Thy Neighbor's Misfortune: Peer Effect on Consumption

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Using a large, representative sample of credit and debit card transactions in Singapore, this paper studies the consumption response of individuals whose same-building neighbors experienced personal bankruptcy. The unique bankruptcy rules in Singapore suggest liquidity shocks drive personal bankruptcy decisions, leading to a substantial drop in consumption for the bankrupt. Peers' monthly card consumption decreases by 3.4 percent over the one-year post-bankruptcy period. There exists no consumption decrease among individuals in immediately adjacent buildings, nor for consumers with diminished post-event social ties with the bankrupt. The findings imply a significant social multiplier effect of 2.8 times the original consumption shock.

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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. 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 using the universe of all personal bankruptcy cases 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). In Singapore, 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 78 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 with 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 an HDB household in 2013 is 3.4). In

[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.

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.

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 neighbor's 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 the event. 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. Using constructed measures of the total monthly spending as well as monthly spending with cash and checks, we further show that peers' cash/check spending is not significantly affected, leading to a 1.9 percent decrease in total monthly spending.

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 A1). 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. This makes residential choice at the building level close to random. 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.

We conduct a variety of empirical analyses to further address potential confounding factors driving residential location sorting. First, we note that the self-selection issue, if any, should apply to larger geographical vicinity than to the same building. However, we find no consumption change among those living in nearby buildings within the 100-meter or 100–300-meter radius. Furthermore, in the private housing market, where housing choice is more discretionary and the sorting concern is more applicable, we fail to find a significant consumption decrease. Second, we explicitly study the occupation concentration for each building and find no evidence of residents clustering by their work occupation. Similarly, we document evidence inconsistent with an interpretation of clustering of co-workers of the same employer in the same building based on their daily work commute patterns.

Additional results dispel the concern that the consumption response may be driven by immediate family members of the bankrupt. We investigate the distribution of the consumption 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 alleviating the possibility of close relatives making consumption adjustments after within-household transfers (to the bankrupt).

In sum, our main finding is unlikely due to endogenous sorting by family relation, friendship, occupation, and employer. Admittedly, our tests cannot completely rule out unobserved grouping of residents in the same building. However, given that our analyses capture the most important sorting mechanisms in residential location choice, the remaining confounding factors, if any, play a limited role in accounting for our results. Lastly, the bankruptcy event also does not trigger tightening of credit constraints by the bank towards peer consumers living in the same building, which lends further credence to the peer effect interpretation.

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) card consumption leads to 0.44 percent card consumption decrease for one peer, or a total of 28 percent consumption decrease for all peers in the same building. That represents an aggregate impact that is 2.8 times the magnitude of the original shock. Finally, we discuss several possible underlying mechanisms and the robustness of our main finding.

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; Gilchrist and Sands, 2016, Agarwal, et al., 2019; De Giorgi, Frederiksen, and Pistaferri, 2020).[2] Our paper directly contributes to this literature by clearly identifying the consumption peer effect based on a unique setting and a comprehensive measure of consumption, and our results imply a sizable social multiplier effect.

Our paper is broadly related to the vast literature on the determinants of consumption 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.

[2] 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 (Bobonis and Finan, 2009; Carrell, Fullerton, and West, 2009); risky behavior like sex, crime, drugs and smoking (Glaeser, Sacerdote, and Scheinkman, 1996; Card and Giuliano, 2013); program participation (Bertrand, Luttmer, and Mullainathan, 2000); workplace (Guryan, Kroft, and Notowidigdo, 2009; Mas and Moretti, 2009; Card, et al., 2012); serving as board of directors (Agarwal, et al., 2016); household savings and debt (Duflo and Saez, 2003; Breza, 2012; Beshears, et al., 2015; Breza and Chandrasekhar, 2019); portfolio choice and asset prices (Abel, 1990; Hong, Kubik, and Stein, 2005; Bursztyn, et al., 2014).

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), Di Maggio, et al., (2017). Agarwal, Pan, and Qian (2018), Baker (2018), Gelman, et al. (2014, 2018), and Gelman, et al. (2017). For a complete 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.

Finally, the literature on bankruptcy has extensively discussed 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 (Agarwal, Mikhed, and Scholnick, 2020). Admittedly, the bankruptcy rules 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 remains relevant, particularly after the recent crisis in which many households experienced financial distress.

The rest of the paper proceeds as follows: Section I introduces the institutional background of bankruptcy and the public housing market in Singapore. Section II describes the data and methodology. Results are presented in section III-IV, and Section V concludes.

I. Institutional Background

A. 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 such as medical expenses, credit card debts, divorce, and unemployment (Domowitz and Sartain, 1999; Sullivan, Warren, and Westbrook, 2001; Warren and Tyagi, 2004).

Similar to many developed economies such as the US, Singapore has strict laws governing bankruptcy. 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 bankrupts 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 notification of bankruptcy so personal bankruptcy is effectively public information. The non-exemption of debt, severe and long-term bankruptcy consequences, as well as the potentially high social stigma for Singapore bankrupts, discourages any incentive for strategic bankruptcy. Bankruptcy events are instead triggered by negative liquidity shocks (please refer to the Online Appendix for more details).

Indeed, both the level and growth of the bankruptcy rate in Singapore are much smaller than those in the US during 1980-2012 (Agarwal, et al, 2016). 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.

B. The Public Housing Market (HDB)

In Singapore, the residential property market mainly consists of two housing types: public and private housing. 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 in Singapore prove central to 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: the racial composition of residents in each HDB building, including both new flats and resale flats, shall satisfy an EPI proportion. If the building's limit in terms of a buyer's ethnic group has been reached, the buyer must 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.[3] 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, discretion over a precise building within that district is close to impossible. This largely alleviates 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.[4] 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

[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

[4] 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). 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 organized to encourage residents to move outside their homes to enjoy the company of neighbors and friends in the community.

housing market thus provide support to our measure of peers with the (same building) neighbors.

II. Data

We use multiple unique datasets for our analysis, 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.

