Gender Gap in Personal Bankruptcy Risks: Empirical Evidence from Singapore

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Abstract

Gender gap can arise due to various factors – socio-economic, culture, risk attitudes, and macro-economic circumstances. Using a unique dataset that merges motor vehicle events with bankruptcy outcomes and personal data from Singapore, this study finds significant evidence of a gender gap in personal bankruptcy risk. We show that women's odds of being involved in bankruptcy events are 28% of those of men after controlling for demographic variables, housing type, cultural and spatial fixed effects. Using motor vehicle accidents as an instrument, we confirm that the gender gap in bankruptcy risk is mainly driven by risk-taking behavior. The heterogeneity analyses show that culture also explains part of the difference. Chinese, Indian and Malay women have differential bankruptcy rates in Singapore.

JEL classification: A12, G02, J16

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1. Introduction

Social scientists have documented gender gaps in many domains – employment, wage, promotion, leadership, investment, academic performance, etc (Sunden and Surette, 1998; Goldin and Rouse, 2000; Barber and Odean, 2001; Bertrand and Mullainathan, 2004; Aterido et al., 2013). The literature has attempted to explain the causes of the gender gap as a function of socio-economic, macro-economic, cultural, and risk attitudes. Persistence of a gender gap can have long term consequences on the economic welfare of women in relation to men. While understanding the causes of gender gap is of the first order of importance, few have, however, found ways to cleanly document the factors causing the gender gap.

We study the gender gap in the personal bankruptcy filings of males and females in Singapore using a unique data of bankruptcies filed from 1980 to 2012. We find that women's odds of bankruptcy are 28% of those of men after controlling for debtors' demographic attributes, housing type and spatial fixed effects. These results can be explained by the differential in risk attitudes, socio-economic, macro-economic, and cultural factors. We use prior motor vehicle accidents as a novel instrument for risk attitudes of men and women, and confirm that the gap in bankruptcy risk is mainly driven by risk-taking behavior. If the innate risk attitudes of men and women influence their driving behavior and financing activities, then we should expect reckless and aggressive drivers with past motor vehicle accident records to take on more financing risk and to have higher bankruptcy risk relative to drivers without past motor vehicle accident records. The lower motor vehicle accident and bankruptcy risks of women in our results support the hypothesis that women are more risk averse than men. Thus, the gender gap in bankruptcy risk is correlated with differences in the innate risk attitudes of men and women.

Next, we conduct a series of robustness tests to rule out alternative explanations. The gender gap persists in our results when we use different matching techniques to pair the male and female samples, including one-to-one matching, nearest-neighbor matching, and kernel-based matching methods. The results are also robust to controlling for various selection concerns. First, in the credit choices of married couples, men, as the household heads of families, take on more credit and have higher bankruptcy risk. To eliminate selection bias, we use only the unmarried samples in our models. The results show that men's role as the household head does not affect the gender gap in bankruptcy events. Second, if banks grant more credit to men than women, then the gender gap in bankruptcy events could be distorted. Using credit card data from a large corporate bank in Singapore, we do not find evidence of gender bias in the credit supply by the bank: credit lines are dependent on the income of borrowers. Third, using housing type as an indirect proxy for income, we add a randomly selected sample of men living in public housing flats (low income) to the group living in private housing apartments (high income) in our test of the income effect. However, we find that the income effect does not significantly change the gender gap in the matching models.

We next evaluate the gender gap in other bankruptcy outcomes. Conditioned on first personal bankruptcy events, women are less likely to be involved in multiple bankruptcies than men. The average claim in female bankruptcy cases is S$222 less than the claims in male bankruptcy cases, which is 4.1% of the average bankruptcy claim of S$5,420 for men. The lower bankruptcy rate and smaller claims in female bankruptcy events are consistent with the hypothesis that women are more risk averse in their financial decisions than men. However, when using bankruptcy proceedings as the outcome, we find no significant gender gap in the time involved (duration) in different stages of bankruptcy proceedings. Thus, the courts are gender-neutral in administrating bankruptcy proceedings and are guided by the stipulated rules at each stage of such proceedings.

Culture shapes the views of men and women of different races in society. The culture factor has been found to cause a gender gap in various activities, such as math performance (Guiso and Monte, 2008) and employment (Çampa et al., 2011). We observe a larger gender gap among Chinese debtors and a smaller gender gap among Malay and Indian debtors relative to the control group ("other" race). As in the early literature, the race-dependent gender gap in bankruptcy risk again shows that cultural diversity influences the risk behavior of men and women of different races.

This study contributes to the literature on experimental and behavioral economics in three ways. First, using empirical data on bankruptcy events and motor vehicle accident events, we find new evidence on the differences in risk-taking behavior between men and women in driving and financing activities. We therefore supplement the findings of many controlled laboratory experiments showing that women are more risk averse than men. Second, we find a significant causal link between antecedent risk-taking attitudes in driving and financial activities. The results show that the past motor vehicle accident events of men and women are robust instruments to predict the gender gap in bankruptcy events. The above findings have significant implications for banks, financial institutions and insurance companies, implying that they should not neglect the gender factor in loan underwriting and risk evaluation processes.

Our third contribution lies with the unique observational dataset used in this study. This study is one of the few to examine the gender gap in bankruptcy risks using data from outside the US. Because US bankruptcy petition data do not contain demographic information (such as gender and race), Agarwal et al. (2010) use the same algorithm applied by Bertrand and Mullainathan (2004) to the labor market to infer the gender and race identities of debtors and judges in their bankruptcy study. A large sample of data is required to improve the efficiency of the algorithm and to reduce errors in the machine-learning process. However, in our study, we use common identification numbers found across three different datasets to match gender, demographic and home address information with bankruptcy and motor vehicle accident data files. With the real outcomes of the two different activities (driving and financing) in our dataset, we can use the observed risk behavior in one activity (driving) as an instrument to predict the risk behavior of the same person in another, independent activity (financing). We find consistent evidence that the risk-aversion behavior of females does influence their driving activities (motor vehicle accident events) as well as their financing activities (bankruptcy events).

The paper proceeds as follows: Section 2 reviews the related literature. Section 3 discusses the institutional background of bankruptcy laws and proceedings in Singapore. Section 4 discusses the data sources and descriptive statistics. Section 5 covers the empirical methodology. Section 6 presents the results of the empirical tests and various robustness tests. Section 7 concludes the study.

2. Related Studies

The current literature examining issues of the gender gap and bankruptcy risks is rather disjointed. While the finance literature is dominated by research on the various triggers of personal bankruptcy events, the experimental economics literature largely focuses on examining differences in risk attitudes between men and women. By using observational data on bankruptcy and motor vehicle accident events that are not replicable in controlled laboratory environments, this study hopes to bridge the gap in the two strands of literature by finding evidence to support the hypothesis that the gender gap in financial risk-taking and driving behavior is correlated with differences in risk attitudes between women and men.

Adverse shocks to income (loss of a job) or expenditures (increases in medical expenses due to illness), credit card debt (Domowitz and Sartain, 1999), and unexpected events such as divorce and unemployment (Sullivan et al., 2000; Warren and Tyagi, 2003) can adversely affect the liquidity and debt-servicing ability of individuals. These issues are examples of negative shocks that can trigger personal default events. However, in cases where net financial debt exceeds the liquidated asset value, rational defaulters who are not liquidity constrained could strategically default even in the absence of negative shocks (Fay et al., 2002).

Bankruptcy events inflict high social, informational and legal costs (Gross and Souleles, 2002). There is also a negative stigma attached to bankruptcy by society. In some countries, financially distressed debtors can use a voluntary bankruptcy filing as a way to partially mitigate consumption losses and get a "fresh start" from a bankruptcy event. In the US, bankruptcy proceedings under Chapter 7 and Chapter 13 are two alternative ways for individuals to file for bankruptcy. Agarwal et al. (2010) use observational bankruptcy data in the US to test the effects of race and gender differences between judges and bankrupt debtors on the judicial outcomes of Chapter 13 petitions. They find that judgments in Chapter 13 bankruptcy petitions are neither race- nor gender-neutral. White male judges are more prejudicial in their judgments involving African American debtors. Chapter 13 petitions by African American debtors were 21% more likely to be rejected compared to petitions by white American debtors.

The gender gap has always been a key research issue in the experimental and behavioral economics literature. Evidence of a gender gap has been found in disparate economic activities, such as labor markets (Bertrand and Mullainathan, 2004; Niederle and Vesterlund, 2007; Bertrand et al., 2010; Bertrand, 2011), marriage markets (Bertrand et al., 2015), and financial markets (Agarwal et al., 2009; Aterido et al., 2013; Beck et al., 2015).

There is an abundance of evidence showing that women are more risk averse than men in selected tasks (Schubert et al., 1999; Hartog et al., 2002; Eckel and Grossman, 2002, 2008; Agnew et al., 2008). Differences in risk attitudes and risk preferences between men and women influence their choice of risky games (lottery) (Byrnes et al., 1999; Eckel and Grossman, 2008; Croson and Gneezy, 2009), driving behavior (Dohmen and Falk, 2011) and financial decisions.[1] For example, men trade securities 45 percent more than women, but the high trading activities of men negatively affect their portfolio returns (Barber and Odean, 2001). In addition, single women take on less risk than single men in defined contribution plans (Jianakoplos and Bernasek, 1998; Sunden and Surette, 1998).

[1] Weber, Blais and Betz (2002) find gender differences in four of five domains, including the financial, health/safety, recreational and ethical domains, but not in the social decision domain. Men who are less risk averse tend to engage in more risky activities.

While evidence of women being more risk averse has been documented in laboratory and field studies, few researchers have offered conclusive explanations for the observed differences in risk attitudes. Croson and Gneezy (2009) identify three possible mechanisms driving gender-biased risk preferences.[2] The first mechanism is related to framing and the perceptions of risk by men and women. Men are more likely to see a risky situation as a challenge that calls for participation, while women view a risky situation as a threat that discourages participation (Arch, 1993; Harris et al., 2006). The second mechanism suggests that the social preferences of women are more situationally specific, and they are also more sensitive to social cues than men in their behavioral responses. The third mechanism is related to differences in attitudes toward competition. Women are more averse to competition than men, and men perform better than women in a competitive environment.

There is a gap between the experiment-based literature and the empirical behavioral literature in gender gap research. On the one hand, it is difficult for laboratory-based experiments to simulate outcomes that mimic real-world outcomes, especially with regard to bankruptcy events. On the other hand, empirical studies are highly data dependent, and tests are constrained by outcomes that must be observable in empirical data. Unlike laboratory-based studies that are designed to reveal the risk preferences of male and female participants, the difficulty in empirical studies is identifying *ex post* risk behavior and explaining its causal link as a gender gap in the selected activities. Our unique dataset, which includes the real outcomes of two different activities (driving and financing) for a large sample of Singaporean residents, is able to overcome these empirical constraints. We instrument the risk attitudes of men and women through their driving activities and use the instrument to test the gender gap in unrelated bankruptcy events.

Based on the risk perception mechanism, men perceive driving as a challenging activity and drive more recklessly; as a result, they are more likely to get into car accidents than risk-averse women. If the same risk-taking attitudes of men motivate them to take more financial risks, we should observe more bankruptcy events for men than women. Our findings support the risk-taking hypothesis and show that men take more risks in both motor vehicle accident events and bankruptcy events than women. The motor vehicle accident outcomes of men and women are

[2] Croson and Gneezy (2009) provide a comprehensive review of the experimental evidence on the risk preference differences between men and women.

a robust instrument for risk attitudes that significantly predicts the gender gap in bankruptcy events.

The culture factor has also been identified in some studies as causing a gender gap in various activities, including math performance (Guiso et al., 2008), employment (Campa et al., 2011), and credit outcomes (Guiso et al., 2006, 2009; Fisman et al., 2012). We also find that the gender gap in Chinese bankruptcy events is larger than the gender gap in Malay and Indian bankruptcy events. Similar to "*the white male effect*" found in the study by Finucane et al. (2000), our results add new insight to the race-dependent gender gap in bankruptcy risk in the Asian context.

3. Institutional Background

Singapore is an island state with a total land area of 719.1 square kilometers as of 2015. It has one of the highest savings rates in the world. Individuals save a large proportion of their monthly income both on a voluntary basis and also through a compulsory pension scheme known as the Central Provident Fund (CPF). Strict laws governing credit default coupled with heavy penalties imposed in bankruptcy proceedings inflict high social costs on financially distressed individuals who fail to avoid bankruptcy events in Singapore.

Figure 1 plots the personal bankruptcy rates in Singapore and the US for the period from 1980 to 2012. There have been clear upward trends in personal bankruptcy rates in the two countries since 1980. The average bankruptcy rate in Singapore is relatively low at 0.24% compared to 0.93% in the US (Narajabad, 2012) over the sample period. However, the bankruptcy rate in Singapore increased by more than ten times between 1982 and 2004, whereas the US bankruptcy rate increased by only three times during the same period (Dick and Lehnert, 2010). The global gender gap index,[3] which ranges from 0 (inequality) to 1 (equality), shows that the gender gaps in Singapore and the US are relatively similar at 0.711 and 0.740, respectively, and their global rankings are 28th and 54th, respectively. The sub-indexes also show that women have a relatively high level of economic participation and opportunity in both countries (Singapore: 0.814; US: 0.825). We therefore do not expect that the empirical results on the gender gap in bankruptcy risk found in our study and in Agarwal et al. (2010) are caused by biases in resource distribution and accessibility to opportunity in the two countries.

