Thy Neighbor's Misfortune: Peer Effect on Consumption*

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Abstract

Using a representative sample of credit and debit card transactions in Singapore, we study the consumption response of individuals whose same-building neighbors experienced personal bankruptcy. The unique setting in Singapore suggests liquidity shocks drive personal bankruptcy and the bankrupts significantly reduce spending afterwards. Peers' monthly card consumption decreases by 3.4 percent during the one-year period. We find no occupation concentration in the bankruptcy-hit buildings, no consumption decrease among individuals in immediately adjacent buildings, or for consumers with diminished post-event social ties with the bankrupt individual. Our findings imply a significant social multiplier effect of 0.8-1.2 times the original consumption shock.

Keywords: Peer Effect, Social Multiplier, Consumption, Spending, Bankruptcy, Debt, Credit Cards, Household Finance, Banks, Loans, Durable Goods, Discretionary Spending

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1. Introduction

Consumption constitutes the most important component of GDP in many countries; 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 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 and other income-transfer programs. Recent studies have documented significant social network effects in consumption (e.g., Bailey et al., 2016; De Giorgi, Frederiksen, and Pistaferri, 2016).

Researchers in general face two key challenges in identifying the peer effect on consumption. First is the difficulty of distinguishing peer influence from the role of correlated background factors that lead to similar individual choices. Second, due to data constraints, existing research typically relies on survey or limited information of direct spending, subjecting the findings to measurement issues which in turn affect interpretation. In this paper, we combine a novel, administrative dataset on individual consumption behavior with a unique setting to study the peer effect.

We identify large individual-specific financial distress events by using the universe of all personal bankruptcy events in Singapore. The bankruptcy shock is large in magnitude: the average bankruptcy amount in our sample is over SGD 100,000 (or equivalently USD 77,600). Several unique institutional settings on bankruptcy in Singapore are pertinent to our study: 1) individuals are required by law to pay back their debt after bankruptcy under government supervision; 2) the bankrupt are prohibited from consuming anything beyond subsistence needs for an extended period of time (e.g., car, luxury goods, travel, taxi, just to name a few); and 3) the Government Gazette publishes a notification so personal bankruptcy is effectively public information. Thus, the obligation to repay debt as well as other severe and long-term bankruptcy consequences eliminate the incentive for strategic bankruptcy. Rather, they reflect large negative liquidity shocks, which prevent debtors from arranging debt renegotiation and thereby force them into bankruptcy. Consequently, personal bankruptcy is an enormous shock to consumption of bankrupt individuals, not only because they have incurred negative liquidity shocks and thus cannot afford to spend, but also because their post-bankruptcy spending is severely constrained by law. We estimate that individuals face 54.4-82.5 percent consumption decrease after bankruptcy.

To measure individual consumption, we use a large representative sample of consumers from a leading Singapore bank, which accounts for a market share of over 80 percent. This dataset covers credit card and debit card transactions, as well as bank account activities between

2010:04 and 2012:03. Similar to the U.S., debit and credit cards are important mediums of disposable consumption in Singapore, and approximately 30 percent of aggregate personal consumption in the country is 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 high frequency. In addition to the spending information, this dataset also provides a rich array of individual-specific demographic information including income, age, gender, ethnicity, nationality, and postal code.

We identify peer consumers as residents living in the same building as the bankrupt individuals. One of the few assets a bankrupt individual can keep is her main residence in the public housing market (i.e., HDB flat). Thus we focus on the peers in the HDB market, where the bankrupt individuals can stay and maintain their ties with neighbors, thereby influence neighbors' consumption behavior. Relative to existing research that uses 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 65 households living in one HDB building (the average size of a HDB household in 2013 is 3.4). 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.

HDB flats are located in housing estates, which are self-contained satellite towns with shared amenities such as schools, groceries, clinics, food courts, and sports and recreational facilities. In addition, it remains the government's top priority to foster community bonding in HDB towns by providing facilities and community spaces for residents to mingle and interact. According to a 2013 survey for public housing residents, almost all residents (97.8 percent) strive to maintain a good neighborly relation.[2] The interactions range from casual conversation, shopping together, borrowing/lending household items, to helping to buy groceries or look after children. Moreover, the same survey reveals that the majority (75.6 percent) of the interactions take place among neighbors within the same building. The cohesive neighborly ties in the public housing market thus provide strong support to our peer measure.

One key identifying assumption is that the bankruptcy events are negative shocks *specific* to the bankrupt individuals, which are uncorrelated with (unobserved) common factors that might affect all consumers living in the same neighborhood. We use several approaches to verify this assumption. 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, Singapore has a unique Ethnicity Integration Policy (EIP) to ensure a balanced mix of the different ethnic groups for each building in HDB towns, applying to both newly built and second-hand houses. The specific rule for the EIP proportion is pre-determined and based

[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.

[2] "Public Housing in Singapore: Social Well-Being of HDB Communities (HDB Sample Household Survey 2013)" by Housing & Development Board. Available at: http://www.singstat.gov.sg/statistics/browse-by-theme/households-and-housing

on the ethnic make-up of Singapore. With a low turnover rate in public housing market (less than 3 percent during our sample period), Singaporeans have restrictedly little ability to choose the precise building of their HDB residence, making residential location (at the building level) close to a random assignment.[3] Our peer group, tightly measured at the building level, largely mitigates concerns of correlated background or preferences driving both residents' building choice and their consumption behavior. Moreover, the self-selection argument should apply to nearby locations within larger geographical vicinity rather than to the precise bankruptcy-hit building only. Therefore, we can explicitly test the identifying assumption by comparing the consumption response between the bankruptcy-hit buildings and other neighboring buildings. Last but not least, given the rich demographic information, we are able to directly check the occupation concentration within building.

The final sample contains 1,655 bankruptcy events and 17,326 peer consumers living in (the bankruptcy-hit) HDB flats during the two-year period (2010:04-2012:03). Our analysis is based on an event-study design that exploits the changes in peer consumption after the same-building neighbors experienced personal bankruptcies. We find that, relative to the period of twelve to two months prior to bankruptcy, peers 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. 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.

Regarding the interpretation of our findings, we find no consumption change among those living in nearby buildings within the 100-meter or 100–300 meter radius. To the extent that individuals in the adjacent buildings are likely subject to similar background factors, this result largely alleviates the correlated factors interpretation. We further examine the consumption response for peers living in the private housing market. The bankrupt individuals are forced to move out after the bankruptcy order, resulting in dampened social connections with their same-building neighbors. Under the plausible assumption that peer influence works mostly through active interaction within a stable social network, we do not expect to find a strong consumption reduction in the private housing market. On the other hand, the concern of correlated shocks and preferences should be more relevant due to a much greater flexibility in residential choice in the private housing market. Yet, we find no consumption decrease among peers living in the same private building as the bankrupt individuals. Moreover, we find no evidence of occupation concentration in those bankruptcy-hit HDB buildings. Consequently, the collective evidence 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.

Additional results further dispel the concern that the consumption response may be driven by immediate family members of the bankrupt. We investigate the distribution of the consumption

[3] Refer to the Housing and Development Board website for key statistics: http://www.hdb.gov.sg/cs/infoweb/about-us/news-and-publications/annual-reports

response and show that the documented effect is not attributable to a few peer consumers (or a small number of bankruptcy-hit buildings). We fail to find a significant change in peer consumers' other banking activities including checking account cash flows and cash spending, further ruling out the possibility of close relatives making consumption adjustments after within-household transfers (to the bankrupt). The bankruptcy event also does not trigger tightening of credit constraints by the bank towards peer consumers living in the same building. Finally, our results are robust to alternative event windows, different choices of bankruptcy events, as well as alternative consumption measures.

To quantify the aggregate impact, we construct an elasticity estimate. Our back-of-the-envelope calculation finds a sizable social multiplier effect: a 10 percent decrease in (the bankrupt individual's) consumption leads to 0.12-0.19 percent consumption decrease for one peer, or a total of 8-12 percent consumption decrease for all peers in the same building. That represents an aggregate impact that is 0.8-1.2 times the magnitude of the original shock.

Finally, we investigate several potential underlying channels. Consumption peer effect could take place through two competing mechanisms: status signalling and "keep up with the Joneses". The status signaling mechanism mainly affects peers' intra-temporal consumption decision. If this is the dominant channel, we should expect to see a disproportionate decrease in conspicuous relative to non-conspicuous consumption. On the other hand, the "keep up with the Joneses" mechanism affects peers' inter-temporal consumption decision, implying a decrease in their overall consumption level. Exploiting the granular spending type information in the credit and debit card transactions, we classify spending into visible (conspicuous) and non-visible (non-conspicuous) categories following Charles, Hurst, and Roussanov (2009) and Heffetz (2011). The finding of equally strong decrease in both types of spending is more consistent with the "keep up with the Joneses" channel: individuals incorporate peers' consumption in deciding their own spending level. We also study the risk sharing channel (Angelucci and De Giorgi, 2009) and social learning channel, and do not find evidence in support of those interpretations.

Existing literature finds evidence suggestive of a strong peer influence on the consumption pattern (Grinblatt, Keloharju, and Ikaheimo, 2008; Cai, Chen, and Fang, 2009; Charles, Hurst, and Roussanov, 2009; Moretti, 2011; Kuhn et al., 2011; Bertrand and Morse, 2013; Bailey et al., 2016; De Giorgi, Frederiksen, and Pistaferri, 2016; Gilchrist and Sands, 2016).[4] Our paper directly contributes to this literature by documenting an important peer effect on consumption based on an accurate and more comprehensive measure of consumption. We exploit a unique

[4] This paper also contributes to the broad 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); workplace (Guryan, Kroft, and Notowidigdo, 2009; Mas and Moretti, 2009; Card et al., 2012); Household savings and debt (Duflo and Saez, 2003; Beshears, et al., 2015; Breza, 2016; Breza and Chandrasekhar, 2016); Portfolio choice and asset prices (Abel, 1990; Hong, Kubik, and Stein, 2005; Bursztyn, et al., 2014)

setting that facilitates clean identification of the consumption peer effect, which in turn implies a sizable social multiplier effect.

The literature on bankruptcy has extensively discussed about the causes and severe consequences associated with bankruptcy filing. Consumer bankruptcy has become more prevalent over time, which is driven by both strategic concerns and liquidity shocks (e.g., Domowitz and Sartain, 1999; Fay, Hurst, and White, 2002; Gross and Notowidigdo, 2011; Gross, Notowidigdo, and Wang, 2014). We contribute to the literature by pointing out the need to incorporate the consumption spillover effect to assess the aggregate impact of bankruptcy. Admittedly, the bankruptcy rules may differ between Singapore and the U.S. and the exact magnitude of such an aggregate effect is not easily generalizable, but the qualitative implication of a significant multiplier through peer influence still remains relevant, particularly after the recent crisis in which many households experienced financial distress.