A. Raw Data

Bankruptcy Data.—We exploit the universe of personal bankruptcy cases during 1980 to 2012 obtained from the Supreme Court of Singapore to identify the bankruptcy event. For each bankruptcy case, we can obtain the following information on related bankrupt(s): 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 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.[5] Furthermore, the Demand date is chosen by creditors which is presumably exogenous to the debtor.

[5] 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.

Demographic Data.—The second dataset we use is a unique proprietary dataset containing demographic information for more than two million (i.e., over 60 percent of) Singaporean residents (including citizens and permanent residents) as of 2012. From this dataset, we observe demographic information including gender, ethnicity, and birthday. More importantly, the data also provide individual's unique personal identifier, residence type (public or private), and related postal code, which allow us to merge all three datasets. There are 2,806 bankruptcy cases that can be merged with demographics during our sample period (2010:04 to 2012:03).[6] We find no geographic nor time clustering of all personal bankruptcy cases in Singapore during our sample period (see Figure A1 in Online 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 (see Table A1 of the Online Appendix).

Consumption Data.—We use a proprietary dataset obtained from a leading bank in Singapore to measure individual consumption. The entire dataset contains consumer financial transactions of a large, representative sample of over 180,000 bank customers between 2010:04 and 2012:03. For each individual, we observe the monthly statement information on their checking accounts, credit cards, and debit cards with the bank. The data also include disaggregated transaction-level information about the individual's credit card and debit card spending, including the transaction amount, transaction date, merchant name, and merchant category. Moreover, the data contains a rich set of demographics and financial information, including age, gender, ethnicity, income, property type (public or private

[6] 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.

housing), property address (postal code), and the length of relationship with the bank.

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. Moreover, 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. 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 observe individuals' checking account cash flows and balances, which 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.

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 detail by Agrawal and Qian (2014), consumer credit also plays a critical role in Singapore, and the specific banking products that we study (credit card, debit card, and bank checking account) are similar to those used in the United States.

One important limitation of our data is that we do not have information about an 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 three cards, which is also the number of cards an average consumer has in our dataset.[7] Hence, we are picking up almost the entire consumption of these households through the spending via various accounts at this bank. We aggregate the credit card, debit card, and total card spending (=debit card spending + credit card spending) at the individual-month level, and winsorize them at 1 percent and 99 percent level.

As an approximation, we follow Agarwal and Qian (2014) and construct the total spending amount as bank balance at the start of the month + income – bank balance at the end of the month. In doing so, we assume that 1) individuals deposit their monthly income in the same bank's checking account, 2) pay their credit card balance from this particular bank's account, and 3) individuals do not transfer the money to other banks/investment accounts or other individuals. The monthly income is measured by the monthly checking account inflow. Then the total cash/check spending is estimated as: monthly total spending – total card spending.[8]

For our analysis, we restrict the main sample to the public housing (HDB) residents. 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 the 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 (our results are insensitive to the three-account restriction). We are left with 86,646 individuals after these restrictions.

[7] Yahoo Finance. 13 April, 2012. "Singapore Top in Asia in Credit Cards Owned per Person: Survey".

[8] When the estimated cash/check spending under this measure is negative (around 10 percent of observations), we conjecture that the individual doesn't pay credit card balance from this bank's account in this month. Then we use the checking account outflow as total cash/check spending instead, and the total spending in the particular month is revised as: cash/check spending + total card spending.

B. Merged Final Sample and Summary Statistics

Among the 2,806 bankruptcy cases recorded during 2010:04-2012:03 (i.e., our sample period), 2,454 are issued against HDB residents. We further restrict the sample to postal codes with only one bankruptcy event during the whole sample period, and we exclude bankruptcy-hit postal codes that are preceded, within a 12-month period, by another bankruptcy case that occurred before 2010:04. 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.[9]

The HDB bankruptcy event sample is then merged with the consumption dataset using postal code. The peer consumers are those who live in the same building as the bankrupt individuals. To cleanly assess the peer effect, we need to exclude the bankrupt individuals. While we cannot directly identify the bankrupt individuals in the bank dataset due to its anonymity, we infer the likely bankrupt consumers in our data as follows. By law, credit card accounts under the bankrupt's name shall be cancelled in Singapore. However, it is possible that the credit card accounts of bankrupt individuals may be closed much later due to the unknown date of bank enforcement. We observe in our sample 250 individuals who have the same gender, age, and ethnicity as the bankrupt(s) in the same building and treat them as likely candidates for the bankrupt consumers in the building. We use these 250 consumers to estimate the magnitude of the spending decline among the bankrupt.[10] In studying the peers' consumption response, we exclude them from the analysis.

[9] We discuss the robustness of our results by relaxing these sample restrictions in Online Appendix.

[10] For the post-bankruptcy spending, we use 0 for their credit card spending, which is strictly required and enforced by Singapore's law, and the observed debit card and constructed cash and check spending to measure the other types of consumption for the bankrupt in the post-bankruptcy period.

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

Our final matched sample includes 1,655 bankruptcy cases and 17,326 peer consumers. Panel A of Table 1 summarizes the bankruptcy cases in our sample, and all HDB bankruptcy cases during the same period. 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. The average dollar amount of a bankruptcy case is around SGD 100,000 for both samples. Differences in means of all characteristics are economically small and statistically insignificant.

[Insert Table 1 Here]

In Panel B of Table 1, we compare the demographic characteristics for peer consumers in our final sample and all HDB consumers. For all HDB consumers (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. The peer consumers in our final sample exhibit similar demographics. Even though some t-test statistics appear significant, the differences are economically small. Overall, the subsample of peer consumers appears to be largely representative of the original sample.[11]

C. Empirical Strategy

We mainly examine the response of consumption by peer consumers to their neighbor's bankruptcy event. Our empirical strategy exploits monthly individual-level data, together with the bankruptcy-hit building and event timing pair during the two-year period. Similar to Agarwal, Pan, and Qian (2020), 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, debit card spending, cash/check spending, or total spending) by individual i at month t.[12] 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). The absorbed benchmark period is from 12 months to 2 months

[11] This statement also holds if we directly compare the characteristics of peer consumers in HDB and the rest of the bank consumers in HDB. In addition, for all tests comparing the analysis sample and the full sample, conclusions remain to hold if we compare the analysis sample and the rest of the sample.

