HOUSEHOLD INDEBTEDNESS AND NON-PERFORMING LOANS IN MALAYSIA

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FACULTY OF ECONOMICS AND ADMINISTRATION UNIVERSITY OF MALAYA KUALA LUMPUR

2021

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THESIS SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

FACULTY OF ECONOMICS AND ADMINISTRATION UNIVERSITY OF MALAYA KUALA LUMPUR

2021

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Field of Study:

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HOUSEHOLD INDEBTEDNESS AND NON-PERFORMING LOANS IN MALAYSIA

ABSTRACT

Aggregate non-performing loan (NPL) ratios in Malaysia have been decreasing steadily. However, there has been increasing awareness concerning predicting banking vulnerability and systemic risk in the financial market when debt grows faster than the economy. At the end of 2018, Malaysia's household debt fell to 83% of the GDP ratio. In fact, in value, total household debt grew from RM1.08 trillion in 2016 to RM1.18 trillion in 2018. Besides, household borrowing has been increasing over recent years. It comprised about 57% of Malaysian banks' total lending, as of 2018, which has exposed the banks to ex-post credit risk. Aggregate NPLs have been considered the transmission channel of macroeconomic shocks to the banks' balance sheets. However, another strand of literature on analysing NPL by category has been less noticed by the researchers. At times of stress, these relationships may be nonlinear. For these reasons, first, the present study examined the relationship between four common household credit facilities and Malaysian household NPLs, controlled by a set of indicators. Narrowing down to household NPLs by economic purpose, this study examined the chosen sets of economic indicators that determine the former movements and their relative strength in their impact. The study also compared the appropriate approaches in capturing the dynamics (linear versus nonlinear) between the tested variables. Using an available monthly dataset of macroeconomic and monetary variables from January 2006 to December 2018, linear and nonlinear autoregressive distributed lags (ARDL) were employed. The findings showed that finance-constrained households were more likely to default on credit card loans than other types of loans during times of financial distress. Household NPLs and personal loan debt were found to be better explained in a linear specification, in a negative direction,

assuming consumers tend to pay off other debt using easy to access loans at any time. There was no long-run relationship between them-properties outstanding loans and household default using the ARDL approach. However, NARDL revealed a possible relationship between loans and NPLs. Both positive and negative property loan changes were significant, whereas negative changes significantly impacted household NPLs. In another direction, the results showed that macroeconomic shocks affected consumer and mortgage loans differently; however, asymmetrical changes of the overnight policy rate (OPR) did not contribute to any type of NPLs. A hike or cutback in the OPR was a response toward the economic outlook and price changes; hence the effect of the OPR was muted, comparatively. In addition to the macroeconomic determinants, this study assessed how the loan portfolio affected each type of NPL. When other debts were factored in, credit card loan borrowers with another loan (s) tended to default on their credit card debt, compared to those without credit cards. Personal loan defaults were not linked to household debt, as personal loan borrowers usually covered their debts by taking up additional personal loans. Lastly, high housing loans and high vehicle loans contributed to the high default rate of residential properties and transport vehicles debts, respectively.

Keywords: asymmetry relationship; household debt; non-performing loan; overnight policy rate; property loan

HUTANG ISI RUMAH DAN PINJAMAN TIDAK BERBAYAR DI MALAYSIA

ABSTRAK

Nisbah pinjaman tidak berbayar agregat (NPL) di Malaysia telah menurun dengan stabil; masih, terdapat peningkatan kesedaran dalam meramalkan kerentanan perbankan dan juga risiko sistemik di pasaran kewangan apabila hutang tumbuh pada kadar yang lebih cepat daripada ekonomi. Pada akhir tahun 2018, hutang isi rumah turun kepada 83% kepada nisbah KDNK, sebenarnya, nilainya, jumlah hutang isi rumah meningkat dari RM1.08 trilion pada 2016 kepada RM1.18 trilion. Tambahan lagi, pinjaman isi rumah meningkat sejak beberapa tahun kebelakangan ini dan merangkumi sekitar 57% daripada jumlah pinjaman bank Malaysia pada tahun 2018, ini mendedahkan bank kepada risiko kredit. NPL agregat telah dianggap sebagai saluran penghantaran makroekonomi shock ke penyata imbang bank, namun, analisis NPL mengikut tujuan economi (kategori) kurang diperhatikan oleh para penyelidik. Pada masa tekanan, hubungan ini mungkin tidak linear. Atas sebab-sebab ini, pertama, kajian mengkaji hubungan antara empat kemudahan kredit isi rumah biasa dan NPL isi rumah Malaysia, dikendalikan oleh petunjuk. NPL isi rumah mengikut tujuan ekonomi, kajian ini mengkaji set petunjuk ekonomi yang dipilih yang menentukan pergerakan dan impaknya. Kajian ini juga membandingkan approach yang sesuai *linear vs nonlinear*, antara pemboleh ubah yang diuji. Menggunakan set data bulanan yang tersedia terdiri daripada pemboleh ubah makroekonomi dan monetari yang merangkumi tempoh 2006 Januari-2018 Disember, autoregressive distributed lags (ARDL) linear dan nonlinear digunakan. Hasil kajian menunjukkan bahawa pada masa kesusahan, isi rumah yang dibatasi kewangan cenderung gagal membayar pinjaman kad kredit., berbanding jenis pinjaman lain. NPL isi rumah dan hutang pinjaman peribadi didapati lebih baik dijelaskan dalam spesifikasi linear dalam hubungan negative, dengan anggapan pengguna cenderung melunaskan hutang lain dengan pinjama akses mudah, pada bila-bila masa. Dynamics antara pinjaman tertunggak kenderaan (sewa-beli) dan NPL isi rumah dikesan secara linear, namun hutang sewabeli kenderaan tidak menyumbang kepada penambahan NPL isi rumah dalam jangka masa panjang. NARDL, berbanding ARDL, mendedahkan kemungkinan hubungan pinjaman tertunggak harta tanah residential dan kredit bermasalah. Kedua-dua perubahan positif dan negatif dalam pinjaman harta tanah residential didapati ketara di mana perubahan negatif dalam pinjaman ini ditunjukkan memberi kesan yang lebih besar kepada NPL isi rumah. Selain itu, hasil kajian ini menunjukkan bahawa makroekonomi shock mempengaruhi pinjaman pengguna dan pinjaman sewa-beli hartanah secara berbeza, namun, perubahan asymmetry kadar polisi semalaman (OPR) tidak menyumbang kepada penambahan sebarang jenis NPL. Kenaikan atau pengurangan OPR adalah tindak balas terhadap prospek ekonomi dan perubahan harga, oleh itu kesan OPR diredam, berbanding dengan macroekoni penentu yang lain. Sebagai tambahan kepada penentu makroekonomi, kajian ini menilai bagaimana portfolio pinjaman mempengaruhi tahap setiap NPL. Apabila hutang lain diambil kira, peminjam pinjaman kad kredit dengan pinjaman lain cenderung membayar hutang kad kredit berbanding dengan yang tidak. Pinjaman peribadi tidak berkaitan dengan bayaran pinjaman bank kerana pemilik pinjaman peribadi biasanya menanggung pinjaman lain dengan mengambil pinjaman peribadi, Dan, pinjaman perumahan dan pinjaman kenderaan tinggi masing-masing menyumbang kepada NPL harta tanah kediaman dan kenderaan pengangkutan yang tinggi.

Keywords: hubungan asimetri; hutang isi rumah; pinjaman tidak berbayar; kadar polisi semalaman; pinjaman harta tanah

ACKNOWLEDGEMENTS

The creation of this masterpiece is indebted to the many people who deliberately made it successful.

Firstly, I would like to express my sincere thanks and appreciation to my supervisor, Dr Ahmad Farid bin Osman, Associate Professor Dr Lau Wee Yeap and Associate Professor Dr Yap Su Fei for their countless support by lending their helping hands to my work, such as providing sufficient and valuable information and giving helpful suggestions. Their insightful comments and encouragement helped me during my time researching and writing this thesis.

Next, I would like to thank my family for their love, support, assistance and continuous encouragement.

Last but not least, I would like to take this opportunity to thank everyone who cooperated with me in completing my studies. Their assistance has helped make this dissertation more interesting in its delivery to the readers.

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LIST OF SYMBOLS AND ABBREVIATIONS

- ADF : Augmented Dickey-Fuller
- AMC : asset management company
- ARDL : Autoregressive Distributed Lags
- BNM : Bank Negara Malaysia
- CCRIS : Central Credit Reference Information System
- CDRC : Corporate Debt Restructuring Committee
- CEE : Central and Eastern European
- CUSUM : Cumulative sum of recursive residuals
- CUSUMSQ : Square of Cumulative sum of recursive residuals
- GDP : Gross domestic product
- KLCI : Kuala Lumpur Composite Index
- KPSS : Kwiatkowski-Phillips-Schmidt-Shin
- MSSVAR : Markov Switching Structural VAR
- NPL : Non-performing loan
- NARDL : Nonlinear Autoregressive Distributed Lags
- OLS : Ordinary Least Square
- PP : Phillips-Perron
- U.S. : The United States

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CHAPTER 1: INTRODUCTION

Economic growth in any country is impossible if its financial sector is less resilient (Rajaraman and Visishtha, 2002). Banks (creditors or lenders) take in funds (deposits) and lend to borrowers as financial intermediaries. Bank loans and credit also increase an economy's money supply (Felix and Claudine, 2008). The interest charged on loans is the primary source of income for banks.