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, 2017), Agarwal, Pan, and Qian (2016), Baker (2016), and Di Maggio et al., (2017). For a review of the literature, please refer to Browning and Collado (2001) and Jappelli and Pistaferri (2010). We contribute to this stream of literature by showing how individual consumption responds to changes in the resources and spending behaviour of their peers.

The rest of the paper proceeds as follows: Section 2 introduces the institutional background of bankruptcy and the public housing market in Singapore. Section 3 describes the data and methodology. Results are presented in section 4-7, and Section 8 concludes.

2. Institutional Background

2.1 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 file 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 other hand, is 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 affect households' liquidity and debt capacity, leading to bankruptcy filing.

Similar to many developed economies such as the US, Singapore has strict laws governing bankruptcy. However, there are key differences in the bankruptcy process as well as rules that eliminate incentives for strategic bankruptcy in Singapore (we leave a detailed discussion in the Appendix A). Rather, bankruptcy events are triggered by negative liquidity shocks.

First, filing for bankruptcy will not erase one's debt. After the Bankruptcy Order, all assets under the bankrupt individual's name will be reported and controlled by an Official Assignee (OA) from the government, and the OA will be administering the bankrupt's affairs, including the selling of bankrupt's assets, verifying the creditor's claims and paying dividends to the creditors. Therefore even after bankruptcy, the debtor still has to pay for the debt claimed by creditors. The government-assigned OA will keep monitoring the debt repayment process. This largely reduces the financial benefits of strategic bankruptcy, as debt cannot be discharged.

Second, the bankrupt individuals face long-term multi-faceted repercussions in their lives. They cannot own any luxury items beyond subsistence needs, and cannot own car, private properties, credit cards, or mobile phone subscription. They also need permission from the High Court or the Official Assignee to travel or remain overseas, take a taxi, start and run their own businesses, or serve as directors of companies. Any interested party (such as employers) can search for one's bankruptcy record from the website of the Insolvency Office, leading to potential labor market externalities.[5] These impacts are long-lasting. The bankruptcy order and the corresponding restrictions will be discharged when most of the debt has been paid off, or upon agreement by most creditors, or when a minimum tenure has been served. Gauging the recent bankruptcy discharge cases, we find that the duration of the bankruptcy order takes 10 years on average.

Moreover, filing for personal bankruptcy is strongly discouraged by the Singapore government. As stated by the Singapore Ministry of Law, that "*the Official Assignee does not provide advice on the procedures for filing a self-petition*", and that "*You should not consider self-petition for bankruptcy as an option to relieve your financial problems. Bankruptcy should be considered as a last resort, as there are restrictions imposed on bankrupts*". Moreover, the government will publicly disclose the bankrupt individuals' information in the Gazette shortly after the bankruptcy order, which can be considered as another attempt to discourage bankruptcy filing.

Taken together, the non-exemption of debt, severe and long-term bankruptcy consequences, as well as the potentially high social stigma 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 in turn suggests that personal bankruptcies arise from large negative liquidity shocks that dried up the debtors' liquid assets. Given such, the personal bankruptcy is an enormous shock to consumption for the bankrupt individuals, not only because they have incurred negative liquidity shocks and thus cannot afford to spend, but also because their post-bankruptcy spending is severely constrained by law.

[5] Website for Insolvency Office from the Ministry of Law is: https://www.mlaw.gov.sg/eservices/io/
[6] Bloomberg News, Javier, Luzi Ann, "Singapore Amends Law to Help People Avoid Bankruptcy Amid Slump," January 19, 2009.

2.2 The Public Housing Market (HDB)

In Singapore, the residential property market mainly consists of two housing types: public house and private house. Contrary to the private housing market, public housing, or HDB flats, is designed for Singaporean citizens and permanent residents. Developed and closely governed by the government, public housing is heavily subsidized by the Singapore government (both through price discounts in the primary market of new flats and via attractive loan financing). According to the Housing and Development Board in Singapore, there are already over 1 million HDB flats in Singapore, which are homes to over 80 percent of the resident population in Singapore. The average (median) household size in the HDB flats is 3.4 (3).

Several key features of the public housing market prove central for our empirical identification. The primary goal of public housing serves to provide affordable and quality homes to a majority of the Singaporean population. Pertinent to our setting is the treatment of the HDB flats after bankruptcy. To ensure the bankrupt individual's primary residence, the bankruptcy law in Singapore exempts HDB flat from being seized and liquidated. This implies that one can keep the HDB flat and live there after bankruptcy, making her continued interaction with peers in the same neighborhood possible.

To promote racial integration and social harmony, the Housing and Development Board implemented the Ethnic Integration Policy (EIP) in 1989. In an attempt to ensure a balanced mix of the different ethnic groups in HDB towns, the government stipulates an EIP proportion for each HDB building. Both new flat and second-hand flat buyers need to satisfy the EIP proportion rule for that specific building. If the building's limit in terms of a buyer's ethnic group has been reached, the buyer has to find a seller of the same ethnic group (and citizenship type). The specific rule for the EIP proportion is pre-determined and based on the ethnic make-up of Singapore. According to the Housing and Development Board, the average turnover rate for HDB flats during 2010-2012 is only 2.7 percent. The thin public housing market, together with the EIP restriction, significantly limits buyers' locational choice. While buyers in general have locational preference and will search in a particular district, choosing a precise building within that district is close to impossible. This largely mitigates concerns of correlated background or preferences driving both neighbors' building choice and their consumption behavior.

Another key priority of the HDB in Singapore is that the government aims to build cohesive communities in the public housing sector. HDB flats are located in housing estates, which are self-contained satellite towns with shared amenities such as schools, groceries, clinics, food courts, and sports and recreational facilities.[7] In addition, the government provides facilities and community spaces for residents to mingle and interact either incidentally or pre-arranged. Events and activities are also organised to encourage residents to move outside their homes to enjoy the company of neighbors and friends in the community.

[7] Such estates are located throughout the residential areas in the country with convenient access to public transportation, and there is no geographical concentration (which is distinct from the private housing market).

Indeed, residents in the public housing market establish strong connections among one another. According to the 2013 HDB survey for public housing residents, almost all residents (97.8 percent) strive to maintain a good neighborly relation. The interaction ranges from casual conversation, shopping together, borrowing/lending household items, to helping to buy groceries or look after children. Moreover, the same survey reveals that the majority (75.6 percent) of the interaction took place by neighbors within the same building, which occurs at common corridors, areas outside flats, lift lobbies and open space on the ground floor of an HDB building. These strong neighborly ties in the public housing market thus provide support to our measure of peers with the (same building) neighbors.

3. Data

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

3.1 Raw Data

3.1.1 Bankruptcy Data

We exploit the personal bankruptcy dataset obtained from the Supreme Court of Singapore to identify the bankruptcy event. This dataset contains information of all personal bankruptcies from year 1980 to 2012. For each bankruptcy case, we can obtain the personal information of related bankrupt 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, when creditors issue a Statutory Demand formally through court requiring for repayment, as the event month for each bankruptcy case. It is the earliest time when the bankruptcy threat becomes real for the debtor, and is also the earliest time the debtor's financial distress information becomes known to neighbors.[8] Furthermore, this choice of the event month further mitigates the concern regarding the debtor making a strategic choice by exploiting the variation in the timing of legal actions, as the Demand date is chosen by creditors which is presumably exogenous to the debtor.

3.1.2 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,

[8] To avoid trapped in the costly bankruptcy situation, the debtor, after receiving his/her creditor's Statutory Demand, is likely to either negotiate with creditors or take immediate actions to cut down consumption in an attempt to repay debt or enter the "Debt Repayment Scheme" (DRS). These changes can be observed, or communicated between the same-building neighbors, especially given the strong neighborly ties and interaction in the public housing market.

the database covers over 60 percent of the Singapore Residents.[9] From this dataset, we observe demographic information such as gender, ethnicity, and birthday. More important, we also have 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 2,806 bankruptcies from 2010:04 to 2012:03 (i.e., our sample period).[10]

We plot the geographical distribution of the personal bankruptcies in Singapore in our sample period in Panel A of Figure 1. There is no clustering pattern in the geographical space—the events span all locations and all areas with housing establishments in the country. We also find that no bankruptcy-hit buildings are within the 300-meter radius of each other, lending further support to the graphical pattern of no clustering. In addition, the bankruptcy events are evenly distributed across months during the 2010:04-2012:03 period (Figure 1, Panel B). This provides assurance that personal bankruptcy events do not seem to correspond to or arise from systematic economic distress that simultaneously affects many people's economic well-being in the same neighborhood.

[Insert Figure 1 about here]

Bankrupt 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 IA1 in the Internet Appendix. Compared to the population, the bankrupt individuals are less likely to be female, less likely to be Chinese, and tend to be younger than the average Singaporean.

3.1.3 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, which is equivalent to over 80 percent of the entire population of Singapore. The entire dataset 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).[11] The data also include disaggregated

[9] According to Department of Statistics Singapore, the total number of Singapore Residents (comprise Singapore citizens and permanent residents) is 3,818,205 by 2012 (http://www.singstat.gov.sg/statistics/latest-data#16). The entire Singapore Population, including both Residents and foreigners, is around 5.54 million by 2015 (http://www.singstat.gov.sg/statistics/latest-data).

[10] The merge success rate is 81.9 percent. We compare the bankruptcy amount of the 2,806 merged cases and the remaining 621 unmerged cases, and the difference is not statistically significant, indicating that there is no systematic bias in the merging process.

[11] 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

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 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, as credit and debit cards account for approximately 30 percent of aggregate consumption in the country.[12]

This dataset offers several key advantages. First, relative to the traditional survey-based datasets in the United States such as the Survey of Consumer Finance (SCF) or Consumer Expenditure Survey (CEX), our administrative dataset records 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 dataset has more comprehensive consumption information. For example, rather than observing a single credit card account, we have information on every credit card and debit card that each individual has with the bank. In addition, we also observe individuals' activities on their checking account balance on a monthly basis, including the inflow, outflow, as well as the month-end balances of the accounts. This also enables us to gauge, albeit at a slightly noisier level, their consumption behavior through cash and checks. Finally, the richness of the individual demographic and transaction-level information allows us to better disaggregate heterogeneity in consumers' consumption response.

One important limitation of our data is that we do not have information about individual's accounts with other banks. Nevertheless, it is likely that the measurement error is minimal given the market share of the bank. For example, an average Singaporean consumer has around

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.

[12] The remaining 70 percent of consumption is transacted via checks, direct transfers, and cash. Consumers with recurring 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.

three cards, which is also the number of cards an average consumer has in our dataset.[13] Hence, we are confident that we are picking up almost the entire consumption of these households through the spending information on the various accounts at this bank. Following Agarwal and Qian (2014), we aggregate the data at the individual-month level. Credit card (debit card) spending is computed by adding monthly spending over all credit card (debit card) accounts for each individual. For all spending and debt variables, we winsorize them at 1 percent and 99 percent level to eliminate the possible influence of outliers.

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 (but our results are insensitive to the three-account restriction). With these restrictions, the resulting sample size is 86,646 individuals.