[12] 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.

before the bankruptcy event month (i.e., month -12 to month -2). 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.[13]

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 event month respectively. If the consumption response truly reflects the influence of the neighbor's bankruptcy event, peer consumers should only respond upon the bankruptcy event, implying a significant negative β, and a γ estimate not different from zero.

III. Main Results

A. The Average Spending Response

We begin the analysis by estimating the consumption decrease of the bankrupt individuals. As described earlier, we have identified 250 individuals who have the same gender, age, and ethnicity as the bankrupt(s) in the same building, and can estimate the bankrupts spending change based on their consumption patterns. As reported in the first column of Panel A, Table 2, the monthly total card spending for bankrupts significantly decreases by 78 percent.[14] With a close to zero estimated cash/check spending response, the total spending drops by 16 percent.

[Insert Table 2 Here]

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

[14] The estimated coefficient for log of total card spending in Panel A of Table 2 is -1.519, which is equivalent to a percentage decline of 78 percent (= exp(-1.519) – 1). All subsequent percentage effect interpretations for log dependent variables follow the same formula.

Given the small sample size and the measurement errors associated with the bankrupt's consumption, we also cross cross-check our estimate using the unique bankruptcy rule in Singapore. The bankruptcy law prohibits the bankrupt from any spending beyond subsistence needs, with which we can infer the bankrupts' spending decrease. As the law implies zero discretionary spending for the bankrupt individuals, we compute discretionary spending as a fraction of total card spending using the entire sample of bank consumers' card spending data. On average, 54.4%-82.5% out of the total monthly card spending is spent on discretionary items. This implies the total card spending likely will decline by an order of magnitude similar to our estimate in Panel A of Table 2.

We then examine the average spending response from the same-building peer consumers. The first column of Panel A Table 2 shows the average response of monthly total 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 12^{th} to 2^{nd} month period before the peer bankruptcy event. The effect is both statistically and economically significant. Decomposing the total card spending into credit card spending and debit card spending, we find the spending responses are similar in the two instruments (columns 2-3), suggesting no switching in the spending instruments by the peer consumers.

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. The F-test suggests that the estimated coefficients for $1_{[-1,-1]}$ and $1_{[0,+12]}$ are statistically different (F-statistic = 3.64). This shows that peer consumption responds only after the bankruptcy event, suggesting the documented spending decrease is indeed responding to peer's bankruptcy event.

Using the constructed measures, we further show the average response of monthly cash/check spending and the total monthly spending (sum of total card spending and cash/check spending). As reported in column 4 of Panel B, Table 2, there is no significant change in peer consumers' cash/check spending after the bankruptcy event. This suggests that the significant 1.9 percent drop in monthly total spending among peer consumers (reported in column 5) is mainly driven by the card spending response. In other words, peer consumers rely on debit and credit cards to adjust their consumption in response to their neighbor's bankruptcy. A possible economic reason for the lack of response in cash/check spending lies in that cash and checks are mainly used to pay recurring expenses such as rent and utility bills, which are less likely to be margins of short-run adjustment (Gelman, et al., 2018). Given the measurement error issues associated with the construction of total spending and cash/check spending, we will focus on card spending results in the subsequent analyses.

Next, we study the cross-sectional heterogeneity in the main result. 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 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 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.[15]

[15] The close age test doesn't include bankruptcy events that has multiple bankruptcy cases. We also considered neighbors with same ethnicity as the bankrupt individuals as close peers. However, as both the consumer sample and bankrupts sample is dominated by Chinese, the lack of variation makes it difficult to isolate the same-ethnicity effect.

Column 1 of Table 2, Panel C shows that 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 (column 2). 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). In unreported results, we also find similar effects when using alternative age brackets including [-3, +3] and [-5, +5] year ranges.

B. Correlated Background Factors

A key challenge in identifying the peer effect lies in the potential background factors that might simultaneously affect the peer sorting and the consumption outcome. In our context, sorting of peers (i.e., same-building neighbors) is largely mitigated given the unique public housing rules in Singapore. However, to further alleviate the identification concern, we conduct the following tests.

Consumption Response in Nearby HDB Buildings.—A common critique of 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 expect to see a similar decrease in consumption among individuals in neighboring buildings. On the contrary, if the response is local with very weak or insignificant consumption decrease for consumers even in the adjacent buildings, then the documented finding 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. As reported in column 1 of Table 3, 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 indifferent from zero. 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 (column 2). The overall results suggest no change in the spending pattern among individuals whose nearby building is hit by a bankruptcy event.

[Insert Table 3 Here]

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 them. 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 a public house. 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 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 of peer consumers in 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).

As reported in column 3 of Table 3, there is no significant consumption decrease by the peer consumers in the private housing market. Given the fact that there is no discernible difference in the geographic distribution between the public and the private housing market (due to Singapore's urban planning), this test provides another piece of strong evidence supporting the peer effect interpretation of our main results in Table 2.

Occupation (Employer) Clustering.—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 for all consumers.[16] 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 the occupation concentration level for each bankruptcy-hit building. Specifically, for each building j with individuals in our sample work in k occupations in total, we construct an "HHI index" for occupation as:

$$(2) \qquad HHI\ occupation_j = Occupation\ \%_{j1}^2 + Occupation\ \%_{j2}^2 + \cdots + Occupation\ \%_{jk}^2$$

where $Occupation\ \%_{jl}$ $(1 \leqslant l \leqslant k)$ is the percentage of peer consumers for building j with occupation l. Similar to 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 in bankruptcy-hit building is quite low (0.32), especially given the HHI value of 0.36 for all buildings.

[Insert Table 4 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

[16] 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 829 individuals whose occupations are not available.