Banks deal with individuals, corporations, and sovereign entities. By the nature of their business, banks are exposed to several types of risks, for instance, operational, liquidity, market, and credit risks. Creditors cause operational and liquidity risks; in contrast, market risk is due to third party events, such as; monetary and interest rate shocks. However, the banks' most apparent and essential form of risk is credit risk, which arises from debtors. Credit risk is not necessarily isolated. Both liquidity risk and credit risk may be related as credit risk increases in the event of high liquidity risk. This study focuses on ex-post credit risk, i.e., non-performing loans (NPLs). NPLs have become one of the contemporary issues in financial risk management due to the global financial crisis, which started in 2008.

The Basel Committee of Banking Supervision (2001) defined credit risk as to the potential loss due to the inability of a borrower to meet their financial obligations. It can also be seen as creditors facing credit risk when a loan defaults (either principal or interest or both). Various indicators show when banks are at credit risk, such as the ratio of loss and doubtful loans to total loans (LLP ratio), the ratio of non-performing loans to loans & advances, the ratio of total loans & advances to total deposits, and the ratio of loan loss provisions to classified loans and the ratio of loan loss provisions to total assets (Vogiazas & Nikolaidou, 2011; Funso, Kolade & Ojo, 2012; Garr, 2013). Non-performing loans

(NPLs) have been the most widely used credit risk indicator in different studies across different countries (Fastein and Noikov (2011); Louzis *et al.* (2012); Janvisloo and Muhammad (2013)) since the emergence of NPLs in the U.S in 1987 due to the severe stock market crash.

According to the IMF (2005), "A loan is non-performing when payments of interest and/or principal are past due by 90 days or more, or interest payments equal to 90 days or more have been capitalised, refinanced, or delayed by agreement, or payments are less than 90 days overdue, but there are other good reasons—such as a debtor filing for bankruptcy—to doubt that payments will be made in full."

The Basel II Capital Accords defined NPLs as past due and unpaid loans past due for 90 days. According to Bexley and Nenninger (2012), NPLs are toxic to banks' books. The Financial Soundness Indicators (FSI) Compilation Guide (2006) classified a loan (or other assets) as an NPL if it were overdue by 90 days or more.

The banks review and monitor their loan portfolios and classify them based on the perceived risks and other loan characteristics. When necessary, they counter bad credit quality with remedy. Under the Bank for International Settlements (BIS) standard loan classification, the five tiers of NPLs have been defined as:

"Passed: Solvent loans;

Special Mention: Loans to enterprises which may pose some collection difficulties, for instance, because of continuing business losses;

Substandard: Loans whose interest or principal payments are longer than three months in arrears of lending conditions are eased. The banks make 20% provision for the unsecured portion of the loans classified as substandard;

Doubtful: Full liquidation of outstanding debts appears doubtful, and the accounts suggest that there will be a loss, the exact amount of which cannot be determined as yet. Banks make 50% provision for doubtful loans;

Bad (Loss or Unrecoverable): Outstanding debts are regarded as not collectable, usually loans to firms that applied for legal resolution and protection under bankruptcy laws. Banks make 100% provision for loss loans."

Late repayment of a loan causes it to be referred to as a delinquent loan. Delinquency indicates an increased risk of loss, and a delinquent loan becomes the default when the chance of repayment is minimal. Default occurs when borrowers fail to (either unwilling or unable) comply with the terms of a loan (CGAP, 1999).

Banks face dilemmas when they lend money. On one side, through lending, banks could maximise their profits by granting loans; on the other side, each granted loan is inevitably exposed to becoming an NPL. The risks that banks are exposed to are categorised as systematic- and non-systematic risks. From the banks' point of view, the systematic risk is not controllable, for example, macroeconomic conditions. At the same time, the non-systematic risk is controllable within a bank, for instance, microeconomic or bank-specific factors.

As an open economy, Malaysia is exposed to different economic and geopolitical events in the external environment. Due to its trade openness, Malaysia is vulnerable to

external shocks or headwinds, such as; the Global Financial Crisis and the Euro Debt Crisis, which affected its domestic credit and monetary policy (T'ng, 2013).

NPLs usually occur when the external economic environment deteriorates, for example, during a depression. According to Ahmad *et al.* (2013) and Quagliariello (2007), banks are more likely to be concerned about borrowers' repayment capabilities due to the imposition of higher interest rates during economic downturns. Due to monetary policy constraints, a considerable proportion of household debt can lower a country's output and demands. In an environment of weak economic growth, high interest rates could lead to more NPLs. Swelling debt could cause an economy to falter, and to some extent, the banks may need more capital to bear default on debt. NPLs are likely to reduce banks' liquidity and decelerate bank performance, implying a weakening banking system.

Therefore, as soon as loans are approved and disbursed, from the perspectives of policymakers and banks', building an early warning system for predicting possible financial distress by analysing the causes of loan default to alleviate the risk of NPLs is vital.

1.1 Overview of Malaysia's NPLs Ratio and NPLs by Economic Purpose

The interest charged to borrowers is the bank's primary source of income; therefore, the accumulation of non-performing loans affects the banks' performance and may lead to a banking crisis (Waweru and Kalani, 2009). For this reason, lending has to be monitored closely to prevent loan losses (Macdonald, 2006). The Malaysian banking system comprises various monetary institutions: the central bank (Bank Negara Malaysia), conventional and Islamic banks, non-monetary institutions, such as credit and insurance companies and development banks, and foreign and offshore banks. According to the latest classification of non-performing loans (NPLs) for substandard, bad and doubtful debts published by Bank Negara Malaysia (BNM) in 2015, a loan is considered impaired:

(*i*) "where the principal or interest/profit or both of the loan/financing is past due for more than 90 days or three months¹. In the case of revolving facilities (e.g. overdraft facilities), the facility shall be classified as impaired where the outstanding amount has remained more than the approved limit for a period of more than 90 days or 3 months; or

(ii) where the amount is past due or the outstanding amount has been in excess of the approved limit for 90 days or 3 months or less, the loan/financing exhibits weaknesses in accordance with the banking institution's credit risk grading framework; or

(iii) when the loan/financing is classified as rescheduled and restructured in CCRIS."

As a consequence of the Asian Financial Crisis in 1997, NPLs swiftly intruded into Asian economies, for example, Thailand, Indonesia and Malaysia. From mid-1997 to Jan 1999, the NPL ratios in these countries peaked at 50.1% in Thailand, 25% in Indonesia and 14.6% in Malaysia. NPLs in Malaysia has increased unabatedly since the onset of the Asian Financial Crisis in 1997. For the early detection of impaired loans, NPLs, formerly defined as loans in arrears by more than six months, were redefined as loans in arrears by more than three months.

The Malaysian government set up the asset management company (AMC), Danaharta, to acquire NPLs for speedy recovery during financial reconstruction. The Malaysian

¹ In the case of credit cards, the amount past due refers to the monthly minimum payment.

government also established Danamodal to inject public funds as an approach for bank recapitalisation and revitalisation. The Corporate Debt Restructuring Committee (CDRC), which dealt with loan amounts exceeding RM50M, aimed to provide a mechanism for banking institutions and debtors to work out feasible debt restructuring schemes. In contrast, the smaller amount of distressed loans was managed by special loan rehabilitation units. The NPL resolution carried out by the AMC, Danamodal, and the CDRC had noticeably improved the NPLs ratio by 2000. However, there was a slowdown in the rate of resolutions in 2000. The NPL ratio did not improve in 2001 due to the rise of NPLs in the property and manufacturing sectors (Ito and Hashimoto, 2007), reflecting increasing difficulties in the economic environment.

Since the 1997-98 Asian Financial Crisis, the net NPL ratio improved from 14.9% (end of 1998) to 3.2% (end of 2007). In 2014, the NPL ratio was below 2%. Table 1.1 shows the composition of NPL's by sector in the Malaysian banking system. The NPLs were dominated by the household, Finance, insurance and business activities, manufacturing (including agriculture) and transport, storage and communication sectors with reported NPL ratios of 39.2%, 14.59%, 10.29% and 9.45%, respectively, as of December 2018.

NPLs, in terms of economic purposes, cover the broad property sector, consumer credit, the purchase of securities and the purchase of transport vehicles under the Financial Institutions Statistical System (FISS). The broad property sectors' loans include; loans granted for construction, residential and non-residential properties and real estate. Consumption credit loans consist of loans for personal uses, passenger cars, consumer durable goods and credit cards. (See details in Appendix A).

Table 1.1: Composition of Non-Performing Loans by Sector, as of December2018

Sector	% of Total NPLs
Primary agriculture	0.69%
Mining and quarrying	2.21%
Manufacturing (including agro-based)	10.29%
Electricity, gas and water supply	0.44%
Wholesale & retail trade and restaurants & hotels	9.40%
Construction	9.16%
Transport, storage and communication	9.45%
Finance, insurance and business activities	14.59%
Education, health & others	1.62%
Household sector	39.16%
Other sector n.e.c	2.99%

Source: Monthly Statistical Bulletin, BNM (2018)

Table 1.2: Distribution of Non-Performing/Impaired Loans by EconomicPurpose as of December 2017 and 2018

	As of December	As of December
Economic Purpose	Impaired Loan (%)	Impaired Loan (%)
Purchase of securities	1.19	1.16
Purchase of a transport vehicle	6.81	6.49
of which: Purchase of passenger cars	5.35	5.05
Purchase of property	32.29	35.95
of which: Purchase of residential property	22.16	24.58
of which: Purchase of non-residential property	10.13	11.38
Purchase of fixed assets, other than land and building	0.7	0.98
Personal uses	6.18	6.28
Credit cards	1.78	1.39
Purchase of consumer durable goods	0.01	0.03
Construction	13.63	14.09
Working capital	32.93	29.27
Other purposes	4.48	4.36

Source: Monthly Statistical Bulletin, BNM (2018)

Table 1.2 presents a breakdown of impaired loans by economic purpose in the Malaysian banking system. Working capital accounted for the most significant proportion of impaired loans, followed by residential property mortgage NPLs and construction NPLs. Also, as of December 2018, compared to the previous year, impaired loans of securities, purchase of residential property, personal uses, credit cards, construction and other purposes were noticeably on the rise, whilst the impaired loans for transport vehicles decreased.

