Overconfidence and Personal Bankruptcy: Evidence from Mispricing in Singapore's Private Housing Markets

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This Version: 31 December 2021

Abstract

This paper examines the mispricing effects in housing markets on bankruptcy risks using a comprehensive dataset merged from various sources, including housing transactions, personal and residence details, bankruptcy filings and lawsuit events in Singapore. We find evidence that mispricing in housing transactions positively impacts bankruptcy risks, but the effects are non-asymmetric and non-linear. Using the policy shocks on liquidity and bankruptcy costs, we find that buyers who underpay in housing transactions respond to the shocks differently from buyers who overpay in housing transactions. When the liquidity shock occurs, buyers who overprice in housing markets are financially distressed and are more likely to become bankrupt. After the bankruptcy costs reduce, buyers who underpay in housing purchases buy multiple houses and undertake risky enterprises, triggering subsequent bankruptcy. The latter aligns with the "overconfidence" channel. Our study implies the importance of avoiding financial mistakes in housing consumption.

Keywords: *Bankruptcy Risks, Mispricing, Housing Markets, Financial Distress, Overconfidence*

JEL Code: D1, G5, R2

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1. Introduction

Bankruptcy associated with default on consumer debts, including mortgages, car loans, credit cards, and others, are usually triggered by adverse financial events (Tabb, 2006)). Mispricing in housing transactions impacts bankruptcy risks of households via different channels. The bankruptcy literature has extensively studied the "financial distress" channel that triggers bankruptcy events (Skiba & Tobacman, 2019; Zinman, 2015). Households with a high debt burden are financially vulnerable to unexpected shocks to income and expenses (Domowitz & Sartain, 1999; Getter, 2003). In comparison, the "overconfidence" channel that induces high risk-taking behaviors of households is relatively under-studied by the literature (Ben-David et al., 2007; Kilborn, 2005; Leng et al., 2021; Malmendier et al., 2011; Manning, 2001). Households who lack self-discipline engage aggressively in activities, such as overspending, credit abuse, and over-investments, and end up filing for bankruptcy when experiencing income shock (White, 1998). "Fresh start" provisions in a more forgiving bankruptcy regime could induce the risk-taking behavior of consumers (Dobbie et al., 2017, 2020; Dobbie & Skiba, 2013; Dobbie & Song, 2015, 2020; Fay et al., 2002; Stiglitz, 1975; White, 1998).

The literature has found a positive relationship between monthly mortgage payments and personal bankruptcy (Agarwal, 2007; Agarwal & Song, 2017). As a "self-discipline device," mortgage debt while accumulating home equity via monthly payments reduces available consumption for the borrower (Fan & Yavas, 2020; Fay et al., 2002; Hurst et al., 1998). Overpaying in housing purchases increases buyers' financial fragility, and a negative income shock could induce financial distress and trigger bankruptcy of the buyers (Hurst et al., 2002; Mian et al., 2013). Underpricing in housing transactions causes "overconfidence" in buyers. Buyers are lax in "self-disciplines" to restrain them from getting involved in overspending, excessive debt, or risky enterprising activities. However, the evidence of underpricing effects on bankruptcy risk is limited in the literature.

This paper empirically examines the effects of mispricing activities in housing markets on personal bankruptcy risks, particularly separating the channels that drive mispricing behaviors of buyers who underpay from those who overpay in housing transactions. We conduct natural experiments using Singapore's housing markets and personal bankruptcy outcomes for three reasons. First, we can merge multiple datasets on housing transactions, personal attributes, residence details, bankruptcy, and lawsuit records via unique identification numbers of individuals in Singapore to obtain clean identifications in the tests. Second, we could use two policy shocks in the difference-in-differences (DID) setup to disentangle the "financial distress" and "overconfidence" channels that drive the mispricing effects in housing markets. The first policy captures the liquidity easing and tightening through the loan-to-value (LTV) limit changes in 2005 and 2010. The second policy coincides with introducing the US-like Chapter 13 option (Dobbie et al., 2017, 2020; Dobbie & Skiba, 2013; Dobbie & Song, 2015, 2020) of Debt Repayment Scheme (DRS) in 2009, which significantly reduces social and financial costs of bankrupt households in Singapore (White, 1998).

Our study covering the period from 1995 to 2012 seeks to investigate three research hypotheses in the bankruptcy and finance literature: 1) Asymmetric mispricing effects in terms of overpricing and underpricing in housing transactions on bankruptcy risks; 2) Differentiated channels that drive overpaying and underpaying housing buyers on their bankruptcy and risk-taking behaviors, and; 3) Impact of liquidity and bankruptcy cost shocks on mispricing responses of overpaying and underpaying buyers in housing markets.

We find that 1) overpricing and underpricing in housing transactions could cause non-linear effects on bankruptcy risks of buyers after controlling for their behaviors using their ethnicity, information advantage, and literacy, other housing attributes. The mispricing effects are stronger at the tailed end, which significantly increases these buyers' bankruptcy risks. 2) Overpricing buyers respond positively to the liquidity shock, whereas underpriced buyers respond to the bankruptcy cost shock. Buyers overpaying their housing purchases may have over-stretched their leverage making them vulnerable to "financial distress" when income shock occurs. However, buyers who underpay in housing transactions are less financially constrained; they behave more aggressively and are over-confident in their spending and investment decisions, triggering bankruptcy when income shock occurs. 3) Buyers who enjoy wealth increases from underpaying in their housing purchases subsequently take more risks by investing in multiple houses and engaging in enterprising ventures. The risk-taking behaviors align with the "overconfidence" channel. However, overpaying and underpaying buyers could still be exposed to financial distress through overleveraging.

This paper makes two contributions to the bankruptcy and finance literature. First, the literature document widely evidence linking financial distress (overpricing in housing transactions) to bankruptcy risks (Agarwal, 2007; Agarwal, Qian, et al., 2021; Agarwal & Song, 2017; Fan & Yavas, 2020; Fay et al., 2002; Hurst et al., 1998, 2002; Mian et al., 2013). However, we find that the underpricing effects increase bankruptcy risks (Ben-David et al., 2007; Kilborn, 2005;

Leng et al., 2021; Malmendier et al., 2011). We also show that overpaying s and underpaying bouse buyers behave differently, and the mispricing effects are non-asymmetric and non-linear. Second, we use two exogenous shocks in the DID setup to show differential responses of overpaying and underpaying house buyers to the liquidity and bankruptcy costs in the markets. We also find evidence that overpaying house buyers take more aggressive spending and investment risks after experiencing housing wealth from underpriced housing purchases. The same effects were muted on buyers experiencing negative wealth shock in their housing purchases. Their bankruptcy is driven more by debt overhang, consistent with the financial distress channel.

The rest of the paper is organized as follows. Section 2 introduces the institutional background of Singapore, mainly focusing on the bankruptcy system, residential property markets, and major policy changes in terms of bankruptcy law and housing credit. Section 3 covers data and empirical strategies. Section 4 discusses empirical design and results on mispricing and bankruptcy, including various robustness and heterogeneity tests, channels, and social and peer effects. Section 6 concludes.

2. Institutional Background

We use two exogenous policy shocks in Singapore in our experiments. The first policy shock involves the new Debt Repayment Scheme that offers an alternative bankruptcy exit to debtors in Singapore, similar to the Chapter 13 Rules of the US. The second policy shock involves changes to the loan to value (LTV) limit from 80% (with effects since 1996) to 90% and the minimum cash down-payment requirement from 10% to 5%.[1] The changes to the LTV and minimum cash down-payment rules are expected to expand credit supply to the housing markets. The two policy shocks allow us to separate the "distress" and the "overconfidence" channels in explaining causal relationships between mispricing in housing markets and bankruptcy risks.

2.1. Bankruptcy Costs in Singapore

Like other Commonwealth countries, such as Australia, Canada, Hong Kong, Malaysia and others, Singapore inherited and encapsulated the UK Insolvency Laws and the UK bankruptcy

[1]Source: Central Provident Fund Board. https://www.cpf.gov.sg/members/News/news-categories-info/cpf-related-announcements/2262

rules into Singapore's Bankruptcy Act (1995) (Chapter 20) (the “BA”). The bankruptcy procedures in Singapore are less forgiving on people adjudged bankrupts before the Debt Repayment Scheme initiated in 2009 and further revisions to the Bankruptcy (Amendment) Act (2015) that came into effect on 1 August 2016.

The revised “BA” 2015 stipulates that a bankruptcy application can be filed either by the debtor or a creditor subject to a minimum debt threshold of S$15,000.[2] For a bankruptcy application by a creditor, a creditor issues a Statutory Demand (SD) to request payments from a debtor. If the debtor fails to make the payments within a stipulated time, 21 days, the creditor could then file a Bankruptcy Application to the Court. A hearing will be fixed approximately 4 to 6 weeks from the filing date. If the payment were still not made before the hearing date, the Court proceeds to issue a Bankruptcy Order against the debtor. Either the Official Assignee (OA) or a Private Trustee-in-Bankruptcy (PTIB) can be appointed to administer the bankruptcy estate and affairs, including selling the bankrupt's assets, verifying claims, and distributing the proceeds to pay off the debt owed to creditors. Any attempt by a bankrupt to sell, transfer or give away his property interests during the period between the bankruptcy application and the Bankruptcy Order shall be void.[3] The Trustee has the discretion to dispose of the bankrupt's property and estates, except for properties protected by the Bankruptcy and Insolvency Act, which include the bankrupt's public housing flat[4], tools of the trade, and general living necessities, and property held in trust for someone else.

Singapore has a strict and more restrictive regime to bankruptcy compared with the bankruptcy system in the US and the UK (Gardner, 2016), There are various restrictions imposed on bankrupts. A bankrupt must keep very strict and accurate records of his expenses. He cannot travel outside Singapore without obtaining permission from the OA (which is generally only provided for work reasons or very extenuating circumstances). He needs to inform a lender that he is bankrupt when obtaining a credit of over S$1,000. He is not allowed to manage a business or act as a company director; and is disqualified from an appointment as a trustee or personal representative.

2 The statutory debt threshold of S$10,000 was defined in the early “BA” 1995.

3 Public housing flats, which were bought either directly from the Housing and Development Board (HDB) or in the resale markets, with at least one Singaporean owner are protected from the creditor. The bankrupts could continue to live in the flats.

4 Public housing flats refer to housing purchased with subsidies from Housing and Development Board (HDB), the government’s agency responsible to provide affordable housing to eligible Singaporean families.

Bankruptcy information is freely available to current and future employers and the general public via the publications in the Government Gazette. Bankruptcy is deemed a "social stigma" in public, and being bankrupt can create difficulties for people when looking for employment.

A significant shift has been made to amend the BA in 2009 to allow a less punitive non-court-based approach for debtors to resolve their debt problems. Modeled after Chapter 13 of the Bankruptcy Code in the USA, the Bankruptcy (Amendment) Bill incorporating a Debt Repayment Scheme (the "DRS") [5] was passed on 18 May 2009. The DRS gives a lifeline to debtors to avoid bankruptcy and social stigma by designing a debt repayment plan that allows a debtor to clear his debt at no additional interest charge levied. The name of a debtor will not be recorded on the bankruptcy register if he discharges the debt obligations according to the plan. However, the OA issues a Certificate of Failure to end the DRS scheme if the debt repayment plan fails.[6] The creditor can then recommence a fresh bankruptcy proceeding against the debtor.

The DRS provides certainty of an exit to bankruptcy to debtors. More importantly, creditors will receive the same debt amount they would have otherwise received in the usual bankruptcy proceedings. The DRS reduces potential bankruptcy costs by encouraging debtors to manage their financial condition without being overly burdened by social pressure and bankruptcy restrictions.

Based on the Statistics of the Insolvency Office, Ministry of Law of Singapore, the annual numbers of bankruptcy applications, bankruptcy orders made, and bankruptcy discharges are shown in Figure 1. The number of bankruptcy discharges fluctuates year by year, with the highest number of discharges of 4574 cases reported in the first year 9 months of 2019. We see a steady decline in new bankruptcy cases as represented by the bankruptcy applications and bankruptcy orders numbers since 2003.

<Insert Figure 1 about here>

[5] Source: Singapore Ministry of Law. Bankruptcy & Debt Repayment Scheme (Alternatives to Bankruptcy). https://www.mlaw.gov.sg/content/io/en/bankruptcy-and-debt-repayment-scheme/debt-repayment-scheme.html

[6] The OA will issue a Certificate of Inapplicability if his debt exceeds S$100,000.

2.2. *Credit supply in Singapore*

Singapore has a dual housing market structure with a large public housing sector and a relatively small private housing sector. About 78.7% of Singapore's residents live in public housing flats built and sold by the Housing and Development Board (HDB), the Government's housing authority.[7] The private housing market serves the housing needs of the balance of 20% Singaporean residents and foreigners. Foreigners can freely own, buy and sell private non-landed housing units[8] without obtaining approvals from the authority. The private non-landed housing market provides 15.9% of Singapore's total housing stock, as reported by Statistics in 2018. This study uses only the non-landed housing transactions in the analyses.

The housing credit is an essential source of liquidity to buyers in the housing markets. The household debt-to-nominal GDP ratio in Singapore stood at around 67.1% as in 3Q2020, and housing loans account for about 76% of the household debts.[9] It is one of the key risk factors affecting the overall financial vulnerabilities. The Monetary Authority of Singapore (MAS), the *de-facto* Central Bank of Singapore, uses various macro-prudential to tightly regulate credit growth and ensure stability in the banking system in Singapore.

