Housing Loan Repayment Behaviour in Malaysia: An Analytical Insight

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Abstract

The present study aims to decipher the drivers of default status (no default, single default, double default, and default to good) of 43,156 home-loan borrowers of a large home-loan lender having a national presence during 2003-18. Using the Multinomial Logit model, we analyse the repayment behaviour controlling the borrowers' loan and socio-demographic characteristics. We find house equity, loan, and borrower characteristics, and ability to pay are the key determinants. We also find that both double default and first default are higher at lower growth rates of house prices. Non-linearity and the inflection points in the profile of age, loan age, loan term, payment to income ratio, loan to value ratio, and loan interest rates vis-a-vis loan default status are significant findings. Tapering-off of default due to seasoning beyond a threshold year is notable. The study is the first of its kind, which uses granular data in its analysis, and hence the results would prove immensely beneficial in the policy formulations and managerial decisions.

Keywords: Default Status, Home Equity, Housing Loan Default, Non-Linearity and the Points of Inflection, Multinomial Logit Model

JEL Classification: D14, G21, G28, G32, G33, R20

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1. Introduction

There is a steady rise in the housing loan portfolio of the commercial and Islamic banks in Malaysia. The housing loan by commercial and Islamic banks went up from RM34,460 million in 2000 to RM 2,19,743 million in 2010 to RM4,73,814 million by the end of 2018: recording a nearly 14-fold rise during the period under reference (Monthly Highlights & Statistics, Bank Negara Malaysia, BNM). The housing loan portfolio accounts for nearly 30 percent of banks' total loan portfolio by December 2018 compared to a mere 11.69 percent in the year 2000. Apart from the country's growth profile, the rising level of income, rapid change in the demographic profile of the Malaysian household, and the growth in the working population are the prime drivers of the housing loan demand. Banks responded to this rising appetite for residential housing loans by expanding their asset base in this category. Needless to mention that inherent diversification might have also been the driver of this portfolio growth. Banks responded to this rising appetite for residential housing loans by expanding their asset base in this category. Needless to mention that inherent diversification might have also been the driver of this portfolio growth.

The nudge by the Malaysian government to promote housing for all has undoubtedly been a prime driver of this growth. The rapid rise in the housing loan book also has a fall-out effect on the non-performing loan position in banks' asset books; the NPL in the housing portfolio was as high as 7.53 percent in 2008 (Monthly Highlights & Statistics, BNM). The data for the earlier years are not available. The NPL percentage of housing loan in the total NPL portfolio in the asset book of banks were as high as 30.87 percent in the said year. However, the percentage of NPL in housing loans to total loans went down sharply during the subsequent years down to 1.56 percent in 2016 but started showing a rising trend since then and reached 1.59 percent by the end of December 2018. The NPL percentage in the total NPL percentage of commercial banks correspondingly came down to 21.85 percent by 2016 but then went up again to 24.58 percent by the end of 2018 despite the regulatory initiatives by the Bank Negara Malaysia (BNM) to foster responsible lending by banks. A World Bank stress test estimate (Buncic and Melecky, 2012) had indicated that the median PD and LGD in the housing loan portfolio of Malaysian banks in the event of international stress scenario would be 18.5 and 42.5 percent, respectively.

The above profile of the housing loan portfolio of commercial banks attracted the attention of researchers to decipher not only the drivers of demand for housing loans in Malaysia but also the drivers of default. It is pertinent to mention here that housing studies have been one of the key research areas globally. Many researchers have delved deep into the arena in deciphering the underlying characteristics of the housing market in Malaysia. Nevertheless, to the best of our knowledge, most of these studies were based on time-series data at the aggregate level, and none has attempted to analyse the housing default using granular data. Our study is based on the entire housing loan portfolio data of 43,156 borrowers' data of a large Malaysian housing society having a national presence. We contribute to the literature by identifying the role of home equity, the ability to pay, the loan characteristics, and the borrower characteristics as key determinants of the default status of Malaysian borrowers. Identifying the non-linear relationship between loan defaults, various loan and borrower characteristics, and the inflection points in such relationships are unique contributions of the paper.

Jones and Sirmans (2015) argue that the first-generation studies (1962–1982) are primarily concerned with explaining the behavior of default of individual borrowers, highlighting the effect of loan characteristics and borrower attributes. The findings reported in these studies show that loan characteristics, such as the loan-to-value (LTV) ratio at the time of origination, are the main predictors of housing loan default. The second-generation studies reaffirm the significance of loan characteristics and have modeled default as an option. These studies also include contemporaneous measures of the explanatory variables, including the current loan-to-value ratio and their statistical significance. However, the evidence reported in these studies on the role of borrower attributes, transaction costs, and trigger events is mixed. Third-generation studies (1985–1992) extended the first and second-generation studies through more comprehensive data sets and more sophisticated estimation techniques. The third-generation studies, in general, found that loan characteristics are the key predictors of a mortgage default and the consequent losses. However, the studies which included roles of borrower and characteristics of properties remained inconclusive. Similarly, the significance of both transaction costs and trigger events are not found to be conclusive. Feldman and Gross (2005) find that the borrowers' features, rather than the features of the mortgage contract, are sound predictors of mortgage default.