1.1.1 Malaysian Household: Debt and Non-performing loans

Household debt is categorised into unsecured and secured debt. Unsecured debt is usually referred to as consumer debt which involves credit cards, personal loans, securities, and consumer durable goods. Secured debt refers to mortgage or automobile debt. If there is a default in repayment, the property or car will serve as collateral. As such, mortgage debt is better secured, while its non-repayment risk is relatively higher.

The development of household debt is good for stimulating economic growth. However, to a certain extent, increased household debt could threaten the financial system. The economy will face a deceleration of positive momentum due to waning consumer spending and confidence (Sassi & Gasmi, 2014). The household sector pushes Malaysian NPLs. Figure 1.1 and Table 1.3 illustrate Malaysian household NPLs from 2006 to 2018. Household NPLs gradually improved from 2006 to 2018. In the first three quarters of 2007, household NPLs accounted for nearly 48% of Malaysia's total NPLs. This ratio dropped (about 1% to 5%) and again recorded between 46% to 48% in the first six months of 2009. Subsequently, household NPLs declined and fluctuated at around 36%-42% of total impaired loans.

With a household debt to GDP ratio of nearly 90% (a level resembling the household debt to GDP ratio in the U.S on the eve of the subprime crisis), Malaysia's ratio was one of the highest in the region as of the end of 2015. Also, Malaysia's household debt to

disposable income ratio reached approximately 150%, indicating that, on average, debt amounted to around 1.5 times more than the household income per household. At the end of 2018, the household debt to GDP ratio fell to 83%; however, it remained elevated among regional peers; however, household debt was expanding y-o-y by 5% in absolute terms. This number has raised concern regarding the risks of debts turning into nonperforming loans when the debt grows faster than the economy.

End of	period	Household sector NPLs
(month)		(of Total NPLs %)
2006	3	44.7%
	6	45.1%
	9	45.1%
	12	47.5%
2007	3	47.7%
	6	47.4%
	9	46.4%
	12	46.0%
2008	3	44.8%
	6	44.8%
	9	44.3%
	12	47.0%
2009	3	48.5%
	6	47.9%
	9	45.9%
	12	46.5%
2010	3	42.5%
	6	39.0%
	9	36.5%
	12	38.0%
2011	3	37.8%
	6	37.5%
	9	37.6%
	12	36.5%
2012	3	37.4%
	6	39.8%
	9	40.4%
	12	39.9%

 Table 1.3: Household Non-Performing Loans 2006- 2018

End of	period	Household sector NPLs
(month)		(of Total NPLs %)
2013	3	39.0%
	6	38.0%
	9	36.9%
	12	39.2%
2014	3	38.6%
	6	39.3%
	9	38.1%
	12	39.8%
2015	3	40.1%
	6	38.3%
	9	38.2%
	12	37.4%
2016	3	37.0%
	6	35.8%
	9	37.1%
	12	37.7%
2017	3	36.4%
	6	36.8%
	9	36.6%
	12	37.5%
2018	3	36.4%
	6	37.3%
	9	37.8%
	12	39.2%

Source: Monthly Statistical Bulletin, BNM (2018)



Figure 1.1: Household Non-performing Loans, in RM million (2006-2018) Source: Monthly Statistical Bulletin, BNM (2018)

Household borrowing has been increasing over recent years and comprised about 57% of the banks' total lending as of 2018 (BNM, 2018). This lending exposes the banks to credit risk and banking instability during periods of uncertainty (Foos *et al.*, 2010; Kukk, 2015).

Figure 1.2 indicates that properties (residential and non-residential), followed by motor vehicles, personal uses, and credit cards, were the most substantial elements in Malaysia's household debt composition. Consumer loans, for example, personal loans, credit cards, purchase of vehicles, and other loans, such as for the purchase of consumer durables, accounted for nearly 40% of total household borrowing. This figure indicates that the banks are highly exposed to unsecured lending default risk as Malaysians spend too much on assets that they do not appreciate in the long run. Compared to the previous year, loans for the purchase of transport vehicles and credit cards were reduced in outstanding loans growth. In contrast, loans for the purchase of residential properties and personal use showed higher growth.





Looking at mortgages, banks require collateral that the borrower is obliged to pay back with a predetermined payment (principal and interest imposed). Macroeconomic shocks significantly impact home financing, leading to credit booms and busts during financial crises (Bianco, 2008; Crotty, 2009; Jickling, 2009). Thus, home financing deserves close monitoring as this loan type is by far the most significant cause of household indebtedness.

Many Malaysians believe that owning or investing in property is an important financial goal (Tan, 2009). Malaysia's mortgage market comprises primary and secondary mortgage markets. Banking institutions lead the primary market, and financial institutions offer both conventional and Islamic mortgages. For conventional mortgages, the interest rate can be fixed or variable. In contrast, for Islamic mortgages, the interest(profit) rate is calculated based on a cost-plus margin basis with a fixed loan instalment paid for the whole term of the loan's duration, with no compounding element involved (Hussain *et al.*, 2016). The secondary mortgage market was formed with the establishment of CAGAMAS Berhad (National Housing Corporation) in 1987 (Chiquier, 2006) to act as an intermediary

between the primary lenders and investors and to solve the shortage of housing loans (Kokularupan, 2005). The banks could sell their mortgages to CAGAMAS to generate additional liquidity or hedge against interest rate volatility risks. The banks needed to bear the default loan, while CAGAMAS only managed the interest payment (Kukularupan, 2005). Most banks offered 80%-90% house financing and the new maximum home loan period was 35 years instead of 45 years.

Credit card usage is similar to obtaining credit or taking a loan. Samuelson and Nordhaus (2001) explained credit as "...the use of someone else's funds in exchange for a promise to repay at a later date." Credit card lending is a double-edged sword that improves banks' profitability but also contributes to the source of credit risk. Firstly, credit card debt is typically unsecured, as the credit card issuer does not require the consumer to post collateral. Secondly, credit card payments are flexible where the credit cardholders can choose only to pay the minimum (affordable) monthly payment, where the card issuers earn interest on the outstanding debt. Credit cardholders will be buried by unpaid debt and continuously revolving credit interest if they delay making significant monthly payments.

Cohen (2007) suggested that credit cards allowed consumers to meet ever-evolving living standards and experience a lifestyle beyond their immediate financial means. Unfortunately, some cardholders misuse their cards and end up with more debt than they can bear. As reported in the BNM monthly statistical bulletin from 2006-2018, the level of Malaysia's credit card NPL has elevated in recent years. The rate of the y-o-y default growth at 11.32% is higher than the mortgage loan default growth of 7.41% (but lower than the personal loan default growth of 16.5%), even though mortgage NPLs are the dominant component of household NPLs. Moreover, credit card default was the most

significant contributor toward bankruptcy among Malaysians aged below 34 (Metro daily newspaper, dated 26 February 2014).

Ahmad and Omar (2013) conducted a study on young Malaysian credit card payment defaulters between September 2011-June 2012. Their results found an increasing trend in the use of credit cards for online shopping. The sampled credit card holders were inclined only to make the monthly minimum payment (5% or RM50, whichever was higher, of the total outstanding balance) and held more than three cards simultaneously.

Effective January 2013, BNM revised its conditions to control credit card use, stating that principal cardholders must be at least 21 years old with a minimum annual income of RM24000. Principal cardholders with an income of RM36000 per annum or less were restricted to (i) hold a maximum of two credit cards from issuers and (ii) a maximum credit limit of two times their monthly income per credit card issuer.

Loans for automobile purchases are one of the most common forms of household lending. In many ways, car financing is similar to home financing, as automobile loans are backed by collateral and held by lenders. Besides that, automobile loan defaults can also be expected due to aggregate shocks (Heitfield and Sabarwal, 2004). As opposed to properties, auto loans are easier to recover in default, and the auto loan tenure is shorter than the former. From 2011 to 2015, one in four marked the highest bankruptcy cases in Malaysia due to default in auto loans (The Sun newspaper, published 9 May 2016). In a recently revised guideline, local banks state that the maximum margin for automobile hire purchase (HP) financing remains at 90%, with the maximum repayment period at nine years.

On the other hand, a personal loan is typically an unsecured consumer loan. It is not backed by any collateral and can be used for various purposes, such as down payments, medical needs, vacations, other uses, or even paying off credit card debt. A personal loan is usually charged at a fixed interest rate, which is charged based on the loan tenure or loan financing amount. All accrued interest is payable as part of the monthly repayment, and these monthly repayments have to be paid until the end of the loan tenure. Previously, the financing tenure could be up to 25 years for personal financing, which reduced the monthly payment; however, in the long run, this increased vulnerability of the household sector as there was the accumulation of debt. Therefore, the maximum personal loan period has been revised to 10 years. Since 2016, the continued increase in the nonperformance of personal loans has become the top reason for bankruptcies (BNM, 2017; Malaysian Department of Insolvency, 2017). Across household loans by purpose, the Central Bank of Malaysia estimated significant potential losses arising from the vulnerable borrowers (monthly earnings below RM3000), particularly for defaults related to personal financing and the purchase of vehicles. For this reason, the factors influencing personal use NPLs should not be underestimated, as accumulated defaulting debts put household resilience and banks' financial stability in danger.