3.2 Merged Final Sample and Summary Statistics

Since our consumption data ranges from 2010:04 to 2012:03, we restrict our study to the bankruptcies recorded during this period (N=2,806). Recall the fact that bankrupt individuals can only keep their main residence if it is in the public housing market. To the extent that the peer effect relies on close interactions, we focus on the bankruptcy cases for individuals living in HDB, which gives 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 case that occurred before 2010:04. In other words, 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.

These restrictions help remove confounding (bankruptcy) events that would contaminate the estimation of the consumption level in the baseline period (pre-event period), thereby leading to (downward) bias in the true consumption response estimation. For example, if building A has two bankruptcy events in 2011:01 and 2011:07 respectively, then 2011:02-2011:06 is the post-event month for the first bankruptcy case, in which we are likely to observe a decrease in peer consumer's consumption. However, it will also be used as pre-event months to measure the baseline period consumption level for the second bankruptcy case, creating a measurement

[13]News source: Yahoo Finance (https://sg.finance.yahoo.com/news/singapore-top-asia-credit-cards-105414790.html)

problem for the baseline period and a downward bias in the estimated consumption response to the second bankruptcy case.[14]

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.[15]

We then merge the final bankruptcy event sample with our consumption dataset using postal code to identify the peer consumers—those who live in the same building 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 that maps to bankruptcy cases, we note that our cleaned consumption sample unlikely captures the bankrupt individuals. By law, credit card accounts under the bankrupt's name shall be cancelled 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.

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 code (i.e., the bankruptcy building) 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. 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 lower bound of the true peer effect on consumption. In section 7.5, we also perform the test using an alternative approach to identify the peer consumers.

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 65 households living in one HDB building. As described earlier, neighbors in the same building maintain strong ties and engage in regular interactions. 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 addition, the low transaction frequency of public houses, together with the Ethnic

[14] We also discuss the robustness of our results by relaxing these sample restrictions in Section 7.4.

[15] One building-month may have more than one bankruptcy cases. Out of the 1,655 bankruptcy cases, 83 cases equivalently 5.29 percent, correspond to such situation. 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 perform a robustness check of our main result by excluding those buildings with more than one bankruptcy case in the same month in Section 7.4.

Integration Policy, further alleviates the concern of self-selection of individuals with a common background into the precise same building.

Our final matched sample includes 1,655 bankruptcy cases and 17,326 peer consumers. 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 that can be merged with the consumption data and included in our main test 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 characteristics for individuals in the consumption dataset before and after the 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; the mean monthly income is SGD 4,354, and the average length of relationship with the bank is 14.2 months. In comparison, the after-merge sample of peer consumers exhibits similar demographics. Even though the t-test statistics appear significant, the difference is economically small. Overall, the subsample of peer consumers appears to be largely representative of the original sample.

3.3 Empirical Strategy

We examine the response of consumption (as well as other financial variables) by peer consumers to their neighbor's bankruptcy event. 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 regression model to estimate the average spending response:

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

In our main analysis, we include observations of the peer consumers in the [-12, +12 month] period around each bankruptcy event, where month 0 is the bankruptcy month. The dependent variable $\ln Y_{i,t}$ represents the log of spending amount (total card spending, credit card spending, or debit card spending) by individual *i* at month *t*.[16] 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

[16] For each dollar amount variable X, we calculate the log of X as log (X + 1) to include 0 values for X. For months without any card spending from the transaction dataset, we assign the spending amount as 0. There are 12,042 out of 278,054 observations with 0 spending (around 4.3 percent), and dropping 0-spending months will not affect our results.

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. Since our hypothesis implies correlated consumption responses by peer consumers in the same building, we cluster the standard errors of our estimates at the building level.[17]

The results can be interpreted as an event study. Specifically, estimated coefficients γ and β approximate, relative to the baseline period, the average monthly (log) 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 influence of the neighbor's bankruptcy event, peer consumers should only change their spending behavior *upon* the bankruptcy event, implying a significant negative β, and a γ estimate not different from zero.

4 Main Results

4.1 The Average Spending Response

We begin by examining the average spending response of the peer consumers to neighbor's bankruptcy. Specifically, we study the change in total card spending, credit card spending, and debit card spending respectively, and report the results in Columns 1-3 of Table 2, Panel A.

The first column shows the average response of monthly total card spending (i.e., debit card spending + credit card spending) by the peer consumers. Overall, peers decrease their total card spending by 3.4 percent per month, relative to the average during the 12th to 2nd month period before the peer bankruptcy event.[18] The effect is both statistically and economically significant. The F-test suggests that the estimated coefficients for $1_{[-1,-1]}$ and $1_{[0,+12]}$ are statistically different (F-statistics = 3.70). We decompose total card spending into credit card spending and debit card spending, and find the spending response with similar magnitudes in the two instruments (columns 2-3), suggesting no switching in the spending instruments by the peer consumers. For brevity, we focus on the total card spending as the dependent variable in subsequent analysis.

[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 peer consumption responds only after the bankruptcy event, suggesting the documented spending decrease more likely works through the peer influence channel rather than being driven by common background factors.

Were the effect due to peer influence, we conjecture that it should operate more strongly for the peer consumers who are more sensitive to their neighbor's bankruptcies. Specifically, peers

[17] The standard error estimates remain quantitatively very similar when we cluster at the individual level.
[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.

who are more active in social interaction are likely to be more aware of the neighbors' bankruptcies and their consumption consequences. We use two individual traits to proxy for (greater) peer awareness. Females are usually more socially minded than men and thus tend to engage more actively in the neighborhood (Bertrand, 2011). Alternatively, peer consumers in the same age group (specifically, within [-4, +4] years) as the bankrupt neighbor are also more aware of the neighbor's bankruptcy events due to plausibly closer social ties or stronger peer pressure.[19] We interact the post-bankruptcy dummy with the two awareness proxies and report the results in columns 1-2 of Table 2, Panel B.

Compared to their male counterparts, female peers 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 peers 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 peer consumers whose ages 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 peer consumers outside this age bracket (=exp(-0.062)-1). Both the total effect and the incremental effect are statistically significant at one percent level. In unreported results, we also find similar effects when using alternative age brackets including [-3, +3] and [-5, +5] year ranges.

4.2 Correlated Background Factors

The unique institutional setting and proprietary data allows us to isolate the peer effect from correlated background factors that simultaneously influence individual choices. To alleviate the identification concerns, we perform the following three empirical tests.

4.2.1 Consumption Response in Nearby HDB Buildings

A common critique about proximity-based peer measures lies in the self-selection of individuals with common economic backgrounds or similar preferences into similar locations. That argument, however, applies to larger geographical vicinity than the building level. This is especially relevant in our context where Singaporeans have restricted ability to choose the precise building of their residence due to the institutional restrictions described earlier.

Therefore, we can explicitly test the identifying assumption by studying the differential consumption response between the bankruptcy-hit 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

[19] 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 peer consumers sharing the same ethnicity as the bankrupt 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.

consumers even in the adjacent buildings, then the documented finding should be 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 or 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. Columns 1-2 of Table 3 report average responses of total spending for consumers living in those adjacent non-bankruptcy-hit HDB buildings. In column 1, 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 negative, it is very small in magnitude (-0.008), 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, we again 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.

[Insert Table 3 about Here]

4.2.2 Consumption Response in Bankruptcy-hit Private Housing

Another identification test is to exploit the differences between the public and the private housing market in Singapore. In our context, there are two key differences between the public and private housing markets. First, the social tie in the private housing market is much weaker in general, partly due to its more privacy-conscious building design. More importantly, the government's agenda to promote social interaction *only* applies in the HDB market. Furthermore, a bankrupt individual has to move out (and liquidate) her private residence, but can keep her home if it is in the public housing market. This suggests even more diminished social connections between the bankrupt individual and her peer consumers in the private building after the bankruptcy event, making the peer effect channel less plausible.

Second, unlike the public housing market, there is no government-stipulated quota system for the private housing market. Buyers can have full discretion over which precise building to purchase, and sellers can freely choose whom to transact with. This implies that correlated background factors, which arise from neighborhood sorting, are more likely to manifest in the private housing market. Thus, we test the consumption response after a bankruptcy event by the same-building neighbors in the private buildings. Peer effect would suggest much weaker or no consumption response of the same-building residents, as it works mostly through active interaction within a stable social group. On the contrary, correlated shocks would suggest a (even stronger) negative consumption response by peer consumers, even though the bankrupt neighbor should have moved out (and thus limiting the peer effect channel).

The results are reported in column 3 of Table 3. There is no consumption decrease by the peer consumers in the private housing market, and the effect is statistically insignificant. It is important to note that there is no discernible difference in the geographic distribution between the public and the private housing market (due to Singapore's urban planning). Taken together, this test provides another strong piece of supporting evidence to the peer effect interpretation of our main results in Table 2.

4.2.3 Occupation Concentration

Last but not least, we directly investigate the possibility of concentrated occupation(s) in the bankruptcy-hit HDB buildings. If commons shocks through employers or occupations are indeed responsible for our finding, we would expect to observe a high concentration of occupations among the peer consumers in the bankruptcy-hit building.

There are 15 occupations in total in our bank consumption dataset.[20] Each bankruptcy-hit building contains an average of 11.6 peer consumers who hold 5.5 occupations. In other words, averagely only 2 peer consumers in a given building have the same occupation. This suggests that the peer consumers living in the bankruptcy-hit buildings do not share the same work background, alleviating the concern that the consumption response might be driven by correlated income shocks through common employer/business/occupation.

Furthermore, we compute occupation concentration level for each bankruptcy-hit building. Specifically, for each building *i* with individuals in our sample work in *k* occupations in total, we construct an "HHI index" for occupation as:

$$HHI\ occupation_i = Occupation\ \%_1^2 + Occupation\ \%_2^2 + \cdots + Occupation\ \%_k^2$$

where $Occupation\ \%_j$ ($1 \leq j \leqslant k$) is the percentage of peer consumers for each building in our sample who work in occupation *j*. Similar as the Herfindahl index, a higher HHI of occupation indicates a stronger clustering of occupations among peer consumers in a given bankruptcy-hit building. As posted in Panel A of Table 4, our computed HHI index for occupation is quite low (0.32), especially given the HHI value of 0.36 for all buildings in our bank sample. This further supports the claim that the peer consumers living in the same building assume diversified occupations.

[Insert Table 4 about Here]

Another relevant test of occupation clustering is to compare the probability of a randomly selected individual in the bankruptcy-hit building sharing the same occupation as a same-building neighbor, with her probability of sharing the same occupation as another individual living in the adjacent building. The comparison in Panel B of Table 4 finds no difference in the

[20] The 15 occupations are: Administrative, Agricultural, Clerical, High Risk Business, Housewife, National Serviceman, Non-Worker, Production, Professional, Retiree, Sales, Self-Employed, Service, Student, and Others. In this analysis, we drop the 829 individuals (around percent of the sample) whose occupations are not available.

probabilities, further suggesting no clustering in specific occupation(s) in the bankruptcy-hit buildings.