[3] The World Economic Forum has published the global gender gap index for 145 economies every year since 2006. The gender gap index measures inequality between men and women in four areas, including economic participation and opportunity, education, political empowerment, and health and survival.

[Insert Figure 1 here]

Singapore's laws governing bankruptcy are delineated in the Bankruptcy Act (Chapter 20) ("the Bankruptcy Act"). According to Chapter 20, a bankruptcy filing is an involuntary event. A bankruptcy proceeding is triggered by a creditor (or a group of creditors) when a notice known as a Statutory Demand is issued to demand payment from a debtor. If the payment is not made within the stipulated 21-day period, or if the debtor refuses to respond or accept the legal notice, the creditor can file a petition in court, and a bankruptcy hearing will then be scheduled. If the payment has still not been made by the hearing date, the court can proceed with an order declaring the debtor bankrupt. An Official Assignee is then appointed to administer the bankruptcy process. In this process, an insolvent debtor has two window periods between the issuance of the Statutory Demand and the bankruptcy petition and between the bankruptcy petition and the final hearing to pay off the debt. A creditor has the discretion to adjust the time (interval) of the first window period (between the issuance of the Statutory Demand and the bankruptcy petition) based on the debtor's willingness to make the payment.

Similar to Chapter 13 in the US, a voluntary scheme called a "Debt Repayment Scheme" (DRS) that is usually initiated by the debtor under Part Five of the Bankruptcy Act (Chapter 20) is also available in Singapore. Under a DRS, the debtor must prepare a proposal to persuade the creditors to halt the bankruptcy process. Thus, a debtor with an unsecured debt of less than S$100,000 can enter into a debt repayment plan ("DRP") with the creditors to avoid the bankruptcy proceeding. If the debtor's financial difficulties are temporary in nature, he/she can commit to the DRP by proposing a debt repayment plan of not more than 5 years.

Theoretically, a bankruptcy proceeding can be initiated by either a debtor or a creditor, depending on the potential implications of bankruptcy. However, bankruptcy is bad news for the debtor. The Official Assignee will seize the debtor's assets, except for necessities such as his/her public housing flat and items needed to continue his/her job or business. A distressed debtor must pay a portion of his/her income to the creditor and must seek consent from the creditor to incur non-essential expenses such as taking a taxi or going on holiday. A bankrupt debtor can still apply for new credit cards, but the interest rate will be higher and the credit limit lower for such cards.

Although bankruptcy does not directly cause unemployment, permission from the High Court or the Official Assignee is needed to run a business or to serve as a director of a company. Permission is also needed if the bankrupt individual wishes to travel and/or remain overseas.

The career prospects of bankrupt individuals are bleak, as employers will be informed and bankruptcy notices are publicized in the Gazette. It is a long road for a bankrupt individual to rebuild his/her credit record.

In July 2015[4], the Bankruptcy (Amendment) Bill was passed by Singapore's Parliament. It allows first-time bankruptcies to be discharged in as little as three years if the debtor makes the full payment on the target contribution. The target contribution is the repayment scheme determined based on the bankrupt individual's target earning potential. If the debtor is unable to meet the target contribution in full, he/she will still be discharged after seven years.

4. Data Sources and Analyses

4.1. Data Sources

We use data from three different sources in this study. The first data source contains 65,147 personal bankruptcy filings at the Supreme Court of Singapore from 1980 to 2012. For each bankruptcy case, we obtain the debtor's personal information (name and a unique identification number), the creditor's name (usually an institution), the total bankruptcy amount, and the three dates in the sequence of bankruptcy events (filing of statutory demand, petition and hearing). Based on the reported dates of the bankruptcy events, we compute two time intervals (by number of days): (1) between the statutory demand and the petition date (Stage 1) and (2) between the petition and the hearing date (Stage 2).

Bankruptcy triggering events, such as delinquencies on credit cards, car loans, and home mortgage payments, are not reported in the bankruptcy dataset. However, credit card bankruptcy cases involve claims that are substantially smaller than claims in home mortgage or car loan bankruptcy cases. Therefore, we can indirectly infer the bankruptcy event types (triggers) based on the bankruptcy claim amount reported in each case. Using the minimum gross income eligibility criterion of S$2,500 per month (or S$30,000 per annum) and the credit limit of 2 to 4 times the applicant's monthly gross income established for credit card applicants by most Singapore banks, the lower bound of the credit limit can range from S$5,000 to S$10,000. We use S$10,000 as the cut-off to separate credit card bankruptcy cases from other bankruptcy cases involving home mortgage and car loan delinquencies. As robustness tests, we also use other cut-off values to separate credit card bankruptcy cases.

[4] Hetty Musfirah Abdul Khamid, "Bankruptcy Amendment Bill Passed," Channel News Asia, July 14, 2015.

Based on the unique identification number and name, we can also separate individuals (debtors) who have been involved in multiple bankruptcy events from first-time bankrupts who have been involved in only a single bankruptcy event. Based on the bankruptcy frequency (single or multiple), we empirically test whether the risk attitudes of recalcitrant debtors in repeated bankruptcy events are different from those of first timers with only one bankruptcy.

The second data source is a unique personal database containing demographic information on more than 2 million individuals in Singapore, constituting nearly 60% of Singaporean residents as of 2012. The dataset contains demographic information such as gender, date of birth, race, marital status, housing address (public or private), and postal code. Using the unique personal identification numbers, we are able to cleanly match the bankruptcy database to the personal database to obtain, with a high degree of accuracy, the demographic profile (including age, race, marital status, and gender) of every insolvent debtor from the bankruptcy database. Compared to the personal bankruptcy dataset of the Administrative Office of the U.S. Courts (AOUSC) (Domowitz and Sartain, 1999; Dick and Lehnert, 2010), our merged dataset contains a richer set of debtor demographic variables that spans a longer sample period.

The third data source contains personal motor vehicle accident events reported in court records. For each case, the record includes the filing date and the names and identification numbers of the parties involved. We link the court records to the bankruptcy records through the unique personal identification number of the person involved.

There are two motivations for the use of Singaporean bankruptcy data in this study. First, the high domestic savings rate in Singapore and the high spending rate in the US offer a clear contrast in terms of institutional structures that may have different effects on bankruptcy behaviors in the two countries. Second, the clean identifications of the gender and other demographic attributes of distressed debtors in our unique dataset are ideal for empirical tests on the gender gap and risk-taking attitudes.

4.2. Summary Statistics

4.2.1. Full Sample

Table I shows the descriptive statistics for the three sets of bankruptcy measures, which include the bankruptcy rate (Panel A), the bankruptcy claim amount (Panel B), and the time intervals for the different stages of the bankruptcy proceedings (Panel C). The table reports the results[5] for the gender gap ("female – male") in the bankruptcy measures for the full sample and different sub-samples sorted by demographic attributes (age, marital status, and race) and housing type (based on housing address) of the debtor.

[Insert Table I here]

Panel A reports the statistics on the personal bankruptcy rate, which is computed as the total number of bankruptcy cases divided by the total resident sample in the personal dataset, and the conditional multiple bankruptcy rate, which is computed as the fraction of the number of multiple bankruptcy cases (individuals with two or more bankruptcy events) over the total number of bankruptcy cases. We also report the gender gap statistics, which are the differences in the means between the female and the male samples, and the corresponding significance levels. The mean gender differences in the personal bankruptcy rate and the conditional multiple bankruptcy rate are estimated to be -2.61 and -3.26, respectively. The results are statistically significant at the 1% level, indicating that females have lower bankruptcy risk than males for both types of bankruptcy events.

Panel B reports the gender gap results by the bankruptcy claim amounts. We compute the average claim amounts for the full bankruptcy sample and the credit card bankruptcy sub-sample involving claims below S$10,000. For the full bankruptcy sample, the average claims against female bankrupts are S$12,100 higher than the average claims against male bankrupts. However, the average credit card claims against female bankrupts are S$130 lower than the average credit card claims against male bankrupts. The gender differences in the claims are statistically significant at the 5% level in both bankruptcy categories.

Panel C reports the gender gap by the time interval (number of days) for the different stages of the bankruptcy proceedings. "Stage 1" is defined by the time interval between the Statutory Demand date and the petition filing date; "Stage 2" is defined by the time interval between the petition filing date and the scheduled hearing (bankruptcy order) date; and the full bankruptcy proceeding time is defined as the time interval from the Statutory Demand date to the hearing event date, which is computed as the sum of the time intervals in "Stage 1" and "Stage 2". The

[5] Due to space constraints, we only report the differences in the means between females and males and the t-test indicators *("** denotes 1% significance, * denotes 5% significance and + denotes 10% significance")* in the table. A negative number indicates that the mean female bankruptcy measure is lower than that of the male sample. The full set of results can be found in the Appendix.

average time interval between the Statutory Demand date and the petition filing date (Female: 66.8 days; Male: 67.2 days) is longer than the average time between the petition filing date and the final bankruptcy order date (Female 60.9 days; Male: 61.1 days). However, the results show no significant gender differences in the time intervals at different stages of the bankruptcy proceedings.

4.2.2. By Demographic Factors

In Table I, we also report the bankruptcy statistics sorted by various demographic attributes of the bankrupts, such as age, race, and marital status. In the gender-age sorted sub-samples, we split the bankruptcy samples by age into three sub-groups: young (under 30 years of age), middle-aged (30 to 60 years of age) and old (over 60 years of age). We find that the gender gaps in the personal bankruptcy rates and the conditional multiple bankruptcy rates are statistically significant across all the age groups. The difference in the bankruptcy rates between young male bankrupts and young female bankrupts is estimated to be 0.08%, and the gender gap in the bankruptcy rate for young bankrupts is significantly lower than the gender gaps of 2.28% and 3.50% for the "middle-aged" and the "old" groups of bankrupts, respectively. The gender-age interactive effects are significant in predicting differences in the conditional multiple bankruptcy rates, where the gender gap for the "old" group is the largest at 4.41%, followed by the "middle-aged" group (0.87%) and the "young" group (0.30%).

For the bankruptcy claims, we find no significant gender difference in the bankruptcy amounts claimed by young men and young women. However, we find that the bankruptcy claims against middle-aged men are S$5,600 lower than the claims against middle-aged women, and the difference in the claims is even larger, at S$21,300, for the "old" bankrupt groups. The age-gender effects on credit card claims are statistically significant and negative across the three age groups. These results imply that the bankruptcy claims against men are higher on average than the claims against women in all three age groups. The results also show that the gender-age gaps in the bankruptcy proceeding times are statistically insignificant.

Rows 5 and 6 of Table I show the results of the gender gap in bankruptcy events interacted with the marital status of insolvent debtors. We observe significant gender gaps in the married and the single (unmarried) groups, and the negative numbers imply that both single and married men have higher bankruptcy risk than women in the corresponding marital groups. The same results are also found for conditional multiple bankruptcy events. However, married men have a higher conditional multiple bankruptcy rate than married women (3.69%) compared to the multiple bankruptcy rates for unmarried men and unmarried women (2.84%). With regard to bankruptcy claims, men in both the married and the unmarried groups have lower bankruptcy claims against them (S$12,600 and S$12,200), on average, compared to married and unmarried women, respectively. Credit card claims against married men are higher than the claims against married women (S$300), whereas credit card claims against unmarried men are lower than the claims against unmarried women (-$40). The gender-marriage effects have no significant explanatory effects on the bankruptcy proceeding times, as shown in Panel C.

Rows 7 to 9 of Table I show the bankruptcy results for the sub-samples sorted by ethnic group (Chinese, Malay and Indian). The gender-race differences in bankruptcy risks and conditional multiple bankruptcy risks are highly statistically significant at less than the 1% level. We observe higher bankruptcy rates and conditional bankruptcy rates for males than females in all the race groups. The largest gender gaps in personal bankruptcy rates (-3.74%) and multiple bankruptcy rates (-3.48%) are found among Indian bankrupts. With regard to average bankruptcy claims, Chinese women (S$17,400) and Indian women ($6,700) have larger claims against them than men in the corresponding race groups for bankruptcy events. For the Malay group, the gender gap is insignificant for total bankruptcy claims but significant for credit card claims, where male credit card debtors face a larger claim of S$610 relative to female credit card debtors. A smaller difference of S$60 in the claim amount is found for male and female credit card debtors in the Chinese group. The gender-race effects on bankruptcy proceeding times are statistically insignificant.