1.1.2 Why Non-Performing Loans (NPLs) matter?

The financial market, by its nature, involves risk. The sovereign debt crisis in Greece jeopardised the resilience of the financial systems in many European countries. Moreover, the bankruptcies of Lehman Brothers Holdings' in 2008 and General Motors Corporation in 2009 triggered economic turmoil. These shreds of evidence are sufficient to reveal the importance of managing debt obligation.

Banks quickly expand their credit portfolios during good times, and non-performing loans are few and far between. In contrast, high-risk loans are typically converted into non-performing loans, especially when such loans were granted to unqualified borrowers and secured against overestimated collateral or resources. Generally, NPLs transmit macroeconomic shocks to banks' balance sheets (Quagliariello, 2004).

Suppose banks are exposed to more credit risk. In that case, banks would be more vulnerable to external shocks (World Bank, 2000). Accumulated bad debt could reduce the public's confidence in the banking system (Chernykh, Davydov & Sihvonen, 2019). Subsequently, a credit crunch phenomenon may occur when financial institutions become newly risk-averse and are reluctant to commit new loans. Over time, reducing new loans and increasing problem loans will lead to high NPL ratios due to lower loan quality in the numerator with decreasing loan growth in the denominator. (De Hass *et al.*, 2010)

Increasing trends in NPLs cause most banking failures. NPLs hamper a country's credit flows (See Albulescu, 2015; Tan & Floros, 2012)., Banks reduce their lending activities, shrinking firms' production and household consumption when a high level of NPLs faces them. In turn, business units facing erosion in profits may cause a prolonged recession (Hou, 2007). The great recession's direct consequences were; adverse economic factors, over-indebted households, and social welfare deterioration. Failure to manage NPLs will impede financial intermediaries' profitability as earnings will convert into bad debts. Therefore, NPLs have gained increasing attention in both developed and developing countries as they serve as a crucial indicator of the banking system's viability, and thereby a country's financial sustainability (Khemraj and Pasha, 2012).

In 2007, the subprime credit market in the United States, which mainly consisted of large subprime mortgages, began to collapse. Subprime loans were considered riskier than

prime loans because the default probability was higher than the latter. It was reported that in 2018Q3, that mortgage debt and securitised mortgage debt were 11.3 trillion and 6.8 trillion USD, respectively. In contrast, the outstanding subprime securitised mortgage debt recorded a value of 1.8 trillion USD. Hence, subprime debt amounted to one-third of the total securitised market in the United States. It was also 16 % of the total US mortgage debt in Q3 2008. (Demyanyk & Hasan, 2010)

Before the crisis, it was hard to believe that the small subprime securitised mortgage market, relative to the entire mortgage market, could cause a significant problem. Since then, financial institutions, including those in emerging Asia, have operated under the effects of financial strain and contagion. It could be said that the roots of the crisis can be traced back to Lehman Brother's bankruptcy. Besides the US and European countries, there has been much evidence showing that the financial crises in East Asia and East Africa were due to those regions holding an overwhelming amount of NPLs.

An Institute of International Finance (IIF) press release in 2014 pointed out that NPL rates in the emerging market would deteriorate. Ernst & Young also forecasted that there would be a continuous rise in NPLs around the world. Besides, there was a flawed assumption that Asia would be protected from any downturn due to its low exposure to the U.S. derivatives and subprime loans market. However, the real GDP in the emerging markets plummeted (Goldstein and Xie, 2009).

Deteriorating macroeconomic factors could make the repayment of the existing financial obligations more challenging. These macroeconomic factors are influential on credit risk changes, particularly at the aggregated level. (Carling *et al.* (2007) and Bonfim (2009))

1.1.3 Current Practices of Credit Monitoring and Loan Loss Provisioning

The Basel Accords aimed to stabilise the financial markets and protect banks from insolvency. Basel I introduced minimum capital requirements; however, the requirements lacked sensitivity to risk. The capital requirements were predefined, based on each type of exposure to a different type of risk category. Banks were required to maintain a ratio of capital to total risk-weighted assets (RWA) of 8% (Gu, 2011). Meaning that bank capital should be at least 8% of the banks' credit risk; however, it was limited to a few risk weighting and did not account for the default risk, currencies, and macroeconomic risk.

In response to criticisms of Basel I, the Basel Committee proposed a more comprehensive framework, namely Basel II, to manage the credit, market, operational and other risks. Under the Basel II guidelines, there were several options to accommodate riskcapital requirements: the standardised approach (SA) and Internal Rating Based (IRB) approach. Banks that operated under the SA required external rating agencies to quantify capital for credit risk. Similarly, the IRB approach allowed banks to use their estimator to quantify the capital requirement for credit risk.

The G10 countries primarily adopt Basel II, but some emerging markets also showed interest in implementing Basel II, including Malaysia. In 2010, Bank Negara Malaysia adopted the IRB approach, which they believed was more suitable than the SA in maintaining a less procyclical capital ratio. Basel II has now been extended and effectively superseded by Basel III, targeted for full implementation by 2019. Basel III has further strengthened banks' capital by holding minimum capital and strengthening their quantity, quality, consistency, and reliability. Malaysian banks have started embracing the Basel III Accord since January 2013.

The Basel committee worked on several principles to ensure the lowest level of risk in credit activities, which have also been implemented by BNM, as the following points:

- At all levels of bank portfolios, the board of directors must perform a periodic credit risk assessment and continually develop new strategies as soon as new information emerges. The General Director enforced the said strategies to handle NPLs.
- ii. Banks are required to investigate if one is eligible for a loan based on one's creditworthiness and clearly define the loan amount, tenure and other terms and conditions, if eligible. The internal credit rating procedure should be unified and unambiguous.
- Borrowers' financial information and compliance status must be kept up to date to detect and manage NPLs.

Besides the principles of the Basel committee, there are some specific requirements stipulated in the guidelines published by BNM on the best practices and mandatory requirements in managing credit risk:

- (i) Banking institutions are required to have an independent credit review unit to audit loan appraisal quality.
- (ii) Banking institutions are required to develop appropriate credit grading systems to grade the credit risk of their loan accounts systematically.
- (iii) Banking institutions are required to assess credits based primarily on repayment capacity rather than on collateral.
- (iv) A banking institution is required to conduct a stress analysis at least once every six months or at any intervals as prescribed by BNM from time to time."

The Basel Committee on Banking Supervision (BCBS, 1996) also emphasised stress testing needs if the banks adopt an internal model to meet risk capital requirements. Stress testing identifies plausible unfavourable events or future influences in the financial and economic condition. The quantitative criteria identify possible stress scenarios that could be reflecting unique risk characteristics.

In contrast, the qualitative element assesses the banks' capital to absorb potential large losses and identify steps the institution can take to reduce risk and conserve capital. A stress test scenario could be a historical scenario based on past events, such as stock market crashes or exchange rate crises or a hypothetical scenario based on an event that has not yet occurred. However, it requires more judgement. Stress testing complements the commonly used risk measure, Value at Risk (VaR)², by quantitatively describing the exposure associated with extreme events. One of the understood limitations of stress testing is that stress testing estimates the exposure to a specified event rather than the probability of the event occurrence; thus, the transparency issue arises. Further, the banks may not effectively choose the right or relevant stress scenario; hence, they underestimate the underlying risk.

Lending activities are associated with credit risk. Banks are required to manage loan default exposure by covering the expected losses via a loan loss provisioning system. Banks are required to reserve a certain percentage of their profits for loan loss provision (Norden & Stoian, 2013). Podder and Al Mamun (2004) referred to loan loss provisions

² VaR is used to provide a probability-based boundary on likely losses for a specified holding period and confidence level.

as the "method that banks use to recognise a reduction in the realisable value of their loans".

The accrual expenses for banks are charged to the profit and loss statement that creates reserves on bank balance sheets. When expected loan losses are crystallised, banks can cover and absorb the losses without ruining the banks' capital and capacity to extend the credit supply. Loan loss provisioning is either backwards-looking or forward-looking. Backwards-looking provisioning is procyclical, as the level of provisioning is low during a boom period.

In contrast, banks build provisions during upswings while drawing down on them during a downturn; hence, forward-looking provisioning is countercyclical (Pool *et al.*, 2015). Banks tend to underestimate loan loss provisions in a procyclical setting if the country has experienced a long upswing. NPLs usually elevate during recessions to make the loan loss provision. When there is an unexpected downturn, it is more challenging or costly for the banks to increase the loan loss provisions drastically.

There are two types of loan loss provisions: specific and general. Specific provisions are applied to expected loan losses that have been identified as impaired. In contrast, general provision is applied to loans that have not been recognised as impaired, but there is a possibility that they will be a default. General and specific provisions are commonly practised in the regulatory framework; however, these may vary across countries as each country has a specific regulatory environment (Pinho & Martins, 2009). The provisioning effort is made according to credit quality.

BNM regularly carries out a stress test to assess the level of NPLs and the capital position under a worst economic scenario and stricter provision requirements. Before
March 1998, there was no specific reserve for a substandard loan, while reserve levels of 50% and 100% were required for the doubtful and bad loans, respectively. In the aftermath of the Asian Financial Crisis, as required by the central bank (BNM), Malaysian banks needed to maintain available reserves of no less than 1.5% of the total loans/financing and specific provisions of 20%, 50% and 100% for substandard, doubtful and bad loans, respectively.