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

Moreover, we conduct supplementary analysis to test sorting of co-workers for the same employer into the same residential building in Singapore. We exploit the universe of the electronic travel cards for Singapore public transportation trips to infer work locations based on work commute patterns. In sum, the collective evidence from the new public transport dataset shows that it is quite unlikely to have sorting of co-workers into the same residential building in Singapore. Workers tend to travel long distances to work and commute to different work locations. This pattern holds in the full sample as well as in subsample of bankruptcy-hit buildings. For brevity, we delegate the details of the analysis to the Online Appendix.

C. Family Members of the Bankrupt

Distribution of Consumption Change.—Are the documented consumption responses driven by outliers, possibly the bankrupt's family members? We investigate this possibility first by studying the distribution of spending changes among peer consumers. For each peer consumer, we calculate an adjusted spending change percentage by properly controlling for time trend and scale differences across individuals (please refer to the Online Appendix for adjusted spending change construction details). The distribution of adjusted spending change plotted in the top panel of Figure 1 suggests that our results are not driven by outliers. 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 (the mode of the distribution). Moreover, the distribution patterns of the pre-event and post-event (trend-adjusted and income-scaled) average monthly spending again suggest that the spending change is not driven by outlier spending levels in both periods (Panel B, Figure 1). 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 1 Here]

Subsample Tests.—Though we cannot observe the exact family relationship between consumers, we perform two subsample tests to further 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 effect should be restricted to a small set of consumers (as we mentioned, average HDB household size is 3.4), suggesting a much-muted average response in a large neighborhood. Contrary to the family member explanation, we find 4 percent monthly spending drop in larger neighborhoods with above-median peer consumer numbers (Table A3, column 1).

Additionally, family members are less likely to be included in buildings where fewer consumers are sampled in our bank's data. Combining the demographic data and random bank customer sample, we compute the sampling rate of the bank's consumers for each building. Column 2 of Table A3 shows an equally strong consumption response in buildings with low and high sampling rates (separated by the median sampling rate of 4.3 percent).

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.

D. Credit Limit Change among Peer Consumers

Another 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 all residents.

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 1,000 of them experienced any change (increase or decrease) in credit limit during our 24-month sample period. The comparison in Table A4 suggests that even for those individuals who experienced credit supply change, generally the change is positive.[17]

IV. Additional Analysis

A. Economic Magnitude

Our main specification estimates a large decrease of 3.4 percent in monthly total debit and credit card spending for peer consumers after their neighbors' bankruptcy. 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-event 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 their monthly income.

Another perhaps more informative approach is to construct an elasticity estimate. That is, by how much would the peers decrease their consumption for a

[17] We also find no significant change in peer consumers' income, as measured by the checking account inflows (Table A5).

10 percent consumption reduction from the bankrupt individual? As estimated in Section 4.1, the bankrupt individuals decrease their total card spending by 78 percent. This suggests that the peer consumers reduce total card spending by 3.4 percent per month in response to 78 percent card spending decrease of the bankrupt neighbor. Equivalently, a 10 percent decrease in (the bankrupt individual's) card spending is associated with a 0.44 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 28 percent. That represents a significant social multiplier effect, which is 2.8 times the magnitude of the original financial distress event.[18]

B. Possible Mechanisms

Finally, we explore the potential economic mechanisms at work. The "keep up with the Joneses" model suggests that peer influence is due to the dependence of a person's utility on the average consumption level of her peers (e.g., Gali, 1994). On the other hand, peer effects may also work through status signalling, which induces more spending on visible goods to signal their status relative to peers (Veblen, 1899; Bagwell, Simon, and Bernheim, 1996). While both are plausible, the two interpretations bear different predictions, with the latter pointing to a stronger decrease in the visible good spending. We find a similar consumption response for both visible and non-visible goods, which appears more consistent with the "keep up with the Joneses" channel (Table 5).

[Insert Table 5 Here]

[18] Using the estimated total spending change in both peer consumers and bankrupts, we obtain a larger multiplier (=7.7 times). But we focus on the multiplier estimated by total card spending, given larger measurement errors in total spending measure.

Risk-sharing among households can be another important mechanism to explain the spending responses of households living in the same building with bankrupted neighbors (Angelucci and De Giorgi, 2009). However, we find it unlikely in this setting since we find no significant wealth transfer through checking account nor cash (Table A5). Last, since bankruptcy is a salient event with severe, long-lasting negative impact, neighbours of the bankrupt may cut their spending—especially spending using credit instruments—to avoid potential financial distress. This again unlikely drives our findings not only because we do not find a greater reduction in the use of credit cards (Table 2), but also because the documented spending response is weaker for the financially more fragile peers (i.e., younger or lower-wealth ones). For brevity, we leave the detailed discussions regarding economic mechanisms in the Online Appendix.

C. Robustness

Last but not the least, we carry out a series of tests to investigate the robustness of our findings, by (1) randomizing the event time for peer consumers, (2) dropping outlier observations, (3) including multiple bankruptcy events in the analysis, (5) investigating the possible secular trend in aggregate bankruptcy, (6) relying on an alternative method to filter out bankrupt individuals, and (7) using alternative event windows and consumption measures. Please refer to the Online Appendix for detailed results.

V. Conclusion

Using a representative sample of consumer financial transactions from a leading bank in Singapore, this paper studies the consumption response of consumers whose same-building neighbor experiences personal bankruptcy. The unique institutional details suggest that personal bankruptcy is liquidity driven, leading to an exogenous and significant consumption decrease for the bankrupt. The housing policy in Singapore also makes the assignment of consumers in the same residential building close to random, allowing us to capture peers who are less likely to share correlated backgrounds but do interact closely.

We document that compared with twelve to two months prior to neighbor's bankruptcy, peer consumers in the same building experience a significant decrease of around 3.4 percent in monthly total card spending during the one-year afterwards. We provide a collection of evidences to support our causal interpretation—in particular by verifying our identifying assumption that our setting and results are not contaminated by common background factors. Given the large multiplier effect of 2.8 times the original shock, our findings highlight the need to incorporate the consumption spillover effects while assessing the aggregate impact of income shocks.