In summary, our empirical evidence supports the hypothesis that women have lower personal bankruptcy risk and conditional bankruptcy risk than men after controlling for demographic attributes (age, marital status and race). The largest gender gap in personal bankruptcy risk and conditional multiple bankruptcy risk is found for debtors from the older group and the Indian group. Upon the occurrence of bankruptcy events, we find that the bankruptcy claims against female debtors are larger on average than the claims against male debtors in all the univariate analyses (controlling for age, marital status, and race). However, on average, the bankruptcy claims against women in credit card cases are lower than the claims against men in most of the demographic categories (except the unmarried group). The gender gap in the time taken for the bankruptcy proceedings, which is institutionalized in the bankruptcy rules, is insignificant after controlling for the demographic factors.

4.2.3. By Housing Type

Similar to many earlier studies (Agarwal et al., 2010 and others), the income of distressed debtors is not observable at the individual level; thus, controlling for income variations is difficult in modelling bankruptcy risks. Housing wealth is not perfect but is a close proxy for individual income, especially in Singaporean society, where a high correlation between income and housing price is observed. We exploit the unique dual housing market structure in Singapore, which consists of a subsidized public housing market and a *laissez-faire* private housing market, to create an approximate but robust identification of individual income. Based on 2010 Census statistics (see Figure 2), the average monthly household income of households living in the largest public housing flat type (5-room and executive flats) is S$10,735, which is 43.6% lower than the average monthly income of households living in private housing (condominiums and apartments) (S$19,026). Therefore, a housing type dummy (public versus private) that is identified based on the home addresses of debtors can be used as a proxy to sort individuals into high and low income groups.

[Insert Figure 2 here]

The last two rows of Table 1 show descriptive statistics for the gender-income (housing type) sorted bankruptcy samples. The results show that the gender gaps in bankruptcy risk and conditional multiple bankruptcy risk are larger in (low income) individuals living in public housing flats (-2.76% and -4.24%) relative to those with private housing addresses (high income) (-1.68% and -3.22%). The negative and statistically significant coefficients suggest that the two bankruptcy outcomes for men are higher than those for women in both the high (in private housing) and low income groups (in HDB flats).

With regard to bankruptcy claim amounts, the average bankruptcy claim against men in the low income group is S$12,300 less than the average claim against women in the low income group (living in public housing units). In addition, the average bankruptcy claim against men living in private estates is S$10,300 less than the average claim against women living in private estates. These gender-income gaps in the average claim amounts are statistically significant for both the low income (public housing) and high income (private housing) groups. As for credit card claims, the gender gap is only marginally significant at the 10% level for the high income (private housing) group, while the effect is not significant for the low income (public housing) group. The gender-income gap is not statistically significant in explaining time variations in the bankruptcy proceedings.

5. Empirical Methodology

5.1. Model Specifications

We first utilize a Logit model to examine the gender gap in personal bankruptcy outcomes for the full resident sample; the model specification is written as follows:

$$BankruptcyEvent_i = \alpha_1 * Female_i + \alpha_2 * X_i + \alpha_3 * Female_i * X_i + \delta_j + \varepsilon_i \quad (1)$$

where *BankrupcyEvent* is a dummy that takes a value of 1 if a personal bankruptcy is filed against individual *i* and 0 otherwise. $Female_i$ is a gender dummy that takes a value of 1 for a female individual and 0 for a male individual (1 = female; 0 = male). X_i is a vector of control variables, including age, race, marital status, and housing type (a proxy for individual wealth). The interaction of gender and the demographic characteristics, which measures the marginal bankruptcy probability, is used to model demographic-related heterogeneity in the gender gap. We use the first four digits of the postal code for the spatial fixed effects, δ_j, to capture observable and unobservable personal characteristics as well as peer effects in neighbors on bankruptcy risk (Agarwal et al., 2012).

For the bankruptcy models that use only the sample of individuals involved in bankruptcy events, we run two models with the multiple (repeated) bankruptcy risk, *BankruptMult* (Equation 2), and the bankruptcy claim amount, *BankruptAmt* (Equation 3), as the dependent variables. The model's structure is similar to Equation (1), and the model specifications are written as follows:

$$BankruptMult_i = \alpha_1 * Female_i + \alpha_2 * X_i + \alpha_3 * Female_i * X_i + \delta_j + \varepsilon_i \quad (2)$$

$$BanktrupAmt_{i,t} = \alpha_1 * Female_i + \alpha_2 * X_i + \alpha_3 * Female_i * X_i + \delta_j + \gamma_t + \varepsilon_{i,t} \quad (3)$$

where *BankruptMult* is a dummy variable that takes a value of 1 if an individual is found to have been charged in two or more bankruptcy events and otherwise 0 if a bankruptcy event occurred only once. *BankruptAmt* is a continuous variable that measures the bankruptcy amount (in S$'000) claimed against bankrupt individual *i*. The same control variables, X_i, that were used in Equation (1) are used in the two models. For the panel structure in Equation (3), a year fixed effect, γ_t, is included in the model to reflect macroeconomic risks surrounding the bankruptcy events.

5.2. Sample Composition

The use of a large personal dataset covering nearly 60% of the Singaporean resident population should eliminate any sample selection bias. Figure 3 plots the distributions of male and female individuals sorted by demographic variables [(A) age and (B) ethnic group] and housing type (C). Figure 3(A) shows the gender distributions by age, where the dashed and darkened lines represent the male and female groups, respectively. The two gender lines are indistinguishable and show very similar distributions for male and female individuals in the middle-aged group (between 40 and 65 years of age). In the younger cohort between 25 and 35 years of age, there are more males than females, whereas fewer males are found in the older cohort of those over 70 years of age. The mean male age of 49.4 years is slightly lower than the mean female age of 50.7 years.

Figure 3(B) shows the male and female distributions sorted by ethnic group (Chinese, Malay and Indian), and no clear differences are found in the distributions of the male and female samples. Chinese is the largest group, constituting 82.3% and 82.6% of the female and male Singaporean residents in our sample, respectively. Malay is the second largest group and constitutes approximately 12.6% and 12.8% of the female and male residents in the sample, respectively. Indian and others (control) constitute the balance of less than 5% of the resident sample.

Figure 3(C) shows the male and female resident distributions by housing type (a pseudo-proxy for income). No significant variations are observed in the housing type shares in the two gender groups, where 84.1% and 84.9% of the female and the male residents, respectively, live in public housing.

5.3. Sample Matching

We next address selection concerns, if any, by sorting the samples into the control (male) and treatment (female) groups using the propensity score matching (PSM) approach (Rosenbaum and Rubin, 1983; Dehejia and Wahba, 1999, 2002). We first estimate a logistic regression with the “female” dummy as the dependent variable and a set of demographic factors, including age, marital status, race, housing type, and location fixed effects as the control variables. The results in the Online Appendix (Panel A of Table A1) show that the demographic variables in the model are all statistically significant in predicting the gender dummy (“female”).

Based on the propensity scores computed in the logistic model, we select the matched control (male) group using the nearest-neighbor algorithm without replacement. The same procedure is used to construct the two other sets of matched samples: the bankruptcy sample (Column 2 of Table AI in the Online Appendix (Panel A)) and the credit card bankruptcy sample (Column 3 of Table AI (Panel A)). Panel B of Table AI computes the differences in propensity scores between the treatment sample and the control samples. The differences are negligible, falling within a range between 0 and 0.016, which indicates that the one-to-one matching process is efficient and robust.

We conduct pairwise comparisons between the treatment (female) and the control (male) groups before and after the matching processes. Table II shows that the gender differences based on demographic attributes and housing type change from being significant in the pre-matching samples to insignificant in the post-matching samples. We also use the variance ratio (Rubin, 2001) to compare the higher order moments of distributions for each observed covariate between the treatment and the control groups. The variance ratio, v, which is not significantly different from one, indicates that the distributions of the observed covariates are well balanced between the two matched groups. We also use other matching estimators, including nearest-neighbor matching (for N= 5 and N=10 male individuals) and the kernel-based matching technique (GUASSIAN and EPANECHNIKOV)[6], and the results in Table III are similar and consistent.

[Insert Table II here]

6. Empirical Results

This section presents the results of the gender gap in bankruptcy outcomes using the matching techniques and the regression models. We discuss the empirical evidence on the gender gap hypothesis and also use the IV approach to identify the risk behavior of men and women in the bankruptcy events.

6.1. Propensity Score Matching

Table III shows the results of gender differences in the three bankruptcy models (personal bankruptcy risk, multiple bankruptcy risk and credit card default claims) and with different PSM estimators. The results reaffirm the earlier findings in Table I (unmatched samples) that

[6] Additional robustness tests are conducted by incorporating recent econometric advances into the estimation of average treatment effects (Adadie and Imbens, 2006, 2008, 2015) (*see Section 6.3*).

gender gaps are significant for both personal bankruptcy risk and conditional multiple bankruptcy risk. The female personal bankruptcy risk is between 2.56% and 2.67% lower than the male personal bankruptcy risk, while the conditional multiple bankruptcy risk for females is between 2.58% and 3.25% lower than that for males. The results are statistically significant and consistent across the five PSM estimators.

In Panel C, we find that the credit card bankruptcy claims against female debtors are lower than the claims against males, which are estimated to be between S$146 and S$202. The gender gap is statistically significant in all the matching estimators except for the one-to-one matching estimator. The one-to-one matching estimator is sensitive to sample size, whereby its performance is weaker in small samples. Overall, the results support the hypothesis that there is a significant gender gap in personal bankruptcy risk measured by the three bankruptcy outcomes.

[Insert Table III here]

6.2. Controls for credit supply

Family credit choices could cause selection bias in the gender gap with regard to bankruptcy outcomes. If men (husbands), who are the household heads, take more credit for the family, they are likely to have higher bankruptcy risk relative to women (wives).[7] We use only the unmarried samples to remove the household heads' selection bias in our models. Table IV shows that the gender gaps are all statistically significant, and the effects are economically and statistically stronger than those found in Table III. In the models with the one-to-one nearest-neighbor matching, the gender gap in personal bankruptcy risk increases from 2.610% (Table 3) to 2.835% (Table 4), and the gender gap in multiple bankruptcy risk increases from 2.760% to 3.092%.

[Insert Table IV here]

Credit supply could also be a source of selection bias. If banks grant more credit to men than women, then men's bankruptcy risks should increase correspondingly. Given that the credit supply is not observable *ex ante* in our data, we use a large sample of credit card data from a large corporate bank in Singapore[8] to empirically test the credit line determinants. The results (Table AII in the Online Appendix) show that the credit line (supply) is independent of gender

[7] We would like to acknowledge the editor and the anonymous referee for comments and suggestions.
[8] We thank Sumit Agarwal and Wenlan Qian for sharing the credit card data for this analysis.

but is dependent on the income of credit card holders. We next use housing type as a proxy for income and test the income effect on the gender gap in bankruptcy events. We randomly assign a sub-sample of men living in public housing flats ("HDB") into the high income group by switching their "HDB" dummy values from one (public housing) to zero (private housing). This exercise deliberately sets the income of the male sample significantly lower than that of the female sample in the three sets of "*pseudo*" matched samples (full sample, full bankrupt sample, and credit card bankrupt sample). We repeat the regression models using the five PSM matching process, and the results are summarized in Table V (Panel A). The results in Panel B (Table V) show that the gender gaps in the personal bankruptcy risk models and the multiple bankruptcy risk models remain significant and strong. However, the gender gaps in the bankruptcy claim amounts (Column 3) are smaller relative to the earlier estimates reported in Table 3.

[Insert Table V here]

6.3. Bias-adjusted Matching

Recent econometric advances have been proposed to remove matching biases in the estimation of average treatment effects (Adadie and Imbens, 2006, 2008, 2015).[9] Abadie and Imbens (2006) provide two extensions of the simple matching estimator developed by Dehejia and Wahba (1999) in their bias-adjusted matching estimator. The first extension uses the matching with replacement approach to reduce asymptotic bias, and the second involves the construction of an additional bias correction term.[10] As the bootstrapping standard error is not generally valid for the propensity score matching estimator (Abadie and Imbens, 2008), we improve our tests by computing robust standard errors following the nonparametric method derived by Abadie and Imbens (2015). We also run additional robustness tests of the average treatment effects on the gender differences in bankruptcy outcomes. The results as reported in Table VI are quantitatively unchanged and consistent, which implies that the gender gap hypothesis is not rejected.

[Insert Table VI here]

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[9] Abadie and Imbens (2006) show that the nearest-neighbour matching estimator generates asymptotically biased results when more than one variable is used in the matching process.

[10] This method has been used in recent studies by Malmendier and Tate (2009) and Beck et al. (2013). Çolak and Whited (2007) provide a heuristic description of the matching technique.

6.4. Regression Results

We present the empirical results on the gender gap in bankruptcy events in two parts. First, we estimate a logit model on personal bankruptcy risk, as in Equations (1) and (2), using the full resident and bankruptcy sample. Second, we run a panel model controlling for demographic, spatial and year fixed effects to test the gender gaps in bankruptcy claims using only the credit card bankruptcy sample.