The central bank requires all Malaysia's commercial banks to disclose their loss loan provisions in their profit and loss statements. On the other hand, while NPLs increase, the banking system will not be threatened if the risk weight capital ratio remains above 10% (BNM, 2000). Credit growth, which affects the NPL ratio through the denominator, plays a crucial role in making lending decisions. Effective from January 2012, banks have approved loans based on the borrower's net income rather than their gross income to control NPLs and offset the effects of sluggish deposit growth, which could cause a high loan to deposit ratio.

1.2 Problem Statement

Even though past literature has not claimed that non-performing loans (NPLs) were directly responsible for financial crises, the build-up of indebtedness explains an undesirable impact on the economy (Drees and Pazarbasioglu, 1998; Kaminsky and Reinhart, 1999). It has been conjectured that macroeconomic fundamentals have a differential impact on NPLs, depending on the type of loan.

The statistics of an 89.1% household debt to GDP ratio in 2015 (Tee, 2016) and the approximate 150% household debt to disposable income ratio in the study of NPLs for economic purposes besides the aggregate NPLs, were alarming. In Standard and Poor's August 2015's report, household debt was accumulating faster than income growth, which

would lead to difficulties in repayment and an increase in the number of bankruptcies if the credit cycle turned.

At the end of 2018, household debt stood at around 83% to the GDP ratio. The total household debt had grown from RM1.08 trillion in 2016 to RM1.18 trillion in 2018 in terms of value. Even though banks' default debt ratios have remained reasonable, household debt to GDP ratio of 60% is prudent for a country's financial health, as recommended in the McKinsey Report in 2015. Lombardi *et al.* (2017) also suggested that there would be a negative effect on economic growth if the household debt-to-GDP ratio exceeded 80%. When the level of household indebtedness is high, it posts a negative impact on both households and financial institutions in the event of adverse external shock,

Theoretically, household credit expansion smooths consumption and is a beneficial factor in driving economic growth; however, a prolonged economic boom phase leads to households and firms taking excessive risks. Excessive household debt could increase banking instability and financial or economic unit vulnerability (Nakornthab, 2010; Borio *et al.*, 2014; Jorda *et al.*, 2016). Household credit is more likely to trigger financial instability than businesses credit since business credit have a better ability to generate profit for loan repayments (Buyukkarabacak & Valev, 2010). Hence, this study has attempted to better understand the movements of household NPLs in response to changes in outstanding household credit by category.

There has been increasing awareness regarding the prediction of banking vulnerability and systemic risk in financial markets. In this respect, household debt has received much attention from regulators. Despite the residential housing and car loans contributing to the substantial amount of household NPLs in Malaysia, the estimated probability of default of personal loans and credit cards, respectively, is two times higher than the former estimations, based on stressed assumptions, which leads to the first research question. It is imperative to identify the potential stress in the four major household loan components, i.e. purchase of residential properties, purchase of transport vehicles, personal uses, and credit cards in the household NPLs to understand the risk associated with household deleverage.

Further, aggregate NPLs have been considered the transmission channel of macroeconomic shocks to banks' balance sheets. However, the researchers have noticed another strand of literature on modelling NPLs for economic purposes. The existing literature relates aggregate NPLs, as discussed in Chapter 2. Most Malaysian NPL analyses have been predominantly on banks' aggregate NPLs, either conventional or Islamic, based on a set of macro and micro-economic indicators. Hence, this motivated the second research question of determining the economic factors impacting NPLs by economic purpose instead of the aggregate NPLs. The tested household NPL categories were the four major household debts, as mentioned in Figure 1.2.

Several past studies have shown that credit expansion and economic variables are significant factors affecting NPLs. However, less attention has been paid to asymmetric credit and economic effects on household deleveraging and sustainability. Positive and negative shocks could not have the same absolute effects on NPLs by different categories. This study attempted to answer the third research question by studying the potential asymmetry in the linkage between the different types of household lending and household NPLs to extend the literature concerning the nonlinear relationship between household debt and household NPLs.

1.3 Research Questions and Research Objectives

Macroeconomic variables might affect the quality of household loans since macroeconomic and asset price shocks are transferred across the economy (Sutherland and Hoeller (2012)). In the context of Malaysia, there has been limited literature investigating the global and domestic economic determinants of household NPLs and NPLs by purpose. The studies conducted did not consider nonlinearity for the study period that covered the Global Financial Crisis and commodity price shocks. These lead to the following research questions:

- 1) What credit facilities determine Malaysian household NPLs and their relative impact on the household NPLs?
- 2) Narrowing down to Malaysia's NPL by economic purpose, what economic variables explain the former's movements? Is this relationship homogenous across different loan categories?
- 3) In terms of predictive ability, what is the suitable approach (linear vs nonlinear) to capture the relationship between Malaysia's household NPLs and the chosen set of indicators

The objectives of this study were:

- To examine the relationship between four major household credit facilities (credit cards, personal uses, purchase of residential loans, and transport vehicles) and Malaysia's household NPLs.
- 2) To investigate the factors that explain Malaysia's NPLs by economic purpose and determine if these relationships are similar across different types of loans.

 To compare the approaches (linear vs nonlinear) in capturing the dynamics between household NPLs and their determinants

Overall, this study aimed to understand to what extent the type of household borrowing was associated with riskier financial stability. On the one hand, the effects of four major household credit facilities, namely credit cards, personal uses, purchase of residential properties, and transport vehicles, were analysed towards Malaysian banks' household NPLs.

This study targeted different macroeconomic variables, such as household income adjusted for inflation, the crude oil price, the overnight policy rate, the unemployment rate and the stock market index, to examine the impact of macroprudential policy in limiting credit risk. On the other hand, linear models may produce misleading inferences for policymakers if there is an asymmetry in the model; hence, this study allowed potential asymmetry in the linkage between different household lending types, the household NPLs and the determinants.

1.4 Significance of the Study

Credit activities play a vital role in economic development. Increasing credit growth strengthens the competition among banks (Salas and Saurina 2003); however, lending usually grows along with the possibility of credit risk, i.e., the non-repayment of loans by borrowers. Credit risk issues remain challenging as they affect banks' profitability and sustainability, leading to adverse reactions throughout the whole economy.

The contributions of the present study are manifold. While most previous papers have focused on aggregate non-performing loans' main factors, this study measured the differential impact of household credit on household NPLs. Firstly, this study has contributed by providing a more in-depth understanding of household vulnerability and credit risk sources from the macroeconomic perspective. The high level of household indebtedness remains challenging, particularly after the onset of the crisis. Next, while most previous studies have analysed the aggregate NPLs, the present study enhanced the available literature regarding the factors antecedent to household NPLs by outlining how macroeconomic uncertainties affect the four major household NPL categories. New insights could be gained if new indicators explain the NPLs for different economic purposes.

Further, an appealing advantage of the asymmetrical approach distinguished this study from the existing literature. This approach captured short run and long run asymmetries through the different directions of the changes in the outstanding loans to achieve household and banking sustainability. The household indebtedness response to positive change may differ from a negative change in the economic fundamental.

In this respect, this study has provided a deeper understanding of household vulnerability and debt default sources. Notably, the differential impacts detected in household credit on household NPLs has enabled banks to design adequate loan loss provisions for different loan categories, besides considering the relationship in the macro stress testing.

1.5 Chapter Organisation

Chapter 1 has provided a brief introduction to NPLs and Malaysia's NPLs Ratio and NPLs by economic purposes. The objectives and the contribution of the present study have been discussed. Chapter 2 reviews related literature, which builds on motivations to carry out this research, while Chapter 3 outlines the methodologies, data used in the study and offers a preliminary analysis. Chapters 4, 5, 6 and 7 focus on the analysis of the

household NPLs. Chapter 8 concludes this study and provides recommendations for further study.

CHAPTER 2: LITERATURE REVIEW

2.1 Theoretical Framework

For a country that is highly dependent on trade, with total exports and imports double that of the national $\frac{1}{9}$ ross domestic product (GDP), it is apparent that the repercussions of low demand from trading partners will be felt throughout the domestic economy (James *et al.* 2008). On the other hand, recent commodity price shocks, particularly oil, led to significant export activity losses for Malaysia's commodity exporters. The commodity price slump adversely undermined economic performance in the emerging commodity producers (BNM, 2014).

As indicated by Villafuerte & Lopez-Murphy (2010) and the IMF (2015), commodity (oil) price shocks are procyclical and provide a feedback loop on banks' balance sheets. With financial market uncertainties in the major advanced economies, volatile global liquidity shifts could pressure emerging economies. The financial accelerator mechanism (Bernanke *et al.*, 1998) amplifies adverse global shock spillovers to the domestic market via the feedback effect from interrelations between the real economy and the credit market.

In this respect, monetary policy should be considered from many angles. These factors include; global stance, commodity demand and price changes, and the monetary policies in major advanced economies. A monetary policy that is induced by changes in interest rates affects domestic financial conditions. It has implications on; credit, the economy, and inflation (T'ng, 2013), leading to a direct effect on household spending and debt repayment obligations.

Bank lending is procyclical, where credit expands faster than the economic growth but grows slowly during recession periods. Credit is significant to economic growth. In contrast, household consumption expenditure is crucial for aggregate demand, as it stimulates economic growth. To a certain extent, rising debt will lead to loan defaults. According to Debelle (2004), increased household debt heightened the household sector's sensitivity to changes in; interest rates, demand and prices. The interest rate, mainly the real interest rate, affects the capacity to service debts or loans, while a price shock reflects the demand-pull theory of inflation. Under a regime of lower interest rates and eased credit constraints, following the transmission mechanism of monetary policy, people are more willing to spend or borrow; hence, credit and consumption levels grow along with the optimistic aggregate demand level and output. Thus, in the short term, the economy grows.