During the sluggish housing markets in the early 2000s, the MAS eased the credit restrictions by allowing commercial banks to increase the loan-to-value (LTV) limit from 80% to 90%.[10] The policy applied with immediate effects from 19 July 2005 to private property transactions, either via signing the option to purchase or the sales and purchase agreement on or after 19 July 2005. The policy to change the down-payment arrangement also took effect simultaneously, allowing buyers to fork out a minimum cash payment of 5% down from 10% in a property purchase. The 5% down-payment could be covered using savings in the Central Provident Fund (CPF) account, a compulsory retirement saving scheme for Singaporean residents. The credit easing policies injected new liquidity into housing markets, which resulted

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7 The flats are sold with huge subsidies only to residents, who form a family nucleus comprising at least one Singaporean citizen (SC) or one SC and one Singapore permanent resident (SPR). SC and SC/SPR families must have a combined income of not more than S$14,000 per month.

8 As governed by the Residential Property Act (RPA), private non-landed housing refers to either housing units in a project with a condominium status or in apartments that are above 6-storey in height. Foreigners are not allowed to buy landed housing without permission from the authority, except for designated areas in Sentosa.

9 "Financial Satiability Review, November 2019," Macro-prudential Surveillance Department, Economic Policy Group, Monetary Authority of Singapore.

10 Source: Singapore government. MAS Issues Revised Housing Loan Rules. http://www.mas.gov.sg/News-and-Publications/Media-Releases/2005/MAS-Issues-Revised-Housing-Loan-Rules.aspx

in a strong surge in private housing prices, culminating to the peak prior to the Global Financial Crisis (GFC) shock in 2007. This is used as the credit expansion shock in the study.

The GFC shocks were short-lived, and private housing prices rebounded sharply in 2009. The Government implemented multiple rounds of intervention starting from 20 February 2010 to allay the fear of overheating in the private housing market. The MAS tightened the LTV ratio from 90% to 80% for the first property purchases by Singaporean buyers. The MAS introduced the second round of cooling measures by increasing minimum cash payment on a loan from 5% to 10% and further tightening the LTV ratio for the second property purchases to 70% in August 2010 to weed out speculative activities in housing markets.[11] This is used as the credit contraction shock in the study.

3. Data Sources and Analysis

This study constructs a comprehensive database by merging datasets from five different sources for the empirical analyses. The study periods span from 1995 to 2012. The first dataset contains private housing transactions obtained from the Real Estate Information System (REALIS) of the Urban Redevelopment Authority (URA). This dataset includes 372,367 (297,708) caveat records of non-landed housing transactions (condominiums and apartments) in Singapore from 1995 to 2017.[12] Figure 2 shows the geographical distributions of the housing transactions across the island. The database contains the property-level information, including housing address with zip code, project name, floor, unit number, floor area (in square meter, m^2), transaction price (in SGD$), contract date, land tenure, property type (condominium or apartment), sale type (new sale or resale), and purchaser type (private or HDB).[13] Based on the unique 6-digit zipcode for each project, we calculate the straight-line distance to the nearest amenities, such as schools, hospitals, Mass Rapid Transit (MRT) stations, and the CBD (using the Raffles Place MRT station as the reference point) using ArcGIS.

[11] In the recent interventions implemented on 5 July 2018, the MAS lowers the LTV limits for the first-time homebuyers to 75%, or 55% if the loan tenure exceeds 30 years or the loan period extends beyond the borrower's age of 65. For buyers obtaining a second (third or subsequent) housing loan, the LTV limit is further lowered to 45% (35%) or 25% (15%) if the loan tenure exceeds 30 years or the loan period extends beyond the borrower's retirement age of 65.

[12] The sample period we used for mispricing calculation is extended from 1995-2012 to 1995-2017. Since housing has the dual role of consumption goods and investment assets, individuals who purchase a house at time t is considering both the historical price and future price $t+n$ for estimation.

[13] We verify the transaction data with a private data source on caveat records to obtain the buyers' identities, which are used for the subsequent cross-matching of the transaction data to other four datasets.

<Insert Figure 2 about here>

The second dataset contains information on licensed real estate agents registered with the Council of Estate Agencies (CEA), the watchdog of real estate salespersons and agencies in Singapore. Based on the details of each transaction record, including date, names, and personal identifiers of buyers and sellers, we match the first dataset with the real estate agents database. We identify transactions linked to real estate agents in the matched data.

The third dataset contains information on personal bankruptcy filings at the Supreme Court of Singapore from 1980 to 2012. The detailed records include information on the debtor's identification, creditor's name, debt details (including the claim amount), and the filing date of a statutory demand, petition, and hearing. We match the dataset to the housing transaction dataset with the unique personal identification numbers and identify if a buyer was involved in a bankruptcy case after a housing transaction.

The fourth dataset contains the Court's 532,000 lawsuit records of credit card and mortgage default from 1994 to 2012. The records contain information on the filing date, names and personal identifications of the plaintiffs and the defendants. The lawsuits cover car accidents, sales of goods, credit cards, and tenancy disputes. We use the law event data to identify sellers' and buyers' "financial" status before and after transactions, respectively.

The fifth dataset contains personal information of more than two million Singaporean residents, including a unique identification number, gender, birth date, race, and marital status. The dataset allows us to match the demographic details to the datasets on housing transactions, bankruptcy, credit card, and mortgage defaults. We connect the above datasets accurately based on a unique identification number assigned to each individual. The final matched sample size covers the period from 1995 to 2012, but the housing transaction sample from 2013 to 2017 has no buyers' details. [14]

Table 1 shows the summary statistics for different mispricing measures. Figures 3(a) and 3(b) show the distributions of the personal bankruptcy rate and number by calendar year and property purchase year. Figures 3(c) and 3(d) show the time interval between bankruptcy hearing and discharge. The average time between bankruptcy hearing and discharge is about

[14] However, the dataset with the buyers' and sellers' details are not available after 2012, due to the removal of the details at the source. More details will be discussed in the section on mispricing measurement.

3.8 years. We find significant temporal variations in bankruptcy outcomes and time between housing purchases and bankruptcy discharges over the sample period.

<Insert Table 1 about here>

<Insert Figure 3 about here>

4. Empirical Strategy and Results

4.1. Mispricing in housing markets

We use the propensity score matching (PSM) approach to select comparable records from the full sample based on the structure, neighborhood, and location attributes, as well as transaction time. This process is necessary for property markets exposed to frequent supply-side policy interventions. Following (Deng et al., 2012) approach, we set the first quarter of 2006 as the base period and estimate a series of logit models for each subsequent quarter represented by an indicator variable $y_t \equiv (year\_quarter = t)$ as the dependent variable and the structural characteristics as explanatory variables, we use the predicted probability of sale in year-quarter t to match each transaction record to its closest counterpart.

Based on the t-test statistics in Table 2, we find no statistically and economically significant differences in the independent variables between the matched and the original samples. Figure 4 affirms that the characteristics of the original and the PSM matched samples are unchanged over the estimation period.

<Insert Table 2 about here>

<Insert Figure 4 about here>

As the unobserved components could be spatially correlated with both property characteristics and transaction time, we use a semi-parametric locally weighted regression (LWR) model to estimate the spatially-adjusted transaction price:

$$P = \beta \boldsymbol{X} + \sum_k \alpha_k T_k + f(z_1, z_2) + \omega \quad (1)$$

where the dependent variable P is the logarithm of the per square meter transaction price of a housing unit. $\boldsymbol{X}$ denotes a vector of property characteristics, and $\{T_k\}$ denotes a set of dummies for the time-fixed effect. z_1 and z_2 represents the latitude and longitude coordinates of a property. The target selection is based on the transaction volume. More details could be found in (Agarwal, Fan, et al., 2021). We recover and use the error terms ω to measure mispricing in the housing market. Figure 5 shows the distributions of mispricing in housing transactions for the matched sample period from 1995Q to 2012Q4 and the extended period from 1995Q1 to 2017Q4 and respectively.

<Insert Figure 5 about here>

The household finance literature considers mispricing in housing purchases as one possible trigger of bankruptcy. Mispricing, or more explicitly overpricing in housing purchases, causes overconsumption or over-leverage, consequently triggering a buyer's bankruptcy via the financial distress channel (Agarwal, 2007; Agarwal & Song, 2017). However, mispricing-induced bankruptcy is not always a one-sided event. “Underpricing” in housing purchases causes over-confidence in buyers and weakens their financial restraints and self-controls, resulting subsequently in bankruptcy (Ben-David et al., 2007; Kilborn, 2005; Leng et al., 2021; Malmendier et al., 2011; Manning, 2001).

We capture asymmetries in our mispricing measures in two ways. First, we derive the estimated (unconditional) mispricing terms from the LWR pricing model, [“mispricing” = ω], and separate the them based on the mispricing signs: [“overpricing” = ω(+)| ω > 0] and [“underpricing’ = ω(-) | ω < 0]. We then normalize the mispricing measures by transaction price : [“over-ratio” = (ω (+)| (ω > 0)/ P] and [“under-ratio” = (ω(-)| (ω < 0)/ P]. Second, as the mispricing effects are not uniformly distributed, where the effects are stronger at the tail-ends than at the margin, we use the two discrete dummies based on the cut-offs of 0.1 and 0.2 at both tail-ends of the mispricing ratio distributions to represent the mispricing effects.

4.2. Determinants of overpricing and underpricing

Housing purchases and financing decisions require financial literacy and analytics on macro-economic factors, such as interest rate, inflation, opportunity cost, and risk diversification.

Sophisticated buyers exploit information advantages to arbitrage in housing prices and financing options.[15]

To understand determinants for the mispricing in housing markets, we estimate the models where the dependent variable, $mispricing_i$, which is represented by [$mispricing_{i,t+}$ = (ω (+)| (ω > 0)/ P] and [$mispricing_{i,t-}$ = (ω(-)| (ω < 0)/ P],[16] using the transaction-level data and the following model specification:

$$mispricing_{i,t} = \alpha + \beta_1 buyer_{i,t} + \beta_2 housing_{i,t} + \beta_3 seller_{i,t} + \sum_r \delta_r + \sum_t \delta_t + \varepsilon_{i,t} \tag{2}$$

where $buyer_i$ represents buyer's information (such as age, gender, ethnic background, whether a real estate agent-buyer dummy, an investor-buyer dummy, and a mortgage dummy[17]); $housing_i$ represents housing information (such as transaction price and unit area); and $seller_i$ represents seller's information (whether a seller is involved in a law event relating to a car accident, sales of goods, credit card, and tenancy disputes). δ_t and δ_r denote the year-month and region-year fixed effects, respectively; and $\varepsilon_{i,t}$ denotes the *iid* error term.[18]

Table 3 shows that determinants for the overpricing and underpricing outcomes are significantly different, controlling for the time and regional fixed effects.[19] The models reveal the characteristics of buyers who are more likely to overprice or underprice in housing markets. Buyer's ethnicity and information advantage, among all potential factors, predict the overpricing outcome. Chinese buyers relative to Malay and Indian buyers; and real estate agents and investors are less likely to overpay in housing transactions. “Weak buyers” who are

[15] Existing literature suggests that financial literacy, education, and experience are correlated with demographic indicators, such as age (Agarwal et al., 2009) and gender (Van Rooji et al., 2011). Information advantages are exclusive to a selected group of buyers, such as real estate agents (Agarwal et al., 2019) and investors (Clapp et al., 1995). Ethnic-based price differentials are also associated with wealth accumulation, risk attitude or potential discrimination (Bayer et al., 2017; Yinger, 1997).

[16] We estimate the model with [“overpricing” = ω(+)| ω > 0] and [“underpricing” = ω(-) | ω < 0] as the depedenent variables, but the results on the determinants are consistent, but the results are not reported here.

[17] In the absence of LTV information, we use a mortgage dummy in housing purchases to separate financially constrained buyers from wealthy buyers.

[18] The controls of housing unit area, floor, type (condo or apartment, new sale or resale, private purchaser or HDB purchaser, etc.), and neighborhood and location information in the mispricing determinants further adjust for the degree of mispricing orthogonal to transaction prices.

[19] We also estimate the determinants for the mispricing ratios as the dependent variables, and the results are shown in Appendix – Table A1.

liquidity constrained, including those with credit card defaults or tenancy lawsuits, are more likely to overpay in housing transactions. The coefficients on housing price, floor area, and mortgage dummy are significant but opposite in explaining the variations in the mispricing outcomes. Overpriced transactions are more likely to occur in housing units that are smaller in size, more expensive, and with mortgages.

<Insert Table 3 about here>

4.3. Impact of mispricing on bankruptcy risk

Does mispricing in housing purchases have an asymmetric impact on bankruptcy risks? We test the mispricing effects using the overpricing ratio [$\widehat{mispricing}_{i,t+} = (\omega\ (+)|\ (\omega > 0)/ P$] and the underpricing ratio [$\widehat{mispricing}_{i,t-} = (\omega(-)|\ (\omega < 0\ )/ P$] as the control variables separately on the likelihood of bankruptcy.