6.4.1. Personal Bankruptcy Risk

Table VII shows the logit regression results for personal bankruptcy risk. The gender dummy ("Female") is the key independent variable in the model after controlling for demographic characteristics such as age, marital status, race, and housing type in the models. We estimate the marginal bankruptcy effects through interactive variables of the gender dummy with the age, marital status, and race variables. The models include the spatial fixed effects represented by the first four digits of the postal codes of the debtors' home addresses.

[Insert Table VII here]

The coefficient for *"Female"* is negative and statistically significant at the 1% level, indicating that women have lower personal bankruptcy risk than men. The odds ratio (in brackets) in Column (1) predicts that the odds of female bankruptcy are only 28% of the odds of male bankruptcy, or we could say that the odds of male bankruptcy are 3.57 times, i.e., [1/0.28], higher than the odds of female bankruptcy. This result is consistent with the unconditional odds ratio on the gender gap in bankruptcy risk of 3.42 times, i.e., [3.69/1.08], as shown in Table 1. The empirical results support the hypothesis that women engage in less risk-taking behavior than men.

Columns 2 to 7 report the results for the interactive variables of the gender gap dummy with the age, marital status, race, and public housing variables. The *"Female"* dummy, which is a proxy of the gender gap effect, is significant and negative in all the models. The *"Female × Age"* coefficient of -0.012 implies that the gender gap in personal bankruptcy risk widens with age. The results imply that more old people are involved in bankruptcy events than young people. The age-based gender gap result is consistent with those found in Ross and Mirowsky (2002). We find no heterogeneity in the gender effect between married and single bankrupts in Column 3. The coefficients for the gender-race interactive terms in Columns 4 to 6 are statistically significant at the 1% level. The gender gap coefficient is negative when interacted with the Chinese race dummy, but the coefficients are positive when interacted with the Malay and Indian race dummies. Using the "other" race as the reference group, the results indicate that the gender gap in Chinese personal bankruptcy events is larger than that in the "other" race ("control group"), whereas the gender gap in the personal bankruptcy risks of the Malay and Indian groups is smaller than that of the control group. For the same number of male debtors, we can expect more Malay and Indian female debtors to face bankruptcy than Chinese female debtors. The racial bias in bankruptcy risk found in Singapore is consistent with the findings in the US personal bankruptcy study by Agarwal et al. (2010).

While we could not rule out the possibility that the minority status of Indian and Malays could influence their risk preference and induce them to take more debt, compared to the majority Chinese in Singapore. We, however, argue that the credit activities and debt behaviors are not correlated with economic differences between the minority Indian and Malay and the majority Chinese. The early robustness test in Section 6.2 shows no significant income effect on the gender gap. This is also consistent with the evidence in Agarwal and Qian (2014), which shows that the consumption and debt responses of Indian Singaporeans and Chinese Singaporeans to an exogenous positive income shock[11] are not explained by income differences between the two ethnicity groups. Our results are thus related to the cultural effects on economic outcomes reported in the literature (Guiso et al., 2006, 2009).

The interactive term with the public housing dummy, "*Female×HDB",* is statistically significant, and the sign of the coefficient is negative. Thus, the gender gap in personal bankruptcy risk is larger for lower income individuals living in public housing flats ("HDB") than for those living in private houses. Thus, we expect fewer bankruptcy events involving female individuals in the public housing market than in the private housing market if the same number of male bankruptcy events are filed in both markets. If housing type can instrument individual income, the results may suggest that high income women (those living in private housing units) engage in more risk-taking behavior than low income women, despite the negative social stigma attached to bankruptcy in Singapore.

As a robustness check, we remove the samples with multiple bankruptcy events and re-estimate the logit model on personal bankruptcy. The results as reported in the Online Appendix (Table

[11] Agarwal and Qian use the Government's Dividend Program announced in the budget on February 18, 2011, as an exogenous shock in the policy experiment. The program disburses a one-time cash payout ranging from US$78 to US$702 per person to 2.5 million adult Singaporeans. The package was estimated to cost US$1.17 billion in the budget, which was 0.5 percent of the annual gross domestic product (GDP) of Singapore in 2011.

A3) are consistent with those reported in Table 7. The predicted odds ratio for female bankruptcy risk increases slightly to 29.1% relative to the odds of male bankruptcy risk (Table A3: Column 1). Thus, the gender gap effect is significant in explaining personal bankruptcy risks, and the results support the hypothesis that females are more risk averse and have lower bankruptcy risks. The next section will empirically test the gender gap for recalcitrant (repeated) debtors.

6.4.2. Multiple (Repeated) Bankruptcy Risks

If a female bankrupt has learned from her previous bankruptcy to become more prudent in managing her personal finances than a male bankrupt, we should expect a lower probability for a woman to repeat bankruptcy than a man. We run a logit regression with the "*BankruptMult*" dummy, which takes a value of 1 if an individual has been charged in two or more bankruptcy events and 0 otherwise, as the dependent variable. The marginal probability effects are represented by the interactive terms of the "*Female*" dummy with age, marital status, race, and housing type. Table VIII shows the results for conditional multiple bankruptcy risks after controlling for demographic variables, housing type, and postal district fixed effects.

[Insert Table VIII here]

The gender dummy coefficients are statistically significant and negative across all the models, which implies that women have lower (repeated) multiple bankruptcy risk. The odds ratio of women becoming involved in multiple personal bankruptcy events is only 64.7% of the men's odds. We find that the odds of males becoming involved in multiple bankruptcy events is 55.5% (i.e., [1/0.647 -1]) higher than females' odds after controlling for demographic variables, housing type and spatial fixed effects. These results are consistent with the unconditional estimates in Table 1, but the conditional odds are stronger than the unconditional odds of 43.0%, thus reaffirming the hypothesis that men are more likely than women to be involved in multiple bankruptcy events, i.e., [(10.84/7.58) -1 = 43.0%].

In Column 2 of Table VIII, the coefficient for the gender-age interactive variable (-0.013) is negative and statistically significant at less than the 1% level, which indicates that the gender gap in multiple bankruptcy events increases with age. Older women are less likely to have multiple (repeated) bankruptcies than younger women. Marital status has no explanatory effects on the gender gap in multiple bankruptcy events. The gender-race coefficients are statistically significant in predicting multiple bankruptcy risk for Chinese and Malay debtors at the 5% level. However, the coefficients' signs are the opposite for the two race groups. Converting the coefficients into odds ratios, we can infer that the gender gap in multiple bankruptcy risk for the Chinese group (1/0.858 < 1) is larger, whereas the gender gap is smaller for the Malay group relative to the control ("other") race group. The gender gap in multiple bankruptcy events is insignificant for the Indian group. The interaction term with the HDB dummy is also not significant.

6.4.3. Bankruptcy Claim Amounts

Based on credit card bankruptcy events with claims of less than S$10,000, we find that the bankruptcy claims against men are higher, on average, than those against women, *ceteris paribus*. We also estimate Equation (3) with the credit card claims, *BankruptAmt* (in S$'000), as the dependent variable after controlling for demographic variables, housing type, the postal district and time fixed effects. The results are summarized in Table IX.

[Insert Table IX here]

We find that the coefficients for the *"Female"* dummy are statistically significant and negative, which indicates that the credit card bankruptcy claims against women are lower than those against men in bankruptcy events. In the baseline model in Column 1, the average bankruptcy claim against women is S$222 less than the average claim against men after controlling for demographic and other heterogeneities. Based on the average credit card bankruptcy claim of S$5,420 against men (see Table I), female bankruptcy claims are 4.1% lower than men's bankruptcy claims, on average.

Columns 2 to 7 include the interactive effects of gender with age, marital status, race, and housing type. The marginal effect of the gender gap in bankruptcy claims is not statistically significant for the age group (Column 2). The gender gap is stronger for the married group. The results show that the relative credit card bankruptcy claims against married women to married men are S$204 lower than the relative claims against single women to single men conditional on the bankruptcy event occurrence (Column 3). Gender-race interactive effects are observed for credit card bankruptcy claims, whereby the gender gap for Chinese debtors in credit card bankruptcy claims is estimated to be S$182, i.e., [-S$403 + S$221 = -$182], which is 19% lower than the average gender gap of S$222 reported in Column 1. The gender difference in bankruptcy claims is higher among Malay debtors, which is estimated to be S$663, i.e., [-S$162-S$501 = -S$663]. The gender effects for distressed Indian debtors and debtors living in public and private housing markets are statistically insignificant.

In summary, conditional on the occurrence of bankruptcy events, bankruptcy claims against women are significantly lower than the claims against men. The results support the hypothesis that the gender gap in risk attitudes explains significant variations in the amounts of bankruptcy claims. The gender gap in bankruptcy claims is lower for single women compared to the married groups. The gender gaps in bankruptcy claims are significant for both the Chinese and Malay groups.

6.5. Gender Gap and Risk Attitudes

Are women more risk averse than men in making financing decisions? We test the above question based on the notion that if personal bankruptcy risk is correlated with the innate risk attitude of debtors, we can then expect individuals who like to take risks in activities such as driving to also take more financial risks and to therefore be exposed to higher bankruptcy risks. We empirically test the gender-risk-taking relationship using motor vehicle accident events from a comprehensive lawsuit dataset as an instrument for risk-taking behavior.[12] The lawsuit dataset for Singapore contains 269,020 motor vehicle accident events from 1980 to 2012. We merge the bankruptcy dataset with the motor vehicle accident database based on the unique personal identification numbers of defendants in the motor vehicle accident events.

We run univariate analyses on the gender gap in bankruptcy risk for the samples sorted by debtors' past experience with motor vehicle accidents. Panel A of Table X summarizes the results of the personal bankruptcy risks sorted by gender (columns) and by the motor vehicle accident occurrences of the debtors (rows). The gender gap in personal bankruptcy risks (in Column 4) is larger, at 3.49%, for debtors with past motor vehicle accident records compared to 2.33% for debtors without past motor vehicle accident records. The results indicate that the treatment using past motor vehicle accident records, which reflect the risk-taking behavior of motorists, is statistically significant in explaining the gender gap in personal bankruptcy risks.

[Insert Table X here]

[12] Female drivers are well represented in vehicle ownership shares (Female: 45% vs. Male: 55%) in Singapore, which provides a useful setup for the IV tests.

Next, we use motor vehicle accident occurrences as the instrument for risk-taking behavior in the IV models to predict the gender gap in bankruptcy outcomes.[13] We carefully reviewed the motor vehicle accident data and retained only those cases with minor injury outcomes in our tests. We take this approach to ensure that the exclusion restriction for the instrumental is not violated, such that a motor vehicle accident is not the direct cause of a personal bankruptcy.[14] We run two-stage least squares (2SLS) regressions, and the first-stage regression results using past motor vehicle accident occurrences as the IV are reported in the Online Appendix (Table AIV). The results are consistent with our hypothesis that the "*Female*" dummy is significantly and negatively correlated with motor vehicle accident occurrences, "*D*(*Motor)*". Female drivers in all three of the bankruptcy groups (personal bankruptcy risk, multiple bankruptcy risk, and credit card bankruptcy risk) are less likely to be involved in motor vehicle accidents compared to male drivers. The results confirm that "*D*(*Motor*)" is a robust and valid instrument for gender-dependent risk-taking behavior. Similar to Stango and Zinman (2015), we also test the weak instrument problem, and the p-values in the AR tests indicate that our instruments are robust.[15]

Panel B (C) of Table X reports the results of the second-stage regressions with the three bankruptcy outcomes (only for the non-married sample) as the dependent variables. The results show strong and consistent evidence that female debtors have lower personal bankruptcy and multiple bankruptcy risks, and they also face lower average bankruptcy claims in bankruptcy events relative to male debtors. The gender effects predicted by the IV models are consistent with those found in the earlier baseline OLS regressions (Tables 2 to 4), although the coefficients in the 2SLS are slightly larger than the corresponding coefficients in the OLS regressions. The noise in the OLS models that causes the differences in the gender gap results is better controlled for in the instrumental variable (IV) approach (Gujarati, 2003)[16]. The IV results support the hypothesis that women engage in less risk-taking behavior and have lower bankruptcy risk than men.

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[13] We thank the anonymous referee for the suggestion to run IV tests.

[14] This approach is similar in spirit to the use of speeding convictions to measure risk-seeking in Grinblatt and Keloharju (2009).

[15] Finlay and Magnusson (2009) discuss the weak instrument problem and include the Stata routine, which is used in our study for the weak instrument robustness tests.

[16] The strength of the instrumental variables in the estimation could also influence the differences between the OLS and 2SLS IV estimates. Given that the F-statistics are larger than 10 (Bound et al., 1995), it is unlikely that the difference in the two coefficients is caused by a weak instrument.

6.6. Time Intervals in Bankruptcy Proceedings

The risk attitudes of men and women matter only if their actions are antecedent to bankruptcy outcomes. We should not find any correlations between risk attitudes and activities that are not directly related to bankruptcy outcomes, such as the time provided by creditors to repay a debt during the bankruptcy process. Bankruptcy proceedings are administrative in nature and thus should be gender-neutral. We use three time periods (measured by the number of days): (i) between the statutory demand and the petition (stage 1); (ii) between the petition and the hearing event (stage 2); and (iii) the whole bankruptcy proceeding (stage 1 + stage 2) as the dependent variables and test whether a gender gap exists in the three time periods after controlling for spatial and year fixed effects. The results are summarized in Table XI.