The objective of our study is to analyse the repayment behavior of the borrowers of housing loans in Malaysia. More specifically, the objectives are: i) to estimate the effect of home equity on the default behaviour of the Malaysian households; ii) to shed light on the mystery of the ability to pay (payment to income ratio) housing loans; iii) to assess the effect of loan characteristics and borrower characteristics on the home loan repayment behaviour in the country. We also analyse the impact of the availability of guarantors on home loan default. We use Multinomial Logit (MNL) model to analyse the repayment behaviour controlling the loan, and socio-demographic characteristics of the home loan borrowers. We stratify our data into four groups: no default at all (no default), default for the first time (first default), default and has defaulted before (default-default), and default previously but currently in non-default status (default-good). We use the State-wise House Price Index from 2001 to 2017 for our analysis.

We present a brief review of literature in Section-2, and in Section 3, we present the data and methodology adopted in our study. The results of our analysis and findings are presented in Section 4, and we draw our conclusions in Section-5.

2. Brief Literature Review

Previous studies on housing loan default focused mainly on the original LTV rather than the current loan to value ratio. Campbell and Dietrich (1983) argued that the two primary drivers of the default decision of the borrowers are the current position of equity of the borrower in the property measured by the LTV ratio and his mortgage payment commitments to the disposable income, which is the ratio of his payment to income. The authors argue that default is inversely related to the difference between the interest rate at the time of origination and the current rate. They also argue that the rise in the spread of interest rates reduces the probability of default. The authors also argue that deterioration in the level of income and the corresponding ability to service mortgage obligations precipitate the incidence of default. According to the authors, rational borrowers will default when their equity position in the home loan has dipped to a level when it is the least-cost option available to them. Hence, default probability is related positively to both the loan to value ratio and the payment to income ratio.

Yang, Buist, and Megbolugbe (1998) use numerical simulations to model CLTV ratios' effect on default. The authors find that default rates increase with the CLTV ratio, and default rates are notably higher at CLTV levels exceeding 90percent. Deng (1997), Ambrose and Capone (1998, 2000), Deng, Quigley, and Van Order (2000), and Ambrose, Capone, and Deng (2001) also report that higher default risk associated with a greater probability of negative equity. Like earlier studies, LaCour-Little (2004), Ghent and Kudlyak (2011), and Archer and Smith (2013) also report that the value of the default option is positively related to the probability of default.

According to the equity theory of default, rational borrowers aim to maximize the equity position in the mortgaged property at any point in time. The ability to pay theory of mortgage default argument is based on cash flows. Alfaro and Gallardo (2012) argue that home loan borrowers would avoid defaulting on their obligation to service the loan up to the point when their cash flow position is sufficient enough to service the instalment without stress. The ability-to-pay theory argues that the probability of default is positively related to adverse shocks to household income. Studies conducted during the period 2000 to 2013 also find that default is positively associated with the unemployment rate. Ambrose and Capone (2000), Deng, Quigley, and Van Order (2000), Noordewier, Harrison, and Ramagopal (2001), Foote, Gerardi, and Willen (2008), Elul et al. (2010), Smith (2011), and Quercia, Pennington-Cross, and Tian (2012) extend the prior studies using data relating to loans originated from the early 1990s to the late 2000s. Consistent with theoretical predictions, they also show that the unemployment rate is positively related to default, and this relation is robust across different geographic regions. Lydon and McCarthy (2013) argue that individual borrower's ability to service mortgage instalment their instalments can be adversely affected by shocks in income or payment. Borrowers stop making payments when the mortgage is in water, i.e., when the market value of the house falls below the outstanding loan balance. There is, however, a consensus that some combination of these two drivers acts as a "double-trigger" in mortgage default. Aron and Muellbaue (2010) argue that in some cases, the effect of negative equity dominates.

Elul et al. (2010) report that both illiquidity and negative equity are significant drivers of mortgage default. The authors also argue that illiquidity and negative equity influence each other. The author argues that, in general, the impact of illiquidity on mortgage default rises with high "combined loan-to-value ratios (CLTV)", though it is also significant even at a low level of CLTV. Quercia, Pennington-Cross, and Tian (2012) estimate the differential impact of the CLTV ratio among households segmented by borrower income. Using moderate-income households as the benchmark, the authors find that the CLTV ratio is positive and significant for the sample of low and very low-income households but is not significant for the extremely low-income households. Qi and Yang (2009) find that the current loan-to-value ratio is the most critical determinant of the loss given default in housing loans. The authors also find that the loss severity is sharper during the period of distress than during the normal conditions in the housing market. However, Vandell and Thibodeau (1985) argue that other factors can overshadow the equity effect on default. The authors note that some households may not default despite having zero or even negative equity, while others default even when the equity position is positive. Campbell and Coco (2015) argue that apart from the extent to which he has negative equity in the mortgage loan, the current low resource constraint of the borrower plays a vital role in determining default.