Suppose a lawsuit involving a "weak seller" at the time of selling their house (either in a case of car accident, sale of goods, credit card, or tenancy dispute) is not likely to impact a buyer's bankruptcy risks but influence housing transaction activities. We adjust for potential endogeneity between mispricing and bankruptcy risks using "weak seller" as an instrumental variable (IV) for the mispricing outcomes. The empirical specifications are written as:

$$Dbankruptcy_{i,t+} = \alpha + \beta_{+}\widehat{mispricing}_{i,t+} + \sum_{x}\delta_{x} + \sum_{r}\delta_{r} + \sum_{t}\delta_{t} + \varepsilon_{i,t} \tag{3a}$$

$$Dbankruptcy_{i,t+} = \alpha + \beta_{-}\widehat{mispricing}_{i,t-} + \sum_{x}\delta_{x} + \sum_{r}\delta_{r} + \sum_{t}\delta_{t} + \varepsilon_{i,t} \tag{3b}$$

where the subscript + (/-) of β denotes over- (/under-) pricing effects, and ($\widehat{mispricing}_{i,t}$) represents the predicted mispricing term derived from the first stage IV model. δ_x is a vector of control variables on buyer characteristics (such as buyer's age, age squared, gender, ethnic background, a real estate agent-buyer dummy, an investor-buyer dummy, and a mortgage dummy) and housing characteristics (such as transaction price and unit area).

If β_+ (β_-) is significant and positive, it implies that buyers who overpay (underpay) in housing transactions face higher bankruptcy risks. While the bankruptcy literature found extensive evidence linking "overpriced" transactions to buyers' financial distress, limited evidence is found on the "underprice" effect on bankruptcy risk. Buyers in underpriced houses are more likely to have more risk-taking behaviors. The "overconfidence" in these buyers is associated with their characteristics that include overspending, debt overhang, and excessive risk exposure.

4.4. Tailed effects of mispricing on bankruptcy risks

The mispricing effects on bankruptcy risks are non-linear but with stronger tailed end effects in the mispricing distributions. In other words, buyers in the highest mispricing quartile are more vulnerable to bankruptcy risks. We run the quantile regression models on Equations (3a) and 3(b) to test the distributional effects of mispricing on bankruptcy outcomes.

Table 4 shows that mispricing has a more salient influence on personal bankruptcy in the higher quartile than the lower quartile. The underpricing event only impacts bankruptcy risks at the highest (fourth) quartile, compared with the overpricing events that significantly affect bankruptcy risks at the third and fourth quartiles. The magnitude of the underpricing shock is substantially stronger than the overpricing shock by more than four times.

<Insert Table 4 about here>

Table 4 (Panel A) reports the IV results that regress the tailed-mispricing dummies on the bankruptcy risks. Based on the quantile regression results, we define the two discrete dummies using the cutoffs at 0.1 and 0.2 of the tailed distributions and use them as the predictors in the IV regressions. At the 0.1 and 0.2 overpricing cutoffs, buyers who overpay in housing transactions face bankruptcy risks between 1.07 and 1.76 percentage points above average buyers. In comparison, buyers who underpay at the tailed-ends of 0.1 and 0.2 of the mispricing distributions face higher bankruptcy risks of between 1.50 and 1.66 percentage points than average buyers.

We conduct the robustness tests by re-estimating the IV regression models using the matched sample derived from the Propensity Score Matching (PSM) approach. The PSM sample is free of selection bias by matching the bankrupt and non-bankrupt household samples based on the observed buyer characteristics (age, gender, ethnicity, real estate agent or investor dummies, and cash dummy). The results in Panel B of Table 5 affirm the early finding that the mispricing effects are not asymmetric. The coefficients on the underpricing and overpricing terms are significant and positive. After correcting the potential sampling bias problems, we find that underpricing in housing purchases significantly increases buyers' bankruptcy risks by 1.79 and 2.06 percentage points, whereas overpricing in housing purchases increases bankruptcy risks by only 0.31 and 0.85 percentage points.

<Insert Table 5 about here>

Overpriced housing transactions increase buyers' monthly mortgage payments, causing them to be more vulnerable to housing debt distresses. Bankruptcy is triggered through the "*financial distress*" channel when they experience negative income shock. However, buyers who cherry-pick bargained purchases at below-market prices are less likely to overleverage housing debt. Motivated by positive income shock, underpriced housing buyers who lack self-discipline tend to overspend and overinvest. The aggressive risk-taking behavior causes these buyers to fall into the bankruptcy trap through the "overconfidence" channel.

We use a machine learning approach, specifically the Gradient Boosting Machines (GBMs) algorithm (More details are found in Appendix B), to derive alternative mispricing measures. We then re-run the IV bankruptcy models and find that the empirical results are robust and consistent, which verify that the findings are independent of the mispricing measures (the results are reported in Appendix – Table A2).

4.5. Heterogeneity and Robustness Tests

We compare the mispricing effects on bankruptcy risks for buyers who either overpay or underpay houses of different attributes: new-sale versus resale, freehold versus leasehold, or central region versus suburban region. Panel A of Table 6 shows that underpricing and overpricing in resale and freehold purchases increase buyers' bankruptcy risks. However, underpricing, but not overpricing, increases bankruptcy risks of buyers of more expensive houses in the central region. This group of buyers is not financially constrained, and they become overly confident and lax in self-disciplines financially after experiencing underpricing events, resulting in bankruptcy.

<Insert Table 6 about here>

Panel B of Table 6 shows the heterogeneity tests on different types of buyers, including between young buyers (below 40 years) versus old buyers, and pre- versus post-independent (after 1965) cohorts of buyers.[20] We find that young buyers and pre-independent born buyers are more likely to bankrupt if they are involved in underpriced housing purchases. Singaporeans born in the post-colonial period had a higher education level, and they grew up during a rapid phase of financial development in the 1970s and 1980s. This cohort of Singaporeans is more prudent in financial management and has relatively lower housing mispricing-induced bankruptcy risk than their older cohort. The results are consistent with the corporate finance literature that finds that younger investors are less conservative and take excessive debts and aggressive investment activities (Andreou et al., 2017).

We also deal with potential selection issues of the bankrupt buyers in Panel C of Table 6, where we sort buyers by unobserved property attributes. From the repeated transaction samples, we identify houses that were persistently overpriced or underpriced in different rounds of transactions (denoted as "quality"), and interact it with the two mispricing dummies (based on the cutoff of 0.2). There is no differentiated mispricing effect on buyers of this housing type.

We further test if selected buyer groups are more prone to bankruptcy risks from housing mispricing experiences. Based on their transaction history, we identify the following sub-groups of buyers: (1) people who overpay (as a buyer) and underpay (as a seller) in two consecutive transactions within six months ("dual-mispricing");[21] (2) those who have credit default history before housing purchases ("default-history"); (3) buyers who upgrade from a public housing flat to a private condominium ("HDB-upgrader"); and (4) buyers who share a close social circle with sellers, based on common last name, race, residence address ("insider").[22] The results show that buyers' unobserved behaviors and past housing-related experiences have no significant impact on the mispricing-bankruptcy relationships.

[20] Singapore separated from Malaysia and gained independent in 1965. The tests on two different cohorts buyers, who was born before and after 1965, to examine their experience in their childhood years on bankruptcy risks of the two cohorts of buyers.

[21] The window size of 6 months is consistent with the Additional Buyer's Stamp Duty (ABSD) rules in Singapore, where buyers simultaneously hold two properties, if they do not sell their current houses within 6 months from a new property purchase, are subjected to ABSD payment.

[22] Related party transactions are usually associated with reciprocity, where sellers may expect other monetary or non-monetary returns from buyers (Nahapiet & Ghoshal, 1998), which weakens the underpricing effects in housing purchases.

We use the post-global financial crisis ("GFC") period to test if bankruptcy risks increase systematically in the adverse economic environment after 2008 but find no significant difference regarding the role of mispricing in bankruptcy along with systematic risks dynamics.

The heterogeneity tests show significant variations in buyers' overpricing and underpricing behaviors that influence bankruptcy outcomes. People who pay below-market prices when purchasing houses in a more competitive resale (non-developers) or more expensive houses are more likely to face bankruptcy risks when negative shock occurs. However, the mispricing-induced bankruptcy effects are orthogonal to other buyers' past housing experiences and behaviors and are not triggered by systematic market shock.

4.6. Difference-in-Differences (DID) tests and liquidity shocks

We set up the difference-in-differences (DID) tests of housing mispricing and bankruptcy risk relationships using two sets of policy shocks. The first set of policy shocks changes the liquidity constraints of buyers in two different periods. The Government loosened the loan to value (LTV) limit from 80% to 90% with effect from 19 July 2005 to help stimulate the sluggish housing markets battered by the various crises, including the dot-com bubble, the 9-11 attack, the SARS pandemic in the early 2000s. A higher LTV limit of 90% increases credit supply that induces buyers to take more debt in housing purchases. These over-leveraged buyers are exposed to "*financial distress*"; if they overpay in housing transactions, they are more likely to face bankruptcy when prices decline.

The Government tightened the loose macro-prudential policy on 19 February 2010, reverting the LTV limit from 90% to 80% after a strong recovery in housing markets after the GFC. The revised LTV limit reduced banks' mortgage quantum to buyers, which in turn curbs the overleveraging behaviors of buyers, especially those who overpay in housing transactions. The LTV policy shocks influence buyers' liquidity, which is more correlated with the "*financial distress*" channel, directly impacting (if significant) bankruptcy risks of overpriced buyers, not underpriced buyers.

We run the DID tests if the liquidity shocks impact bankruptcy risks of overpriced buyers (treatment) more than average buyers (control). If underpaid buyers' bankruptcy was not triggered via the financial distress channel, we should observe no differential bankruptcy outcomes between underpriced buyers and other buyers (control). The DID frameworks with the exogenous shocks on credit easing and tightening are written below:

$$Dbankruptcy_{i,t+} = \alpha + \beta_{+} \widetilde{mispricing}_{i,t+} \times policy_t^{LTV} + \sum_x \delta_x + \sum_r \delta_r + \sum_t \delta_t + \varepsilon_{i,t} \tag{4}$$

where $policy_t^{LTV(2005)}$ has a value of 1 if a buyer purchases a house after the LTV limit easing on and after 19 July 2005; whereas $policy_t^{LTV(2010)}$ has a value of 1 if a buyer purchases a house after the LTV limit tightening on and after 19 February 2010.

We estimate the marginal impact of mispricing (based on the 0.2 tail-end cutoff) on bankruptcy risks and plot the trends in Figure 6. We find no pre-trend effects of the LTV period shock, which were shown by a co-movement pattern between the treatment group (mispriced buyers) and the control group. The post-policy shock trends suggest structural changes to bankruptcy risks of the treatment group relative to the control group after the liquidity easing.

<Insert Figure 6 about here>

The DID results in Panel A of Table 7 affirm the treatment effects of the LTV shocks. We find that after loosening the LTV limit on 19 July 2005, buyers involved in overpriced transactions face a higher bankruptcy risk than buyers who did not overpay in housing purchases, which is consistent with the debt burden hypothesis in Agarwal and Song (2017). However, we find no significant impact of the LTV limit easing on buyers who underpay in housing transactions.

Using the 2010 reversion of the LTV limit as a counterfactual, we repeat the DID tests and summarize the results in Panel B. We find a negative DID coefficient ("mispricing×LTV(2010)"), though insignificant, for the overpricing model, which implies diminishing overpricing effects with a tighter LTV limit. Again, no significant impact is found in the underpriced model.

The DID results align with the financial distress channel, implying that individuals who have overpaid in housing purchases are more prone to liquidity shocks after the Government has loosened the LTV limit in 2005. These buyers who use more debt to finance their overpriced housing purchases are more likely to go bankrupt when negative income shock occurs than other buyers who do not overpay. However, the bankruptcy risk of overpriced buyers is not incrementally higher in a tightened liquidity environment after 2010, when they can use more mortgage loans to finance their overpriced purchases relative to other buyers.

<Insert Table 7 about here>

4.7. DID tests and bankruptcy costs

The second policy shock is on the introduction of DRS to the BA with effect from 18 May 2009. The DRS reduces social stigma and bankruptcy costs, which induce buyers of underpriced housing to engage in high-risk ventures and financial arrangements. Unlike the liquidity shocks that cause bankruptcy through "financial distress," the DRS shock does not increase the debt burden; instead, it promotes the risk-taking behavior of buyes through the "overconfidence" channel. The shock impacts underpriced buyers, not overpriced buyers, who are more likely to bankrupt when negative income shock occurs. We conduct the DID tests on the shock of bankruptcy costs using the following framework:

$$Dbankruptcy_{i,t+} = \alpha + \beta\_mis\widetilde{prici}ng_{i,t-} \times policy_t^{DRS} + \sum_x \delta_x + \sum_r \delta_r + \sum_t \delta_t + \varepsilon_{i,t} \tag{5}$$

where $policy_t^{LTV\,(2009)}$ has a value of 1 if a buyer purchases a house after the DRS introduction that offers an alternative but less punitive exit for debtors after 18 May 2009.

The results in Panel C of Table 8 show that the bankruptcy cost reduction (i.e., following the implementation of DRS) has no significant impact on bankruptcy risks for buyers who have overpaid in housing transactions. However, it significantly increases bankruptcy risks of buyers who have paid below-market values in housing purchases.