To summarize, results from Table 3 and 4 collectively provide strong evidence in support of the peer effect—when individuals experience large negative liquidity shocks (and 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 effect is unlikely to be explained by other confounding factors such as correlated income shocks or preferences that drive consumption behavior in a way orthogonal to the peer effect.

4.3 Family Members of the Bankrupt

4.3.1 Distribution of Consumption Change

Are the documented consumption responses driven by outliers, possibly by the bankrupt's family members? We first investigate this possibility by studying the distribution of spending changes in our sample of peer consumers. In order to do so, we need to have an estimate of the consumption change for each peer consumer and thus cannot rely on the regression framework. Instead, we compute the spending change for each peer consumer by properly controlling for time trend and scale differences across individuals. Please refer to the Appendix B for detailed description of the computation.

We plot the distribution of the spending change for each peer consumer in our analysis sample in the top panel of Figure 2. The evidence suggests that our results are not driven by outliers. In particular, it shows that the mode of the distribution sits in the range of [-5%, 0]. That is, more than 22 percent of the peer consumers, relative to others living in the nearby unaffected buildings, decrease their average monthly spending during the post-event period by up to 5 percent of their pre-event monthly income. Moreover, we plot separately the distributions of the pre-event and post-event (trend-adjusted and income-scaled) average monthly spending in the bottom panel of Figure 2. The patterns again suggest that the spending change is not driven by the change in outliers in the pre-event period or post-event period spending levels. Since the distribution in Figure 2 is based on the pooled sample of all peer consumers across buildings, we further calculate the percentage of individuals in a given building that experienced a decline in their adjusted spending, and the mean (median) is 54 (55) percent.

[Insert Figure 2 about Here]

4.3.2 Subsample Tests

Though we cannot observe the complete information on consumers' background and family relationships in our data, the subsample tests below shall further help in alleviate the family member concerns.

First, the argument that the consumption response is driven by bankrupt individuals' family members (such as spouses and/or relatives) living together implies that the consumption response is restricted to a small set of consumers (as we mentioned, two family members on average). Therefore, it implies that our identified consumption response will be much muted in buildings with a larger size of peer consumers. In that regard, we study the (incremental) consumption response for the buildings with greater than 11 peer consumers (the median number of peer consumers in one HDB building in our sample). Contrary to the family member explanation, we find a greater spending decrease in buildings with more peer consumers (Table 5, column 1). In fact, the effect in buildings with a smaller peer consumer size is insignificant, while the effect in buildings with a larger number of peer consumers is 4 percent per month and statistically significant at the 1 percent level.

[Insert Table 5 about Here]

Additionally, we are less likely to include family members in our sample for buildings where fewer consumers are sampled in our bank's data. From the demographic data, we are able to identify the total number of residents for each HDB building in Singapore, base on which we can compute the sampling rate of the bank's consumers at building level. The mean (median) sampling rate for HDB buildings in our sample is around 4.6 (4.3) percent, and the standard deviation is 2.1 percent. We then study the consumption response among peer consumers in the bankruptcy-hit HDB buildings with sampling rates smaller than the median rate. Column 2 of Table 5 shows an equally strong consumption response in the low sampling rate buildings, compared to the high sampling rate buildings.

Furthermore, we examine the consumption response among single peer consumers, and continue to observe a significant consumption decrease. The coefficient is -0.042 and is statistically significant at the 5 percent level.

4.4 Credit Limit Change among Peer Consumers

One other potential confounding factor arises from the bank's restriction on credit supply to all consumers living in the bankruptcy-hit buildings after the bankruptcy event, resulting in more binding credit constraints in the event building and thus reduced spending among peer consumers.

We explicitly examine the change in credit limit among peer consumers after their neighbors' bankruptcy event. We find that among the 17,326 peer consumers in our sample, only 995 of them experienced any change (increase or decrease) in credit limit during our 24-month sample period. For those 995 individuals, we calculate their average credit limit during the pre-event period and post-event period, and compare the average credit limit. Results in Table 6 suggest that even for those individuals who experienced credit supply change, generally the change is positive.

[Insert Table 6 about Here]

5. Economic Significance

5.1 Other Consumption Channels

As described earlier, 30 percent of Singapore aggregated consumption is completed via card transactions, while the rest 70 percent are transacted via direct transfers, checks, and cash. We study the potential consumption response using other payment instruments by analysing the consumers' monthly checking account activities. First, we examine peer consumers' monthly checking account outflow and inflow response after the bankruptcy shock. As reported in columns 1 and 2 of Table 7 below, we do not detect significant change in checking account outflow nor inflow, and both changes are statistically insignificant and economically small.

[Insert Table 7 about Here]

To further investigate if peer consumers increase the cash they take out, we study the change in peer consumers' cash or check spending during the post-event period. Though the bank does not provide the transaction-level data on cash or check spending, we can estimate (a noisy measure of) the monthly cash/check spending as: bank balance at the start of the month+income–total card spending–bank balance at the end of the month, following Agarwal and Qian (2014). We report the response of cash spending in column 3 of Table 7. We find that peer consumers experience an insignificant decrease in cash or check spending. We also perform an analysis using the number of bank transactions (such as via ATM, branch, or online) that offer a coarse measure of cash and check transaction, and find no change around peer bankruptcy events.

No significant change in other bank account activities suggests that peer consumers rely on debit and credit cards to adjust their consumption in response to their neighbor's bankruptcy.[21] This finding further alleviates the concern that our main result is driven by the bankrupt's family members who need to make consumption adjustments after transferring wealth to the bankrupts.

5.2 Discussion on the Economic Magnitude

In our main specification, we estimate that after their neighbors' bankruptcy events, peer consumers experience a large and statistically significant decrease of around 3.4 percent in monthly total debit and credit card spending. One way to interpret the economic magnitude is to compare the dollar amount of the consumption decrease relative to the peers' income level. Given the average pre-bankruptcy period monthly total card spending of SGD 801 for the peer consumers, this result suggests a total decrease of SGD 327 in one year (12 months) following the bankruptcy event, or equivalently close to 8 percent of the treated individual's monthly income.

Another perhaps more informative approach is to construct an elasticity estimate. That is, by how much would the peers decrease their consumption if the bankrupt individual reduced consumption by 10 percent? First, we note that credit card and debit card spending comprise

[21] This finding also implies an increase in their savings, and we find consistent evidence through a decrease in their credit card debt (please refer to the Internet Appendix).

of 30 percent of the total consumption on average. Given that we find no evidence of spending response using cash or checks, the estimated 3.4 percent decrease in total card spending corresponds to around one percent drop in total consumption.

Next, we estimate the consumption decrease for the bankrupt individual. Although we cannot directly identify them or their spending from our consumption data, we exploit the unique bankruptcy rule in Singapore which prohibits the bankrupt from any spending beyond subsistence needs. That implies zero discretionary spending for the bankrupt individual. We then infer one's pre-bankruptcy total discretionary consumption fraction from the average proportion consumers dedicate to discretionary spending from the full bank sample. Specifically, from the transaction-level consumption data in the full sample, we classify spending into discretionary and non-discretionary categories, from which we estimate an average discretionary spending proportion of 54.4-82.5 percent from consumers' total card expenditure.[22] This suggests that the peer consumers reduce consumption by 1.0 percent per month in response to (at least) 54.4-82.5 percent spending decrease of the bankrupt individual.

Taken together, we derive that a 10 percent decrease in (the bankrupt individual's) consumption is associated with 0.12-0.18 percent consumption decrease for one peer. Since an HDB building on average has 65 households, the total consumption impact, by aggregating all peer households in the same building, is 8-12 percent. That represents a significant social multiplier effect, which is 0.8-1.2 times the magnitude of the original financial distress event.

6 Economic Mechanisms

6.1 Keeping Up with the Joneses and Status Signaling

We consider two major competing mechanisms through which consumption externalities could take place through peer effects. Both channels incorporate peers' consumption into an individual's utility function, thereby allowing the peers' consumption decisions to influence her own. The "keep up with the Joneses" mechanism models an individual's utility as a function of the average consumption level of her peers, and thus peers' consumption shall affect the inter-temporal substitution of her consumption decision (e.g., Gali, 1994). On the other hand, the status signaling mechanism creates distortions in the intra-temporal consumption decision of peers, whereby the allocation of consumption is tilted towards more visible or conspicuous goods (Veblen, 1899; Bagwell, Simon, and Bernheim, 1996).

[22] We start by defining the non-discretionary spending according to the merchant categories in card transaction data. For the narrower version of definition, we only include spending on local transportation and food as non-discretionary spending (including spending on "local conveyance & taxi", "supermarkets", "food & beverage stores"), and the rest as discretionary spending. As a result, the average proportion of non-discretionary spending for an HDB resident with all bank accounts is 17.5 percent, suggesting a discretionary spending proportion of 82.5 percent. We also consider an alternative definition, which accounts for more daily activities as non-discretionary spending, including spending on "fuel", "telecommunications", "medical", "electronic and computer", "education", "government", "repair", "utilities", "postal services", "nets-kiosk", "child & mother care". According to this definition, the average proportion of non-discretionary spending for an HDB resident with all bank accounts is 45.6 percent, suggesting a discretionary spending proportion of 54.4 percent.

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

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

6.1.1 Visible and Non-Visible Consumption

First, we exploit the granular information on the merchant types from the credit and debit card transactions in our consumption dataset. Transactions are grouped into the visible and non-visible categories following the definitions in Charles, Hurst and Roussanov (2009) and Heffetz (2011). The details of the classification can be found in the Appendix C. In columns 1-2 of Table 8, we find similar extent of consumption responses for both visible-goods and non-visible goods (the Chi-statistic suggests two regression coefficients for the $1_{[0,+12]}$ dummy are not statistically different—*p*value=0.947).

[Insert Table 8 about Here]

6.1.2 By the Value in a Single Purchase

The second pattern we exploit from the disaggregated spending transactions is to detect luxury spending on merchandise or services by the spending amount in a single purchase. Specifically, we study the entire (credit and debit) transaction dataset during the full sample period (2010:04-2012:03) to find the single-purchase amount cutoff 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 peer consumers, the average dollar amount for *Total card spending on high-value single purchase* is SGD 335, and the average dollar amount for *Total card spending on normal-value single purchase* is SGD 520.

We repeat the consumption response specification with these two spending measures as dependent variables and report the results in columns 3-4 of Table 8. The monthly spending response on high-value purchases is statistically insignificant. However, we cannot reject the hypothesis that the spending decrease on high-value purchase is equal to the spending decrease on normal-value purchase (the Chi-statistic suggests two regression coefficients for the $1_{[0,+12]}$ dummy are not statistically different—*p*value=0.750).