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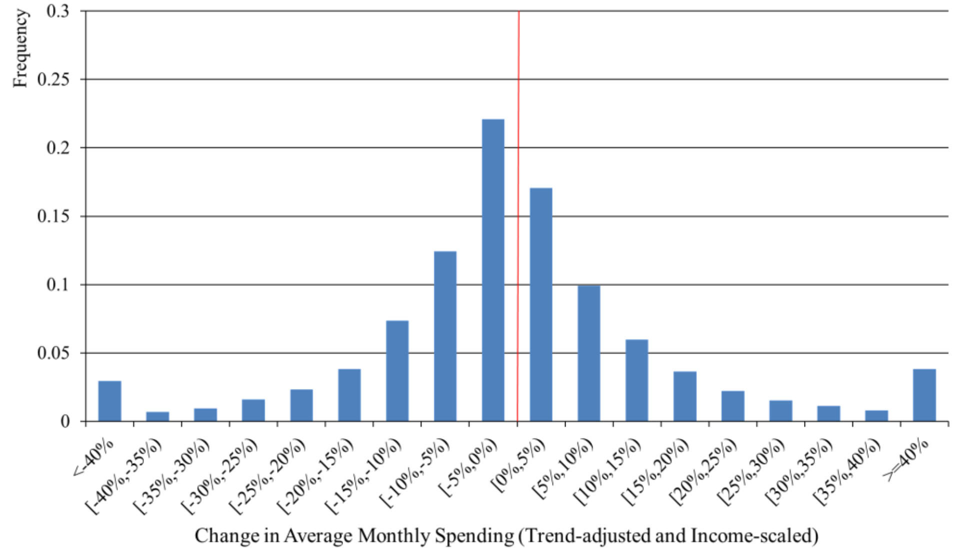
Panel A. Distribution of trend-adjusted and income-scaled spending change



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

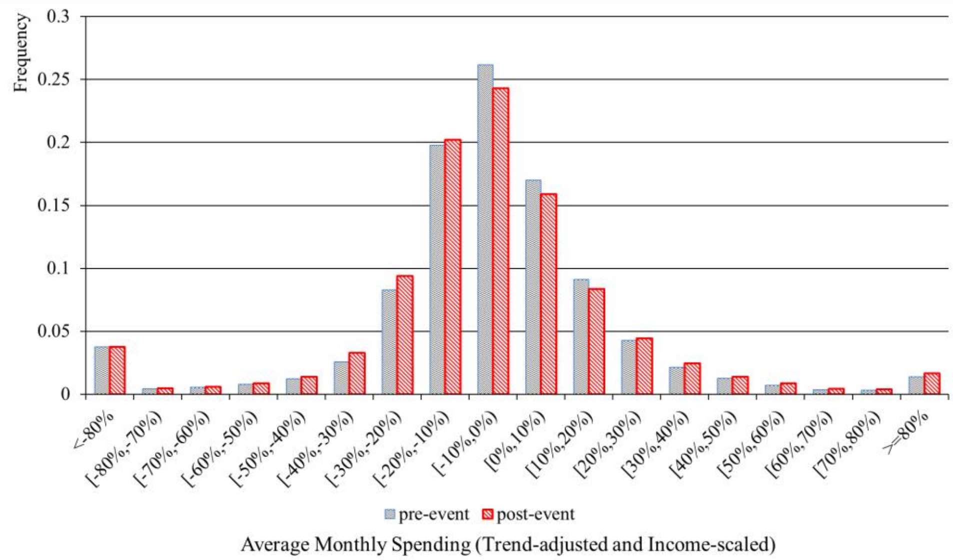


FIGURE 1. DISTRIBUTION OF CHANGE IN SPENDING (TREND-ADJUSTED AND INCOME-SCALED)

Notes: 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 Online Appendix for detailed variable definitions.

TABLE 1. SUMMARY STATISTICS

Panel A. Comparison of bankrupt individuals

	Bankrupt individuals in sample			All bankrupt individuals			Diff. in
	Mean	SD	Med	Mean	SD	Med	means
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female (%)	23.8	42.6	0	24.4	43.0	0	-0.6
Chinese (%)	63.4	48.2	100	63.9	48.0	100	-0.6
Bankrupt age	42.2	10.3	42	42.3	10.3	42	-0.1
Bankruptcy amount (SGD)	103064	573134	23631	95179	492524	24267	7885
Number of cases	1655			2454			

Panel B. Comparison of bank consumers

	Bank consumers in sample			All bank consumers			Diff. in
	Mean	SD	Med	Mean	SD	Med	means
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female (%)	43.0	49.5	0	42.6	49.4	0	0.5
Chinese (%)	76.0	42.7	100	78.2	41.3	100	-2.2***
Age	38.0	9.8	36.4	38.7	10.1	37.2	-0.7***
Income (SGD)	4165	2997	3498	4354	3273	3606	-189***
Bank relationship (in months)	13.8	5.6	12.4	14.2	5.5	12.4	-0.4***
Number of individual	17326			86646			

Notes: This table provides summary statistics for the public housing market (thereafter HDB) residents. Panel A compares demographic information between bankruptcy cases included in our final sample and all bankruptcy cases during our sample period (i.e., 2010:04-2012:03). Panel B reports demographic and financial information of the HDB peer consumers in our merged sample, and that for all HDB consumers. *Female* is a dummy variable equal to one if the individual is female (expressed in percentage). *Chinese* is a dummy variable equal to one if the individual is ethnic Chinese (expressed in percentage). *Bankrupt age* measures the individual's age at bankruptcy year. *Bankruptcy amount* is the dollar amount associated with the bankruptcy event in Singapore dollars. *Age* measures the age (in years) of consumers during our sample period. *Income* is the consumer's (verified) monthly income during our sample period in Singapore dollars. *Bank relationship* is the consumer's length of relationship with the bank measured in months. 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.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE 2. AVERAGE SPENDING RESPONSE