We calculate the "distance-to-bankruptcy" defined as the interval between housing purchase date and subsequent bankruptcy filing date (if occurs) and plot the kernel density distributions in Figure 7. Consistent with the mortgage literature, we find a U-shape pattern of the duration between housing purchase and bankruptcy filing with significantly higher bankruptcy risk in the first two years of housing purchases.[23]

<Insert Figure 7 about here>

When started in 2009, the DRS applies to debtors with unsecured debts of not exceeding $100,000.[24] Figure 8 shows a discontinuity in the distributions of unsecured debt at the DRS threshold of S$100,000 before and after 2009. However, we observe the structural break for the underpricing cases, but not for the overpricing cases. The Locally Weighted Scatterplot Smoothing (LOWESS) method also reveals a flat distribution before 2009 and a weak inverted U-curve distribution after 2009, indicating that the bankruptcy risks of underpriced buyers increase when the unsecured debt is within the range of between S$100,000 and S$120,000. In the unsecured debt range of 100% to 120% of the threshold, individuals are lax in self-discipline on financial decisions if they could easily meet the DRS cutoff when bankrupt. In Column (3), we test specifically for bankruptcy cases involving unsecured debt above S$120,000 and find that underpricing buyers still have a significantly higher bankruptcy risk than other buyers.

In general, the DID tests based on both the LTV and DRS policy shocks show significant variations in the treatment effects on the bankruptcy risks of overpriced and underpriced buyers. We find that the less restrictive borrowing policy shock influences bankruptcy risks of overpriced buyers, whereas the bankruptcy cost shock positively impacts the bankruptcy risks of underpriced buyers. The results suggest different channels via which the mispricing impacts bankruptcy risks of the two groups of buyers. Buyers who underpay in housing purchases are not financially distressed. Instead, their bankruptcy outcomes are more likely caused by risk-taking behavior, i.e., they are overly confident with their consumption and investment decisions.

<Insert Figure 8 about here>

23 With the highest density personal bankruptcy risks in the first two years, we use a delayed policy shock, $policy_{t+2}^{DRS}$, that takes a value of 1 if a buyer purchases a house two years before the DRS implementation as a robustness check. The results remain consistent but not reported here due to space constraints.

24 The debt threshold has been increased from $100,000 to $150,000 with effect from 30 July 2020 to allow more debtors to be eligible for the Debt Repayment Scheme. This allows debtors to avoid the stigma of bankruptcy and its restrictions whilst continuing to service their debts.

4.8. Potential channels

We test for potential channels triggering bankruptcy outcomes for buyers who underpay in housing purchases using three events: multiple housing transactions, debt overhang, and enterprise venture. We identify underpriced buyers who either purchase more than one house, overspend on credit cards, or purchase houses via an institution (non-individual buyers). As in (Agarwal et al., 2018), we separate home mortgage and car loan bankruptcy claims from the credit card claims (at below the cutoff of $10,000) and use these home mortgage and car loan bankruptcy cases to represent debt overhang by buyers.

Overpriced buyers are more restrained in spending, investments, and risk-taking decisions. These activities involving overinvestment, overspending, and enterprising risks are not correlated with financial distress-triggered bankruptcy. However, buyers who have the courage and confidence to undertake these activities are likely to be those who have realized positive income shock from the early underpriced housing purchases.

We further test the correlations between mispricing purchases and buyers' spending and investment activities by substituting the dependent variables in Equations 3(a) and (b) with the three dummies on spending and investment. Table 8 shows that individuals who pay below-market prices in housing transactions are more likely to purchase additional houses.[25] These underpriced buyers are more likely to file bankruptcy associated with mortgage debt and car loans but not with credit card default. They are more likely to hold properties through their enterprises. The above behaviors are associated with over-confidence in underpriced housing buyers who experience positive income shocks. They tend to be lax in self-disciplines in financial decisions.

Overpriced buyers are less likely to buy multiple houses and hold these houses through enterprises. We find that they overstretched their debt overhang in home mortgages and car loans that triggered the bankruptcy filing. However, the debt overhang outcome is not inconsistent with the early results showing bankruptcy of overpriced buyers triggered via the financial distress channel.

[25] We run the DID tests using the same dependent variables on spending, debt overhang and enterprise, and the results remain unchanged, and reported in Appendix – Table A3.

<Insert Table 8 about here>

4.9. Neighborhood and peer effects

Finance literature finds that neighborhood and peer effects significantly influence the financial behaviors of mispriced buyers (Agarwal, Qian, et al., 2021). We expect an enhanced mispricing impact on bankruptcy risks if individuals live in neighborhoods with a high degree of social coherence. Social coherence is associated with concentrations of people of the same social-economic type. Based on the demographic dataset, we measure the concentration ratio of households of different races: Chinese, Indian and Malay, and others, at the building level (each building has a unique 6-digit zip code). Figure 9[26] shows the race distributions at the subzone level. Similarly, we estimate the concentration indicators by overpriced and underpriced transactions and by year at the zip code level, denoted by "*neighbor-overpricing*" and "*neighbor-underpricing*."

<Insert Figure 9 about here>

We include an interaction term between mispricing and the concentration indicators in the IV regressions to test if social and peer effects by race (Chinese concentration) and neighbors with mispricing experiences could influence bankruptcy risks of buyers who overpay and underpay in housing purchases. The results in Table 9 show the significant asymmetric impact of social and peer effects in neighborhoods in the overpricing and underpricing models.

<Insert Table 9 about here>

More specifically, underpriced housing buyers in buildings with a higher concentration of Chinese neighbors have higher bankruptcy risks. Underpriced buyers will also face different bankruptcy outcomes depending on their neighbors' mispricing experiences in housing transactions. In buildings with more neighbors overpay in housing purchases, underpricing buyers are more aggressive in their risk-taking activities resulting in higher bankruptcy risks. If more neighbors underpay in housing transactions, underpriced buyers are more restrained in risk-taking activities leading to lower bankruptcy risks. One possible explanation is that the effects of perceived "gains" from underpriced transactions are weakened when the same

[26] To facilitate urban planning, the Urban Redevelopment Authority (URA) divides Singapore into regions, planning areas and subzones. The Planning Regions are divided into smaller Planning Areas. Each Planning Area is further divided into smaller subzones which are usually centered around a focal point such as neighborhood centre or activity node.

outcomes are also observed in other neighbors. In contrast, buyers' confidence in realizing underpricing gains in a building with more neighbors overpricing their houses is more likely to be amplified by social and peer perception. The bankruptcy risk thus increases through the "overconfidence" channel.

However, the neighborhood and peer effects have no significant spillovers to bankruptcy risks of buyers who overpay in housing purchases. The results suggest that the financial distress channel is associated with debt burden of which buyers are less likely to share the information, and their mispricing effect is not affected by social and peer effects.

5. Conclusion

We use the housing market imperfection as one possible cause-link to explain the bankruptcy outcomes of house buyers. Using comprehensive data from multiple sources, including housing transactions, bankruptcy filing records, personal data, and lawsuit events in Singapore from 1995 to 2012, we find significant effects of mispricing in housing transactions on bankruptcy risks in our IV regression model. Unlike the extensive overpricing literature, we find that the mispricing effects are not asymmetric and non-linear, and underpricing housing transactions increase bankruptcy risk. Buyers who underpay and those who overpay are found in different segments of housing markets, and their respective mispricing effects on bankruptcy risk are independent of unobserved quality, past experiences, and selection in housing transactions.

We conducted the DID tests using two policy shocks on changes to the LTV limit in 2005 and 2010 and the DRS implementation in 2009. We find that the easing of liquidity when the LTV limit was raised from 80% to 90% increases the bankruptcy risks of buyers who overpay in housing transactions but has no impact on the bankruptcy risk of buyers who underpay in housing transactions. When the LTV limit was tightened in 2010, we found no significant effects on overpaying and underpaying housing buyers. The asymmetric bankruptcy outcomes in the liquidity expansion period indicate that the two buyers have different response channels to the mispricing events. When we shock the system with the new but less punitive DRS bankruptcy option introduced in 2009, underpriced buyers respond more positively to the ease in bankruptcy costs, increasing their bankruptcy risks relative to other buyers after 2009. The asymmetric responses to the two DID shocks imply that different channels could have driven the bankruptcy outcomes of overpaying and underpaying housing buyers.

The changes to the LTV rules expand the debt burden of buyers, who overpay in housing transactions, which subsequently cause their bankruptcy when negative income shock occurs. The results are consistent with the broader finance literature that argue for the “financial distress” channel. However, the mispricing effects on the bankruptcy risks of underpaying housing buyers are not apparent and less studied in the literature. We use multiple housing purchases, credit overhang, and enterprise ventures activities between underpaying and overpaying housing buyers. Our results show that credit overhang, which is a financially driven cause, has the same and significant impact on the bankruptcy risks of the two buyers. Buyers are more likely to purchase multiple properties and get involved in enterprise ventures after purchasing underpriced houses. The outcomes are unlikely to be linked to the financial distress channel. Therefore, we could not rule out that underpaying housing buyers' bankruptcy outcomes are driven by their “overconfidence” and risk-taking behaviors.

We test if social and peer effects reinforce the “overconfidence” channel using various social cohesiveness measures, including concentrations of neighbors of the same race and neighbors sharing similar housing purchasing experiences in the same buildings. Our results affirm that individuals living in communities with a high social cohesion respond more significantly to underpricing effects. The effects were muted for buyers involved in overpricing transactions.

Our findings contribute to the finance and bankruptcy literature by highlighting the asymmetric effects triggered by two different channels: the financial distress and overconfidence channels. As bankruptcy affects household financial wellness, our results on mispricing in housing purchases reveal the significance of avoiding financial mistakes in consumption and investment commitments. Our results have policy implications in promoting “Fintech” as an automatic evaluation tool to help improve buyers' information discovery process in imperfect housing markets.

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Tables

Table 1 Statistics of mispricing variables (multiple definitions)

		mispricing	overpricing (+)	underpricing (-)
Mispricing: value				
	Mean	37.010	618.467	670.247
	Std. Dev.	936.295	629.289	724.516
Mispricing: ratio				
	Mean	0.010	0.078	0.093
	Std. Dev.	0.130	0.064	0.089
Mispricing: cutoff percentile				
0.1	Mean	0.102	0.102	0.102
	Std. Dev.	0.302	0.302	0.302
0.2	Mean	0.201	0.201	0.202
	Std. Dev.	0.401	0.401	0.401

Note: We consider three types of definitions on mispricing: the continuous measurement of price deviation from the underlying price, the ratio of price deviation to the transacted price, and dummy variables defined by different cutoff percentiles of the continuous measurement.

Table 2 Cross-validation check of sample in our regression

Variables	Explanations	Our sample		Matched dataset		Mean difference
		Obs	Mean	Obs	Mean	
agent	Whether the buyer is a real estate agent	59,104	0.077	13,784	0.074	0.003
male	Whether the buyer is male	59,104	0.608	13,784	0.596	0.012***
Chinese	Whether the buyer is Chinese (race)	59,104	0.938	13,784	0.932	0.006***
age	Age of the buyer	58,867	43.003	13,784	43.463	-0.46***
agesquare	Age square	58,867	1956.177	13,784	2003.103	-46.926***
investor	Whether the buyer is an investor	59,104	0.285	13,784	0.320	-0.035***
mortgage	Whether there is a mortgage originated with the transaction	59,104	0.705	13,784	0.692	0.013***
housingprice	Logarithm of the transaction price of the unit per square meter	58,651	8.838	13,494	8.903	-0.065
housingarea	Floor area of the unit in square meter	59,104	124.623	13,784	128.828	-4.205
car-accident	Weak seller proxy: involved in car accidents before the transaction	54,623	0.106	12,684	0.103	0.003
sale-of-good	Weak seller proxy: involved in sales of goods before the transaction	54,623	0.004	12,684	0.004	0.000
credit-card	Weak seller proxy: involved in credit card defaults before the transaction	54,623	0.009	12,684	0.01	-0.001
tenancy	Weak seller proxy: involved in tenancy disputes before the transaction	54,623	0.004	12,684	0.005	-0.001**

Notes: ** $p<0.05$, *$p<0.1$, *** $p<0.01$.

Table 3 Individual and housing characteristics on mispricing outcomes

	Mispricing: value		Mispricing: ratio	
	Overpricing	Underpricing	Overpricing	Underpricing
	(1)	(2)	(3)	(4)
agent	-0.001	0.000	0.666	5.462
	(0.002)	(0.001)	(9.663)	(10.95)
male	0.002**	0.001	10.04*	7.611
	(0.001)	(0.001)	(5.952)	(6.600)
Chinese	-0.002	0.008***	-18.13	78.400***
	(0.002)	(0.002)	(12.38)	(15.68)
age	0.000*	0.001**	3.831**	5.699**
	(0.000)	(0.000)	(1.937)	(2.303)
agesquare	-0.000*	-0.000*	-0.0397*	-0.0546**
	(0.000)	(0.000)	(0.0208)	(0.0248)
investor	-0.005***	0.004***	-22.72***	30.37***
	(0.001)	(0.001)	(6.893)	(7.631)
mortgage	-0.006***	0.004***	-41.69***	27.01***
	(0.001)	(0.001)	(7.708)	(8.617)
matchedprice	0.250***	-0.130***	709.9***	-1,985***
	(0.003)	(0.003)	(18.77)	(30.79)
housingarea	-0.000*	-0.000***	-0.283***	-2.939***
	(0.000)	(0.000)	(0.102)	(0.132)
car-accident	-0.001	-0.000	-12.20	-4.496
	(0.001)	(0.001)	(8.877)	(9.769)
sale-of-good	-0.001	-0.002	27.40	-41.47
	(0.006)	(0.005)	(37.78)	(50.01)
credit-card	-0.002	-0.005	-9.300	-51.90*
	(0.005)	(0.004)	(30.62)	(31.50)
tenancy	-0.021***	-0.013**	-76.24	-89.26*
	(0.008)	(0.006)	(54.30)	(49.72)
Observations	26,351	27,582	26,351	27,582
R-squared	0.444	0.286	0.413	0.503
Region FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES

Note: This table reports effect of individual and housing characteristics on mispricing outcomes. The dependent variable is mispricing outcomes using continuous indicators (value and ratio). Robust standard errors are reported in parentheses: *** denotes p <0.01, ** denotes p<0.05, and *denotes p<0.1.