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

6.2 Risk Sharing

The previous literature has documented that risk sharing among households can be an important mechanism to explain the expenditure responses of households living in the same neighbourhood with households experiencing exogenous income shocks (Angelucci and De Giorgi, 2009). As a way of helping out the bankrupt individual, her peer consumers who live in the same building could reduce their spending on debit and credit cards but increase the amount of transfers they make (to the bankrupt individual). However, as peer consumers are not transferring wealth (to the bankrupt) via bank account nor cash (Table 7), risk sharing is an unlikely explanation for the documented consumption response in our setting.

6.3 Bankruptcy Event as an Information or Salience Shock

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

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

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

In contrast to the prediction of the information channel, we find evidence of a much stronger consumption response among older, higher-income, or longer banking relationship peers (Table 9). We also construct dummy indicators based on the value of these measures, and continue to find the same results.

[Insert Table 9 about Here]

Perhaps the bankruptcy event does not provide new information to consumers but instead triggered the behavioral change purely due to its salience (Han and Hirshleifer, 2015). However, the salience-based explanation is also difficult to reconcile with our existing finding on the private market effect. The salience of the event holds equally for bankrupt individuals living in the public housing market and those living in the private housing market. However, we do not find any consumption decrease among peer consumers living in the private bankruptcy-hit buildings (Table 3, column 3).

7. Further Analysis

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

7.1 Alternative Event Windows

Our spending behavior results are robust to the pre-bankruptcy control period (for parallel trends verification) and event window choice. We study the average spending response by using the three-month pre-bankruptcy period to test the parallel trends assumption, extending the event window to [-12, +18] month range, and shortening the event window to [-6, +12] month range. The results remain qualitatively and quantitatively similar. For brevity, we report the results in the Internet Appendix (Table IA2) from now on.

7.2 Additional Falsification Tests

We present additional falsification tests. First, we hold the bankruptcy-hit buildings and peer consumers constant and randomly assign the timing of each bankruptcy event from our bankruptcy sample. Then we repeat our main specification on the total card spending response as in column 1 of Table 2. Next, we hold the bankruptcy-hit buildings as well as the event time fixed, and randomly assign peer consumers into the building from our treatment sample. For each building, we ensure the number of "pseudo" treated consumers randomly assigned equals to the number of true peer consumers. We repeat our main specification as in column 1 of Table 2. Both exercises find no significant consumption response (Table IA3).

7.3 Additional Tests on Outliers

We remove individuals with the most extreme changes in spending during the post-event period from our sample. We find a similar spending decrease of around 3.6 percent per month as in the full sample, and the effect is statistically significant at the 1 percent level (Column 1, Table IA4).

To further dispel the notion that outlier individuals drive the consumption response, we randomly pick and remove one treated individual from our sample and repeat the analysis in Table 2, column 1. We iterate this analysis 100 times and obtain 100 coefficient estimates for the post- and pre-bankruptcy dummies. The average coefficient for the post-bankruptcy dummy is -0.033 with an average *p*value of 0.019. In contrast, the average of the pre-bankruptcy dummy estimates is small and insignificant (average *p*value=0.425) (Figure IA2).

We also study whether the consumption decrease is driven by a few HDB buildings that have large bankruptcy shocks. We create a dummy variable equal to one if the building's bankruptcy event amount is among the top 10 percentile of the cross-sectional distribution of all bankruptcy cases in our sample. Peer consumers living in buildings associated with a greater bankruptcy amount did exhibit a greater reduction of total card spending, consistent with the implication of a stronger financial distress affecting their bankrupt neighbors. On the other hand, peers living in buildings with lower than 90 percentile of the bankruptcy amount distribution also reduce their monthly spending after the event by 2.9 percent, and the effect is statistically significant at the 5 percent level (Column 2, Table IA4). Taken together, our evidence suggests that the consumption decrease is not driven by outlier individuals or buildings.

7.4 Sample Selection Concerns

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

Excluding the multiple bankruptcy event buildings may, however, raise sample selection concerns. We check and verify that there are no significant differences between the single-bankruptcy-event and multiple-bankruptcy-events buildings in terms of both the bankrupt individuals' characteristics and the peer consumers' observable characteristics (Table IA5). Moreover, despite the poor measurement of pre-event period and the associated estimation bias, we conduct a robustness check by including the multiple-bankruptcy-events buildings in our sample and continue to find a significant consumption decrease (Column 1, Table IA6).

On the other hand, some bankruptcy-hit buildings in our sample contain multiple bankruptcy cases (and individuals). Even though it is a small subsample, we conduct a robustness check by removing all those multiple bankruptcy case events (N=82). We continue to find a similar response, both in statistically significance and economic magnitude (Column 2, Table IA6).

Another potential concern regarding our treatment sample is the higher number of bankruptcy events in the last two months of our sample period. One question remains is whether this represents an aggregate (upward) trend or a temporary spike. In unreported results, we tabulate the number of bankruptcy cases until 2012:09 (end of our raw bankruptcy data), and find that the number of bankruptcy cases went back to the average level by August of 2012. In addition, we remove the bankruptcy events during these two months and repeat the main analysis. Our results remain robust: the estimated average reduction in total card spending is 3.5 percent per month and the effect is statistically significant at the 1 percent level (Column 3, Table IA6).

7.5 Alternative Measures

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

Finally, we use the number of purchases as alternative measures of consumption and continue to find a significant decrease in the number of transactions for total card spending, credit card and debit card spending (Table IA7).

8 Conclusion

This paper documents significant peer effect on consumption exploiting the setting of personal bankruptcies in Singapore. The inability to discharge debt as well as the severe and long-term bankruptcy consequences in Singapore make liquidity constraints the driver for filing bankruptcy, leading to significant consumption decrease of the bankrupt individual.

Using the universe of personal bankruptcy cases in Singapore, we identify the bankrupt individuals' same building neighbors, and measure their consumption based on a proprietary dataset of credit and debit card transactions from a leading bank in Singapore. Relative to existing studies that use geographical proximity to classify peers, our data allows for a finer measure of the neighborhoods within which individuals (more) closely observe and interact with each other. In Singapore, the location identifier – (six-digit) postal code—corresponds to a unique building with about 65 households, who maintain a tight social connection. Furthermore, the Ethnicity Integration Policy in place makes home purchase *in a specific building* close to a random assignment, facilitating our identification.

Our analysis is based on an event-study design that exploits changes in consumption among peers after their same-building neighbors experience personal bankruptcies. We find that, relative to the period of 12 months to two months prior to neighbor bankruptcy, peer consumers in our sample experience a large and statistically significant decrease of around 3.4 percent in monthly total card spending during the year afterwards. We provide a collection of evidence in strong support of our identifying assumption that personal bankruptcy events are not confounded by common factors that may independently drive consumption behavior in the neighborhood. Given the large multiplier effect of 0.8-1.2 times the original shock, our findings highlight the need to incorporate the consumption spillover effects while assessing the aggregate impact of personal bankruptcies.

Appendix A. Bankruptcy in Singapore

Similar to many developed economies such as the US, Singapore has strict laws governing bankruptcy, which are encompassed in the Bankruptcy Act (Chapter 20) ("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. But as we discussed in Section 2.1, the self-filing bankruptcy is quite unlikely. Debtors have alternative options before going through the bankruptcy procedure. Similar to Chapter 13 in the United States, there is a "Debt Repayment Scheme" (DRS) under Part VA of the Bankruptcy Act, which went into effect on 18 May 2009. Under DRS, debtors with unsecured debt not exceeding SGD 100,000 are allowed to enter into a "debt repayment plan" (DRP) with their creditors and avoid bankruptcy.[1] The debtors can commit to repay their debt over a fixed period of time, not more than five years (60 months).

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

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

The Official Assignee will seize a debtor's assets, with a few exceptions including her public housing flat (HDB), properties held in trust, CPF monies and basic everyday necessities for life and work.[3] This implies that if public housing flats are their main residence, individuals can keep the flats and live there after bankruptcy. In addition, family members' assets are also exempt, unless the family members are the co-borrowers, guarantors or sureties of the debt. The bankrupt shall distinguish the assets under his/her own name, and other family members'

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

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

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

names very clearly in the Statement of Affairs form, and omitting information or providing false information could bring a fine of up to $10,000 and/or up to two years' jail.

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

The bankruptcy order and the corresponding restrictions can be discharged when most of the debt has been paid off, or upon agreement by most creditors, or when a minimum tenure has been served.[4] Gauging the recent bankruptcy discharge cases published on the Government Gazette, we find that the duration of the bankruptcy order takes 10 years on average.

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

Appendix B. Definition of Trend-adjusted and Income-scaled Spending Change

We compute the consumption change for each peer consumer in the following steps (by properly controlling for time trend and scaling income differences across individuals).

A. For each event building in our sample, we calculate the average total card spending for each month from other non-event buildings in the same postal sector. The purpose of this step is to create a counterfactual consumption level using spending from consumers living in the nearby, unaffected buildings.[5] This is meant, similar to the fixed effects in the regression framework, to control for common trends in consumption (in a time frame when Singapore experienced strong economic growth in general).
B. Then we adjust the monthly spending for consumers living in bankruptcy-hit buildings by subtracting the postal-sector-average spending in the same month.
C. For each peer consumer, we calculate the average of the adjusted monthly spending during the pre-event period and the average of the adjusted monthly spending during the post-event period. We scale both the pre-event and post-event average adjusted spending by the pre-event period average monthly income.
D. Finally, the spending change is defined by subtracting the pre-event period average adjusted spending (scaled by income) from the post-event period equivalence.

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

Appendix C. Definition of Visible and Non-visible Goods

We define "visible goods" and "non-visible goods" base on the merchant categories provided by card transaction data, and the definitions of visible goods from Charles, Hurst and Roussanov (2009) (CHR thereafter), and Heffetz (2011).

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

Specifically, there are 10 categories of goods out of 31 categories in Heffetz (2011) that have VI≥0.6, including cigarettes (VI=0.76), cars (VI=0.73), clothing (VI=0.71), furniture (VI=0.68), jewelry (VI=0.67), recreation 1 (VI=0.66), food out (VI=0.62), alcohol home (VI=0.61), barbers etc. (VI=0.60), and alcohol out (VI=0.60). There is another category of recreation goods in Heffetz (2011)—"recreation 2"—with a VI of 0.58, which ranks next to the visibility of "barters etc." and "alcohol out". Because the merchant categories provided in our card transaction data do not cleanly distinguish between the two types of recreational activities/goods, we classify all goods/services in "recreation 1" and "recreation 2" defined in Heffetz (2011), together with the other 9 categories of goods that with VI≥0.6 as "visible goods".

We report how we correspond the merchant categories in card transaction data to the visible goods categories defined in CHR(2009) and Heffetz (2011) in Table C1 (debit card) and Table C2 (credit card) below. Note that if any categories of goods among the above-mentioned 11 types in Heffetz (2011) are not reported in Table C1 or Table C2, it means that there is no corresponding expenditure category in our debit card or credit card transaction.