Panel A. Estimated spending change of bankrupts

	Log(Total card spending) (1)	Log(Cash/check spending) (2)	Log(Total spending) (3)
$1_{[-1,-1]}$	-0.049	0.036	0.032
	[0.126]	[0.102]	[0.091]
$1_{[0,+12]}$	-1.519***	0.001	-0.179**
	[0.178]	[0.100]	[0.090]
Constant	3.898***	7.467***	7.701***
	[0.196]	[0.145]	[0.147]
Fixed Effects		Individual, year-month	
Observations	4,356	4,129	4,129
R-squared	0.72	0.68	0.67

Panel B. Average spending response of peer consumers

	Log(Total card spending) (1)	Log(Credit card spending) (2)	Log(Debit card spending) (3)	Log(Cash/check spending)	Log(Total spending)
$1_{[-1,-1]}$	-0.011	-0.016	-0.005	-0.001	-0.003
	[0.013]	[0.019]	[0.017]	[0.011]	[0.008]
$1_{[0,+12]}$	-0.035***	-0.036*	-0.039**	-0.014	-0.019**
	[0.013]	[0.020]	[0.016]	[0.011]	[0.008]
Constant	5.574***	3.623***	4.239***	7.733***	8.092***
	[0.020]	[0.027]	[0.024]	[0.014]	[0.011]
Fixed Effects			Individual, year-month		
Observations	278,054	278,054	278,054	268,402	268,402
R-squared	0.47	0.55	0.50	0.62	0.61

Panel C. 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]
Fixed Effects	Individual, year-month	
Observations	278,054	261,764
R-squared	0.47	0.47

Notes: This table reports the average card spending response after the bankruptcy event during 2010:04-2012:03. Panel A reports the estimated spending change of bankrupts. Dependent variables in columns 1–3 are logs of monthly total card spending, cash/check spending, and total spending respectively. Panel B shows the average spending response of the same-building peer consumers. Dependent variables in columns 1–5 of Panel B are logs of monthly total card spending, credit card spending, debit card spending, cash/check spending, and total spending respectively. Panel C documents the cross-sectional heterogeneity. Dependent variables in Panel C 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, and we investigate spending activities in [-12,+12] months event window. $1_{[-1,-1]}$ is a binary variable equal to one for the one month 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., $\geqslant$month 0). Close in age is a dummy variable equal to one if the peer consumer's age is within four years range of the bankrupt neighbor. Individual and year-month fixed effects are included. Standard errors clustered at the building level are reported in brackets.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE 3. CONSUMPTION RESPONSE IN NEARBY BUILDINGS AND 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]	[0.018]	[0.037]
$1_{[0,+12]}$	-0.008	0.006	0.033
	[0.011]	[0.018]	[0.034]
Constant	5.614***	5.613***	6.055***
	[0.017]	[0.027]	[0.062]
Fixed Effects	Individual, year-month		
Observations	347,221	136,440	33,344
R-squared	0.48	0.48	0.53

Notes: This table report average spending responses of consumers living in nearby non-bankruptcy hit buildings, and in the private housing market. 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 residents from 0m-100m radius of the bankruptcy-hit HDB building (the bankruptcy-hit building itself excluded). Column 2 presents the average response of residents from 100m-300m radius of the bankruptcy-hit HDB building. Column 3 reports the consumption response of peer consumers in the private housing market. Bankruptcy month is defined as month 0, and we investigate spending activities in [-12,+12] months event window. $1_{[-1,-1]}$ is a binary variable equal to one for the one month 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., $\geqslant$month 0). Individual and year-month fixed effects are included. Standard errors clustered at the building level are reported in brackets.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE 4. OCCUPATION CONCENTRATION IN THE BANKRUPTCY-HIT BUILDINGS

Panel A. HHI Index for occupation

	Buildings in sample			All buildings			Diff. in
	Mean	SD	Med	Mean	SD	Med	means
	(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 the same occupation

	Two random consumers from same bankruptcy-hit building			One random consumer from buildings in the sample, and one random consumer from adjacent buildings			Diff. in means
	Mean	SD	Med	Mean	SD	Med	
	(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						

Notes: This table presents the comparison of occupation concentrations. Panel A reports the summary statistics for occupation HHI index, number of bank consumers, and the number of occupations at building level, for buildings in our sample and all HDB buildings. For each building j with individuals work in k occupations, the HHI index for occupation concentration is: $HHI\ occupation_j = Occupation\ \%_{j1}^2 + Occupation\ \%_{j2}^2 + \cdots + Occupation\ \%_{jk}^2$, where $Occupation\ \%_{jl}$ ($1 \leqslant l \leqslant k$) is the percentage of peer consumers in building j working in occupation l. Columns 1-3 present the statistics for bankruptcy-hit 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* equal to one when two randomly drawn consumers share the same occupation. This variable is constructed in following 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; third, randomly draw another individual (c) from an adjacent building within 100m radius of the bankruptcy-hit building, and assign a dummy variable $same\ occupation_{(a)=(c)}$ equal to 1 if (a) and (c) has the same occupation. 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.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE 5. 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]
Fixed Effects	Individual, year-month			
Observations	278,054	278,054	278,054	278,054
R-squared	0.46	0.47	0.27	0.50
Mean share of the category	0.34	0.66	0.26	0.74

Notes: 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 Online Appendix for 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. 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. *Mean share of the category* reports the pre-event mean share of each category spending. 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.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Online Appendix

Thy Neighbor's Misfortune: Peer Effect on Consumption

Sumit Agarwal, Wenlan Qian, and Xin Zou

Not Intended for Publication

1. More Information on Bankruptcy in Singapore

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

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

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

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

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

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

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.

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

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

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

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

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

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

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

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

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

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

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

Public transportation is the dominant mode of work trip for Singapore workers across all industries and occupations. One important reason lies in the fact that Singapore is the most expensive country in the world to own a car. To accommodate the transportation needs, the

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

government has developed a highly convenient public transportation system supporting all commercial and residential areas of Singapore: six out of ten households can access a subway station within 10 minutes' walk, and bus stops are within 300-400 meters away from each other. It is also reliable and affordable, ranking among the best public transport system in the world.[6] According to the 2015 Singapore Household Survey, 63 percent of Singapore adult workers living in public houses (i.e., HDB) use public transport daily to commute to work.