Bhutta, Shan, and Dokko (2010) argue that one of the key challenges in the mortgage default literature is to estimate the point at which underwater homeowners default in their mortgage payment obligation even when they can service the same. As estimated by the authors, the median borrower stays put until the equity drops to 62 percent of the value of their home as they face the high cost of default and the transaction cost. The authors also show that the combined effect of income shocks and negative equity explains around 80 percent defaults in their sample, but as equity dips below 50 percent, it is negative equity that purely drives half of the default. These findings support both the theory of "double-trigger" of mortgage default as well as the view that home loan borrowers exercise the 'put option' implicit in the loan contract when it suits their interest.

Guiso et al. (2009) estimated that strategic defaults account for 30 percent of the mortgage defaults in the US. It is believed that a substantial position of negative equity drives the choice of strategic defaulters. White (2010), however, argues it is not the negative equity, but the anxiety coupled with a sense of hopelessness and the government's reluctance to help are the prime drivers of default. The survey data by Guiso et al. (2013) show that the propensity of households to mortgage default increases in tandem with the shortfall in home equity both in absolute and in terms of relative size. According to Collins, Harrison & Seiler (2015), the three top determinants of strategic default are negative equity, the growth rate in house prices, and the likelihood that the lender will exercise its legal right to recourse. Wilkinson-Ryan(2011) reports that borrowers with fewer qualms of morality are more likely to default if the economic factors indicate that direction. Seiler (2016) argues that though there is a perception that mortgage default is immoral, the public accepts a borrower in default when he earns a negative or zero return on his investment but not when they default with strategic intent.

Based on the above reviews, three hypotheses are formed. First, home equity has a significant effect on loan default behaviour. Second, the ability to pay has a significant effect on loan default behaviour. Third, other loan characteristics and borrower characteristics have a significant effect on loan default behaviour.

3. Data and Methodology

In this study, we use micro-level data consisting of 43,156 housing loan borrowers from a well-established Housing society with a national presence in Malaysia from 2002-03 to 2016-17[1]. The data was retrieved on October 31, 2017 (data censor date). The data consists of the socio-demographic information of borrowers, loan characteristics, date of first loan disbursement, date of first default, current default status, months in arrears, and locations. The bank defined default as the loan account with three or more than three numbers in arrears in its monthly instalment. Based on the information provided, we classify the default status into four groups. First, no default (never defaulted) from the date of loan disbursement until the data censor date. Second, first default (the default is the first) from the loan disbursement date until the data censor date. Third, default-default (defaulted before) and the current status (as on the data censor date) is default. Forth, default-good (it has defaulted before) and the current status (as on the data censor date) is no default.

It is important to note that the data is not longitudinal. The four default statuses are classified using the date of data extraction, first occurrence, and current loan default. We include the loan duration (the age of a loan) as a control variable to control the censoring bias. In addition, we estimate the survival functions and cox proportional hazard models to evaluate the censoring bias. The Multinomial Logit (MNL) model is employed to estimate the

[1] The data collected from the Building Society cannot be shared due to the ‘non-disclosure agreement’ signed by the authors.

probability of the status of default. Assume that there is a latent variable that represents his or her tendency to default for each borrower. This unobserved tendency of default is associated with the borrower (x_i), loan (z_i) and other (w_i) characteristics. Let y^* represent this latent variable and assume that y^* is a linear function of x, z, and w; then, we obtain the equation (1) as below:

$$y_j^* = \beta' Z + u \quad \ldots(1),$$

where

y_j^* = the unobserved tendency to be employed,

Z = the matrix of variables of borrower, loan, and other characteristics,

u = the error term.

If y is the random variable which represents the four default status, j, of the borrowers, where j=0 if no default, j=1 if first default, j=2 if default-default and j=3 if default-good, and assume that the error is logistically distributed; we have the following MNL model where the Prob(y=0) represents the probability of no default, Prob(y=1) represents the probability of first default, Prob(y=2) represents the probability of default-default, and Prob(y=3) represents the probability of default-good. We can get the maximum likelihood parameter estimates (MLE) by maximizing the log of likelihood function. The model is estimated with the robust variance estimates (Huber/White/sandwich estimator of variance).

4. Analysis and findings

4.1 Sample Profile

Table 1 present the sample profiling by the default status. We find from Table 1 that in terms of age, there are no substantial differences across the default status. On the other hand, the lower PTI, lower loan age, availability of guarantor, lower loan term, lower interest rate, and lower LTV appear to have a relatively higher percentage of non-default than default. Male borrowers are seemingly more default-prone.