Table 4 Asymmetric effect of mispricing on personal bankruptcy (continuous measures)

	Mispricing (value) on bankruptcy		Mispricing (ratio) on bankruptcy	
	Overpricing	Underpricing	Overpricing	Underpricing
	(1)	(2)	(3)	(4)
Panel A: Continous measures				
mispricing	0.001***	0.001**	4.348***	18.200**
	(0.000)	(0.000)	(1.448)	(8.295)
Observations	26,899	27,724	26,899	27,724
Chi2	8.120	4.426	9.014	4.814
Prob > Chi2	0.004	0.035	0.003	0.028
Panel B: Non-linearity				
Quartile 1	-0.000	-0.002	2.928	4.397
	(0.000)	(0.002)	(2.119)	(13.610)
Quartile 2	0.002***	0.000	3.260	10.640
	(0.001)	(0.000)	(3.132)	(7.720)
Quartile 3	0.001**	0.000	3.835**	5.899
	(0.000)	(0.001)	(1.884)	(7.310)
Quartile 4	0.001***	0.001***	3.838***	16.84***
	(0.000)	(0.000)	(0.393)	(4.574)
Control variables	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES

Note: This table reports the effect of mispricing outcomes (using continuous value and ratio measures) on buyer's probability of bankruptcy ex-post based on IV regression (weak seller identifiers as instrumental variables for "mispricing"). Control variables include buyer's information (age, gender, ethnic background, whether the buyer is a real estate agent, whether the buyer is an investor, and mortgage origination) and housing information (the transaction price and transaction area). The dependent variable is bankruptcy filings. Robust standard errors are reported in parentheses: *** denotes p <0.01, ** denotes p<0.05, and *denotes p<0.1.

Table 5 Asymmetric effect of mispricing on personal bankruptcy (cutoff measures)

	Mispricing (0.1 cutoff) on bankruptcy		Mispricing (0.2 cutoff) on bankruptcy	
	Overpricing	Underpricing	Overpricing	Underpricing
	(1)	(2)	(3)	(4)
Panel A: Cutoff measures				
mispricing	1.758***	1.655**	1.069***	1.500***
	(0.627)	(0.841)	(0.334)	(0.472)
Observations	26,899	27,724	26,899	27,724
Chi2	7.870	3.867	10.250	10.110
Prob > Chi2	0.005	0.049	0.001	0.002
Panel B: PSM				
mispricing	0.308*	2.063*	0.850***	1.794*
	(0.162)	(1.152)	(0.267)	(1.015)
Observations	3,971	3,995	6,338	6,344
Chi2	3.599	3.203	10.160	3.124
Prob > Chi2	0.058	0.074	0.001	0.077
Control variables	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES

Note: This table reports the effects of mispricing outcomes (using 0.1 and 0.2 cutoff measures) on buyer's probability of bankruptcy ex-post based on IV regression (weak seller identifiers as instrumental variables for "mispricing"). Control variables include buyer's information (age, gender, ethnic background, whether the buyer is a real estate agent, whether the buyer is an investor, and mortgage origination) and housing information (the transaction price and transaction area). Panel A reports the effect estimated based on the full sample, and Panel B reports the effect based on the restricted sample selected by PSM. The dependent variable is bankruptcy filings. Robust standard errors are reported in parentheses: *** denotes p <0.01, ** denotes p<0.05, and *denotes p<0.1.

Table 6 Heterogeneity in mispricing and bankruptcy (property/buyer attributes and selection)

	Mispricing on bankruptcy	
	Overpricing	Underpricing
	(1)	(2)
Panel A: Property attributes		
mispricing × resale	1.274**	1.214***
	(0.551)	(0.470)
mispricing × freehold	0.733**	1.012***
	(0.343)	(0.346)
mispricing × central	0.009	0.732**
	(0.231)	(0.287)
Panel B: Buyer attributes		
mispricing × young	-0.054	0.783**
	(0.265)	(0.333)
mispricing × pre-independence	1.440***	1.530***
	(0.526)	(0.485)
Panel C: Potential selection		
mispricing × quality	-3.245	0.170
	(3.886)	(0.417)
mispricing × dual-mispricing	0.070	-27.700
	(0.051)	(46.630)
mispricing × default-history	1.598	0.997
	(3.566)	(1.511)
mispricing × HDB-upgrader	0.433	-0.541
	(0.296)	(1.558)
mispricing × insider	0.837*	-1.566
	(0.459)	(1.640)
mispricing × GFC	0.249	0.954
	(0.361)	(0.811)
Control variables	YES	YES
Year-Month FE	YES	YES
Region-Year FE	YES	YES

Note: This table reports the effects of mispricing outcomes on buyer's probability of bankruptcy based on IV regression (weak seller identifiers as instrumental variables for "mispricing"). The dependent variable includes bankruptcy filings, whether the individual purchases additional housing later, whether the debt amount is above S$10,000 (higher probability to be associated with mortgage and car loan delinquencies instead of credit card default), and whether the bankruptcy defendant is an institution instead of a natural person). Control variables include buyer's information (age, gender, ethnic background, whether the buyer is a real estate agent, whether the buyer is an investor, and mortgage origination) and housing information (the transaction price and transaction area). Robust standard errors are reported in parentheses: *** denotes $p<0.01$, ** denotes $p<0.05$, and * denotes $p<0.1$.

Table 7 LTV and DRS policy shock and the effect of mispricing on personal bankruptcy

	Mispricing and bankruptcy		
	Overpricing	Underpricing	Underpricing
	(1)	(2)	(3)
Panel A: LTV loosening (2005)			
mispricing × LTV	0.394***	0.248	0.221
	(0.087)	(0.458)	(0.250)
Observations	23,614	24,825	24,825
Chi2	88.730	28.100	15.610
Prob > Chi2	0.000	0.000	0.001
Panel B: LTV tightening (2010)			
mispricing × LTV	-0.652	1.800	1.330
	(0.435)	(2.088)	(1.284)
Observations	4,035	3,660	3,660
Chi2	32.820	1.075	3.939
Prob > Chi2	0.000	0.783	0.268
Panel C: DRS implementation			
mispricing × DRS	-4.241	1.495***	1.079***
	(4.495)	(0.461)	(0.360)
Observations	26,899	27,724	27,724
Chi2	11.780	19.810	14.270
Prob > Chi2	0.008	0.000	0.003
Control variables	YES	YES	YES
Year-Month FE	YES	YES	YES
Region-Year FE	YES	YES	YES

Note: Panel A reports causality test on the impact of mispricing outcome on later bankruptcy filings through LTV and DRS policy shock based on IV regression (weak seller identifiers as instrumental variables for "mispricing"). The dependent variable in columns (1) and (2) is bankruptcy filings. The dependent variable in Column (3) is whether the total amount of unsecured debt is 20% higher than the upper bound cutoff of DRS requirement (S$100,000 Singapore dollars). Control variables include buyer's information (age, gender, ethnic background, whether the buyer is a real estate agent, whether the buyer is an investor, and mortgage origination) and housing information (the transaction price and transaction area). Robust standard errors are reported in parentheses: *** denotes p <0.01, ** denotes p<0.05, and *denotes p<0.1.

Table 8 Mispricing on risk taking behaviors

	Overpricing on risk taking			Underpricing on risk taking		
	Following purchase	Over S$10,000	Entrepreneur defendant	Following purchase	Over S$10,000	Entrepreneur defendant
	(1)	(2)	(3)	(4)	(5)	(6)
mispricing	0.287	0.158*	-0.058	0.687**	0.731***	0.238*
	(0.249)	(0.088)	(0.043)	(0.336)	(0.253)	(0.132)
Observations	26,899	26,899	26,899	27,724	27,724	27,724
Chi2	1.329	3.199	1.817	4.189	8.371	3.240
Prob > Chi2	0.249	0.074	0.178	0.041	0.004	0.072
Control variables	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES	YES	YES

Note: This table reports the effects of overpricing outcomes on buyers' risk-taking ex-post based on IV regression (weak seller identifiers as instrumental variables for "mispricing"). The dependent variable includes whether the individual purchases additional housing later, whether the debt amount is above S$10,000 (higher probability of mortgage and car loan delinquencies instead of credit card default), and whether the bankruptcy defendant is an institution instead of a natural person). Control variables include buyer's information (age, gender, ethnic background, whether the buyer is a real estate agent, whether the buyer is an investor, and mortgage origination) and housing information (the transaction price and transaction area). Robust standard errors are reported in parentheses: *** denotes p <0.01, ** denotes p<0.05, and *denotes p<0.1.

Table 9 Social and peer effects

	Mispricing on bankruptcy		Underpricing on risk taking		
	Overpricing	Underpricing	Following purchase	Over S$10,000	Entrepreneur defendant
	(1)	(2)	(3)	(4)	(5)
Panel A: Social cohesion					
mispricing × Chinese (%)	0.194	1.383***	0.170	0.577**	0.195
	(0.224)	(0.535)	(0.283)	(0.284)	(0.168)
Observations	26,899	27,724	27,724	27,724	27,724
Chi2	8.987	13.340	5.588	10.76	2.269
Prob > Chi2	0.030	0.004	0.133	0.013	0.518
Panel B: Neighbor effect					
mispricing × neighbor-overpricing	0.009	1.745**	0.634*	0.593**	0.370**
	(0.085)	(0.767)	(0.374)	(0.289)	(0.159)
Observations	26,899	27,724	27,724	27,724	27,724
Chi2	0.968	7.545	71.46	7.679	7.112
Prob > Chi2	0.123	0.056	0.000	0.053	0.068
mispricing × neighbor-underpricing	-0.034	-1.143**	0.559	-0.332**	-0.037
	(0.094)	(0.488)	(0.404)	(0.137)	(0.058)
Observations	26,899	27,724	27,724	27,724	27,724
Chi2	0.803	5.737	79.27	6.951	1.269
Prob > Chi2	0.849	0.125	0.000	0.074	0.737
Control variables	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES	YES

Note: Panel A report test on the impact of perceived mispricing outcome on later bankruptcy filings and risk taking behaviors, including the interaction term of mispricing and the ratio of local Chinese buyers at ZIP code level. Panel B reports the tests on the impact of perceived mispricing outcome on later bankruptcy filings and risk taking behaviors when there is a mispricing outcome in the same building in the follow-up year. It is based on IV regression (weak seller identifiers as instrumental variables for "mispricing"). Control variables include buyer's information (age, gender, ethnic background, whether the buyer is a real estate agent, whether the buyer is an investor, and mortgage origination) and housing information (the transaction price and transaction area). The dependent variable is bankruptcy filings and multiple housing purchases, excessive debt and filing for bankruptcy as entrepreneurial firms. Robust standard errors are reported in parentheses: *** denotes p <0.01, ** denotes p<0.05, and *denotes p<0.1.