[Insert Table XI here]

The *"Female"* coefficient is insignificant, implying that a gender gap is irrelevant in predicting the duration of the different stages of bankruptcy proceedings. However, the "*Age*" coefficient is statistically significant and has a negative sign, which suggests that bankruptcy events involving older debtors are resolved quicker. Bankruptcy proceedings are also not race-neutral in Singapore. The results show that the time involved in the stage 2 process between the petition and the hearing is longer for cases involving Malay and Indian debtors relative to other ("control") debtors. The time involved in the stage 2 process for low income bankrupts living in public housing ("HDB") is also shorter than that for bankrupts living in private housing (high income debtors). The shorter time for the stage 2 proceeding could be due to smaller claims in bankruptcy cases involving public housing (low income) debtors relative to private housing (high income) debtors.

6.7. Thresholds for Credit Card Bankruptcy Claims

We conduct further robustness tests that use different cut-offs to create credit card bankruptcy sub-samples. Instead of using the S$10,000 cut-off as in the early tests (Table IX), we filter the credit card bankruptcy cases from the full bankruptcy sample using four different cut-off values: (S$5,000, S$7,500, S$12,500, and S$15,000) and repeat the univariate analyses using both the unmatched (Panel A) and the matched (Panel B) bankruptcy samples. The results are summarized in Table XII.

[Insert Table XII here]

Panel A of Table XII reports the gender gap estimates for the full sample and the sub-samples sorted by the demographic and housing type variables. The results are consistent with the earlier results reported in Table 1 (Panel C). We find significantly lower personal bankruptcy claims in a range between S$100 and S$270 on average against female debtors than male debtors across all the cut-off categories. We also observe a clear pattern that the gender gap widens with the cut-off values, except for selected groups of young, Chinese, and private housing debtors in the S$12,500 cut-off category. These results reaffirm the hypothesis that credit card bankruptcy claims against women are lower than those against men, and the results are independent of the choice of cut-off value.

Panel B of Table XII shows the results of the univariate analyses on the gender gap in credit card bankruptcy claims using the PSM-sorted samples of different cut-off categories. The results show that women's credit card bankruptcy claims are significantly lower than the claims against men in all the cut-off and PSM categories. Thus, the robustness test results rule out any potential selection bias associated with the credit card thresholds. The gender gap evidence supports the hypothesis that women engage in less risk-taking behavior than men with regard to credit card bankruptcy events.

7. Conclusions

This study is one of the few that uses data from outside the US to examine the gender gap in bankruptcy risks. Based on the unique personal identification information in the datasets, we are able to match a personal bankruptcy database in Singapore with demographic (including age, gender, race, and marital status) and housing type variables in a personal database. We empirically test the gender gap in three different bankruptcy outcomes, including personal bankruptcy risk, repeated (multiple) bankruptcy risk, and conditional bankruptcy claims. We also merge motor vehicle accident data with the bankruptcy data to further test whether the gender gap in bankruptcy events is associated with different risk-taking behaviors of male and female debtors.

First, the logit regressions show that women have a lower probability of being involved in bankruptcy events than men after controlling for demographic factors, housing type and spatial fixed effects. The odds of women's bankruptcy are 28% of those of men. We also find that the gender gap in personal bankruptcy risks widens with age. The gender gap is not race-neutral; the effect is smaller among Chinese debtors and larger among Malay and Indian debtors relative to the “other” race (control group). In addition, the gender gap is smaller among high income individuals relative to low income individuals.

Second, the odds ratio of women being involved in multiple bankruptcy events is 64.7% of that of men, *ceteris paribus*. The negative gender-age relationship indicates that older women are less likely to have multiple (repeated) bankruptcies than younger women. The gender-race coefficients show that the gender gap for Chinese debtors with regard to multiple bankruptcy risk is lower (negative) and that of Malay debtors is larger (positive) than the gender gap for the “other” race (control) group. Third, conditional bankruptcy claims against women are S$222 less than those against men, which is equal to 4.1% of the average bankruptcy claim of S$5,420 against men. The gender gap in bankruptcy claims is 19% lower than the average gender gap, whereas the gender gap effect is larger among Malay debtors. The gender gap persists after controlling for various confounding factors, including married couples’ credit choice, the credit supply, debtors’ differential treatment and income (using housing type as a proxy).

Based on the merged dataset of bankruptcy events and motor vehicle accident events, we instrument the risk-taking behavior of debtors using their past motor vehicle accident events, and our results affirm that the gender gap in bankruptcy events is correlated with differential risk-taking behaviors of male and female debtors. We show that the gender gap in bankruptcy risks is larger for debtors with past motor vehicle accident records than for those without past motor vehicle accident records. Our results also show that past motor vehicle accident events are a robust instrument for the risk-taking behavior of debtors in predicting the gender gap in bankruptcy events. When we test the procedural times in different stages of bankruptcy proceedings (statutory demand, petition, and hearing), the gender gap effect is not significant. However, similar to Agarwal et al. (2010), we find evidence of race-bias in the time between petition and hearing in bankruptcy events in Singapore.

Using observational data on bankruptcy and motor vehicle accident events in Singapore, our results show evidence of a gender gap that is in line with the findings in the broader economic literature and in controlled laboratory environments. With high social costs associated with credit default, Singaporean women are likely to be more sensitive to social stigma attached to bankruptcies; and they will take more precautionary steps to minimize financial risk and avoid negative consequences. We thus argue that the social preference, as identified by Croson and Gneezy(2009), is the main factor explaining the gender gap in the bankruptcy outcomes in our results. One significant implication is that banks and financial institutions should not neglect the gender factor when assessing financial risks in loan underwriting. For the insurance industry, pricing differential gender risks could help reduce the information asymmetry between insurers and the people insured.

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Table I. Gender gap in bankruptcy outcomes

The table summarizes the statistics on the gender gap for different bankruptcy outcomes. In Panel, *personal bankruptcy frequency* is computed as the ratio of bankruptcy events to the total resident samples; and *conditional multiple bankruptcy events* are computed as the ratio of individuals having more than bankruptcy records to the total bankruptcy samples. The results in Panel B and C are computed based on the bankruptcy samples. In column 1 of Panel B, differences in the mean bankruptcy claims amount (in S$'000) for the full samples are computed, while for column 2, the differences are computed for sub-samples involved only cases with claim amounts below S$10,000. In Panel the time intervals (by days) between various stages in the bankruptcy proceedings, which are divided into three activities including statutory demand, petition filing and hearing, are computed. "Stage 1" is the time intervals between statutory demand and the petition filing dates; and "Stage 2" is the time intervals between petition and scheduled hearing dates; and the last column represent the full proceeding time from statutory demand to hearing (days). + denotes P < .10; * denotes P < .05; and ** denotes P < .01

		Panel A Personal Bankruptcy Frequency (%)		**Panel B** Bankruptcy Claim Amount (S$000) (conditional on bankruptcy event occurrence)		**Panel C** Time Interval of Personal Bankruptcy Procedure (days)		
Sample sorted by demographic and housing characteristics:		Personal bankruptcy Events	Conditional Multiple Bankruptcy Events	All Bankruptcy Claims	Credit Card Bankruptcy Claims (≤ 10,000 S$)	Stage 1: Between Statutory Demand and Petition Filing	Stage 2: Between Petition Filing and Hearing	Full period: From Statutory Demand to Hearing
All		-2.61**	-3.26**	12.10*	-0.13*	-0.40	-0.20	-0.60
By Age	Young	-0.08**	-0.30**	-4.60	-0.12*	2.30	-1.60	0.70
	Middle-Aged	-2.28**	-0.87*	5.60**	-0.07*	9.10	-0.10	9.00
	Old	-3.50**	-4.41**	21.30**	-0.31+	-17.60	-0.60	-18.20
By Marital status	Married	-2.39**	-3.69**	12.60**	-0.30**	-12.30	-0.30	-12.60
	Unmarried	-2.81**	-2.84**	12.20**	0.04+	11.20+	-0.30	10.90
By Race	Chinese	-2.52**	-3.36**	17.40*	-0.06+	-1.20	-1.40	-2.60
	Malay	-2.21**	-1.95**	-0.20	-0.61*	3.30	3.30	6.60
	Indian	-3.74**	-3.48**	6.70**	-0.27	-0.70	-0.70	-1.40
By Housing Type	HDB	-2.76**	-4.24**	12.30**	-0.09	-7.50	-6.10	-13.60
	Non-HDB	-1.68**	-3.22**	10.30**	-0.32+	7.40	0.40	7.80

Table II. Descriptive statistics for the pre- and post-matching samples

The table shows the summary statistics for the demographic variables for the pre- and the post-matching samples. The results are also divided into three categories based on (A) full samples; (B) bankruptcy samples; and (C) credit card default samples (the size of each sample is reported in N). For each sub-sample group, the ratio (%) statistics are computed with respect to the sample size of the respective groups and the mean age statistics are computed in years for the full sample, bankrupt samples and the credit card default samples, respectively. The post-matching samples are derived using the propensity scores estimated from the Logit regressions in Table 2. The matching procedure here is one-to-one nearest-neighbor matching (based on the estimated propensity scores) between the treatment and the control groups without replacement. The table shows statistics for female and male samples, and also the differences between female and male sample (gender gap). The last column compares the variance between the treatment and the control groups using the variance ratio (Rubin, 2001). + denotes P < .10; * denotes P < .05; and ** denotes P < .01

	Pre-Match			**Post-Match**			
Variable	Female	Male	Difference	Female	Male	Difference	Ratio
Panel A: Full Sample							
Age (year)	50.770	49.400	1.370**	49.446	49.400	0.046	1.025*
Race (%)							
Chinese	0.823	0.826	-0.003**	0.826	0.826	0.000	1.012
Malay	0.126	0.128	-0.002**	0.128	0.128	0.000	0.995
Indian	0.036	0.035	0.001**	0.034	0.035	-0.001	1.001
Married Status (%)	0.479	0.504	-0.025**	0.501	0.504	-0.003*	0.999
HDB (%)	0.841	0.849	-0.008**	0.850	0.849	0.001	1.014*
N	1189723	1142655		1142642	1142642		
Panel B: Bankruptcy Sample							
Age	51.710	53.170	-1.460**	51.710	51.579	-0.131	0.986
Race (%)							
Chinese	0.733	0.780	-0.047**	0.733	0.738	-0.005	1.001
Malay	0.181	0.151	0.030**	0.181	0.181	0.000	1.000
Indian	0.065	0.053	0.012**	0.065	0.065	0.000	1.000
Married Status (%)	0.488	0.535	-0.047**	0.488	0.488	0.000	1.000
HDB (%)	0.891	0.902	-0.011**	0.891	0.897	-0.006	0.994
N	12910	42169		12910	12910		
Panel C: Credit Card Default Sample							
Age (year)	54.090	55.530	-1.440**	54.090	53.942	0.148	0.931
Race (%)							
Chinese	0.739	0.788	-0.049**	0.739	0.757	-0.018	0.961
Malay	0.152	0.129	0.023	0.152	0.154	-0.002	1.033
Indian	0.073	0.064	0.009	0.073	0.058	0.015	0.808*
Married Status (%)	0.452	0.523	-0.071**	0.452	0.461	-0.009	1.004
HDB(%)	0.882	0.906	-0.024**	0.882	0.900	-0.018	0.965
N	537	2358		537	537		

Table III. Gender difference in personal bankruptcy under propensity score matching

The table provides the estimates of gender difference in different bankruptcy outcomes, which include personal bankruptcy probability (%) in Panel A; conditional multiple bankruptcy probability (%) in Panel B; and claim amount in credit card default cases (S$'000) in Panel C. We compute the propensity scores using Logit models as in Table A1 of the Online Appendix, and the results are used in the matching processes. Different matching estimators are used in the table including one-to-one matching, nearest neighbor matching using "n" male individuals and kernel-based matching techniques (GUASSIAN and EPANECHNIKOV) (see Appendix B of Drucker and Puri, 2005 for details). We report t-statistics in parentheses, which are calculated using standard errors in the bootstrapping with 50 replications. + denotes P < .10; * denotes P < .05; and ** denotes P < .01.