Table 1. Profile of Housing Loan Default

Particulars	Overall	Default status			
		No default	First default	Default-default	Default-good
Age at loan disbur. year	35	35	34	34	35
Male	71.40%	69.80%	77.00%	74.90%	71.80%
Married	82.00%	80.60%	79.00%	82.70%	83.40%
Payment-to-income	28.90%	26.90%	28.50%	31.40%	30.30%
Loan duration	3415	3404	3746	3505	3384
Availability of guarantor	56.40%	55.40%	51.40%	54.90%	57.90%
Loan tenure	310	303	326	321	313
Loan interest rate	7.67%	7.27%	8.75%	8.41%	7.83%
Build up area m^2	117	119	116	118	115
Loan to value	89.10%	88.70%	90.20%	89.70%	89.30%
Selangor State & KL	46.10%	45.90%	42.10%	42.70%	47.10%
Malay	64.22%	63.00%	53.54%	63.55%	66.10%
Chinese	6.86%	9.59%	3.04%	2.96%	5.36%
India	12.25%	11.04%	14.18%	13.36%	12.99%
Others	16.67%	16.37%	29.24%	20.14%	15.55%
Gov	20.37%	19.91%	16.93%	19.73%	21.14%
Semi-skilled/skilled	18.04%	17.86%	20.72%	19.34%	17.78%
Management	7.75%	8.30%	5.49%	7.91%	7.41%
Executive	34.40%	34.48%	36.54%	34.53%	34.14%
Non-Executive	6.20%	6.33%	5.42%	5.24%	6.30%
Self-employed	5.77%	5.84%	5.95%	5.76%	5.70%
Eco - inactive/unemployed.	7.47%	7.28%	8.95%	7.49%	7.53%

In terms of ethnic composition, Chinese consists of about 7 percent of our sample. The percentage of no default by Chinese borrowers is around 10 percent, and default-default is only 3percent compared to about 13 percent double default in the case of Indians. Though Malay has a relatively higher percentage of default-good (66.1 percent), double default is also high (63.5percent). The default profile is therefore varied across the ethnic groups in Malaysia. It is not surprising that borrowers in government jobs with a stable source of income are less default prone compared to others. In contrast, skilled and semi-skilled workers with less stable sources of income have a higher percentage of first default and double-default.

4.2 Status of Default of borrowers

The status of default is divided into four categories: no default at all (no default), default for the first time (first default), presently in the status of default and has been in the default status before (default-default), has defaulted earlier but currently in good status (default-good). It can be seen from Table 2 that on the data censor date (i.e., October 31, 2017), about 89 percent of the borrowers are in the no default status; however, 53 percent in this group have defaulted before. On the whole, around 11 percent of the borrowers are in the default status on the censor date. Among this group of default borrowers, 31.69 percent are in the first default status, and 68.31 percent are in the double-default status. We also find that there is heterogeneity in the loan default status across the different regions in Malaysia.

Table 2. Status of default

	Freq.	**%**
a. No default	38,326	88.80
No default at all	*18,101*	*47.23*
Default-good	*20,225*	*52.77*
b. Default	4,830	11.20
First default	*1,530*	*31.69*
Default-default	*3,300*	*68.31*
TOTAL	43,156	100

4.3 Housing price growth and house equity

To view whether the house price index has any role in the default profile of the borrowers, in Table 3, we present the status of default by housing price growth and house equity. We calculate the house equity based on the difference between the original loan amount and the house price that considers the housing price growth (refer to the footnote of Table 3). We find that regions with a relatively low percentage of first default and double default have registered a much steeper rise in the House price index.

Table 3. Status of default by housing price growth and house equity

Particular	**Overall**	**No default**	**First default**	**Default-Default**	**Default-Good**
	Mean	**Mean**	**Mean**	**Mean**	**Mean**
Housing price growth at:					
NPL year[1]	0.8264	n.a.	0.4792	0.6012	0.8894
Data censored (2017)[2]	1.1185	1.1113	1.1937	1.1122	1.1202
House equity at (RM'000):					
Loan disbur. Year[3]	16.1058	17.2833	13.0084	15.9741	15.3109
NPL year[4]	120.4653	n.a.	75.4815	96.3245	127.8142
Data censored (2017)[5]	158.9946	157.3057	166.2143	164.6484	159.0113

Note:
1. Housing price growth at NPL year refers to the borrowers' house price growth at the year of their default in their housing loan (compared to the house price at the year of loan disbursement).
2. Housing price growth at data censor (2017) year refers to the borrowers' house price growth in 2017 (compared to the house price at the year of loan disbursement).
3. House equity at loan disbursement year refers to the difference between house price at the year of purchase and the original loan balance (RM'000)
4. House equity at NPL year refers to the differences between the original loan balance (RM'000) and house price at the year of the loan default (considers the house price growth)
5. House equity at data censor year (2017) refers to the difference between the original loan balance and house price in 2017 (considers the house price growth) and original loan balance (RM'000)

Table 3 also reflects that on an overall basis, the average housing price growth in the NPL year of defaulted borrowers is around 82 percent. By default status, borrowers in the default-good category have the highest average housing price growth of about 89 percent, and in the case of First default and default-default it is about 48percent and 60 percent, respectively. It is found that the house equity as of the loan disbursement year (2017) is around RM16,000. At the NPL year, the equity is also the highest among the default-good (RM12781), whereas the average house equity is around RM12046. This highlights the house equity is a crucial driver in turning the default loan account to good status. However, in the case of first default and default-default, borrowers have relatively low house equity.