Figures

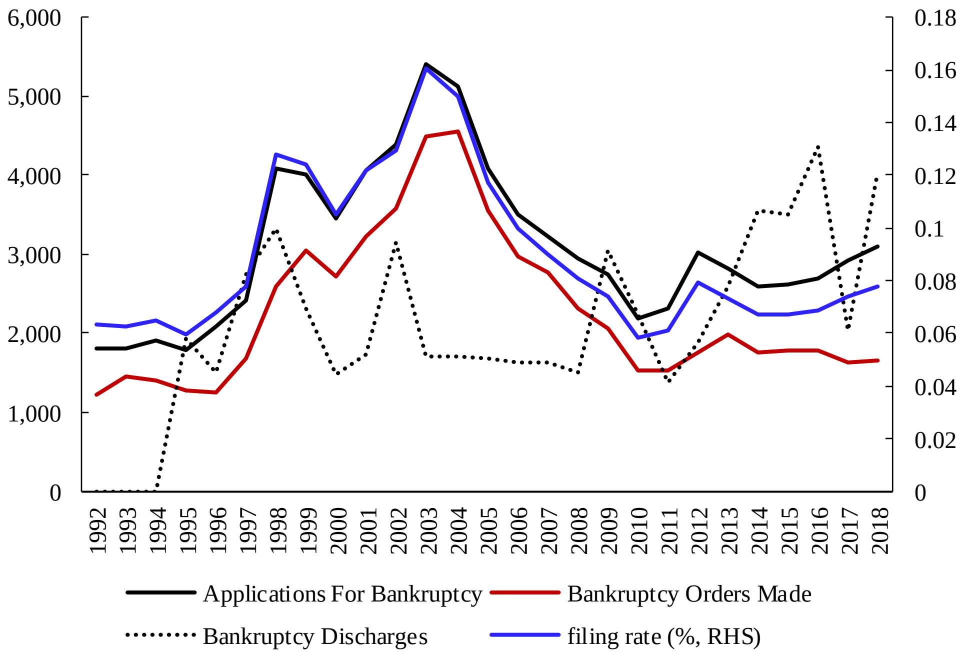


Figure 1 Number of bankruptcy applications, orders made and discharges (annual)

Data source: Insolvency Office in Singapore

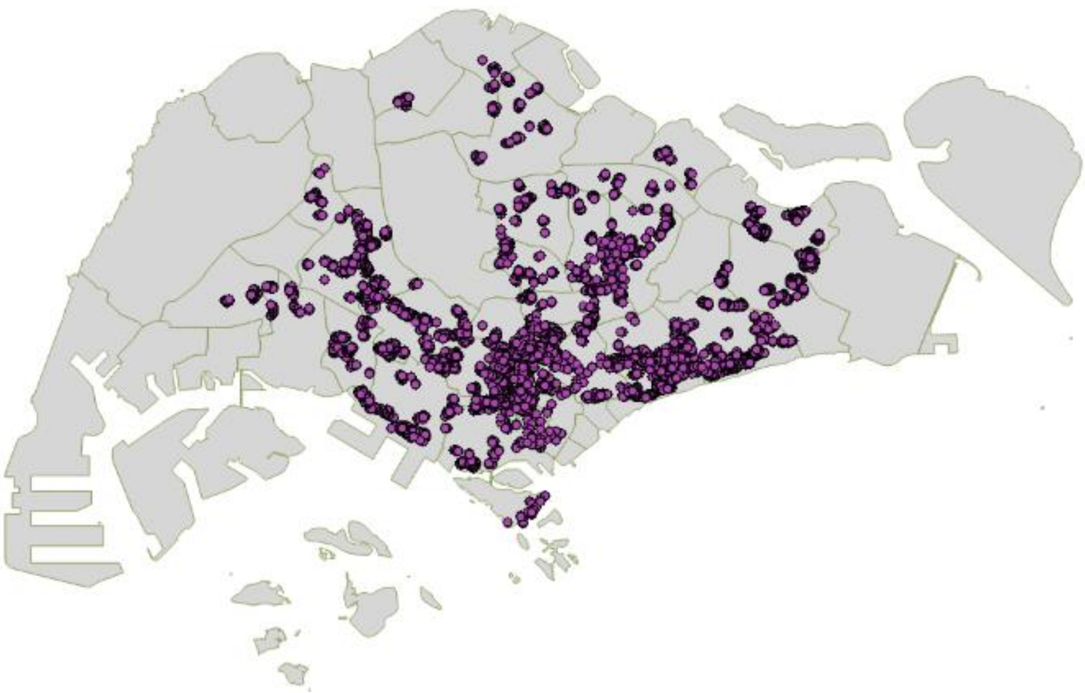
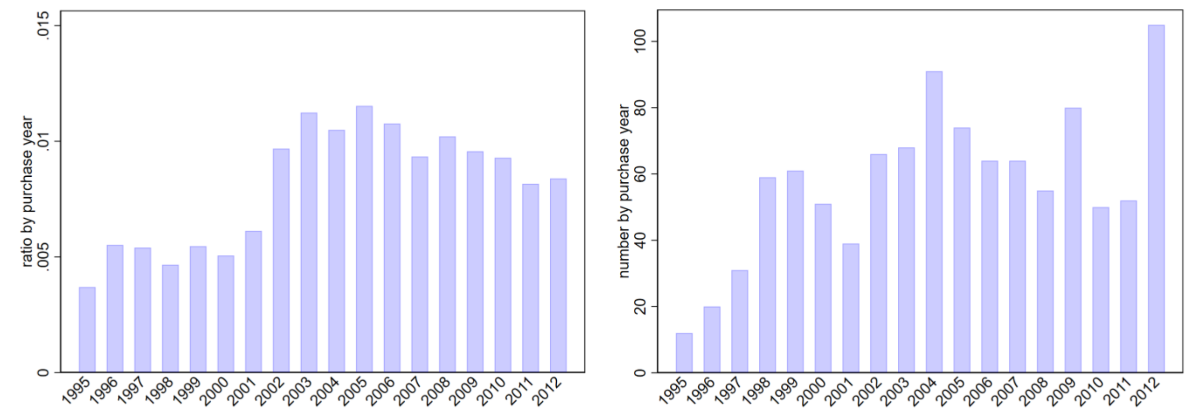
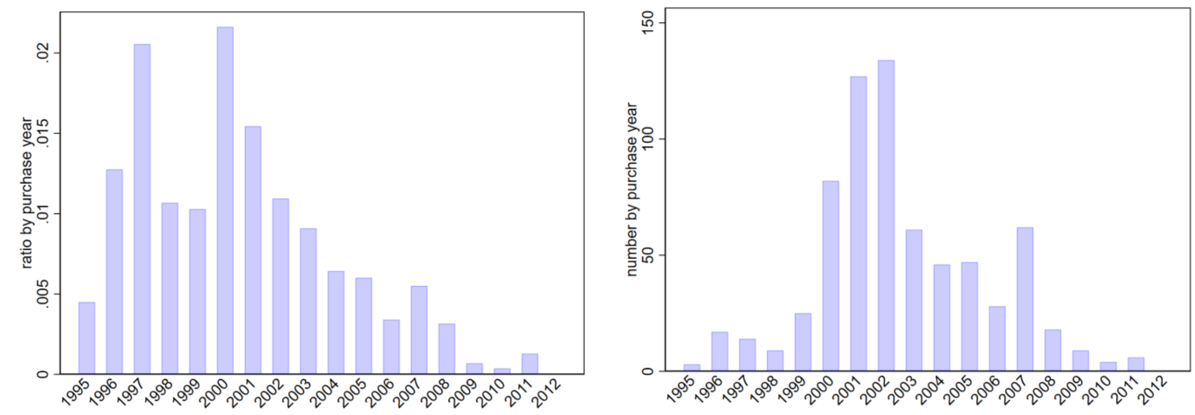


Figure 2 The spatial distribution of transactions (1995-2017)

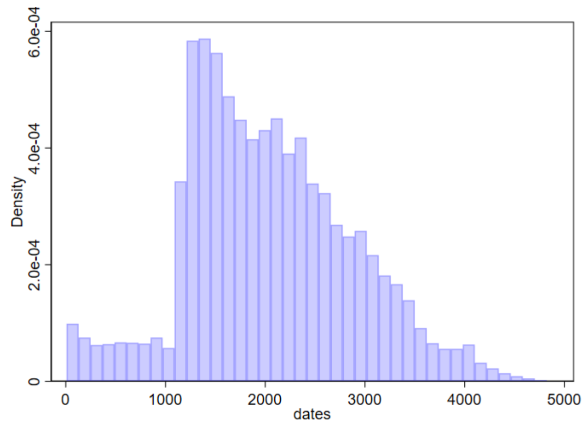
Note: The purple dots denote the private non-landed property (including condominiums and apartments) transaction activities that occurred from 1995q1 to 2017q3 in Singapore. The data are collected from caveat records published by the Government agency, Urban Redevelopment Authority (URA), via the database system known as Real Estate Information System (REALIS).

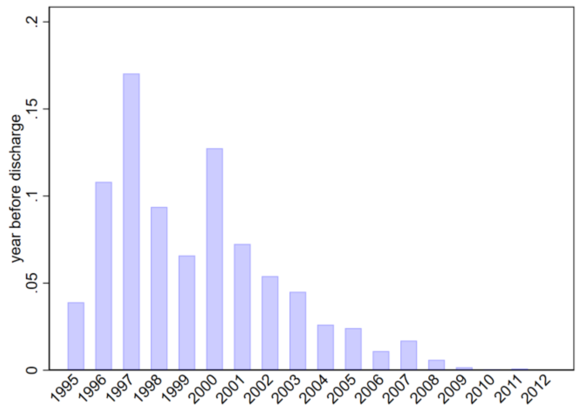


(a) Distribution ratio and number of personal bankruptcy by calendar year



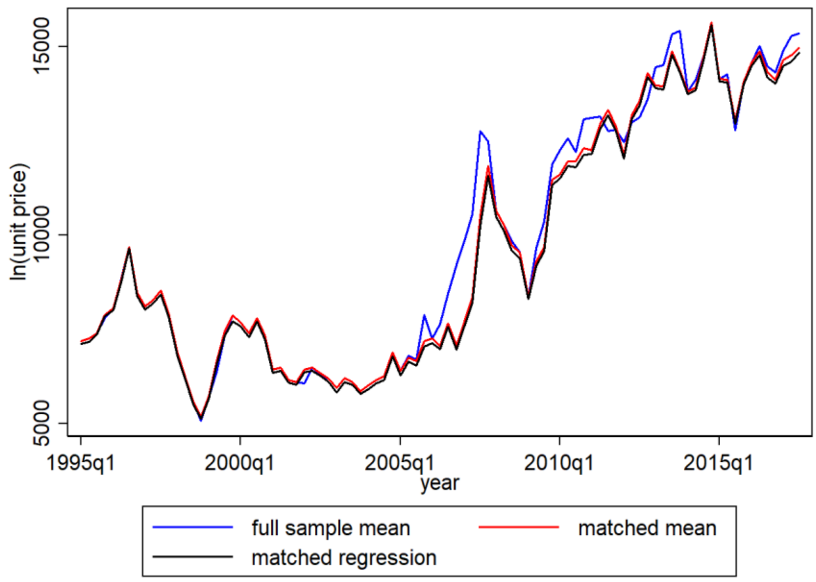
(b) Distribution ratio and number of personal bankruptcy by property purchase year



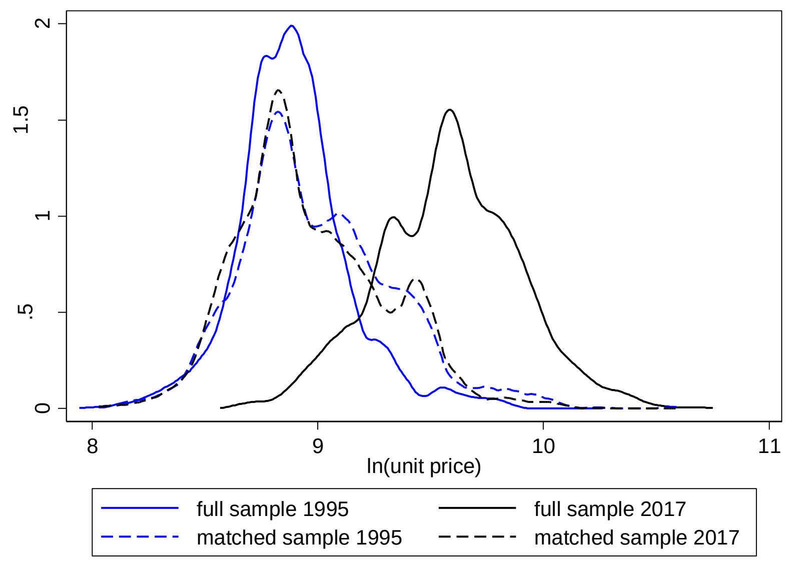


(c) time difference between hearing and discharge   (d) time before discharge by purchase year