Excess investment, excess lending and rocketing housing prices are the counterparts to high inflation but produce greater credit risk in the long term. As the price level increases, real wages reduce and preserve real income; therefore, there is more demand for a real wage, leading to a lower unemployment rate.³ Known as Okun's Law, the unemployment rate and real GDP growth are usually inversely related. Linked by the Philips curve theory, accelerating economic growth triggers high inflation, thereby lowering unemployment. Rises in inflation are associated with reduced total real outstanding loans; however, real income reduces, therefore, weakening borrowers' ability to repay debt. When debt grows faster than wages, this leads to high debt and builds impaired loans.

During the inflationary boom, monetary authorities will raise the interest rate to encourage savings instead of spending. This initial choke in household spending triggers adverse multiplier effects. Excess aggregate supply causes a fall in the price level and,

³ Wages and prices are positively related, this relationship is widely interpreted as a trade-off between inflation and unemployment, where policymakers could "buy" a lower rate of unemployment at the cost of a higher rate of inflation.

thus, further reducing aggregate demand. Shrinking businesses will sell their products at lower prices to stimulate demand and subsequently cut back on wages, lay off people, or just maintain the existing ones. This observation implies overwhelming impacts on; investors' confidence, the employment rate, and positive economic momentum. Moreover, the deterioration in household's ability to service loans and the erosion of profits in the business sector will increase non-performing loans due to decreased employment and domestic demand.

As the price level decreases, the economy will experience deflation, and during deflation, households may become trapped in debt due to their previous over-borrowing. However, loan repayments do not decrease as prices fall; therefore, the real debt burden is heavier. To stay solvent, some people may borrow, creating more room for debt takeup. Eventually, borrowers will be forced to cut their spending sharply when their debt to income ratio becomes too high. In some cases, debt could become unserviceable and nonperforming (Westpac Institutional Bank, 2016). As Chaibi and Ftiti (2015) pointed out, these events continue to worsen when monetary authorities raise the interest rates to maintain lenders' real returns. This observation assumes monetary policy to influence the level of NPLs and a more sluggish economy in a vicious cycle.

Debt deflation theory: (Fisher, 1933) proposed that deflation affects borrowers balance sheets, where decreases in prices or wages along with decreases in the price level tighten borrowers' constraints when the nominal debt and interest payments are fixed. According to Fisher, the subsequent effect of a decrease in the price level may not bring output back towards its full employment level immediately. Moreover, deflation reduces real collateral values, hence making the cost of borrowing more expensive, causing debtors to be unable to fulfil their current obligations. When over-indebtedness exists between debtors, creditors, or both, this produces events, such as; debt liquidation, contraction of deposit currency, more difficulty in obtaining loans, and reductions in aggregate demand or output in the trade and employment markets, eventually resulting in recession or depression.

Lokare (2014) indicated that there was a strong association between the economic condition and loan quality. A lender commonly requires borrowers to set forth their repayment ability, usually in the form of collateral assets. During a cyclical upswing, banks tend to underestimate or be optimistic. They may provide loans to borrowers against insufficient collateral and allocate fewer loan loss provisions to cover such risk. Moreover, increases in asset price result in inflated collateral valuations, increasing borrowing capacity and credit growth. Once the business cycle turns down, banks face provisioning burdens, resulting in capital shortages.

Excessive reductions in lending will lead to a credit crunch, especially if banks comply with the minimum risk-weighted ratio. Such tightening of lending requirements will lead to the erosion of banks' profitability. A credit crunch may lead to an economic downturn, thereby increasing the unemployment rate. This mechanism is named the *financial accelerator theory*, where lenders and borrowers are primarily affected by the initial changes in economic shocks amplified by a worsening credit market (Bernanke *et al.*, 1998). Suppose the financial accelerator is operative due to the effect of an economic downturn. In such a case, there would be a decline in the amount of credit extended to borrowers prone to have difficulties in obtaining credit. These borrowers will account for a reduction in spending or production, further exacerbating the economic downturn. Another related implication of this theory would be that the stronger the acceleration, the deeper the economic recession and the weaker the borrowers' balance sheets. Nonlinearity follows a similar theoretical consideration, where borrowers with low net worth encounter

a greater impact due to changes in lending cost. However, financially stable borrowers should not be affected by the cost of lending

Existing literature has shown that macroeconomic forces can amplify loan defaults; Hence, it is crucial to study the indicators of NPLs based on the macro-prudential concept of credit risk. Figure 2.1 outlines the theoretical underpinnings.



2.2 Determinants of Credit Risk

Supported by the theories, this section provides evidence of the determinants of bank credit risk, including; macroeconomic factors, monetary indicators, financial and capital market indicators.

2.2.1 Interest Rates

Interest rates represent the rate of return of banks' lending activities. The portfolio theory mentions that each bank maximises returns and minimises loan risks by charging the optimum lending rate. From the borrowers' point of view, interest rates represent the cost of borrowing, at the same time, they bear credit risk since households' indebtedness is sensitive to fluctuations in the cost of borrowing, especially for loan types with variable interest rates (Louzis, Vouldis & Metaxas, 2012 and Zaman & Meunier, 2017). A hike in interest rates usually curtails borrowers' ability to meet their debt obligations, and, thus, interest rates positively affect non-performing loans (NPLs) (Nkusu, 2011 and Adebola *et al.*, 2011). However, banks have different levels of NPLs even though they offer the same lending rate. This observation may be due to several possible reasons, such as banks' management and borrowers' credit risk (Bahruddin & Masih, 2018). On the other hand, Taylor (2009) and Justiniano *et al.* (2015) discovered that low federal fund interest rates were primarily responsible for increasing household indebtedness associated with the housing boom, which was the largest component of household debt.

2.2.2 Household income adjusted for the inflation rate

Household income is essential in determining consumption and repayment ability. The price level can be costly to the economy (Skarica, 2013). As identified by previous studies, income can be used as a proxy variable to determine borrowers' wealth and debt repayment ability (Dinh & Kleimeier, 2007; Alfaro & Gallardo, 2012; Bonilla, 2012).

On the one hand, inflation devalues the real value of debt, stimulates more household borrowing, and even reduces the unemployment rate (Phillips curve). On the other hand, inflation erodes real income value, which makes debt repayment more difficult. When inflation is high, the cost of borrowing increases and ultimately deteriorates the quality of banks loan portfolios. Nominal debt repayment values remain the same, but the real debt values are more significant if borrowers' income has not risen with the living cost (Skarica (2013), Klein (2013) and Nkusu (2011)), leveraging in a higher NPLs level. Therefore, the expectation of higher real income improves the availability of cash flow and reduces the probability of default.

2.2.3 Global Commodity Prices: Crude oil Price

A decline in commodity prices can reduce commodity exporters' revenue, affecting the economy and causing revenue shortfalls. These disruptions constrain households or firms' spending limits or consumption, leading to loan delinquency and default. (Poghosyan & Hesse,2009). Idris & Nayan (2016) also indicated that crude oil price appreciation tended to improve borrowers' wealth position and lowered the chances of default. More business units closed down due to reduced fiscal revenue due to lower consumption by unemployed economic units, leading to low cash flows and default. Supported by Hesse & Poghosyan (2009), Miyajima (2016), Lopez-Murphy Villafuerte (2010) and Callen *et al.* (2015), commodity (oil) price shocks are procyclical and provide a feedback loop on the banks' balance sheet.

2.2.4 Unemployment rate

The International Labor Organization (ILO) defines an unemployed person as someone actively looking for work but not having a job. The unemployment rate is one of the popular lagging indices. As per Okun's Law, if economic growth is hampered, the unemployment rate will be high. Unemployed borrowers will limit their spending due to less liquid cash flow and weakened ability to meet their loan obligations. Therefore, impaired loans are formed (See Castro (2013), Messai and Jouni (2013) and Beck, Jakubik and Polaiu (2015))

2.2.5 Stock market index

Booming stock markets reflect a positive outlook on firms' profitability and increase individuals' capacity to repay their loans. Kalirai and Scheicher (2002) and Jakubik and Reininger (2013) found that high stock market returns were associated with low levels of NPLs. Espinoza & Prasad (2010) also outlined that the markets experienced higher numbers of impaired loans during periods of a deflated stock market as liquidity was impaired.

2.2.6 Outstanding loans

Banks are more likely to expand financing to relatively risky borrowers during periods of credit expansion, thereby causing a higher probability of defaults when a recession sets in. Notably, regions with higher household debt growth before a financial crisis tend to experience more severe banking instability due to loan losses (Mian & Sufi, 2011). In Reinhart & Rogoff's (2010) findings, mortgage credit was negatively related to banking stability. Banks face large losses at the point of a credit bubble bursting due to a high number of defaulting loans. Kraft and Jankov (2005) supported a credit boom being one factor for banking and currency crises.

Bussiere and Fratzscher (2006) also observed that credit growth was a predictor in the early warning system model of financial stability. Using aggregate loans, Salas & Saurina (2002) and Foos *et al.* (2010) found that the relationship between credit growth and loan losses was significant and positive. Jakubík & Reininger (2013) indicated that past credit

growth was one factor that explained NPL changes. This observation was also evident during the Global Financial Crisis in 2018.

If households have accumulated too much debt, their level of indebtedness makes them more susceptible to unexpected financial distress, such as; unemployment, income and interest rate shocks. Given limited financial buffers and debt repayment capacity, managing household credit risk is an ongoing and challenging task (Nakornthab, 2010; Kukk, 2015).