4.4 Housing price growth, default, and the ability to pay

To gain further insights, we classify the housing price growth by its percentile: top 25 percent, bottom 25 percent, and middle 50 percent, and analyse the average house price growth and the status of default. Table 4 presents the percentage of distribution of default status by house price growth. The table reflects that high house price growth facilitates converting default borrowers into good (default-good), reduces the persistent default (default-default), and also reduces the occurrence of first default (first default). Thus, house price growth (at NPL year) helps prevent default, reduce default rate, and recover from the housing loan default borrowers. It is interesting to note that both double default and first default are higher at lower growth rates of house prices. On the other hand, the house price growth at data censor year (2017) appears to have no effects on the default (see Table 4). The average growth rate of house price seems to have no substantial differences by the default status.

Table 4. Housing Price growth and status of default (percent)

Particular	Housing price growth (at NPL, %)		
	Top 25%	**Middle 50%**	**Bottom 25%**
no default	n.a.	n.a.	n.a.
first default	0.43	4.46	15.28
default-default	7.51	9.30	26.89
default-good	92.06	86.24	57.82
	Housing price growth (2017, %)		
	Top 25%	**Middle 50%**	**Bottom 25%**
no default	43.30	40.73	43.05
first default	4.76	3.46	2.50
default-default	7.01	8.14	7.28
default-good	44.93	47.67	47.17

Note: n.a. = not applicable

We find that the average growth rate at the censor year also indicates that a higher rise in house price results in greater conversion of borrowers from default to good status both at the

NPL year and the censor year 2017. The higher precipitation of double default in the NPL year, even at the high percentile of house price rise, may be the result of cash-flow shocks like loss of employment, and other exigencies, which might have adversely affected the ability to pay of the borrowers. Borrowers in these groups might not even have been able to sell the house property at short notice (the NPL classification is based on overdue of 90 days and above from the due date) to settle their mortgage obligations.

Relating ability to pay, Table-5 presents the cross-tabulation of the payment to income ratio (PTI) and the default status. The bottom 25percent of PTI (low PTI and thus, high ability to pay) is associated with a higher percentage of no default and a lower percentage of default-default, than the top 25percent and the middle 50percent of PTI. This implies that the higher ability to pay reduces the default, in particular, the persistent default (default-default).

Table 5. Payment to Income Vs. default status of borrowers

Particulars	Payment -to-Income (PTI)		
	Bottom 25%	Middle 50%	Top 25%
No default	48.53	41.33	35.62
First default	3.06	3.10	3.93
Default-default	5.47	7.47	9.51
Default-good	42.94	48.10	50.94

Note: PTI from lowest to highest values. For example, the bottom 25percent refers to the 25th percentile and below (low value of PTI).

4.5 Distribution of default status over select borrower and loan characteristics

We plot the percentage distribution of the four statuses of default over the age of the borrower, loan age, loan term, Payment to Income ratio (PTI), Loan to value ratio (LTV), and loan interest rate (see Appendix 1). The non-linearity in the respective profile provides valuable insights for managerial decision-making. By age, the highest percentage of first default occurs at the age of around 26 years, whereas the default-default, default-good, occurs at the age of around 31 years. On the other hand, the profile of loan age with default status (see Appendix 1b) reflects that the default percentage is low during the initial six years from the dates of disbursement. Then the percentage increases sharply from year 7 until year 12, where the default percentage is persistent at around 4 percent to 12 percent (first default, default-default, and default-good), and then they taper off after around 13 years. It indicates that lending institutions need to be extremely careful after a loan reaches 6-years from the disbursement date, and the said loans should be under strict vigil (intense monitoring) until they become 12 years old in the institution's books. After around 13 years, default rates die down due to seasoning.

There is a striking finding on the percentage distribution of default over the loan terms: the default percentages show a substantial spike at loan term (more than 30 years). Almost half of the defaults (first default, default-default, or default-good) occur for loans with more than 30-year terms, indicating that lending institutions should avoid extending very long term (30 years) loans.

A high percentage of default is associated with a high-interest rate (beyond 7 percent). Similarly, high default is associated with high LTV (see Appendix 1e): the default rates start rising beyond 70percent and begin a sharp upward journey beyond 85percent. The availability of guarantor is expected to help reduce the incidence of default: however, it reflects that though the availability of guarantor is not significantly different between first default and double default, it has resulted in a higher conversion of default to good borrowers (see Appendix 1f).

4.6 Determinants of default status: estimated MNL model

Table 5 presents the estimated Multinomial Logit (MNL) model. As expected, the house equity, borrower, and loan characteristics are found to be the significant determinants of loan default. The house equity is calculated at the NPL year for the default case, and it is calculated at the censor year (2017) for the no default case. To estimate the effect of house equity on the default status, we have to combine these two calculations of house equity. The combined variable (HoEqAFTER) represents the house equity values at the year of NPL (default case) and at the year of data censor (no default case).