Table C1. Visible Goods in Debit Card Transactions

Category Name in Debit Card Transaction Data	Category Name in CHR (2009)	Visible Goods in CHR (2009)	Category Name in Heffetz (2011)	Visibility Index in Heffetz (2011)
(1)	(2)	(3)	(4)	(5)
Driving centers	Vehicle (expanded)	Yes	Cars	0.73
departmental stores	Clothing/jewelry	Yes	Clothing	0.71
fashion accessories & apparel	Clothing/jewelry	Yes	Clothing	0.71
jewelry	Clothing/jewelry	Yes	Jewelry	0.67
electronic & computer		No	Recreation 1	0.66
sports merchandise		No	Recreation 1	0.66
entertainment & recreational		No	Recreation 1/ recreation 2	0.66/0.58
restaurants, cafe, bars		No	Food out/alcohol out	0.62/0.60
beauty salons & cosmetics & spa	Personal care	Yes	Barbers, etc.	0.60
child & mother care	Personal care	Yes	Barbers, etc.	0.60

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

Table C2. Visible Goods in Credit Card Transactions

Category Name in Credit Card Transaction Data	Category Name in CHR (2009)	Visible Goods in CHR (2009)	Category Name in Heffetz (2011)	Visibility Index in Heffetz (2011)
(1)	(2)	(3)	(4)	(5)
specialty retail	Clothing/jewelry	Yes	Cigarettes/jewelry/alcohol home	0.76/0.67/0.61
automotive related	Vehicle (expanded)	Yes	Cars	0.73
rental	Vehicle (expanded)	Yes	Cars	0.73
apparel	Clothing/jewelry	Yes	Clothing	0.71
departmental stores	Clothing/jewelry	Yes	Clothing	0.71
watches & jewelry	Clothing/jewelry	Yes	Clothing	0.71
home/office furnishing & appliances		No	Furniture	0.68
electronic and computer		No	Recreation 1	0.66
music		No	Recreation 1	0.66
entertainment & recreational		No	Recreation 1/ recreation 2	0.66/0.58
dining		No	Food out/alcohol out	0.62/0.60
associations/ memberships	Personal care	Yes	Barbers, etc./ recreation 2	0.60/0.58
pets		No	Recreation 2	0.58

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

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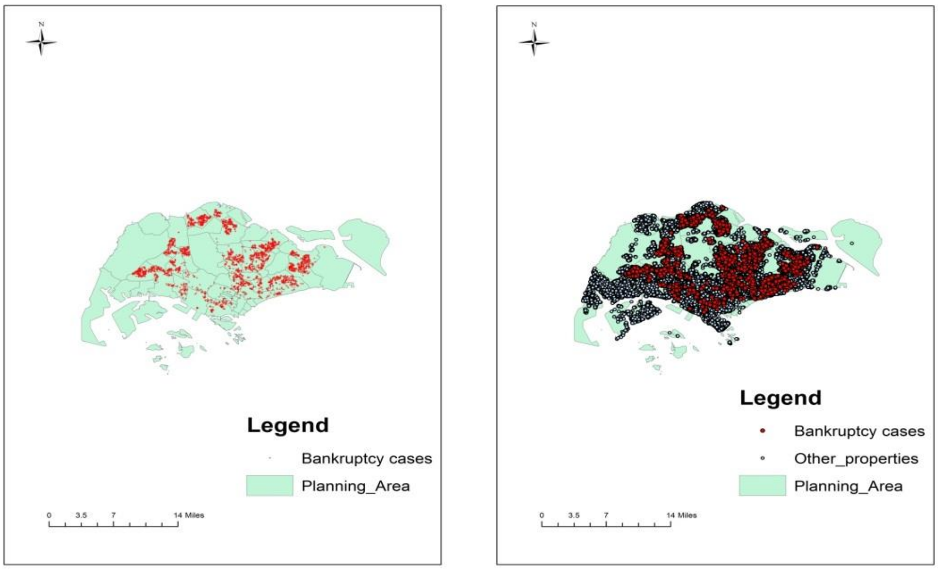
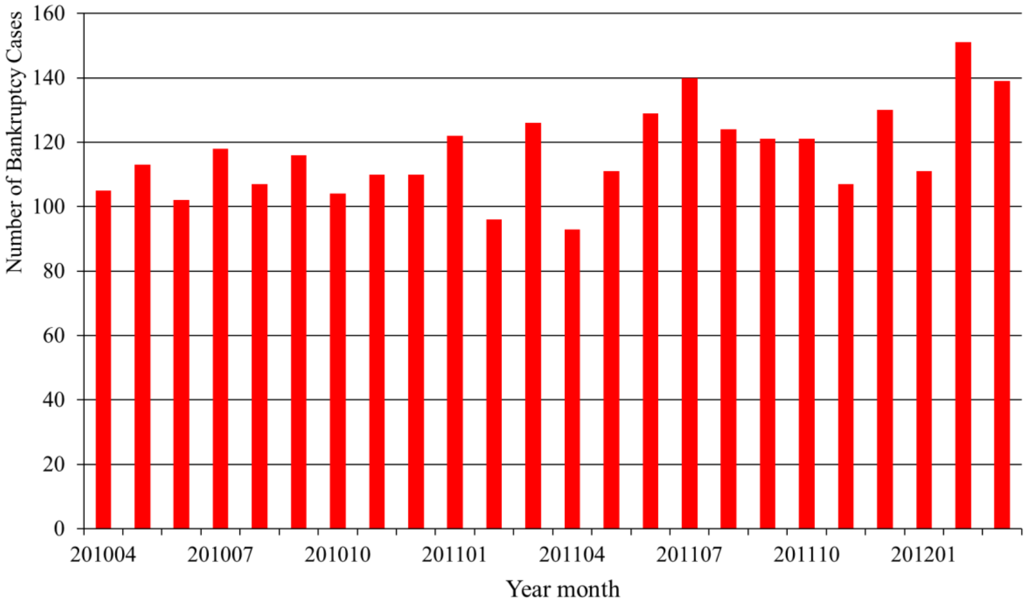
Figure 1. Distribution of Personal Bankruptcy Events

Panel A: By location



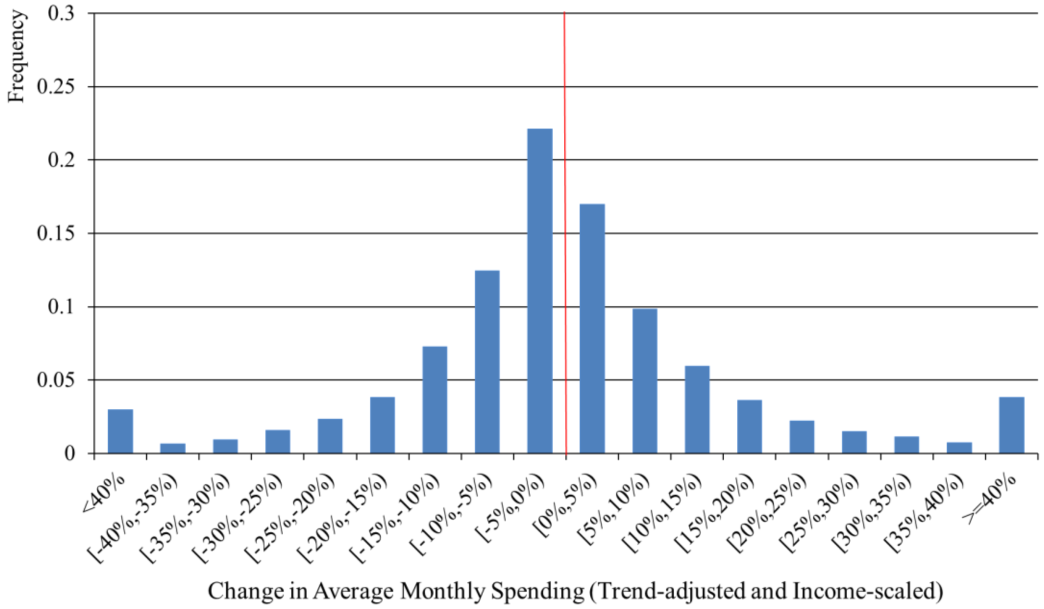
Panel B: By calendar time



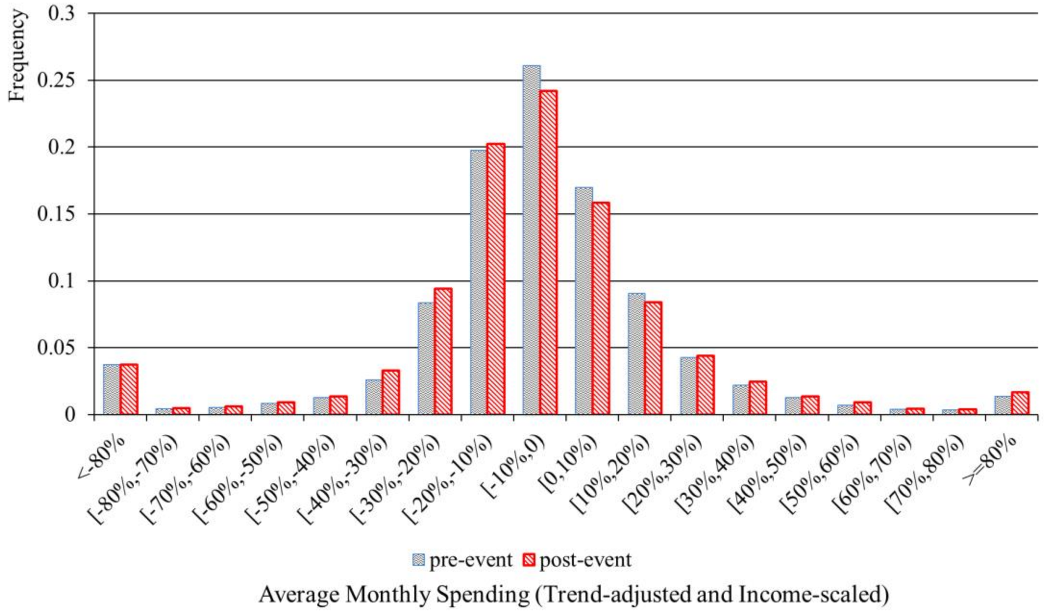
Note. Panel A plots the location distribution of all bankruptcy cases during our sample period (2010:04-2012:03). Panel B plots the time distribution of all bankruptcy cases during our sample period with identifiable timing of the bankruptcy event.

Figure 2. Distribution of Change in Spending (Trend-adjusted and Income-scaled)

Panel A: Distribution of trend-adjusted and income-scaled spending change



Panel B: Distribution of trend-adjusted and income-scaled average monthly spending



Note. Panel A plots the distribution of trend-adjusted and income-scaled spending change. Panel B plots the distribution of trend-adjusted and income-scaled monthly average spending for the pre-event period and post-event period respectively. Please refer to Appendix B for detailed variable definitions.

