildings during the [-12, +12 month] window. Please refer to Table 1, Table 2, and Table 3 for more detailed variable definitions. Only HDB residents and [-12,+12 month] window are considered. We calculate logs of spending as log (spending + 1) to include 0 spending cases. Individual and year-month fixed effects are included. Standard errors clustered at the individual level. T-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Panel B. Log of total card spending on non-visible goods

	(1)	(2)	(3)	(4)	(5)	(6)
$1_{[-1,-1]}$	-0.021	-0.017	-0.018	-0.017	-0.018	-0.021
	(-1.48)	(-1.17)	(-1.30)	(-1.18)	(-1.28)	(-1.47)
$1_{[0,+12]}$	0.012	-0.005	-0.029**	-0.031**	-0.029**	-0.032**
	(0.73)	(-0.33)	(-2.06)	(-2.18)	(-2.02)	(-2.26)
$1_{[0,+12]}$×Female	-0.104***					
	(-5.03)					
$1_{[0,+12]}$×Close in age		-0.080***				
		(-3.39)				
$1_{[0,+12]}$×Standardized age			-0.081***			
			(-7.78)			
$1_{[0,+12]}$×Standardized income				-0.051***		
				(-4.23)		
$1_{[0,+12]}$×Standardized bank relationship (in mos.)					-0.055***	
					(-5.05)	
$1_{[0,+12]}$×Premium bank account						-0.054
						(-0.52)
Individual FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Observations	278,054	261,764	261,413	258,759	261,413	278,054
R-squared	0.49	0.48	0.48	0.48	0.48	0.49

Panel C. Log of total card spending on high-value single purchase

	(1)	(2)	(3)	(4)	(5)	(6)
$1_{[-1,-1]}$	-0.008	-0.010	-0.009	-0.009	-0.008	-0.008
	(-0.32)	(-0.37)	(-0.33)	(-0.35)	(-0.32)	(-0.32)
$1_{[0,+12]}$	-0.028	-0.017	-0.034	-0.034	-0.033	-0.031
	(-1.07)	(-0.66)	(-1.47)	(-1.49)	(-1.46)	(-1.38)
$1_{[0,+12]}$×Female	-0.009					
	(-0.34)					
$1_{[0,+12]}$×Close in age		-0.035				
		(-1.08)				
$1_{[0,+12]}$×Standardized age			-0.050***			
			(-3.74)			
$1_{[0,+12]}$×Standardized income				-0.016		
				(-0.94)		
$1_{[0,+12]}$×Standardized bank relationship (in mos.)					-0.036**	
					(-2.53)	
$1_{[0,+12]}$×Premium bank account						-0.070
						(-0.47)
Individual FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Observations	278,054	261,764	261,413	258,759	261,413	278,054
R-squared	0.27	0.27	0.27	0.26	0.27	0.27

Panel D. Log of total card spending on normal-value single purchase

	(1)	(2)	(3)	(4)	(5)	(6)
$1_{[-1,-1]}$	-0.000	0.003	0.003	0.005	0.003	-0.000
	(-0.01)	(0.28)	(0.24)	(0.41)	(0.25)	(-0.01)
$1_{[0,+12]}$	0.009	-0.004	-0.020	-0.020*	-0.019	-0.024**
	(0.59)	(-0.29)	(-1.60)	(-1.65)	(-1.58)	(-1.98)
$1_{[0,+12]}$×Female	-0.077***					
	(-4.28)					
$1_{[0,+12]}$×Close in age		-0.056***				
		(-2.77)				
$1_{[0,+12]}$×Standardized age			-0.068***			
			(-7.32)			
$1_{[0,+12]}$×Standardized income				-0.046***		
				(-4.85)		
$1_{[0,+12]}$×Standardized bank relationship (in mos.)					-0.038***	
					(-3.90)	
$1_{[0,+12]}$×Premium bank account						-0.050
						(-0.61)
Individual FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Observations	278,054	261,764	261,413	258,759	261,413	278,054
R-squared	0.50	0.50	0.50	0.50	0.50	0.50

Table A3. Credit Card Cash Advance Fee Response to Peer Bankruptcy

	Log (credit card cash advance fee)						
	Full	Peer awareness		Financial sophistication			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$1_{[-1,-1]}$	0.001	0.001	-0.001	0.001	0.001	0.001	0.001
	(0.29)	(0.29)	(-0.25)	(0.20)	(0.22)	(0.20)	(0.29)
$1_{[0,+12]}$	-0.001	0.002	-0.002	-0.002	-0.002	-0.002	-0.001
	(-0.40)	(0.47)	(-0.65)	(-0.62)	(-0.70)	(-0.61)	(-0.37)
$1_{[0,+12]}$×Female		-0.007					
		(-1.64)					
$1_{[0,+12]}$×Close in age			0.000				
			(0.03)				
$1_{[0,+12]}$×Standardized age				-0.002			
				(-1.00)			
$1_{[0,+12]}$×Standardized income					-0.004*		
					(-1.68)		
$1_{[0,+12]}$×Standardized bank relationship (in mos)						-0.002	
						(-0.61)	
$1_{[0,+12]}$×Premium bank account							-0.008*
							(-1.84)
Individual FE	Y	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y
Observations	278,054	278,054	261,764	261,413	258,759	261,413	278,054
R-squared	0.34	0.34	0.35	0.34	0.34	0.34	0.34