Table 6 shows the estimated MNL model results. It is found that house equity (HoEqAFTER) has a significant influence on the default status. The house equity is found to be able to reduce the probability of default. The house equity can prevent the occurrence of default, either the first default, default-default, or the default-good. This effect is found to be significant with p-value of almost equal to zero. On the other hand, the house equity at the beginning of the loan disbursement year is found to have a positive and significant effect on the probability of default. This results from self-selection bias by the lender where lending institution insists higher margin to customers with lower creditworthiness. In due course, these customers turn defaulters negating the hope of the lending institutions of such borrowers remaining in non-default status.

Relating to the borrower's characteristics, the age of the borrower has a significant non-linear (inverted U-shape) effect on the probability of default, in particular, the default-default. The increase of the younger borrowers increases the probability of default until a certain level of age. After that age, the increase in age is found to be associated with decreasing probability of default. The non-linear relationship of default with of age indicates that among the young borrowers, higher age is more prone to default; whereas, among the old borrowers, borrowers in higher age are less likely to default.

Table 6. The estimated MNL model

Particulars	Comparison group: no default (0)		
House Equity			
HoEqORI (house equity at loan disbursement)	0.087***	0.062***	0.028***
HoEqAFTER (house equity at NPL/Data retrieved yr)	-0.024***	-0.016***	-0.005***
Borrower's characteristics			
age_loanDisb (age at loan disbursement year)	0.113*	0.108***	0.088***
age_loanDisb2 (squared age_loanDisb)	-0.001*	-0.001**	-0.001***
male	0.277***	0.347***	0.095**
MarMarried	0.123	0.089	0.154***
RaceMalay[2a]	-0.265	0.681***	0.505***
RaceIndian[2a]	-0.114	0.662***	0.562***
RaceOther[2a]	0.443**	0.950***	0.773***
S_KL_SEL (Selangor/Kuala Lumpur)[2b]	-1.422***	-0.177	0.016
OccSemi/Skilled (semi-skilled and skilled)[2c]	-0.041	0.166	0.105
OccMft (Management) [2c]	-0.092	0.389***	0.133
OccExec (Executive) [2c]	-0.369***	-0.408***	-0.181***
OccNonExec (Nom-executive) [2c]	0.122	0.048	0.150**
OccSelfEmp (Self-employed) [2c]	0.093	0.284*	0.236***
OCCUnemIna (unemployed/economically inactive) [2c]	-0.323*	-0.374***	-0.122*
Loan characteristics			
PTI (Payment to income)	1.425***	1.964***	1.001***
loanDisb_day (loan duration)	0.000	-0.002***	-0.001*
loanDisb_day2 (squared loanDisb_day)	0.000	0.000**	0.000
DgurantorG (availability of guarantor)	-0.290***	-0.168**	0.010
loan_term (loan tenure)	0.007***	0.005***	0.002***
loan_int_rate (loan interest rate)	2.161***	1.850***	1.075***
build_up_area_sqm (build up area squared meter)	0.000***	0.000***	0.000*
LTV (Loan to value)	9.060***	6.163***	3.132***
Other control variables			
D2010 (Government policy of 2010)[3]	-3.351*	-1.493***	-0.421**
ss_transact1 (Number of transacted residential property)	2.986***	0.644*	0.486**

Note:

1. ***, **, * represent 1%, 5% and 10% significant level respectively
2. Comparison groups of dummy variables (more than two categories): a. Ethnicity:Chinese; b. States:Other states; c. Occupation:Government.
3. D2010 = 1 if year 2011 and onwards, =0 if year 2010 and below

Our results suggest that compared to females, male borrowers are more likely to default. Marital status does not affect the probability of first default and default-default; however, it affects the default-good percentage. This implies that married borrowers are more likely to recover from default status and turn to the non-default category. Compared to the Chinese borrowers, borrowers belonging to the other ethnic groups are more likely to be in double default and default-good status. There are significant effects of the location and the types of occupations on the default behaviour of the borrowers. The borrowers from Selangor and

Kuala Lumpur are less likely to have ‘first default’ than to borrowers from other parts of Malaysia. Compared to the government staff, the private sector workers are more likely to default on their home loans.

The loan characteristics like the PTI ratio, loan term, loan interest rate, LTV, and built-up area have significant positive effects on default. On the other hand, the availability of guarantors has a significant negative effect on default. The loan age has a U-shape relationship with default-default status. This highlights that at the beginning of the loan, the increase of loan age will decrease the probability of default-default. However, after certain loan age, an increase in loan age increases the chances of being default-default.

In 2010, BNM lowered the LTV ratio and encouraged responsible lending by the banking institutions in the country. The said policy is found to be very effective in reducing the probability of default-default, and default-good. It has, however, a weak impact on the probability of first default. From the supply side point of view, the number of transacted residential properties in the market positively impacts the probability of default.