Table 1. Summary Statistics

Panel A: Comparison of Bankrupt Individuals

	Bankrupt individuals in sample			All bankrupt individuals			Difference in means
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	(1) – (4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female (%)	23.8	NA	NA	24.4	NA	NA	-0.6
Chinese (%)	63.4	NA	NA	63.9	NA	NA	-0.6
Age	42.2	10.3	42	42.3	10.2	42	-0.1
Bankruptcy amt (SGD)	103,064	573,134	23,631	95,179	492,524	24,267	7,885
Number of cases	1,655			2,454			

Panel B: Comparison of Bank Consumers

	Bank consumers in sample			All bank consumers			Difference in means
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	(1)-(4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female (%)	43.0	NA	NA	42.6	NA	NA	0.5
Chinese (%)	76.0	NA	NA	78.2	NA	NA	-2.2***
Age	38.0	9.8	36.4	38.7	10.0	37.2	-0.7***
Income (SGD)	4,165	2,997	3,498	4,354	3,273	3,606	-187.9***
Bank relationship (in mos)	13.8	5.6	12.4	14.2	5.5	12.4	-0.4***
Number of individuals	17,326			86,646			

Note. This table provides summary statistics for individuals in the public housing market (thereafter HDB) in our final sample. Panel A compares demographic information between all bankruptcy cases in Singapore that occurred in our sample period (i.e., 2010:04-2012:03) and bankruptcy cases that are included in our final merged sample. Panel B reports demographic and financial information of the full sample of HDB consumers from the bank provided data, as well as the subsample of HDB consumers living in the bankruptcy-hit buildings (i.e., our merged sample). In Panel B, the statistics are reported for bank consumers that have all three accounts (credit card account, debit card account, and checking account). *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 (in years) during our sample period. *Bankruptcy amt* is the dollar amount associated with the bankruptcy event in Singapore dollars. *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. In Panel B, the age, income, and bank relationship variables are computed as the average value during our sample period for each individual, based on which we report the cross-sectional statistics. The 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 2. Spending Response among Peer Consumers

Panel A: Average spending response

	Log(Total card spending)	Log(Credit card spending)	Log(Debit card spending)
	(1)	(2)	(3)
$1_{[-1,-1]}$	-0.011	-0.016	-0.005
	[0.013]	[0.019]	[0.017]
$1_{[0,+12]}$	-0.035***	-0.036*	-0.039**
	[0.013]	[0.020]	[0.016]
Constant	5.574***	3.623***	4.239***
	[0.020]	[0.027]	[0.024]
Individual FE	Y	Y	Y
Year-month FE	Y	Y	Y
Observations	278,054	278,054	278,054
R-squared	0.47	0.55	0.50

Panel B: Cross-sectional heterogeneity

	Log(Total card spending)	
	(1)	(2)
$1_{[-1,-1]}$	-0.011	-0.007
	[0.013]	[0.013]
$1_{[0,+12]}$	-0.002	-0.011
	[0.016]	[0.015]
$1_{[0,+12]}$×Female	-0.076***	
	[0.018]	
$1_{[0,+12]}$×Close in age		-0.062***
		[0.021]
Constant	5.573	5.573
	[0.020]	[0.020]
Individual FE	Y	Y
Year-month FE	Y	Y
Observations	278,054	261,764
R-squared	0.47	0.47

Note. This table shows the spending response of the peer consumers living in the same building with bankrupt individuals during our sample period (2010:04-2012:03). Panel A shows the average spending response, and Panel B documents the cross sectional heterogeneity in the spending response. Our sample includes individuals living in the HDB buildings during the [-12, +12 month] event window. Dependent variables in columns 1 – 3 of Panel A are logs of monthly total card spending, credit card spending, and debit card spending respectively. Dependent variables in Panel B are logs of monthly total card spending. We calculate logs of spending as log (spending + 1) to include 0 spending cases. 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). *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 bankrupt people living in the same building. This variable is assigned as missing when more than one neighbors are bankrupt in the same event month. Individual and year-month fixed effects are included. Standard errors are clustered at the building level, and are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table 3. Consumption Response in Nearby Buildings and in Private Housing Market

	Neighboring Buildings		Private Housing Market
	(0m,100m]	(100m,300m]	
		Log(Total card spending)	
	(1)	(2)	(3)
$1_{[-1,-1]}$	-0.006	0.019	0.037
	[0.012]	[0.019]	[0.037]
$1_{[0,+12]}$	-0.008	0.006	0.033
	[0.011]	[0.019]	[0.034]
Constant	5.614***	5.613***	6.055***
	[0.017]	[0.028]	[0.059]
Individual FE	Y	Y	Y
Year-month FE	Y	Y	Y
Observations	347,221	136,440	33,344
R-squared	0.48	0.48	0.53

Note. This table report results of the spending responses of consumers living in buildings close to the bankruptcy-hit HDB buildings, and the spending response of consumers living in the private market buildings that experienced a bankruptcy event during our sample period. Our sample includes individuals living in the HDB buildings during the [-12, +12 month] event window. The dependent variables are log of total card spending. We calculate logs of spending as log (spending + 1) to include 0 spending cases. Column 1 presents the average response of neighbors living in 0m-100m radius of the bankruptcy-hit HDB building (the bankruptcy-hit building itself excluded). Column 2 presents the average response of neighbors living in 100m-300m radius of the bankruptcy-hit HDB building. All neighboring buildings are also required not to contain bankruptcy events during the sample period (2010:04-2012:03). In column 3, we investigate the consumption response of peer consumers in the private housing market, and repeat the analysis on the average total card spending response in Table 2 (column 1, Panel A). Please refer to Table 1 and Table 2 for more detailed variable definitions. Individual and year-month fixed effects are included. Standard errors are clustered at the building level, and are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table 4. Occupation Concentration in the Bankruptcy-hit Buildings

Panel A: HHI Index for occupation

	Buildings in sample			All buildings			Difference in means
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	(1)-(4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HHI occupation	0.32	0.16	0.28	0.36	0.20	0.30	-0.04***
# bank consumers in bldg.	11.58	5.74	11.00	11.06	6.27	11.00	0.52***
# occupations in bldg..	5.47	1.94	6.00	5.16	2.10	5.00	0.31***
# of bldg.	1,556			8,971			

Panel B: Probability of having same occupation

	Two random consumers from buildings in sample			One random consumer from buildings in sample, and one random consumer from adjacent buildings			
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	Difference in means
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Same occupation	0.21	0.41	0.00	0.22	0.42	0.00	-0.01
# of bldg	1,087						

Note. This table presents the comparison of occupation concentrations. Panel A reports the summary statistics for within-building HHI index for occupation, number of bank consumers in building, and number of occupations in building. For each building *i* with individuals in our sample work in *k* occupations in total, we construct an HHI index as: $HHI\ occupation_i = Occupation\ \%_1^2 + Occupation\ \%_2^2 + \cdots + Occupation\ \%_k^2$, where $Occupation\ \%_j$ ($1 \leqslant j \leqslant k$) is the percentage of peer consumers for each building in our sample who work in occupation *j.* Columns 1-3 present the statistics for buildings in our sample, and columns 4-6 present the statistics for all HDB buildings in the consumption dataset. Panel B reports the summary statistic for a dummy variable *Same occupation,* and we construct this variable in the following three steps: first, for each bankruptcy-hit building, we randomly draw an individual (a) from this building; second, randomly draw another individual (b) from the same bankruptcy hit building, and assign a dummy variable $Same\ occupation_{(a)=(b)}$ equal to 1 if (a) and (b) has the same occupation, and 0 otherwise; third, randomly draw an individual (c) from an adjacent building within the 300m radius, and assign a dummy variable $Same\ occupation_{(a)=(c)}$ equal to 1 if (a) and (c) has the same occupation, and 0 otherwise. Columns 1-3 report the statistics for $Same\ occupation_{(a)=(b)}$, and columns 4-6 report the statistics for $Same\ occupation_{(a)=(c)}$. 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 5. Are Family Members of the Bankrupt Individuals Driving the Result?

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

Note. This table investigates the possibility that family members of bankrupt individuals are driving the consumption response. In column 1, we investigate if the consumption response for peers living in large neighbourhood is different from that in small neighborhoods. *High # of peer* is a dummy variable equal to one if the number of peers in a building is higher than median number of peers among all buildings (around 11). In column 2, investigate if the consumption response for peers living in low sampling rate buildings is different from that in high sampling rate buildings. *Low Sampling Rate* is a dummy variable equal to one if the sampling rate of a building is lower than the median sampling rate among all buildings. For each bankruptcy-hit HDB building, the sampling rate = $\frac{\text{number of peer consumers in sample}}{\text{total number of residents in a building}} \times 100\%$, and the median sampling rate is around 4.3 percent. 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 are clustered at the building level, and are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table 6. Credit Limit Change among Peer Consumers

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

	Pre-event period			Post-event period			Difference in means
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	(1)-(4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Credit limit (SGD)	8,538	5,362	7,063	12,526	8,340	10,500	-3,988.4
Number of individuals	930			966			

Panel B: Regression analysis

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

Note. This table investigates the change of credit limit among peer consumers after their neighbors' bankruptcy event. Panel A compares the average monthly credit limit for peer consumers in our sample during the pre-event period (i.e., event month -12 to event month -1) and during the post-event period (i.e., event month 0 to event month +12). Panel B presents the regression result when log of credit limit is used as dependent variable. Please refer to Table 1 and Table 2 for more detailed variable definitions. We calculate log of credit limit as log (credit limit + 1). Individual and year-month fixed effects are included. Standard errors are clustered at the building level, and are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table 7. Checking Account and Cash Spending Response

	Log(Checking account outflow)	Log(Checking account inflow)	Log(Cash spending)
	(1)	(2)	(3)
$1_{[-1,-1]}$	-0.001	-0.002	-0.039
	[0.010]	[0.017]	[0.026]
$1_{[0,+12]}$	-0.015	0.001	-0.026
	[0.011]	[0.016]	[0.028]
Constant	7.153***	7.260***	-0.110***
	[0.015]	[0.026]	[0.034]
Individual FE	Y	Y	Y
Year-month FE	Y	Y	Y
Observations	278,054	278,054	277,528
R-squared	0.67	0.63	0.56

Note. This table shows the checking account and cash spending response of the peer consumers living in the same building with bankrupt individuals during our sample period (2010:04-2012:03). Column 1 reports the average response of peer consumers' monthly checking account outflows. Column 2 reports the average response of peer consumers' monthly checking account inflows. Column 3 reports the average response of peer consumers' monthly cash spending, where cash spending is estimated as bank balance at the start of the month + income – total card spending – bank balance at the end of the month. Please refer to Table 1 and Table 2 for more detailed variable definitions. We calculate logs of cash flows or spending as log (spending + 1) to include 0 cash flow or spending cases. Individual and year-month fixed effects are included. Standard errors are clustered at the building level, and are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table 8. Consumption Response by Type of Spending