Propensity Score Matching Estimator	Female	Male	Difference (Female - Male)
Panel A: Probability of Personal Bankruptcy (%)			
ONE-TO-ONE MATCHING	1.080	3.690	-2.610**
			(-6.99)
NEAREST NEIGHBORS(n=5)	1.080	3.750	-2.670**
			(-14.78)
NEAREST NEIGHBORS(n=10)	1.080	3.710	-2.630**
			(-6.29)
GUASSIAN	1.080	3.700	-2.620**
			(-7.25)
EPANECHNIKOV	1.080	3.640	-2.560**
			(-7.11)
Panel B: Probability of Conditional Multiple Personal Bankruptcy (%)			
ONE-TO-ONE MATCHING	7.580	10.340	-2.760**
			(-8.69)
NEAREST NEIGHBORS(n=5)	7.580	10.160	-2.580**
			(-4.71)
NEAREST NEIGHBORS(n=10)	7.580	10.450	-2.870**
			(-5.45)
GUASSIAN	7.580	10.830	-3.250**
			(-8.73)
EPANECHNIKOV	7.580	10.750	-3.170**
			(-8.17)
Panel C: Bankruptcy Claim Amount for Credit Card Default (S$'000)			
ONE-TO-ONE MATCHING	5.282	5.423	-0.141
			(-1.45)
NEAREST NEIGHBORS(n=5)	5.282	5.484	-0.202+
			(-1.79)
NEAREST NEIGHBORS(n=10)	5.282	5.444	-0.162+
			(-1.76)
GUASSIAN	5.282	5.429	-0.147*
			(-2.03)
EPANECHNIKOV	5.282	5.428	-0.146+
			(-1.66)

Table IV. Restricting to non-married sample

The table provides the estimates of gender difference in different bankruptcy outcomes for samples with non-married individuals. The bankruptcy outcomes include personal bankruptcy probability, conditional multiple bankruptcy probability and claim amount in credit card default cases (S$'000). We compute the propensity scores using Logit models as in Table A1 of the Online Appendix, and the results are used in the matching processes. Different matching estimators are used in the table including one-to-one matching, nearest neighbor matching using "n" male individuals and kernel-based matching techniques (GUASSIAN and EPANECHNIKOV) (Drucker and Puri, 2005). We report standard errors in parentheses, which are calculated in the bootstrapping with 50 replications. + denotes P < .10; * denotes P < .05; and ** denotes P < .01

Matching Estimator	**Personal Bankruptcy (%)**	**Conditional Multiple Personal Bankruptcy (%)**	**Bankruptcy Claim Amount (S$'000)**
ONE-TO-ONE MATCHING	-2.835**	-3.092**	-0.246
	(0.029)	(0.363)	(0.186)
NEAREST NEIGHBORS(n=5)	-3.067**	-3.254**	-0.452*
	(0.282)	(0.532)	(0.182)
NEAREST NEIGHBORS(n=10)	-2.636**	-2.961**	-0.435*
	(0.223)	(0.422)	(0.192)
GUASSIAN	-3.019**	-3.578**	-0.296*
	(0.281)	(0.370)	(0.140)
EPANECHNIKOV	-3.204**	-3.204**	-0.315**
	(0.306)	(0.474)	(0.155)

Table V. Controlling for credit supply

Panel A shows the summary statistics for the demographic and housing variables for the post-matching sample where female and male individuals have similar characteristics except that female has more wealth (low-income group include individuals living in public housing flat, as reflected by the variable 'HDB'). We first randomly re-assign a proportion (10%) of low-income males to the high-income category, and use the new sample in the matching process. As a result, we would obtain a matched sample, in which male are similar with female in most characteristics except for the income level, which show that females have significantly higher income than males. Panel B provides the estimates of gender difference in different bankruptcy outcomes for the matched sample, similar to Table 6. + denotes P < .10; * denotes P < .05; and ** denotes P < .01.

Panel A Summary Statistics of the matched sample

Variable		**Female**	**Male**	**Difference**	**T-test**
(a) Full Sample					
Age (year)		50.772	50.757	-0.015	0.72
Race (%)	Chinese	0.823	0.824	-0.001	-0.90
	Malay	0.127	0.127	0.000	-0.23
	Indian	0.037	0.036	0.001	0.74
Married Status (%)		0.479	0.480	-0.001	-0.24
Low Income dummy (%)		0.841	0.879	-0.038**	-86.50
(b) Bankruptcy Sample					
Age		51.718	51.727	-0.009	-0.07
Race (%)	Chinese	0.734	0.734	0.000	0.06
	Malay	0.181	0.181	0.000	0.03
	Indian	0.065	0.064	0.001	0.23
Married Status (%)		0.488	0.489	-0.001	-0.10
Low Income dummy (%)		0.892	0.941	-0.049	-14.53
(c) Credit Card Default Sample					
Age (year)		54.446	54.325	0.121	0.28
Race (%)	Chinese	0.741	0.770	-0.029	-1.21
	Malay	0.147	0.140	0.007	0.39
	Indian	0.073	0.058	0.015	1.10
Married Status (%)		0.449	0.443	0.006	0.22
Low Income dummy (%)		0.882	0.943	-0.061**	-3.99

Panel B Gender Difference in the Matched Sample

Matching Estimator	Personal Bankruptcy (%)	Conditional Multiple Personal Bankruptcy (%)	Bankruptcy Claim Amount (S$'000)
ONE-TO-ONE MATCHING	-3.153**	-2.734**	-0.212+
	(0.416)	(0.340)	(0.113)
NEAREST NEIGHBORS(n=5)	-2.339**	-3.070**	-0.208+
	(0.182)	(0.345)	(0.119)
NEAREST NEIGHBORS(n=10)	-2.857**	-2.649**	-0.226+
	(0.130)	(0.354)	(0.116)
GUASSIAN	-2.962**	-3.019**	-0.118
	(0.234)	(0.281)	(-0.100)
EPANECHNIKOV	-2.301**	-2.881**	-0.097
	(0.277)	(-0.281)	(-0.117)

Table VI. Bias-adjusted matching

This table provides the estimates of gender difference in different bankruptcy outcomes, which include (A) personal bankruptcy probability (%); (B) conditional multiple bankruptcy probability (%); and (C) claim amount in credit card default cases (S$'000) when we conduct the nearest neighbor matching to create the matched sample. The bias-adjusted matching estimator follows the procedure in Abadie and Imbens (2006, 2011) and corrects the asymptotic bias present in simple matching estimators. The standard errors for the estimated treatment effect is derived from the nonparametric method in Abadie and Imbens (2015) and reported in last column. The matching estimators include cases when N=1, 5, and 10. + denotes P < .10; * denotes P < .05; and ** denotes P < .01

Matching Estimator	**Bias-Adjusted Difference**	**Standard Error**
Panel A: Probability of Personal Bankruptcy (%)		
1-to-1 Matching	-2.668**	(0.065)
N=5	-2.672**	(0.064)
N=10	-2.667**	(0.062)
Panel B: Probability of Conditional Multiple Personal Bankruptcy (%)		
1-to-1 Matching	-2.784**	(0.278)
N=5	-2.821**	(0.277)
N=10	-2.900**	(0.283)
Panel C: Bankruptcy Claim Amount for Credit Card Default (S$'000)		
1-to-1 Matching	-0.207+	(0.117)
N=5	-0.137	(0.115)
N=10	-0.116	(0.106)

Table VII. Gender gap in personal bankruptcy risks

This table shows the Logit regression results estimated using the full resident samples (2,332,378). The dependent variable is represented by a dummy on personal bankruptcy event, which has a value of 1, if an individual in the full resident is bankrupt at least one time throughout the sample period; or 0 otherwise. The control variables in the models include age (year), ethnic group dummies that identify the three major races - Chinese, Malay, and Indian, (with the "other" race as the control group), marriage status (1, if an individual is married; and 0 otherwise), and a low income dummy (has a value of 1, if an individual live in public housing flat; and 0 if an individual live in private houses). Location dummies (the first four digits of the postal code) are included to control for other observable and unobservable personal characteristics. We only report the statistics for the interactive variables of the gender and control variables due to space constraints. Standard errors are clustered by location and reported in parenthesis. Estimated odds ratios for the Logit regression are reported in brackets. + denotes P < .10; * denotes P < .05; and ** denotes P < .01

Dependent Variable: Dummy on Personal Bankruptcy Events

Independent Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-1.268**	-0.619**	-1.268**	-1.093**	-1.309**	-1.278**	-1.202**
	(0.014)	(0.028)	(0.016)	(0.021)	(0.016)	(0.014)	(0.034)
	[0.280]	[0.538]	[0.281]	[0.334]	[0.270]	[0.278]	[0.300]
Female*Age		-0.012**					
		(0.021)					
		[0.988]					
Female*Married			-0.002				
			(0.020)				
			[0.998]				
Female*Chinese				-0.232**			
				(0.029)			
				[0.792]			
Female*Malay					0.238**		
					(0.035)		
					[1.269]		
Female*Indian						0.150**	
						(0.040)	
						[1.162]	
Female*HDB							-0.074*
							(0.035)
							[0.927]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2332378	2332378	2332378	2332378	2332378	2332378	2332378
Pseudo-R^2	0.081	0.082	0.082	0.082	0.082	0.081	0.082

Table VIII. Gender gap in conditional multiple bankruptcy risks

This table shows the Logit regression results. The dependent variable is represented by a dummy on conditional multiple personal bankruptcy events, which has a value of 1, if an individual has at least two or more bankruptcy records during the sample period; or 0 otherwise. The models are estimated using the sub-samples that include individuals with at least one bankruptcy event during the sample period. The control variables include age, ethnic group, marriage status and low income dummy. The detail definitions are in Table 2. Spatial fixed effects (the first four digits of the postal code) are included to control for other observable and unobservable personal characteristics as well as peer effect among neighbors. We only report the statistics for the interactive variables of the gender and control variables due to space constraints. Standard errors are clustered by location and reported in parenthesis. Estimated odds ratios for the Logit regression are reported in brackets. + denotes P < .10; * denotes P < .05; and ** denotes P < .01.

Dependent Variable: Dummy of Conditional Multiple Personal Bankruptcy Events

Independent Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.435**	-0.281+	-0.419**	-0.319**	-0.457**	-0.448**	-0.396**
	(0.038)	(0.167)	(0.065)	(0.071)	(0.042)	(0.039)	(0.106)
	[0.647]	[0.756]	[0.657]	[0.727]	[0.633]	[0.639]	[0.673]
Female*Age		-0.013**					
		(0.003)					
		[0.987]					
Female*Married			-0.034				
			(0.092)				
			[0.967]				
Female*Chinese				-0.152+			
				(0.080)			
				[0.858]			
Female*Malay					0.171+		
					(0.097)		
					[1.186]		
Female*Indian						0.155	
						(0.138)	
						[1.168]	
Female*HDB							-0.046
							(0.116)
							[0.955]
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	60,147	60,147	60,147	60,147	60,147	60,147	60,147
Pseudo-R^2	0.035	0.034	0.036	0.035	0.036	0.035	0.037

Table IX. Gender effect on credit card bankruptcy amount

The table shows the OLS regression results, where the dependent variable is represented by claim amounts (in S$'000) in the credit card bankruptcy events, i.e. for cases involving claim amount that are lower than S$10,000. The models are estimated using the sub-samples that include individuals with at least one bankruptcy event during the sample period. The control variables include age, ethnic group, marriage status and low income dummy. The detail definitions are in Table 2. Spatial fixed effects (the first four digits of the postal code) are included to control for other observable and unobservable personal characteristics as well as peer effect among neighbors. Year fixed effects are also included to control for the time-varying factors. We only report the statistics for the interactive variables of the gender and control variables due to space constraints. Standard errors are clustered by location and reported in parenthesis. + denotes P < .10; * denotes P < .05; and ** denotes P < .01.