4.7 Further analysis

To evaluate the censoring bias and gain more insights, we use the date information of loan disbursement, first and current loan default occurrence to convert the data into duration data. First, we construct nonparametric Kaplan–Meier survivor functions (Kaplan and Meir,1958), perform the Wilcoxon tests (Breslow,1970) to validate the equality of the survivor functions, and estimate a Cox proportional hazard model.[2]

The growth of house price distinguishes the survival of the loan borrowers – where the high price growth has a high probability of survival. These survival differences are found to be highly significant. On the other hand, the lower the PTI, the higher the survival rate. In the case of the old borrowers (loans that have been disbursed for a long time), lower loan terms, lower LTV, and lower interest rates have higher survival rates. All the survival functions are found to be statistically different. These findings are consistent with the estimated results of the original multinomial logit model.

We note that the lowest interest rate (4% and below) has a high survival rate throughout the period, as found in the estimated multinomial logit model. We also find that the interest rate of 4%-6% has the lowest survival rate. However, for the high-interest rate (more than 6%), the survival functions are not substantially different from the lowest interest rate until the period of around 2,200 days.

From the estimated Cox proportional hazard model, the independent variables that are

[2] Due to page limitation, results of the Kaplan–Meier survivor functions and Wilcoxon tests are not presented here. Results are, however, available from the corresponding author on request.

found to be significant and have a positive effect (higher probability of being loan default) are HoEqORI, age, male, non-Chinese, non-executive and self-employed occupation, high PTI, high loan term, high loan interest rate, high LTV, and high number of transacted residential property. The variables that are significant but with a negative effect (lower probability of being loan default) are HoEqAFTER, executive occupation, unemployed/economically inactive, shorter loan disbursement, and periods after implementation of 2010 government policy. These estimated effects are mostly similar to the original multinomial logit model except non-Chinese.

In short, the survival analysis indicates that most of the estimated results of multinomial logit model are robust to the censoring bias, except the interest rate (where high-interest rate have a low probability of default at the beginning of spell), and the effects of non-Chinese (Malay and Indian) are reversed for first default.

5. Discussions and conclusion

There is a nearly 14-fold rise in the home loan portfolio of the banks in Malaysia from 2000 to 2018, and it constituted about 30 percent of the total loan portfolio of banks by December 2018. The NPL percentage in the total NPL percentage of commercial banks came down to 21.85 percent by 2016 but went up again to 24.54 percent by the end of 2018. In this paper, we estimate the effect of home equity and house price rise on the home loan default in Malaysia. We assess the role of the ability to pay on home loan default and also evaluate the impact of borrower and loan characteristics on default behaviour. We stratify our granular data of 43,156 individual borrowers from the file of a Malaysian home loan lender with national presence into four groups: no default at all (no default), default for first time (first default), default and has defaulted before (default-default), default previously but currently in the non-default status (default-good). We use the Multinomial Logit (MNL) model, to analyse the repayment behaviour controlling the loan and socio-demographic characteristics of the home loan borrowers.

We find that there is heterogeneity in the loan default status across the different regions in Malaysia, and home equity is one of the key drivers in turning the default loan account to good status. In the case of first default and default-default, borrowers have relatively low house equity. We find that regions with a relatively low percentage of first default and double default have registered a much steeper rise in the House price index. The house price growth at the year of default (NPL) helps to turn the status of default into good (default-good), reduces the persistent default (default-default), reduces the occurrence of first default (first default). The higher precipitation of first-default and double default in the NPL year, even at the high percentile of house price rise may be the result of other cash-flow shocks like loss of employment and other exigencies that might have adversely affected the ability to pay.

Borrowers in these groups might not even have been able to sell the house property at short notice to settle their mortgage obligations. We find that the bottom 25percent of PTI (low PTI and thus, high ability to pay) is associated with a higher percentage of no default and a lower percentage of default than the top 25percent and middle 50percent of PTI. This implies that the higher ability to pay reduces the default, in particular, the persistent default (default-default).

We identify non-linearity and the inflection points in the profile of age of the borrower, loan age, loan term, payment to income ratio, loan to value ratio, and the interest rates with loan default are significant findings of our study. We find that the highest percentage of first default occurs at around 26 years, whereas the default-default, default-good, occurs at the age of around 31 years. The profile of loan age indicates that during the initial six years from the dates of disbursement, the percentage of default is low, but it increases quite sharply from year 7 until year 12 and tapers off after 13 years due to seasoning. We also find that default percentages show a spike at loan term that more than 30 years, clearly indicating that lenders may like to avoid giving home loans beyond the said term. We also find that a high percentage of default is associated with a rate of interest beyond 7percent. Similarly, the default rates start rising beyond 70percent and then rise sharply beyond 85percent. These are threshold values of importance to the policy planners and the top management of the lending institution. We find that though the availability of guarantor is not significantly different between first default and double default, it has resulted in a higher conversion of default to good borrowers.