Note. This table shows the credit card cash advance fee response to peer bankruptcy events. Our sample includes individuals living in the bankruptcy-hit HDB buildings during the [-12, +12 month] window. We calculate log of credit card cash advance fee as log (Credit card cash advance fee + 1) to include 0 sfee cases. Individual and year-month fixed effects are included. Standard errors clustered at the individual level. T-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table A4: 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		
	(0.13)		
$1_{[-1,-1]}$		-0.011	-0.010
		(-0.85)	(-0.74)
$1_{[0,+12]}$	-0.030*	-0.038***	
	(-1.91)	(-2.84)	
$1_{[0,+18]}$			-0.032**
			(-2.52)
Individual FE	Y	Y	Y
Year-month FE	Y	Y	Y
Observations	278,054	219,080	305,325
R-squared	0.47	0.5	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 as well as alternative pre-bankruptcy window control. All three specifications include treated individuals in the HDB buildings only. In column (1), we include observations in the same event window as the main specification in Table 2 (column 1) in our analysis and use 3 months before the bankruptcy event as the control variable. In column (2), we use observations in a shorter event window—[-6, +12 month] in the anlaysis. In column (3), we include observations in the extended event window—[-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 clustered at the individual level. T-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table A5: Consumption Response: More Heterogeneity Tests

	Log (Total card spending)			
	Buildings with		Treated individuals with	
	more treated individuals	fewer treated individuals	no joint account	joint account
	(1)	(2)	(3)	(4)
$1_{[-1,-1]}$	-0.003	-0.019	-0.018	0.008
	(-0.22)	(-0.86)	(-1.19)	(0.36)
$1_{[0,+12]}$	-0.032**	-0.030	-0.039**	-0.025
	(-2.04)	(-1.36)	(-2.54)	(-1.07)
Individual FE	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
Observations	174,145	103,909	207,063	70,925
R-squared	0.48	0.47	0.47	0.49

Note. In this table, we repeat our analysis in Table 2, column 1 in various subsamples. Column 1 (2) restricts the sample to the buildings with more (fewer than) than 11 treated individuals, or equivalently the median of treated individuals per building in our sample. Column 3 (4) restricts to the subsample of treated individuals without (with) a joint bank account. All dependent variables are log of total card spending. Please refer to Table 1 and Table 2 for more detailed variable definitions. We calculate 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 clustered at the individual level. T statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table A6: Exclude Events with Multiple Bankruptcy Cases

	Log (Total card spending)	Log (Credit card debt)	Credit card delinquency (%)
	(1)	(2)	(3)
$1_{[-1,-1]}$	-0.006	-0.003	0.036
	(-0.49)	(-0.17)	(0.45)
$1_{[0,+12]}$	-0.027**	-0.015	-0.070
	(-2.02)	(-0.73)	(-0.94)
Individual FE	Y	Y	Y
Year-month FE	Y	Y	Y
Observations	262,391	262,391	223,764
R-squared	0.47	0.68	0.22

Note. This table repeats the analysis on the average response of total spending (Table 2, column 1), credit card debt (Table 5, column 1), as well as credit card delinquency (Table 6, column 1) by excluding HDB buildings containing more than one bankrupted individual during the event month 0. Please refer to Table 1 and Table 2 for more detailed variable definitions. We calculate log of total card spending and credit card debt as log (Total card spending + 1) and log (Credit card debt + 1) to include 0 spending and debt cases. Individual and year-month fixed effects are included. Standard errors clustered at the individual level. T-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table A7: Alternative Definition of Financial Sophistication

	Log (Total card spending)	Log (Credit card debt)	Credit card delinquency (%)
	(1)	(2)	(3)
Panel A: Older age dummy			
$1_{[-1,-1]}$	-0.010	0.001	0.035
	(-0.77)	(0.08)	(0.45)
$1_{[0,+12]}$	-0.016	0.031	-0.037
	(-1.16)	(1.49)	(-0.47)
$1_{[0,+12]}\times$ Older	-0.112***	-0.243***	-0.172*
	(-4.45)	(-6.28)	(-1.78)
Panel B: High income dummy			
$1_{[-1,-1]}$	-0.007	0.004	0.028
	(-0.52)	(0.24)	(0.36)
$1_{[0,+12]}$	-0.023*	0.024	-0.051
	(-1.68)	(1.18)	(-0.66)
$1_{[0,+12]}\times$High income	-0.099***	-0.287***	-0.206*
	(-3.17)	(-6.56)	(-1.81)
Panel B: Long bank relationship dummy			
$1_{[-1,-1]}$	-0.009	0.003	0.039
	(-0.73)	(0.16)	(0.50)
$1_{[0,+12]}$	-0.026*	0.012	-0.023
	(-1.92)	(0.59)	(-0.29)
$1_{[0,+12]}\times$Long bank relationship	-0.071**	-0.182***	-0.385***
	-0.009	0.003	0.039

Note. This table uses dummy variables for age, income, and length of bank relationship and repeats the analysis in Table 3 (columns 3-5), Table 4 (columns 3-5), and Table 5 (columns 3-4). *Older* is a dummy variable equal to one if the treated individual's mean age during the 3 months period before the bankruptcy event (i.e., month -3 to -1) is greater than 50 (i.e., ≥ 50). *High income* is a dummy variable equal to one if the treated individual's mean monthly income during the 3 months period before the bankruptcy event is in the top 10 percentile among all treated individuals. *Long bank relationship* is a dummy variable equal to one if the treated individual's mean length of bank relationship measured at the 3 months period before the bankruptcy event is in the top 10 percentile among all treated individuals in our sample. Please refer to Table 1 and Table 2 for more detailed variable definitions. We calculate log of total card spending and credit card debt as log (Total card spending + 1) and log (Credit card debt + 1) to include 0 spending and debt cases. Individual and year-month fixed effects are included. Standard errors clustered at the individual level. T-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.