	Dependent Variable: Bankruptcy amount(S$K)						
Independent Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.222**	-0.075+	-0.135+	-0.403**	-0.162**	-0.230**	-0.275
	(0.059)	(0.041)	(0.076)	(0.120)	(0.065)	(0.061)	(0.194)
Female*Age		-0.005					
		(0.004)					
Female*Married			-0.204+				
			(0.101)				
Female*Chinese				0.221+			
				(0.120)			
Female*Malay					-0.501**		
					(0.156)		
Female*Indian						0.137	
						(0.264)	
Female*HDB							0.050
							(0.197)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13853	13853	13853	13853	13853	13853	13853
Adjust-R^2	0.311	0.311	0.312	0.314	0.314	0.311	0.313

Table X. Explore the risk channel – occurrence of motor accidents

The table studies the underlying channel for the gender gap in bankruptcy risk. Panel A presents the univariate difference-in-difference result for bankruptcy event conditional on gender and the occurrence of motor accident. Panel B reports the second-stage regression results of the IV estimation as in Table 2-4. The dependent variables are D(personal bankruptcy), Dummy(multiple personal bankruptcy) and bankruptcy claim amounts (in S$'000) in the credit card bankruptcy events, i.e. for cases involving claim amount that are lower than S$10,000. The endogenous variable is the dummy for female and IV is the occurrence of motor accident. The control variables include age, ethnic group, marriage status and low income dummy. The detail definitions are in Table 2. Spatial fixed effects (the first four digits of the postal code) are included in all specifications and year fixed effects are in Column 3. For Column 1 and 2, the marginal effects (dy/dx) are presented in brackets and calculated as the discrete change in expected value of the dependent variable as the dummy variable changes from zero to one. Standard errors are clustered by location and presented in parenthesis. + denotes P < .10; * denotes P < .05; and ** denotes P < .01

Panel A Personal Bankruptcy Risk and Motor Accidents

	Male	Female	Difference(%)
With Motor Accident (%)	6.73	3.24	3.49^{**}
Without Motor Accident (%)	3.37	1.04	2.33^{**}
Difference (%)	3.36^{**}	2.20^{**}	1.16^{**}

Panel B Instrumental Variable Estimation 2nd Stage Regression Result

	(1)	(2)	(3)
Female (IV)	-1.424^{**}	-0.728^{**}	-0.315^{+}
	(0.001)	(0.011)	(0.170)
Control	Y	Y	Y
Spatial FE	Y	Y	Y
Year FE	N	N	Y
N	2332378	60,147	13,853
Pseudo-R^2	0.022	0.019	0.060

Panel C Instrumental Variable Estimation 2nd Stage Regression Result - Non-married Sample

	(1)	(2)	(3)
Female (IV)	-1.801^{**}	-0.644^{**}	-0.298^{*}
	(0.003)	(0.017)	(0.150)
Control	Y	Y	Y
Spatial FE	Y	Y	Y
Year FE	N	N	Y
N	1185135	28,629	6,897
Pseudo-R^2	0.027	0.026	0.050

Table XI. Gender gap and time intervals in bankruptcy procedures

This table shows the OLS regression results, where the dependent variable is represented by the time intervals (in days) between different bankruptcy proceedings, which include statutory demand, petition and hearing. Three different stages are estimated: stage 1- between statutory demand and petition; stage 2 – petition and hearing; and full period – statutory demand and hearing. The models are estimated using the sub-samples that include individuals with at least one bankruptcy event during the sample period. The control variables include age, ethnic group, marriage status and low income dummy. The detail definitions are in Table 2. Spatial fixed effects (the first four digits of the postal code) are included to control for other observable and unobservable personal characteristics as well as peer effect among neighbors. Year fixed effects are also included to control for the time-varying factors. Standard errors are clustered by location and reported in parenthesis. + denotes P < .10; * denotes P < .05; and ** denotes P < .01

Dependent variable = Time intervals (in days) between different bankruptcy proceedings			
	Stage 1: Between Statutory Demand and Petition	Stage 2: Between Petition and Hearing	Full period: Between Statutory Demand and Hearing
Independent Variable:	(1)	(2)	(3)
Female	-1.189	-0.944	-0.698
	(7.764)	(0.668)	(10.311)
Age	-0.232+	-0.193**	-0.710**
	(0.120)	(0.049)	(0.166)
Married	3.147	-4.111**	3.952
	(5.281)	(0.910)	(6.406)
Chinese	1.084	-1.635	-3.406
	(4.421)	(2.410)	(5.716)
Malay	1.964	5.121+	7.161+
	(3.761)	(2.670)	(4.109)
Indian	1.268	15.000**	16.778**
	(2.477)	(3.298)	(4.571)
HDB	16.968	-10.316**	17.173
	(15.078)	(1.523)	(24.524)
Spatial FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	28,613	33,362	21,739
Adjust-R^2	0.011	0.011	0.004

Table XII. Gender gap in claim amounts using different cutoffs for credit card bankruptcy events

The table presents results of gender difference in bankruptcy claim amounts when different cut-off values are used to identify credit card default cases. As robustness tests, we use four different cut-off values: S$5,000, S$7,500, S$12,500 and S$15,000. Panel (A) reports the univariate statistics that are computed as the difference in claim amounts (S$'000) in the respective credit-card default samples (sorted by the cut-offs) between female and male samples. The results are further sorted by demographic variables and housing type. Panel (B) shown the claim amount differences (in S$'000) between female and male using post-matching samples. The matched samples are derived using the propensity scores estimated by the Logit regression (Table 2) and also different estimators (one-to-one matching, nearest "n" neighbors matching and kernel matching). We report t-statistics in parentheses, which are calculated using standard errors from the bootstrapping with 50 replications. + denotes P < .10; * denotes P < .05; and ** denotes P < .01.

Panel A Univariate Analysis

	Cut-off	S$5,000	S$7,500	S$12,500	S$15,000
	All	-0.10	-0.17	-0.22	-0.27
By Age	Young	-0.03	-0.28	-0.03	-0.18
	Middle-Aged	-0.10	-0.11	-0.19	-0.27
	Old	-0.66	-0.41	-0.22	-0.35
By Race	Chinese	-0.04	-0.11	-0.08	-0.15
	Malay	-0.27	-0.54	-0.37	-0.39
	Indian	-0.01	-0.16	-0.59	-0.65
By Marital Status	Married	-0.15	-0.33	-0.34	-0.40
	Unmarried	-0.05	-0.02	-0.10	-0.19
By Housing Type	HDB	-0.09	-0.19	-0.24	-0.32
	Non-HDB	-0.10	-0.10	-0.09	-0.42

Panel B Gender difference in Bankruptcy amount (SG$K)

Propensity Score Matching Estimator	S$5,000	S$7,500	S$12,500	S$15,000
ONE-TO-ONE MATCHING	-0.061	-0.093	-0.280**	-0.077
	(1.06)	(1.16)	(2.70)	(-0.71)
NEAREST NEIGHBORS(n=5)	-0.138+	-0.186*	-0.187*	-0.160*
	(1.67)	(1.98)	(2.17)	(2.08)
NEAREST NEIGHBORS(n=10)	-0.129+	-0.147+	-0.154+	-0.110+
	(1.84)	(1.71)	(1.76)	(1.84)
GUASSIAN	-0.096+	-0.14	-0.143	-0.069
	(1.74)	(1.37)	(1.01)	(0.81)
EPANECHNIKOV	-0.099+	-0.148*	-0.111+	-0.124
	(1.89)	(2.02)	(1.68)	(1.35)

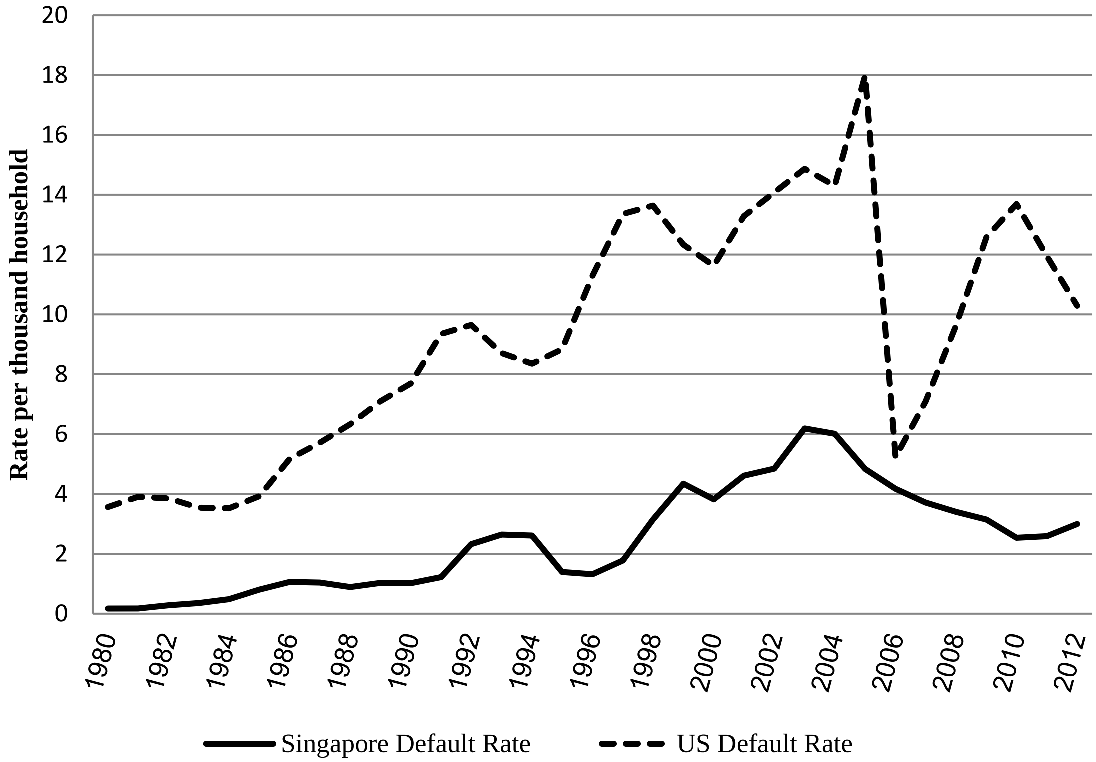


Figure 1. Personal bankruptcy rates in Singapore and US. The figure shows the historical trends in the personal bankruptcy rates of Singapore (darken line) and US (dashed line) for the periods from 1980 to 2012. The time series of Singapore's bankruptcy rates are computed from our data, and the US bankruptcy data are computed using the data on the number of bankruptcy filings from the American Bankruptcy Institutes.

(http://www.abiworld.org/AM/AMTemplate.cfm?Section=Home&CONTENTID=66471&TEMPLATE=/CM/ContentDisplay.cfm)

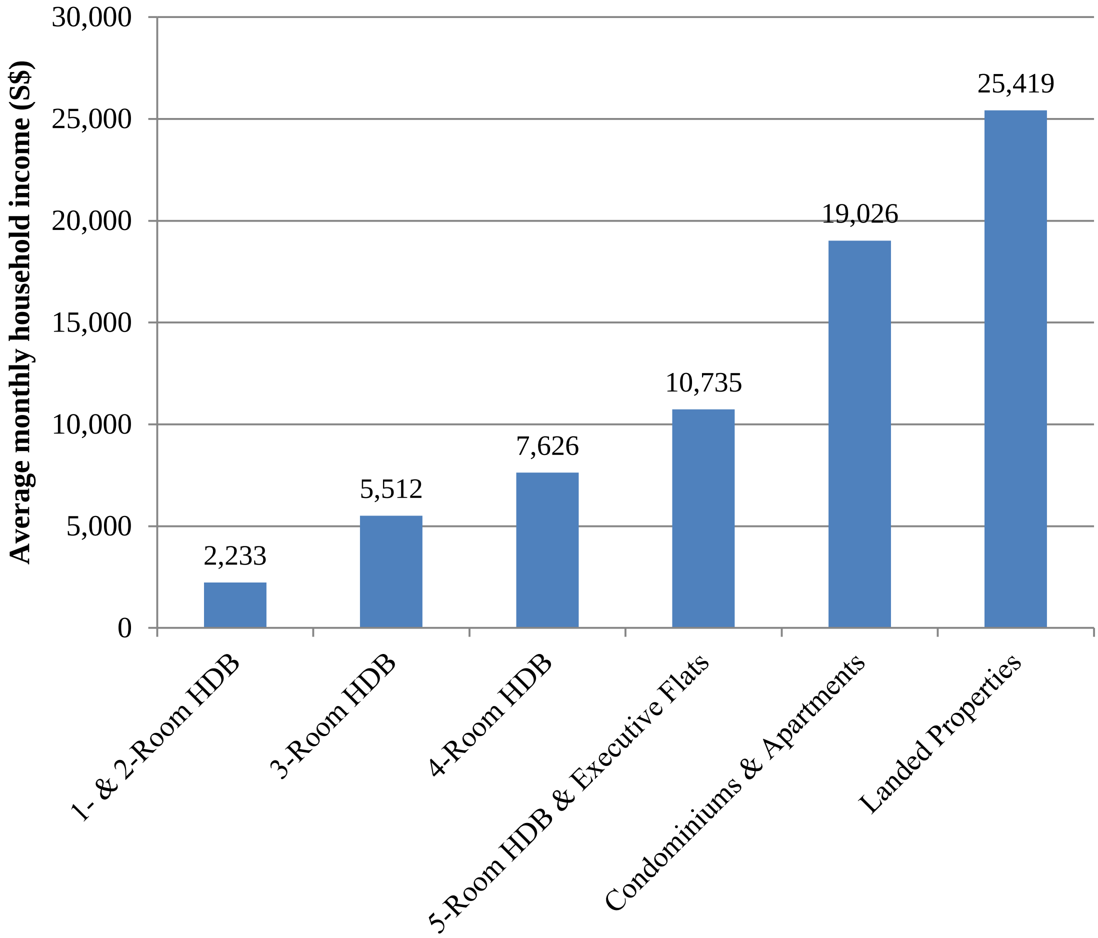
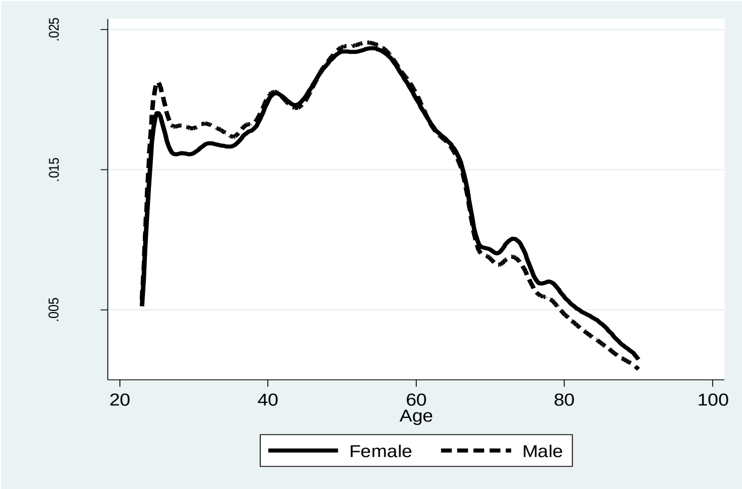
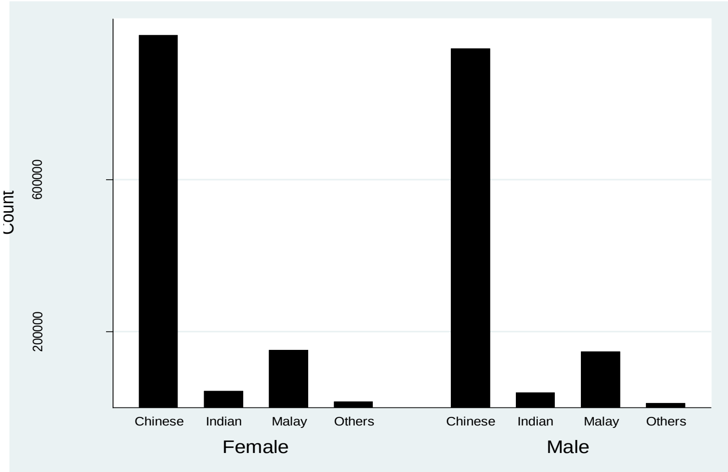


Figure 2. Average monthly household income by dwelling type. The figure shows the average monthly income (in Singapore $) of employed households sorted by dwelling type. The data are obtained from the Census 2010, published by Department of Statistics, Singapore. The public housing (Housing Development Board (HDB) flats) of different types and the private housing consisting of non-landed (condominiums and apartments) and landed housing are shown.