2.3 Empirical Evidence

Loan default varies for different causes in different countries with multidimensional aspects in developing and developed countries. Empirically, there are reasons why loans fail to perform, from the perspectives of macro (both internal and external characteristics) and microeconomic indicators.

2.3.1 Analysis of Non-performing loans - developed vs developing countries

A study by Vogiazas & Nikolaidou (2011) utilised loan loss provision as the proxy of credit risk to determine its relationship between; macroeconomic cyclical indicators, monetary indicators, financial market indicators, Greek specific variables and Romanian bank-specific factors. Estimated by the ordinary least square (OLS) method, there was sufficient evidence to conclude that Romanian credit risk was responsive to the neighbouring risk, as Greek specific indicators influenced Romanian loan quality. Their findings indicated that; the unemployment rate, total gross external debt to GDP ratio, lagged spread differential between the Greek and German sovereign debt, inflation rate, construction expenditure and the money supply M2 influenced the Romanian credit risk.

Bofondi & Ropele (2011) studied banks' loan quality from 1990 to 2010 in Italy. The authors regressed a set of explanatory variables at different time lags to measure the quality of households and firms loans. The predictive power of the models was assessed using a recursive out of sample forecast. The household NPL ratio was negatively related to the real GDP growth and house prices. In contrast, it was positively related to the unemployment rate and short term nominal interest rate. The firms' NPLs were sensitive to the unemployment rate, the ratio of net interest expenses to gross operating profits, and durable goods consumption growth. These models' prediction accuracy was proven robust to macroeconomic condition changes during the financial crisis. The prediction accuracy in the firms' loan model improved for all forecast horizons during the crisis, which implied that macroeconomic variables explained loan quality during the crisis.

Fanstain & Novikov (2012) and Novikov (2011) employed a vector correction model to study the impact of macroeconomic variables, the banking sector, and the real estate market on NPL levels in the three Baltic States. Macroeconomic and banking sector variables had a long term effect on changes in NPLs. The real estate market variable has a short term impact on the NPL, where this impact was the co-influence of other variables. The GDP was the most significant factor that explained changes in NPLs. The rapid growth of indebtedness that followed the real estate market's increased price level was crucial to NPL growth. On the other hand, the unemployment rate determined problem loan growth, while the relationship between the unemployment rate and NPLs was only be based on mortgage loans.

Moinescu (2012) employed dynamic panel regression to assess NPLs sensitivity to the Central and Eastern European (CEE) countries' macroeconomic variables during 2003-2011. The empirical results revealed that real GDP growth was critical for the default rate dynamic and the short-run changes in the output gap. However, the monetary condition (money market interest rate 3M) was also essential to a lesser extent. Labour market indicators affected NPLs due to their strong dependency on economic growth variables. They also concluded that there was no difference across the CEE economics in terms of credit discipline.

Beck *et al.* (2013) explained differences in bank asset quality across countries and over time by studying the determinants of the NPL ratio for 75 countries. Using panel data analysis, they found that real GDP growth was the most critical risk for bank asset quality. They suggested that the impact of the exchange rate and stock prices on NPLs depended on their characteristics. A country with a high degree of currency lending may face a high NPL ratio when the foreign exchange rate depreciates. Furthermore, a drop in stock prices could reduce bank asset quality, especially in a larger stock market.

Klein (2013) conducted a study on NPLs in Central, Eastern and Southeastern Europe between 1998-2011 using panel Vector Autoregression (VAR) analysis. Changes in NPLs were explained by macroeconomic and bank-specific variables, albeit the latter had relatively low explanatory power. Notably, an increase in GDP growth and credit (GDP ratio) reduced the NPL rate. However, the unemployment rate, exchange rate and inflation rate influenced NPLs positively. The feedback effect indicated that a high NPL rate deteriorated the credit to GDP ratio, real GDP and employability. In turn, inflation rose. Among the bank-specific factors, high equity to asset ratio and higher profitability reduced NPLs; therefore, the moral hazard and the bad management hypotheses were supported. A high loan to asset ratio (excessive lending) and lagged lending also led to impaired loans. These bank-specific factors were significant during pre-and post-crisis periods. A study concerning the determinants of NPLs across Central and Eastern Europe using the fixed-effect model was conducted by Skarica (2013). The results revealed that real GDP growth was one factor that drove up NPLs. Increases in the inflation and unemployment rates caused growth in the NPL level. The fixed effects estimator eliminated the impact of time-invariant characteristics from the explanatory variables. The fixed effect model assumes that these time-invariant characteristics are unique to each entity (country); therefore, the entity's error term and intercept should be independent.

Louzis *et al.* (2012) hypothesised that macroeconomic and bank-specific variables explained loan quality and that these effects differed across loan categories. For all loan categories (business loans, consumer loans and mortgages), the NPLs in Greece were proven to be affected by macroeconomic variables and management quality in a dynamic panel data specification. Generally, NPLs were negatively related to the GDP, and the impact of economic growth on business NPLs was the strongest, followed by consumer NPLs and mortgages NPLs. Similarly, business NPLs were the most sensitive NPL type to the unemployment rate, while mortgage NPLs were the least. On the other hand, changes in the lending rate significantly impacted NPLs, so did sovereign debt, with consumer NPLs being the most responsive. This research also supported the bad management hypothesis, and the impact was quantitatively similar across the loan categories.

Further, leverage affected business NPLs and mortgage NPLs positively, up to a certain size threshold. No impact of leverage on NPLs could be inferred if the threshold was exceeded. The ROE also played an essential role in determining changes in NPLs. This adverse impact was pronounced on consumer and mortgage NPLs only, favouring the bad management II hypotheses.

Messai & Jouini (2013) identified the factors that influenced loan quality for a sample for European countries, i.e. Italy, Greece and Spain, using the sample period of 2004-2008. They found a negative relationship between the GDP growth rate and NPLs, as NPLs improved during the economic boom. As for the high unemployment rate, it was estimated that unemployed borrowers could not meet their financial obligations, and consequently, impaired loans were formed. They observed a positive relationship between the real interest rate and NPLs. Borrowers were burdened by higher interest charges leading to an increase in NPL. Concerning the bank-specific factors, the ROE was estimated to be negatively associated with NPLs because it was more prone to grant risky loans and, thus, increased the probability of default. The loan loss provisions of banks also increased with the level of NPLs.

Bucur & Dragominascu (2014) explored macroeconomic determinants on credit risk in the Romanian banking system during the economic crisis (2008-2013). The regression analysis results revealed that money supply growth and foreign exchange rate volatility significantly affected credit risk, and a higher unemployment rate elevated NPLs. However, this research identified no relationship between credit risk and real GDP growth.

Makri *et al.* (2014) identified NPL determinants in the Eurozone during the prerecession period (2000-2008). Using aggregate data of 14 countries, they employed a differenced Generalized Method of Moment (GMM) estimation on a set of first and second period lagged explanatory variables with NPLs as an endogenous variable. Besides macroeconomic variables and bank-specific factors, the model included a lagged NPL term to test NPL persistence. The findings indicated that a deterioration of the ROE marked an increase in NPLs, which led to poor performance in line with bad management. The bank capital and reserves to total assets ratios, which determines the bank's risk behaviour, had a significant and negative relationship with NPLs. The moral hazard hypothesis supported this finding as a low capital ratio increased the risk of NPLs.

On the other hand, they found a positive relationship between public debt and NPLs, where fiscal policy was crucial in assessing credit risk.

Furthermore, unemployment led to low loan quality due to borrowers incapability to make loan repayments. Last but not least, as expected, the GDP exerted influence on NPLs. Specifically, loan quality improved during boom periods.

Filip (2014) determined the linkage between Romanian NPLs and their determinants using the OLS method and Pearson Correlation analysis between 2001-2012. The findings underlined the reverse dependencies of NPLs on the GDP and changes in loan interest rates. Lagged NPLs, inflation rate changes, and bank loans' total volume explained NPLs in a positive relationship. The impact of NPLs on the GDP and changes in the interest rate charged on the bank loan was also significant and negative, while NPLs affected the volume of bank loans positively.

On the other hand, there have been several studies conducted in developing countries as well. Ahmad & Bashir (2013) employed the OLS regression method and affirmed that the macroeconomic variables, i.e. GDP growth, the interest and inflation rates, exports and industrial production, were negatively related to NPLs. In contrast, the CPI was positively related to NPLs, using Pakistani banking data from 1990 to 2011.

In another study, Ahmad & Bashir (2013) explained NPLs using Pakistani bankspecific variables and tested ten bank-specific hypotheses using an OLS estimation. The findings showed the validity of the moral hazard hypothesis, i.e. an increase in the loan to deposit ratio increased NPLs, as banks still provided credit to firms/individuals even though the banks had thin capital. The bad management II hypothesis was supported, which assumes a positive relationship between return on asset and NPLs.⁴ Bank management portrayed the wrong picture relating to the future profitability of investors. Consequently, the return on investment was not up to investors' expectations, resulting in high NPLs due to borrowers incapability to meet loan repayment's. Lastly, a significant relationship was found between credit growth and NPLs, thus, providing validity of the procyclical credit policy hypothesis.

Endut *et al.* (2013) examined the implications of macroeconomic indicators on NPLs during 2000-2008. The study was limited to two South Asia countries and ten Asia Pacific countries. Applying the random effect generalized least square (GLS) panel data analysis technique, the results indicated that high interest rates significantly contributed to high NPLs. A rise in the interest rate weakened borrowers' ability to repay loans; thus, NPLs increased. Besides that, the effect of the inflation rate on NPLs was estimated positive in the long run since a low inflation rate led to improved NPLs. There was an inverse relationship observed between NPLs and the GDP. When an economy is expanding, more revenue is obtained and, therefore, significantly reducing impaired loans as borrowers have a greater ability to settle their debts.