Our MNL model results suggest that house equity has a significant influence on the default status at the NPL year, and it can prevent the occurrence of default, either first default, default-default, or default-good. On the other hand, the house equity at the beginning of the loan disbursement year has a positive and significant effect on the probability of default. This results from self-selection bias by the lender where lending institutions insist on higher-margin to customers with lower creditworthiness; these customers turn defaulters in due course, belying the hope of the lending institutions. The findings suggest that loan age has a significant inverted U-shape on the default-default behaviour. The non-linear relationship of default with age indicates that among the young borrowers, higher age is more prone to default; whereas, among the old borrowers, higher age is less likely to default.

The findings of our study are unique and are expected to have significant policy implications for the Malaysian government and BNM. The reported results would facilitate housing loan decisions and monitoring the portfolio of housing loans by the banks in the country.

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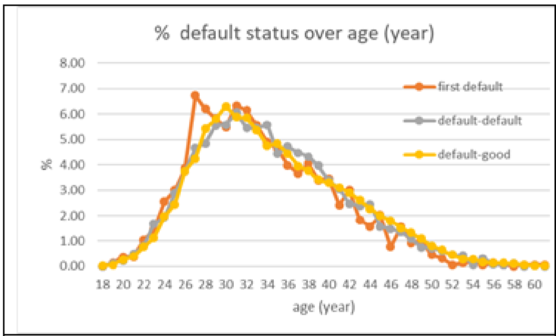
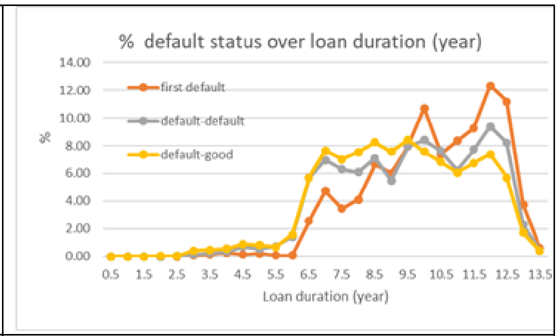
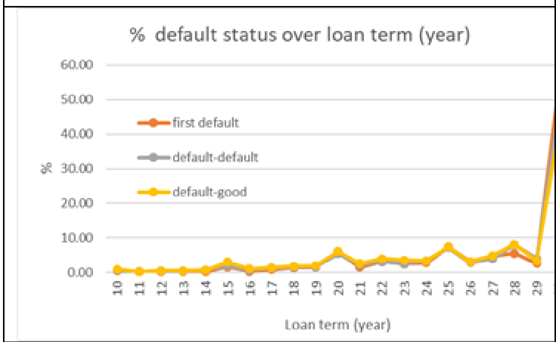
Appendix 1 Default status distribution by borrower and loan characteristics



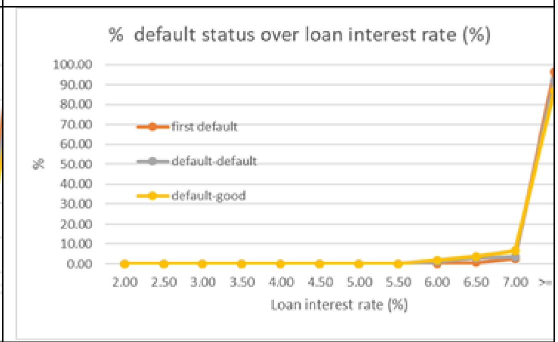
a. Age (yrs.)



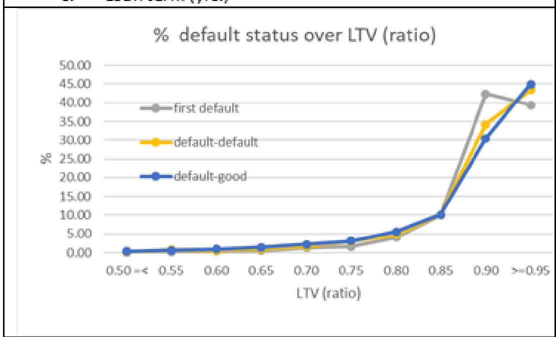
b. Loan age(yrs.)



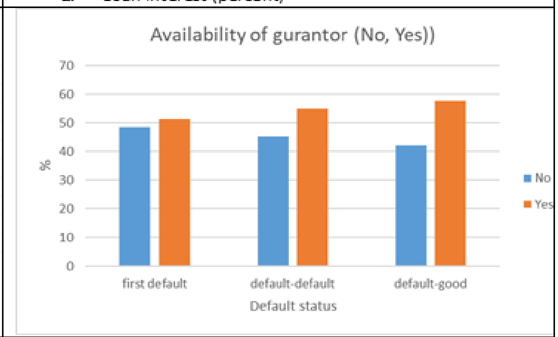
c. Loan term (yrs.)



d. Loan Interest (percent)



e. Loan-to-value (LTV)



f. Availability of guarantor