(A) Gender distributions by age



(B) Gender distributions by race



(C) Gender distributions by housing type

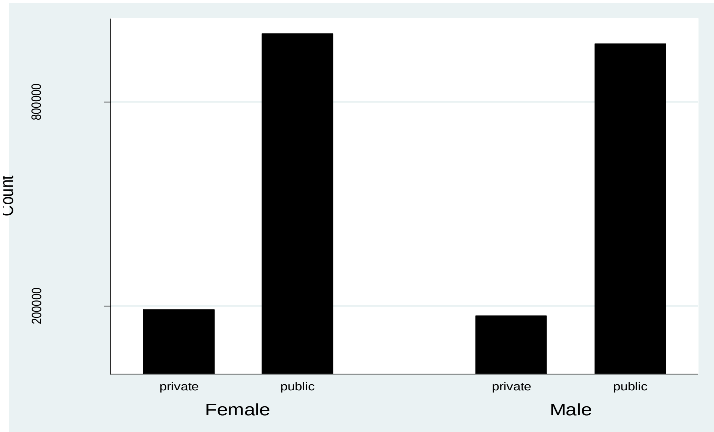


Figure 3. Demographic characteristics by gender**.** The figures show distributions of male and female samples sorted by (A) age (kernel density plot), (B) race (Chinese, Malay, India and others); (C) by housing type, which is identified based on address of the samples. The results are estimated from the full resident sample.

Gender Gap in Personal Bankruptcy Risks: Empirical Evidence from Singapore

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Online Appendix

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Table AI. Propensity score matching using logit regressions

Panel A displays the Logit regression results, where the "Female" dummy variable, which is equal to one if an individual is a female (treatment group); and zero if he is a male, is regressed against demographic and housing control variables. Married is a binary variable that has a value of 1, if an individual is married; and 0 otherwise; and the three different race groups (Chinese, Malay, and Indian) are respectively controlled by the "Chinese", "Malay" and "Indian" dummy indicators, and the reference (control) group in the model is the "other" race group (which include Eurasian and other minority races). For housing type, a "HDB" dummy is included to separate individuals living in public housing ("HDB =1") from those living in private housing ("HDB =0"). We also include the location fixed effects in the model. Column (1) shows the result for the full sample; Column (2) and (3) are estimated using the sub-sample of bankruptcy cases and also the credit card cases (cases with bankruptcy claim amount ≤ $10,000), respectively. The estimated coefficients are shown in the first row, and standard errors are shown in the Parentheses below. The propensity score for the female and male samples are computed from the models and are used in the second stage matching processes. Panel B summarizes the distributions of the differences in the estimated propensity scores between the treatment (female) and the control (male) groups using the one-to-one matching strategy. The mean, standard deviation and percentile values for the difference are reported. + denotes P < .10; * denotes P < .05; and ** denotes P < .01.

A) *Regression Results*

	Dependent Variable: "Female" dummy		
Independent Variable:	(1) Full Sample	(2) Bankruptcy Sample	(3) Credit Card Default Sample
Ln(Age)	0.270**	-0.614**	-1.386**
	(0.004)	(0.048)	(0.346)
Married	-0.132**	-0.181**	-0.282**
	(0.003)	(0.021)	(0.099)
HDB	-0.046**	-0.087*	-0.250
	(0.004)	(0.038)	(0.178)
Chinese	-0.195**	-0.323**	-0.816**
	(0.012)	(0.075)	(0.287)
Malay	-0.181**	-0.097	-0.527+
	(0.013)	(0.078)	(0.310)
Indian	-0.140**	-0.058	-0.588+
	(0.014)	(0.084)	(0.334)
Constant	-0.707**	1.747**	4.594**
	(0.023)	(0.232)	(1.622)
Location Effect	Yes	Yes	Yes
N	23323780	55078	2895
Pseudo-R^2	0.024	0.078	0.025

B) *Differences in Estimated Propensity Score*

	Mean	**Std**	**Min**	**P25**	**Median**	**P75**	**Max**
Full sample	0.000	0.000	0.000	0.000	0.000	0.000	0.003
Bankruptcy Sample	0.000	0.001	0.000	0.000	0.000	0.000	0.002
Credit Card Default Sample	0.000	0.001	0.000	0.000	0.000	0.001	0.016

Table AII. Tests on gender gap in credit allocation and usage

The table examines the gender difference in the credit allocation and usage based on an external credit card data from the largest bank in Singapore (Agarwal and Qian, 2014). We first perform the matching methodology using the nearest neighbor propensity score matching based on available demographics (income, age, ethnic group, HDB, banking relationship, dummy for cell phone and dummy for high education). We focus on the non-married sample to exclude the concern that male is more likely to take the lead in the household financial matters. The dependent variable in Column 1 and 2 are the total credit line (computed as the sum of credit limits granted for all the credit cards within this bank) and monthly credit card spending. Spatial fixed effects are included to control for other observable and unobservable personal characteristics. We include card origination month and month fixed effects in Column 1 and 2, respectively. Standard errors are cluster by the postal code; and t-statistics are reported in parenthesis. + denotes P < .10; * denotes P < .05; and ** denotes P < .01.

VARIABLES	Credit Line	Credit Spending
	(1)	(2)
Female	-313.29	0.76
	(-1.47)	(0.20)
Age	65.01***	-1.26***
	(3.99)	(-3.49)
Income	0.76***	-0.00
	(8.24)	(-0.80)
Chinese	382.11	-2.65
	(0.84)	(-0.25)
Malay	-366.44	13.11
	(-0.66)	(1.07)
HDB	-1,825.29	-46.10
	(-1.16)	(-1.04)
Banking Relationship	41.86	0.51
	(1.35)	(0.62)
Cell Phone	-1,215.40*	12.25
	(-1.68)	(1.42)
D(High Edu)	4,313.77**	-6.17
	(2.35)	(-0.69)
Constant	3,797.09**	-1.55
	(2.57)	(-0.58)
Spatial FE	Y	Y
Origination Month/Month FE	Y	Y
Observations	11,119	207,865
R-squared	0.910	0.347

Table AIII. Gender gap in personal bankruptcy risks of individuals with only single bankruptcy event

This table shows the Logit regression results. The dependent variable is represented by a dummy on personal bankruptcy event, which has a value of 1, if an individual in the full resident is bankrupt at least one time throughout the sample period; or 0 otherwise. The models are estimated using the sub-samples that exclude individuals that have multiple bankruptcy cases during the sample period. The control variables in the models include age (year), race dummies that identify the three major races - Chinese, Malay, and Indian, (with the “other” race as the control group), marriage dummy (1, if an individual is married; and 0 otherwise), and a housing dummy “HDB” that that has a value of 1, if an individual live in public housing flat; and 0 if an individual live in private houses. Location dummies (the first four digits of the postal code) are included to control for other observable and unobservable personal characteristics. We only report the statistics for the interactive variables of the gender and control variables due to space constraints. Standard errors are clustered by location and reported in parenthesis. Estimated odds ratios for the Logit regression are reported in brackets. + denotes P < .10; * denotes P < .05; and ** denotes P < .01.

Dependent Variable: Dummy on Personal Bankruptcy Events							
Independent Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-1.231**	-0.625**	-1.230**	-1.063**	-1.268**	-1.240**	-1.151**
	(0.011)	(0.027)	(0.015)	(0.021)	(0.012)	(0.011)	(0.033)
	[0.291]	[0.535]	[0.292]	[0.345]	[0.281]	[0.289]	[0.316]
Female*Age		-0.012**					
		(0.001)					
		[0.988]					
Female*Married			-0.002				
			(0.021)				
			[0.998]				
Female*Chinese				-0.223*			
				(0.024)			
				[0.800]			
Female*Malay					0.221**		
					(0.027)		
					[1.246]		
Female*Indian						0.151**	
						(0.044)	
						[1.162]	
Female*HDB							-0.089*
							(0.035)
							[0.914]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2326827	2326827	2326827	2326827	2326827	2326827	2326827
Pseudo-R^2	0.078	0.079	0.079	0.078	0.078	0.079	0.079

Table AIV. First-stage regression result

This table reports the first-stage regression results of the IV estimation in Panel B of Table 10. In the first stage of the IV analysis, we regress the female dummy, "D(female)", on the instrument variable (IV), "D(motor)" and other control variables, X:

$$D(Female)_i = \alpha + \beta \times D(Motor)_i + \gamma \times X_i + \delta_j + \varepsilon_i$$

The instrumental variable, "D(motor)", has a value of one, if an individual has had a motor accident, and was the defendant in an bankruptcy event. The control variables, X, include age (year), race dummies that identify the three major races - Chinese, Malay, and Indian, (with the "other" race as the control group), marriage dummy (1, if an individual is married; and 0 otherwise), and a housing dummy "HDB" that has a value of 1, if an individual live in public housing flat; and 0 if an individual live in private houses. Spatial fixed effects (the first four digits of the postal code) are included to control for other observable and unobservable personal characteristics. Standard errors are clustered by location and reported in parenthesis. + denotes P < .10; * denotes P < .05; and ** denotes P < .01.

Panel A Full Sample			
	Dependent Variable = D(Female)		
Independent Var.	D(Bankruptcy)	D(Multiple Bankruptcy)	Claimed Amount
	(1)	(2)	(3)
Instrument Variable:			
D(Motor)	-0.379**	-0.183**	-0.154**
	(0.001)	(0.005)	(0.009)
Controls:			
Age	0.001**	-0.002**	-0.001**
	(0.000)	(0.000)	(0.000)
Married	-0.024**	-0.032**	-0.045**
	(0.000)	(0.003)	(0.006)
Chinese	-0.043**	-0.047**	-0.059**
	(0.003)	(0.014)	(0.024)
Malay	-0.042**	-0.014	-0.015
	(0.003)	(0.015)	(0.025)
Indian	-0.029**	-0.003	-0.031
	(0.003)	(0.015)	(0.027)
HDB	-0.017**	-0.017**	-0.039**
	(0.001)	(0.007)	(0.011)
Spatial FE	Y	Y	Y
Year FE	N	N	Y
N	2,332,378	60,147	13,853
Pseudo-R^2	0.033	0.031	0.026
AR weak-instrument robust test (p-value)	0.00	0.00	0.03

Panel B Non-married Sample			
	Dependent Variable = D(Female)		
Independent Var.	D(Bankruptcy)	D(Multiple Bankruptcy)	Claimed Amount
	(1)	(2)	(3)
Instrument Variable:			
D(Motor)	-0.355**	-0.172**	-0.165**
	(0.002)	(0.007)	(0.014)
Controls:			
Age	0.004**	0.000	0.001*
	(0.000)	(0.000)	(0.000)
Chinese	-0.039**	-0.036*	-0.068*
	(0.004)	(0.018)	(0.034)
Malay	-0.043**	0.026	-0.007
	(0.004)	(0.019)	(0.037)
Indian	-0.022**	0.024	-0.021
	(0.005)	(0.021)	(0.040)
HDB	-0.030**	-0.034**	-0.043**
	(0.001)	(0.010)	(0.015)
Spatial FE	Y	Y	Y
Year FE	N	N	Y
N	1,185,135	28,629	6,897
Pseudo-R^2	0.041	0.027	0.024
AR weak-instrument robust test (p-value)	0.00	0.00	0.04