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

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

As shown in the first row of Panel A, Table A2, among the population of HDB buildings in the entire Singapore, the average and median commute time for work trips are both 33 minutes. Since the Singapore Island is only 42 km long and 23 km wide, a 33-minute public transport can travel around 11 km. As a comparison, it only takes about 40 minutes to drive through the island (between east and west).[7] Therefore, the stats in the table suggest that on average Singaporeans do not live close to their work locations. Note that this is likely an underestimate of the distance

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

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

to work because our calculation does not consider the distance from home to the public transport stations, nor from the stations to employers.[8] Furthermore, comparing the bankruptcy-hit buildings in our sample versus other HDB buildings, the average commute time stays around 33 minutes for both groups, and the difference is economically negligible (and statistically insignificant). It suggests that the bankruptcy-hit buildings do not differ from the other HDB buildings in residents' average work commute time, alleviating the concern of a closer distance between home and work for the bankruptcy-hit building residents.

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

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

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

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

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

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

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

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

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

D. Finally, the spending change is defined by subtracting the pre-event period average adjusted spending (scaled by income) from the post-event period equivalence.

4. Economic Mechanisms

4.1 Keeping Up with the Joneses and Status Signaling

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

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

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

4.1.1 Visible and Non-Visible Consumption

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

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

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

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

4.1.2 By the Value in a Single Purchase

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

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

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

4.2 Bankruptcy Event as an Information or Salience Shock

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

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

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

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

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

5. Further Analysis

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

5.1 Alternative Event Windows

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

5.2 Additional Falsification Tests

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

5.3 Additional Tests on Outliers

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

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

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

5.4 Sample Selection Concerns

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

Excluding the multiple bankruptcy event buildings may, however, raise sample selection concerns. We check and verify that there are no significant differences between the single-bankruptcy-event and multiple-bankruptcy-events buildings in terms of both the bankrupt

individuals' characteristics and the peer consumers' observable characteristics (Table A11). Moreover, despite the poor measurement of the pre-event period and the associated estimation bias, we conduct a robustness check by including the multiple-bankruptcy-events buildings in our sample and continue to find a significant consumption decrease (Column 1, Table A12).
On the other hand, some bankruptcy-hit buildings in our sample contain multiple bankruptcy cases (and individuals). Even though it is a small subsample, we conduct a robustness check by removing all those multiple bankruptcy case events (N=82). We continue to find a similar response, both in statistical significance and economic magnitude (Column 2, Table A12).

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

5.5 Alternative Measures

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

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

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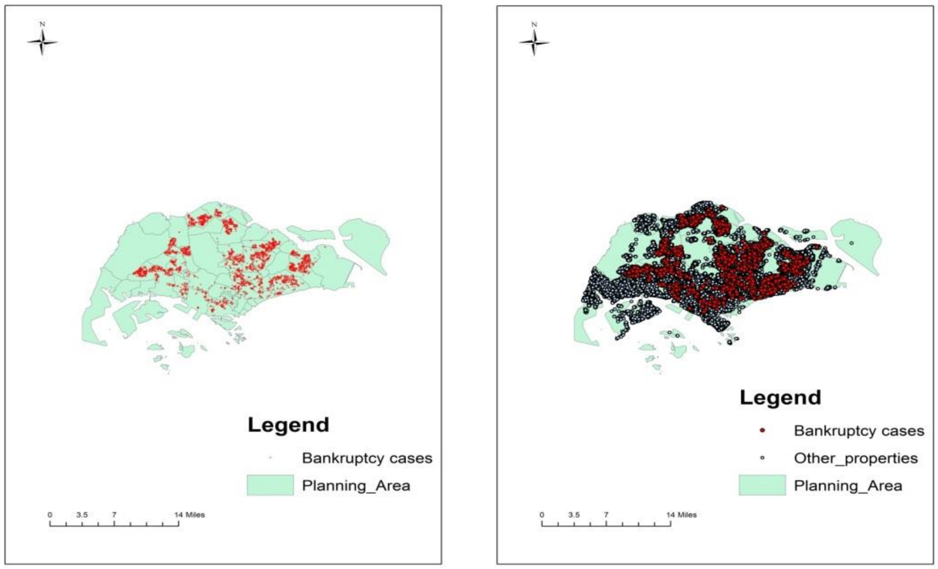
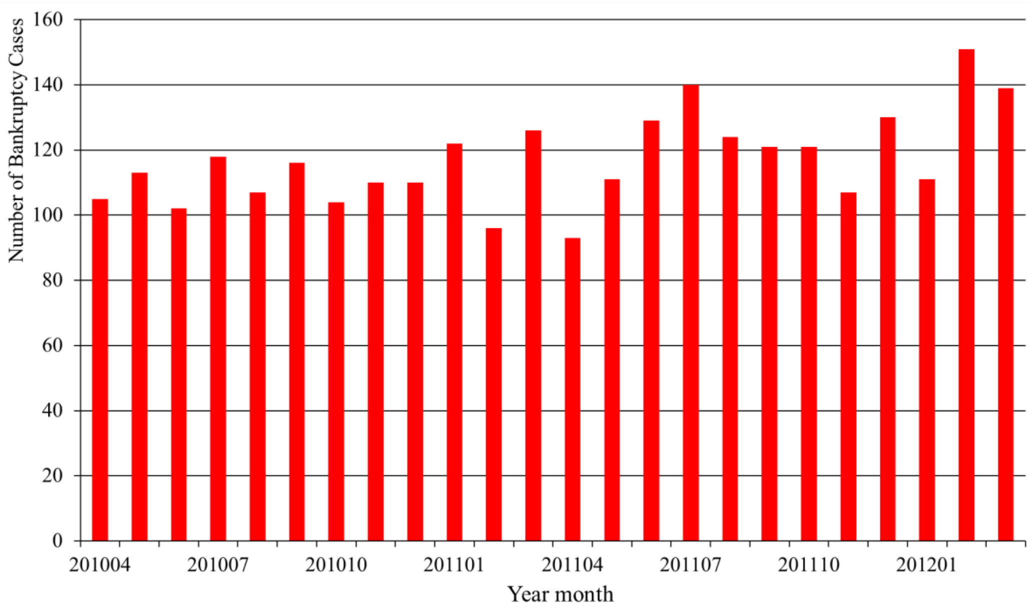
Figure A1. Distribution of Personal Bankruptcy Events