	(log) Total card spending on			
	visible goods	non-visible goods	high-value single purchase	normal-value single purchase
	(1)	(2)	(3)	(4)
$1_{[-1,-1]}$	-0.019	-0.017	-0.008	-0.000
	[0.019]	[0.014]	[0.025]	[0.012]
$1_{[0,+12]}$	-0.044**	-0.046***	-0.032	-0.025**
	[0.020]	[0.014]	[0.023]	[0.012]
Constant	3.447***	4.958***	1.309***	5.331***
	[0.028]	[0.022]	[0.033]	[0.018]
Individual FE	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
Observations	278,054	278,054	278,054	278,054
R-squared	0.46	0.47	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 for columns 1-2 are the log of monthly total card spending on visible goods and the log of monthly total card spending on non-visible goods. We follow the definitions from Charles, Hurst and Roussanov (2009) and Heffetz (2011) in classifying visible goods and please refer to the Appendix C for the detailed definitions. For column 3, we define high-value purchase spending as the 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). For column 4, we define normal-value single purchase spending as the 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 building level, and are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table 9. Bankruptcy Event as an Information Shock

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

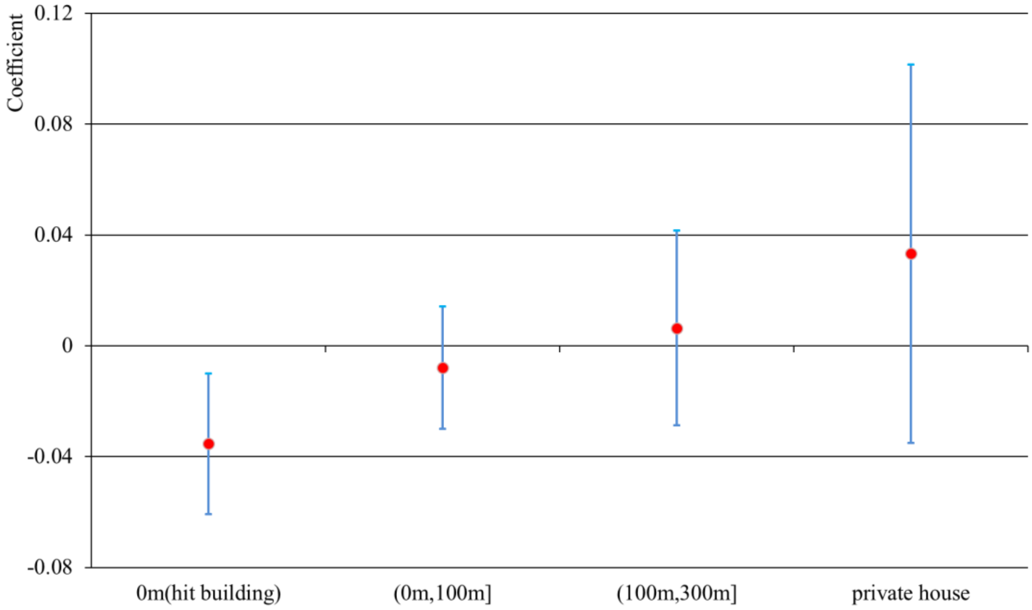
Note. This table reports the heterogeneity across individuals in their total card spending responses. Our sample includes individuals living in the bankruptcy-hit HDB buildings during the [-12, +12 month] event window. *Standardized age*$_i$ = *(average age*$_i$*-mean age)/sd age*, where *average age*$_i$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

Internet Appendix

Thy Neighbor's Misfortune: Peer Effect on Consumption

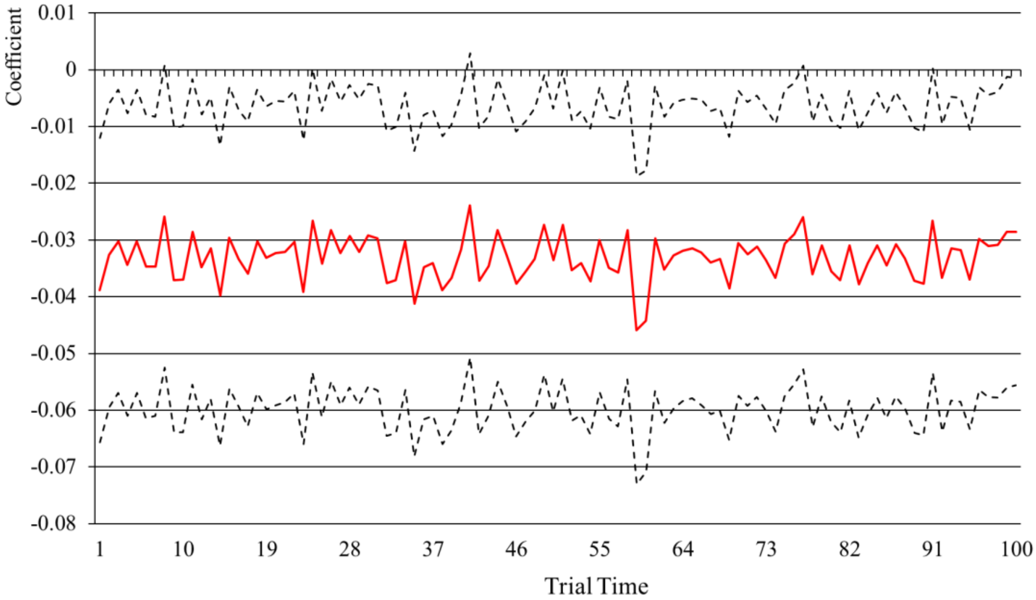
Not Intended for Publication

Figure IA1. Spending Response in Nearby HDB Buildings and Private Housing Market



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

Figure IA2. Distribution of Spending Response Coefficients after Randomly Dropping One Peer in Each Building



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

Table IA1. Demographics of the Bankrupt Individuals

	Bankrupt individuals			Singapore residents			
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	Difference in means (1) – (4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female (%)	24.2	NA	NA	51.0	NA	NA	-26.9***
Chinese (%)	69.9	NA	NA	82.3	NA	NA	-12.4***
Age	43.2	10.5	43.0	46.9	14.8	47.0	-3.7***
Number of individuals	2,806			2,353,550			

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

Table IA2. Alternative Pre- and Post-bankruptcy Windows

	Log (Total card spending)		
	Event window [-12,+12]	Event window [-6,+12]	Event window [-12,+18]
	(1)	(2)	(3)
$1_{[-3,-1]}$	0.002		
	[0.011]		
$1_{[-1,-1]}$		-0.011	-0.010
		[0.012]	[0.013]
$1_{[0,+12]}$	-0.030*	-0.038***	
	[0.016]	[0.014]	
$1_{[0,+18]}$			-0.032***
			[0.013]
Constant	5.574***	5.553	5.577
	[0.020]	[0.028]	[0.019]
Individual FE	Y	Y	Y
Year-month FE	Y	Y	Y
Observations	278,054	219,080	305,325
R-squared	0.47	0.50	0.46

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

Table IA3. Additional Falsification Tests

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

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

Table IA4. Influence of Outlier Bankruptcy Buildings or Outlier Peers

	Log (Total card spending)	
	Exclude outlier consumers	Interact with the high bankruptcy amount dummy
	(2)	(1)
$1_{[-1,-1]}$	0.003	-0.011
	[0.013]	[0.013]
$1_{[0,+12]}$	-0.037***	-0.029**
	[0.013]	[0.014]
$1_{[0,+12]}\times$ Large amount		-0.060**
		[0.031]
Constant	5.704***	5.573***
	[0.021]	[0.020]
Individual FE	Y	Y
Year-month FE	Y	Y
Observations	227,368	278,054
R-squared	0.48	0.47

Note. This table reports the effect of the Outliers. In column 1, we exclude the individuals with the most extreme consumption change after the bankruptcy event in each building, and estimate the average consumption response for the remaining peer consumers. For each bankruptcy-hit building in our sample, we get the average monthly spending from each peer consumers during the pre-event period (i.e., from event month -12 to event month -1) and post-event period (i.e., from event month 0 to event month +12). Then we construct the percentage change in total card spending for each peer consumer as (post event average monthly spending – pre event average monthly spending)/pre event average monthly spending × 100%. Then for each building, we drop the peer consumers with the most extreme change in total card spending. Note that buildings with less than 3 peer consumers identified are automatically dropped in this test. In column 2, we check the possible effect of bankruptcy events with extremely high bankruptcy amount. *Large amount* is a dummy variable equal to one if the related bankruptcy event amount is greater than 90th percentile among all bankruptcy events in our sample (i.e., S$ 110,139.4). Please refer to Table 1 and Table 2 for more detailed variable definitions. We calculate log of spending as log (spending + 1) to include 0 spending cases. Individual and year-month fixed effects are included. Standard errors are clustered at the building level, and are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table IA5. Single Bankruptcy Event Buildings vs. Multiple Bankruptcy Event Buildings

Panel A: Bankrupt Individuals in Single-event Buildings vs. Multiple-event Buildings

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

Panel B: Bank Consumers in Single-event Buildings vs. Multiple-events Buildings

	Single-event buildings			Multiple-events buildings			Difference in means
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	(1)-(4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female (%)	42.9	NA	NA	43.3	NA	NA	-0.3
Chinese (%)	77.1	NA	NA	77.3	NA	NA	-0.1
Age	38.2	4.6	38.0	37.5	4.7	37.7	0.7**
Income (SGD)	4,003	1,265	3,833	3,997	1,276	3,966	5.9
Bank relationship (in mos)	14.0	2.3	14.0	14.0	2.2	14.0	0.0
Number of buildings	1,485			313			

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

Table IA6. Choice of Bankruptcy Events

	Include multiple bankruptcy event buildings (1)	Exclude multiple-case events (2)	Exclude events in last 2 months (3)
$1_{[-1,-1]}$	-0.010	-0.006	-0.013
	[0.010]	[0.013]	[0.013]
$1_{[0,+12]}$	-0.020**	-0.027**	-0.036***
	[0.010]	[0.013]	[0.014]
Constant	5.584***	5.576***	5.576***
	[0.016]	[0.020]	[0.020]
Individual FE	Y	Y	Y
Year-month FE	Y	Y	Y
Observations	418,825	262,391	256,390
R-squared	0.48	0.47	0.47

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

Table IA7. Alternative Consumption Measures: Number of Purchases

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

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

Table IA8. Response of Other Financial Outcomes among Peer Consumers

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

Panel B: Incidence of delinquency on credit cards

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

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

Note. This table shows the response of other financial outcomes from peer consumers after their same-building neighbors' bankruptcy. In Panel A, we report the response of peer consumers' credit card debt, and the dependent variables are log (credit card debt+1). In Panel B, we report the response of peer consumers' credit card delinquency status. For each individual-month, we assign a dummy variable equal to 1 if the individual is at least 30 days late in payment on (one of) the credit card(s) with the bank in that month. The dependent variables are credit card delinquency dummy×100%. In Panel C, we report the response of peer consumers' credit card cash advance fee, and the dependent variables are log(credit card cash advance fee+1). Please refer to Table 1, Table 2, and Table 7 for more detailed variable definitions. Individual and year-month fixed effects are included. Standard errors are clustered at the building level, and are reported in brackets. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.