Figure 3 Statistics on personal bankruptcy



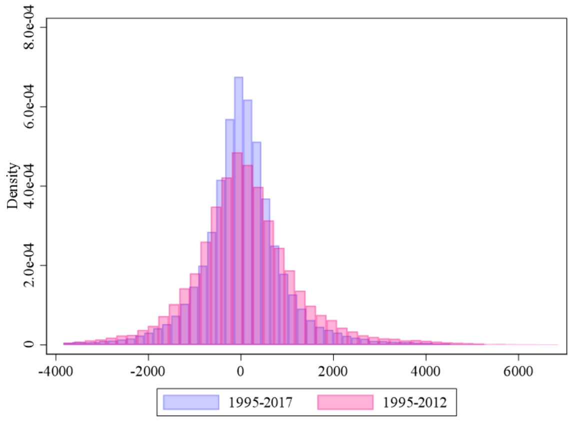
(a) Mean of unit price



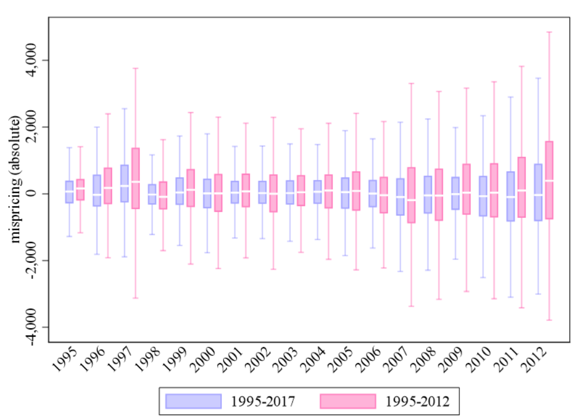
(b) Kernel Density before and after PSM

Figure 4 Comparison between full sample and matched sample

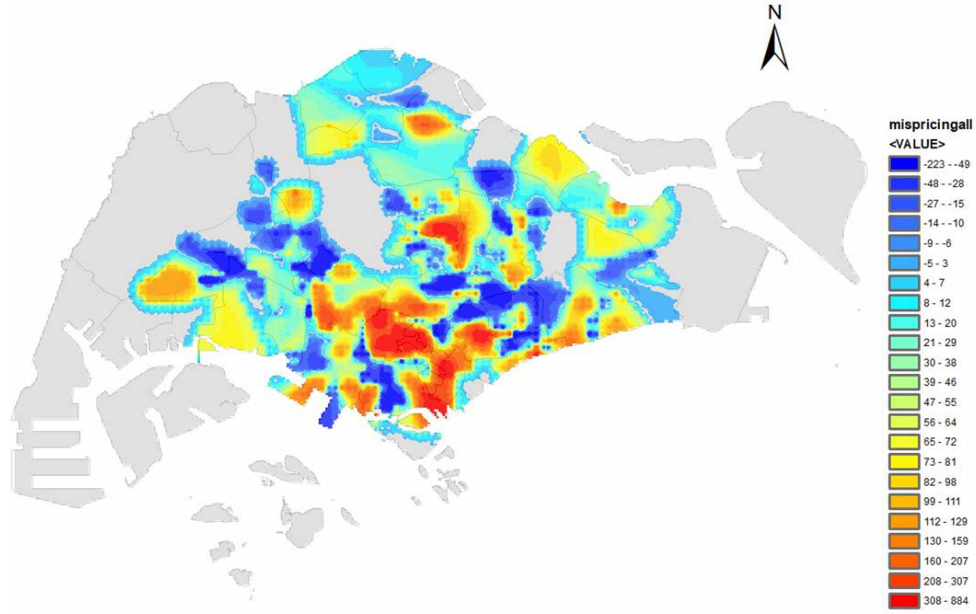
Note: Figure (a) compares the mean unit price for the whole sample, matched sample selected from a PSM process, and estimation based on PSM. Figure (b) shows the kernel density of log-sales prices for the full sample and the matched sample for 1995 and 2017, respectively. The solid curves denote the logarithm of unit price distribution for the whole sample. In contrast, the dashed line curves represent the distribution of the logarithm of unit price for the matched sample extracted based on a probit estimation.



(a) density



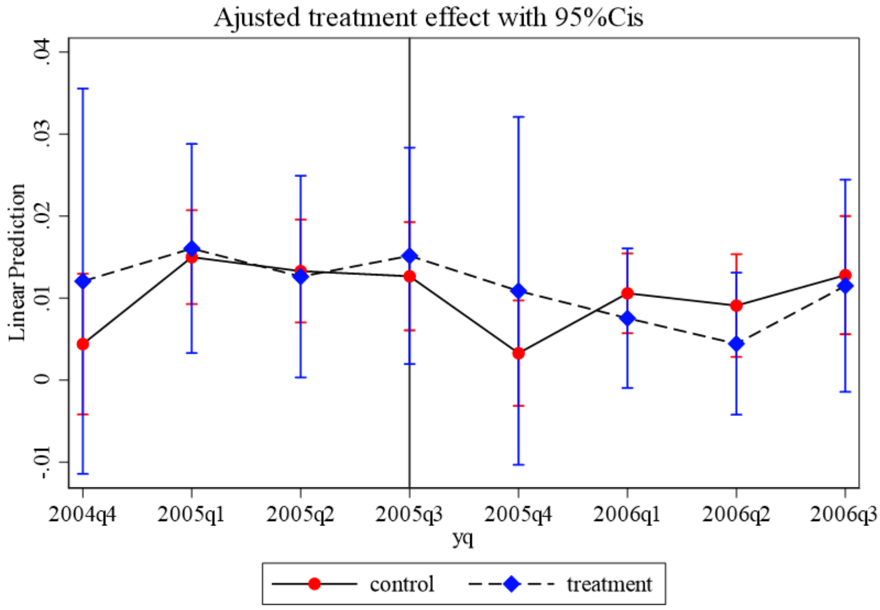
(b) dynamics over years



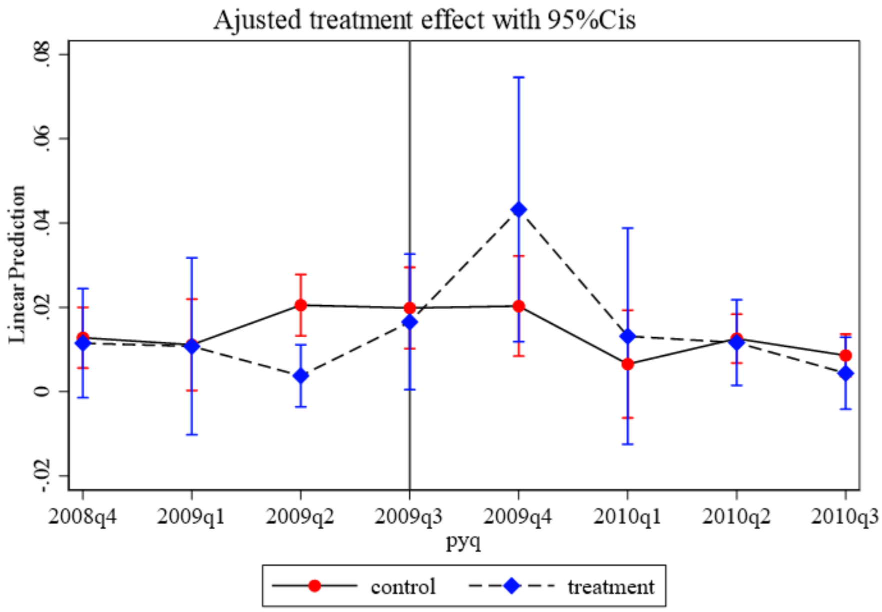
(c) geographic distribution

Figure 5 Distribution of mispricing

Note: Figures (a) and (b) show the overall dynamics distribution of mispricing based on universal transaction records during 1995Q1-2017Q4 and 1995Q-2012Q4. Figure (c) shows the spatial distribution of average regional mispricing in the unit price (quantile).



(a) Pre-trend test for the LTV policy shock



(b) Pre-trend test for the DRS policy shock

Figure 6 Pre-trend parallel test of bankruptcy filings

Note: This figure reports the dynamics of the adjusted treatment effect (using the 0.2 cutoff percentile as treatment identifiers) around the LTV and DRS policy shocks. y-axis is the marginal effect of mispricing on bankruptcy.

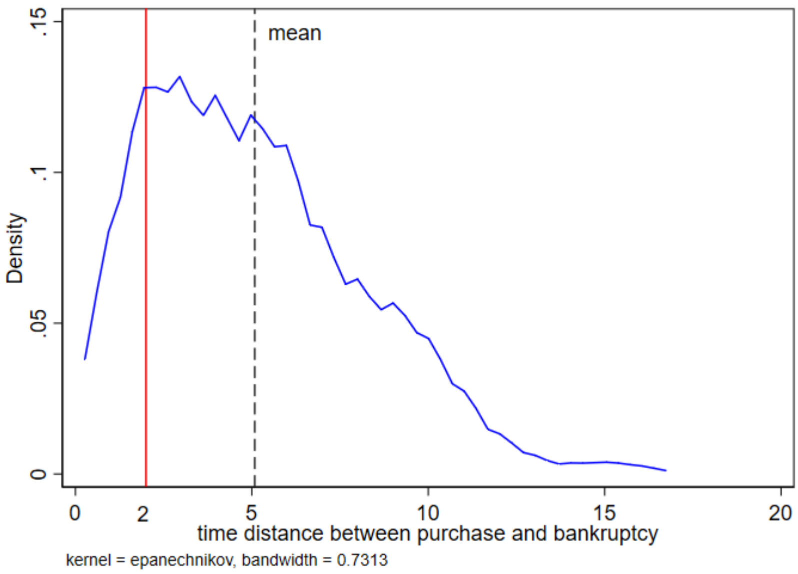
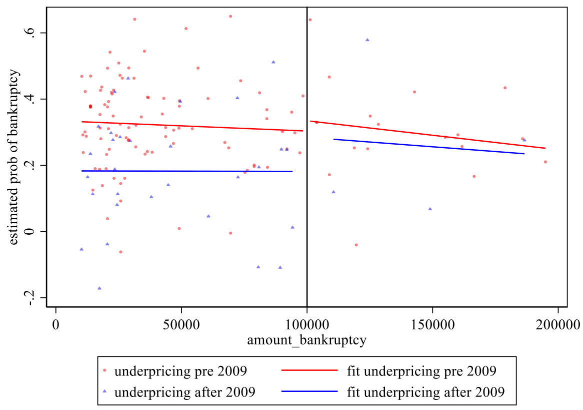
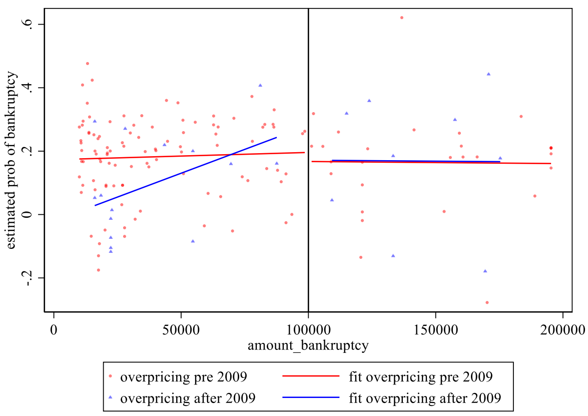


Figure 7 Time distance between housing purchase and personal bankruptcy (in years)

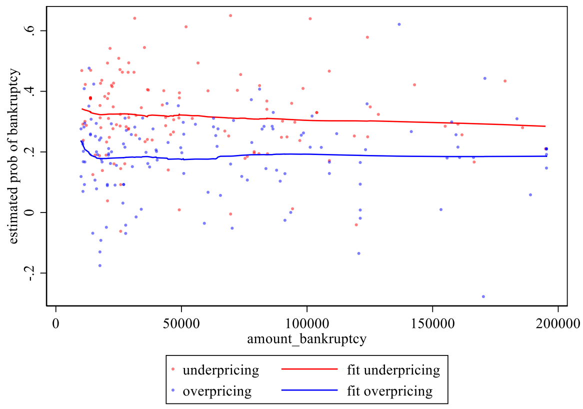
Note: This figure shows the kernel density of the distribution of the "distance-to-bankruptcy," defined as the interval between the purchase date of the housing and the date of subsequent bankruptcy filings.



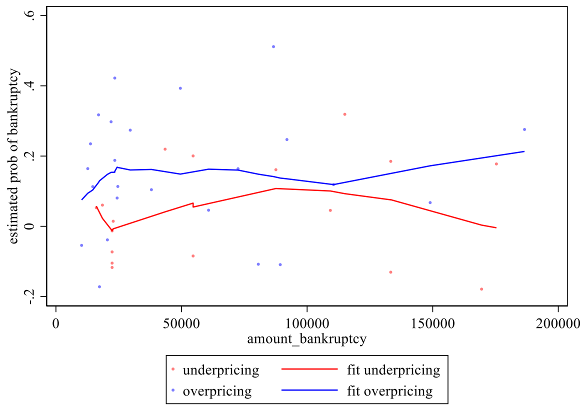
(a) Linear fit (underpricing scenario)



(b) Linear fit (overpricing scenario)



(c) LOWESS fit (pre 2009)



(d) LOWESS fit (after 2009)

Figure 8 Discontinuity of the debt amount

Note: This figure majorly concentrates on the fact that unsecured debts are below S$20,000. Figures (a) and (b) compare the distribution and linear estimation of unsecured debts for the bankrupts before and after 2009, respectively, for the overpricing and underpricing episodes. Figures (c) and (d) show the distribution and its linear estimation of unsecured debts for the bankrupts before and after 2009, based on the Locally Weighted Scatterplot Smoothing (LOWESS) method.

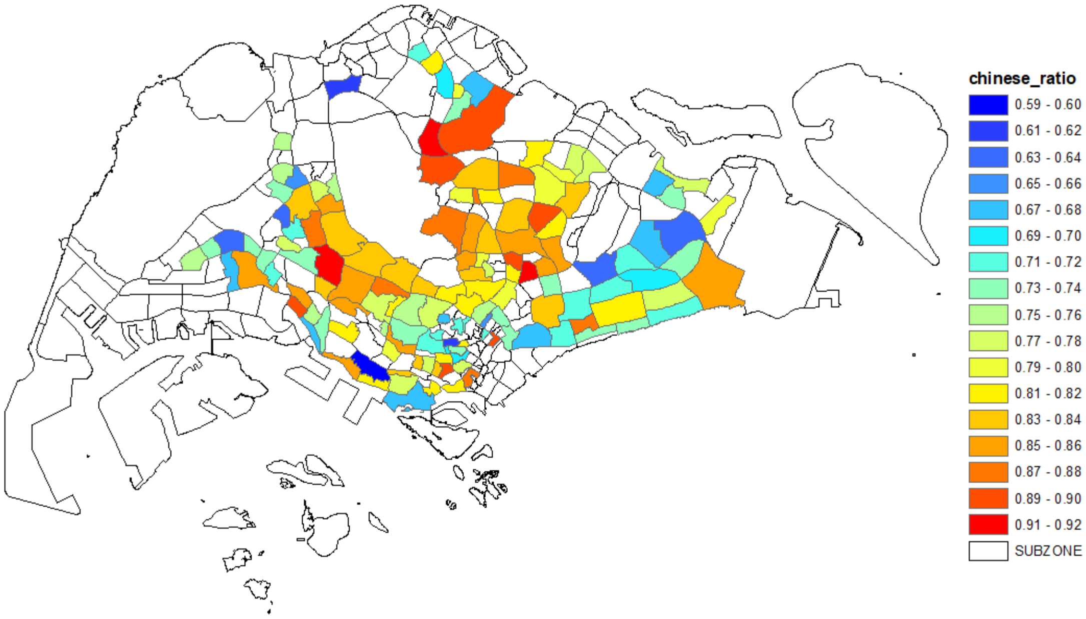


Figure 9 Race distribution by subzone

Note: This figure shows the race distribution by subzone in Singapore. The demographic data reveals four different types of race: Chinese, Indian, Malay, and others. With the knowledge of the exact residence of these people, we establish a homogeneity index using the share of Chinese purchasers (the absolute majorities) for a specific building.