Panel A: By location

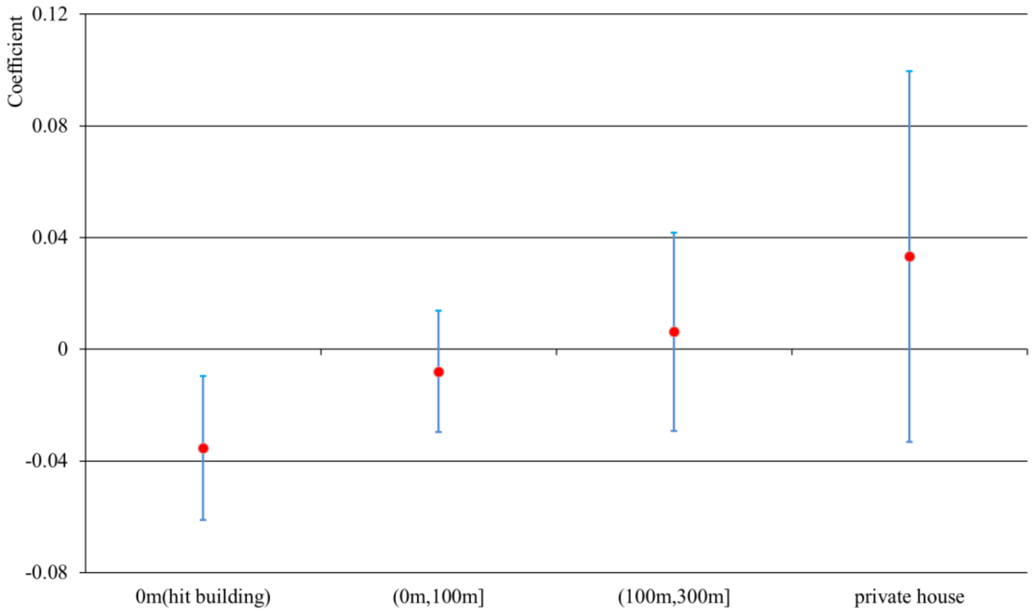


Panel B: By calendar time



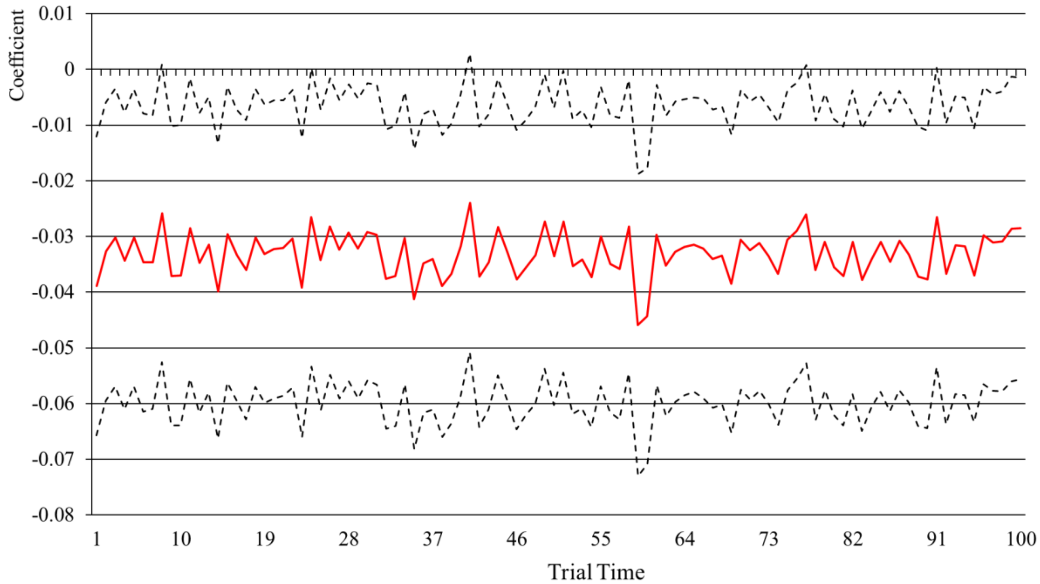
Note. Panel A plots the location distribution of all bankruptcy cases during our sample period (2010:04-2012:03). Panel B plots the time distribution of all bankruptcy cases during our sample period.

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



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

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



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

Table A1. Demographics of the Bankrupt Individuals

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

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

Table A2. Work Commute Time and Co-worker Fraction

Panel A: Building-level commute time

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

Panel B: Within-building variation of commute time

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

Panel C: Building-level co-worker fraction

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

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

Table A3. Heterogeneity by Neighborhood Size and Sampling Rate

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

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

Table A4. Post-Bankruptcy Credit Limit Change

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

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

Panel B: Regression analysis

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

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

Table A5. Checking Account Inflow Response

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

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

Table A6. Visible Goods Classification

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

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

Table A7. Bankruptcy Event as an Information Shock

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

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

Table A8. Alternative Pre- and Post-bankruptcy Windows

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

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

Table A9. Additional Falsification Tests

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

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

Table A10. Influence of Outlier Bankruptcy Buildings or Outlier Peers

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

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

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

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

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

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

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

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

Table A12. Choice of Bankruptcy Events

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

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

Table A13. Alternative Consumption Measures: Number of Purchases

Panel A: Number of transaction count

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

Panel B: Count of ATM, branch, online transaction

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

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

Table A14. Response of Other Financial Outcomes among Peer Consumers

Panel A: Credit card debt amount

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

Panel B: Incidence of delinquency on credit cards

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

Panel C: Cash advance fee amount on credit cards

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

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