Appendix A

Table A1 Individual and housing characteristics on mispricing outcomes

	Mispricing: 0.1 cutoff percentile (dummy)		Mispricing: 0.2 cutoff percentile (dummy)	
	overpricing	underpricing	overpricing	underpricing
	(1)	(2)	(3)	(4)
agent_buyer	0.000	-0.003	-0.002	-0.008
	(0.005)	(0.006)	(0.007)	(0.007)
male	-0.007**	-0.006*	-0.008*	0.001
	(0.003)	(0.003)	(0.004)	(0.004)
Chinese	0.000	-0.028***	0.008	-0.034***
	(0.007)	(0.008)	(0.010)	(0.010)
age	-0.001	-0.001	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)
agesquare	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
investor	0.008**	-0.012***	0.010**	-0.012**
	(0.004)	(0.004)	(0.005)	(0.005)
mortgage	0.013***	-0.008*	0.027***	-0.014**
	(0.004)	(0.004)	(0.006)	(0.005)
matchedprice	-0.223***	0.608***	-0.485***	0.876***
	(0.012)	(0.014)	(0.015)	(0.015)
housingarea	0.000***	0.001***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
car-accident	0.002	0.001	0.001	0.001
	(0.005)	(0.005)	(0.007)	(0.006)
sale-of-good	0.001	0.044	-0.012	0.074**
	(0.024)	(0.029)	(0.029)	(0.033)
credit-card	0.017	0.007	0.010	0.027
	(0.019)	(0.016)	(0.023)	(0.021)
tenancy	0.028	0.042	0.053	0.127***
	(0.031)	(0.030)	(0.039)	(0.039)
Observations	26,351	27,582	26,351	27,582
R-squared	0.223	0.283	0.264	0.314
Year-Month FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES

Note: This table reports the effect of individual and housing characteristics on mispricing outcomes. The dependent variable is mispricing outcomes using dummy variables based on different cutoff percentiles (0.1 and 0.2). Robust standard errors are reported in parentheses: *** denotes p <0.01, ** denotes p<0.05, and *denotes p<0.1.

Table A2 Asymmetric and policy effect of mispricing on bankruptcy (machine learning)

	Mispricing on bankruptcy	
	Overpricing	Underpricing
	(1)	(2)
Panel A: Asymmetric effect		
mispricing	3.809***	2.078***
	(0.808)	(0.294)
Observations	27,353	24,648
Chi2	22.210	50.020
Prob > Chi2	0.000	0.000
Panel B: LTV policy effect		
mispricing × LTV	1.571***	0.213
	(0.310)	(0.489)
Observations	25,082	19,466
Chi2	74.230	21.260
Prob > Chi2	0.000	0.000
Panel C: DRS policy effect		
mispricing × DRS	0.134	0.824*
	(0.114)	(0.483)
Observations	27,353	24,648
Chi2	98.180	19.190
Prob > Chi2	0.000	0.000
Control variables	YES	YES
Year-Month FE	YES	YES
Region-Year FE	YES	YES

Note: This table reports the tests on the impact of mispricing outcomes identified by machine learning techniques on bankruptcy filings. It is based on IV regression (weak seller identifiers as instrumental variables for "mispricing"). Control variables include buyer's information (age, gender, ethnic background, whether the buyer is a real estate agent, whether the buyer is an investor, and mortgage origination) and housing information (the transaction price and transaction area). The dependent variable is bankruptcy filings. Robust standard errors are reported in parentheses: *** denotes p <0.01, ** denotes p<0.05, and *denotes p<0.1.

Table A3 Mispricing on risk-taking behaviors

	Overpricing on risk-taking			Underpricing on risk-taking		
	Following purchase	Over S$10,000	Entrepreneur defendant	Following purchase	Over S$10,000	Entrepreneur defendant
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: LTV policy effect						
mispricing × LTV	0.116	0.058***	-0.134*	1.197***	0.156	0.124
	(0.521)	(0.009)	(0.069)	(0.344)	(0.220)	(0.098)
Observations	23,614	23,614	23,614	24,825	24,825	24,825
Chi2	697.600	199.000	19.790	194.700	51.490	12.070
Prob > Chi2	0.000	0.000	0.000	0.000	0.000	0.007
Panel B: DRS policy effect						
mispricing × DRS	-2.119	-0.698	-0.630	1.495***	1.079***	0.428*
	(2.236)	(0.780)	(0.727)	(0.461)	(0.360)	(0.237)
Observations	26,899	26,899	26,899	27,724	27,724	27,724
Chi2	4.609	8.662	1.552	19.810	14.270	64.290
Prob > Chi2	0.203	0.034	0.670	0.000	0.003	0.000
Control variables	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES	YES	YES

Note: This table reports the effect of overpricing outcomes on buyer's risk-taking ex-post through LTV and DRS policy shock based on IV regression (weak seller identifiers as instrumental variables for “mispricing”). The dependent variable includes whether the individual purchases additional housing later, whether the debt amount is above S$10,000 (higher probability of mortgage and car loan delinquencies instead of credit card default), and whether the bankruptcy defendant is an institution instead of a natural person). Control variables include buyer's information (age, gender, ethnic background, whether the buyer is a real estate agent, whether the buyer is an investor, and mortgage origination) and housing information (the transaction price and transaction area). Robust standard errors are reported in parentheses: *** denotes p <0.01, ** denotes p<0.05, and *denotes p<0.1.

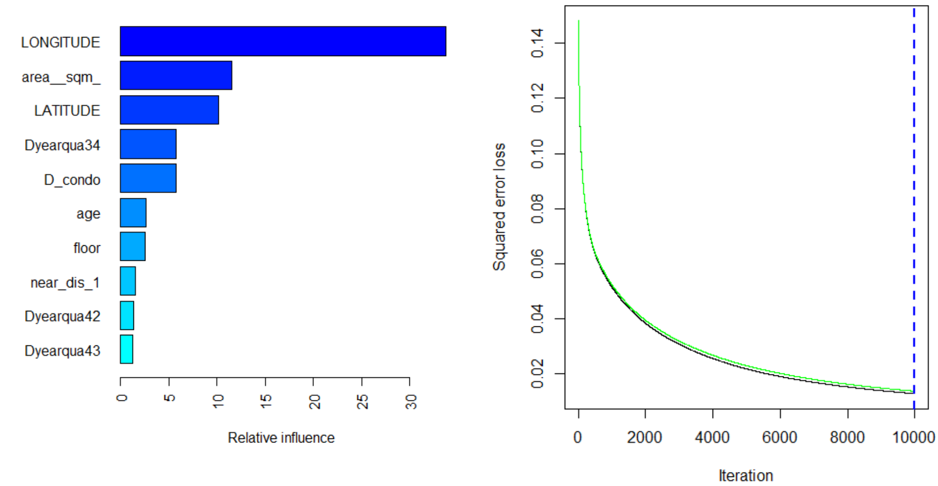
Appendix B: Gradient Boosting Machine (GBM) estimator

Boosted trees are grown sequentially by using information from previous trees. Specifically, we use Gradient Boosting Machines (GBMs) algorithm to build an ensemble of shallow and weak successive trees with each tree learning and improving on the previous. The basic algorithm is as follows.

(1) Fit a decision tree to the data: $F_1(x) = P$
(2) Fit the next decision tree to the residuals of the previous: $h_1(x) = P - F_1(x)$
(3) Add this new tree to the algorithm: $F_2(x) = F_1(x) + h_1(x)$
(4) Fit the next decision tree to the residuals of the previous: $h_2(x) = P - F_2(x)$
(5) Continue the above (2)-(4) process until cross-validation is valid.
The basic algorithm for boosted regression trees can be generalized to the following where the final model is simply a stagewise additive model of b individual regression trees:

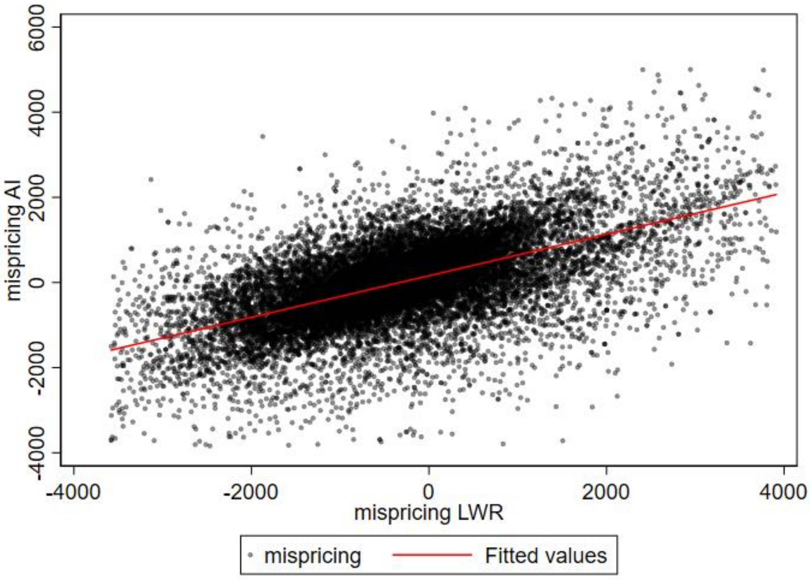
$$f(x) = \sum_{b=1}^{B} f^b(x)$$

GBM procedure as a gradient descent algorithm focuses on the loss function of mean absolute error (MAE). Since the cost function is convex, it measures the local gradient of the loss (cost) function for a given set of parameters and takes steps in the direction of the descending gradient. The key hyperparameters include the number of trees, depth of trees, and learning rate (shrinkage). GBMs can overfit so the goal is to find the optimal number of trees that minimize the loss function of interest with cross-validation. The total number of trees to fit in this study is set to be 10000. The number of splits in each tree controls the boosted ensemble's complexity. We take the depth to be 1 in which case each tree is a stump consisting of a single split. Shrinkage controls how quickly the algorithm proceeds down the gradient descent. Smaller values reduce the chance of overfitting and increase the time to find the optimal fit. The shrinkage in this study is set to be 0.01. For each planning area in Singapore, we run GBM independently. Take planning area Ang Mo Kio as a plotting example; the relative influence of key variables and performance using 5-fold cross-validation is shown in Figure B1.

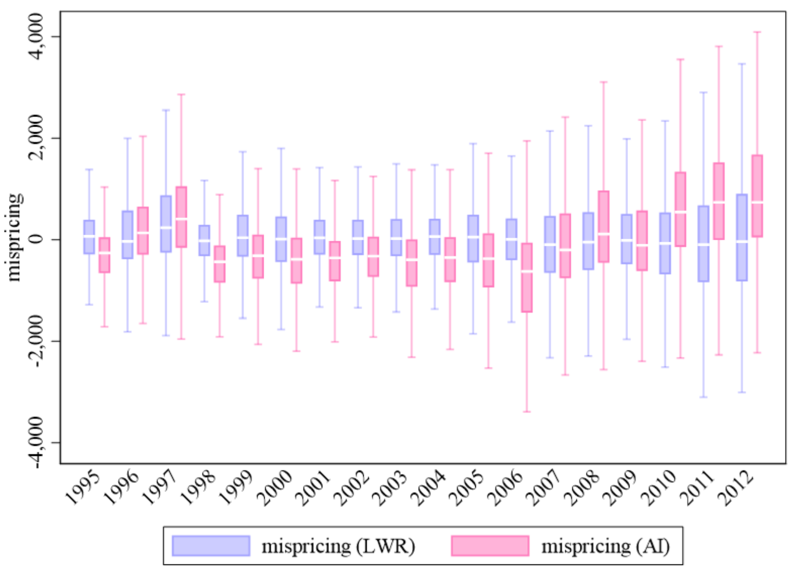


(a) relative influence of key variables (b) performance using 5-fold cross-validation

Figure B1 Estimation evaluation for sample region (Ang Mo Kio)



(a) Correlation of two identifications



(b) Distribution comparison of two identifications

Figure B2 Comparison between different identification of mispricing

Figure (a) shows the correlation of our baseline identification and the estimation based on the GBM algorithm with machine learning techniques. The Pearson correlation coefficient between the two identifications is 0.5859 and statistically significant at 1% level. Figure (b) compares the dynamic distribution of our baseline identification and the alternative estimation based on the GBM algorithm with machine learning techniques. Note: This figure demonstrates a comparison between different identification of mispricing.