Hà *et al.* (2014) analysed the determinants of bank NPLs and developed a macro stress testing framework for credit risk in the Vietnamese commercial banking sector. Between 2002-2012, the pooled OLS results shown lagged NPLs, and the lending rate positively explained NPLs. In contrast, GDP growth and NPLs were negatively related. In the macro stress test, they computed the VaR and carried out a forecast on NPLs. The forecast

⁴ Rajan (1994) justified the positive relationship between past earnings and future problem loans. Management are likely to inflate current earnings by undertaking negative net present value, especially by resources of a more liberal lending policy, at the expense of future problem loans

results indicated that the minimum capital requirement for Vietnamese banks' stability was 6%, lower than the Basel I 8% benchmark.

2.3.2 Past research of Non-performing loans in Malaysia

Few studies have been conducted in Malaysia, focusing on the determinants of aggregate NPLs.

Karim *et al.* (2010) estimated the relationship between non-performing loans and bank efficiency from 1995 to 2000. Using data from Malaysian and Singaporean banks, the Tobit simultaneous equation model results indicated that an increase in bank efficiency decreased non-performing loans. This result validated the bad management hypothesis, where poor bank management leads to bad loan quality.

Likewise, banks suffering from severe non-performing loans experienced a negative effect on cost efficiency. Hence Banks are required to reserve a certain percentage of their profits for loan loss provision (Norden & Stoian, 2013 and Podder & Al Mamun, 2004)

Adebola *et al.* (2011) proposed the ARDL approach to determine the factors determining Islamic banks' non-performing loans in Malaysia from 2007:1 to 2009:12. The average lending rate had a significant positive short and long-run impact on NPLs, while the producer price index had a significant negative long-run impact. The impact of the industrial production index was insignificant in the long and short run. The findings also indicated that the crisis episode did not cause instability in the level of non-performing loans.

Research conducted by Asari *et al.* (2011) presented findings on the sensitivity of Malaysian NPLs towards macroeconomic variables and bank-specific factors. They investigated time series data ranging from 2006 to 2009 using the Vector Correction Error Model. The Granger Causality test showed that the base lending rate and inflation rate significantly explained the long-run relationship of Malaysian NPLs. They also found a negative relationship between the base lending rate (BLR) and NPLs, contradicting the economic theory. An increment in the BLR tended to burden borrowers in repaying their loans. Nonetheless, they highlighted a positive relationship between the inflation rate and the default rate. In contrast, these variables did not influence NPLs in the short run.

Janvisloo & Muhammad (2013) analysed the relationship between commercial bank NPLs and macroeconomic factors using the GMM panel data analysis method on data spanning 1997 to 2012. Factors with a two-year lag were included in the model. According to the results, increased foreign investment outflows led to a higher level of NPLs; however, foreign investment reduced NPLs after a year. As for the GDP growth, loan quality deteriorated during economic downturns. Besides, if there were a drop in domestic credit growth, NPLs would gradually lessen over the coming year. The lending rate and the percentage of foreign investment in the GDP were the most prominent factors affecting NPLs, and these effects lasted for two years.

Another Malaysian study conducted by Senawi & Mat Isa (2014) examined the relationship between Malaysian Islamic banks' NPLs and economic variables (i.e. gold price, the CPI, money supply and the exchange rate) from 2007 to 2009. Using the OLS estimation method, their results indicated that the gold price, exchange rate, and money supply affected the growth of NPLs. An increase in the gold price and appreciation of currency did not boost NPLs. In this study, gold was recommended as an alternative currency as gold's impact towards NPLs was lower than that of the Malaysian Ringgit. On the other hand, the money supply was positively related to NPLs. A higher money

supply was a source of inflation that burdened borrowers in repaying their loans, resulting in growing NPLs.

Shamsudheen & Masih (2015) estimated both the long and short-run relationships between the interest Rate (KLIBOR) and Islamic banks' non-performing loans by using controlling variables, such as; the loan growth rate, unemployment rate and the industrial production index. This study, covering Malaysian, spanned data from 2005Q1 to 2014Q4. The results of ARDL estimation showed that the KLIBOR impacted nonperforming loans only in the short run. In contrast, the industrial production index was used as the proxy to the GDP and had the most positive significant long-run effect on NPLs statistically. Loan growth and the unemployment rate had no long and short-run impacts on the NPLs. There was no structural change in non-performing loans during the crisis period.

In the study of Isaev & Masih (2017), macroeconomic changes such as; the unemployment rate, real gross domestic product growth and real lending rates were analysed with Islamic bank loan defaults across the three financing types, namely, mortgage, consumer and business. The results of the Dynamic OLS estimation indicated that the impact of economic growth and unemployment were most prominent on business loans. In contrast, consumer loans were most sensitive towards the lending rate.

Using the ARDL approach, Zainol *et al.* (2018) found that the GDP affected banks' NPLs significantly and negatively; meanwhile, the lending rate and income distribution related to NPLs positively and significantly; however, inflation was not adequate to explain NPL movements.

2.3.3 NPL analysis using a non-linear modelling technique

Many macroeconomic variables have non-linear characteristics. They are asymmetries in terms of effect. It means the effect of these economic variables when they rise is different from the effect when they fall (Neftci,1984; Falk, 1986). The relationship between credit and economic indicators may be non-linear due to information asymmetry and contractual rigidities (Calza & Sousa, 2006). Juselius and Drehmann (2015) suggested that household debt was beneficial; however, over-indebtedness, especially when it exceeds a certain threshold (Reinhart & Rogoff, 2010), may make households more vulnerable to income and interest rate shocks. Thus, consumption and growth are impacted.

Some existing literature has used econometric regime models to address the credit market's non-linearity issues. Markets are split into tight and loose credit conditions. The common flaw of the reduced-form VAR model when mimicking the relationship between financial and economic activity during a crisis is that the VAR model does not take timevarying phenomena into account. Therefore, a time-varying parameter or regime dependent modelling is introduced to overcome the issue.

Bofondi & Ropele (2011) and Caporale *et al.* (2013) presented analyses on macroeconomic and financial determinants seeking evidence of asymmetric responses to the credit shocks on loans. They examined if excessive loans granted during expansionary phases could explain a more proportional increase in non-performing loans during contraction phases. Applying the SVAR approach, the macroeconomic variables affected loan repayments at lagged time. All the bad loans were affected by the cost of debt variables (3-month Euribor interest rate and ten months IRS rate), the economic variables (for example, the unemployment rate and consumer price index) and the real

and financial wealth indicators (such as the housing price index and FTSE Mib stock exchange). This study confirmed that the bad loan surplus during recession periods resulted from excessive lending before economic contraction. The permanent shock of bad loans on excess credit was significant for firms' bad loans but not significant for household's bad loans.

Guy & Lowe (2012) found that the NPL estimates were lower than the actual NPL outcomes at turning points of the economic cycle. They argued that the non-linear modelling approach better explained the association between variables to adjust at different phases of the economic cycle. Gorton (2012) suggested that a crisis was a regime switch-type event that put under scrutiny the assumed linearity of models (Blanchard, 2014). The typical vector autoregression (VAR) model does not take time-varying phenomena into account. The generated impulse responses could not be given any structural interpretation because their innovations were not identified with the underlying structural error.

Markov switching (MS) or regime-switching models are the most popular non-linear time series models. The regimes capture cycles of economic activity around a long-term trend. The MS approach allows different behaviour in different states of the variable while simultaneously estimating when there is a movement to another state; hence, the MS model captures more complex dynamic patterns, such as conditional heteroscedasticity asymmetry. The MS model switching mechanism is controlled by an unobservable state variable that follows a first-order Markov chain. While the specification within each regime is linear, the resulting time series is non-linear, as transition probabilities are estimated to rule the transition between different regimes (Doornik & Hendry, 2009). The general form of the MS model incorporating dependent and independent variables is below:

$$y_t = \beta_0(s_t) + \sum_{i=1}^n \beta_i x_{it}(s_t) + \varepsilon_t$$

where s_t is the regime or state. Given two regimes, 0 and 1, at period t and t - 1, the transition probabilities⁵ may be written as

$$Pr(s_{t} = 1 | s_{t-1} = 1) = p_{1|1}$$

$$Pr(s_{t} = 0 | s_{t-1} = 1) = p_{0|1}$$

$$Pr(s_{t} = 0 | s_{t-1} = 0) = p_{0|0}$$

$$Pr(s_{t} = 1 | s_{t-1} = 0) = p_{1|0}$$

Grosnevor & Guy (2013) considered a Markov Switching (MS) approach, first introduced by Hamilton (1989, 1990), to explore the effects of nonlinearity in NPL series. The MS models were estimated using a Maximum Likelihood procedure, and the presence of significant nonlinearity in the series was determined using the likelihood ratio (LR) statistic. In the sample period of 1996 to 2011, Barbados's NPL cycle was not symmetrical, as the periods of low NPLs (Regime 0) were more extended than those with high NPLs (Regime 1). The GDP was negative on NPLs, more significant with low NPLs (Regime 0) than high NPLs (Regime 1). Loan growth was positively associated with NPLs in Regime 0 and negatively in Regime 1 but insignificant. Inflation was negatively significant to NPLs in Regime 0, while the opposite result was shown in Regime 1, with a more significant impact. The transition probability showed a 6 per cent chance that high

⁵ If the unobserved state variable at time t - 1 is in regime *i*, there is a probability $p_{j|i}$ will move to regime *j* at time *t*

NPLs would follow a period of low NPLs. On the other hand, the probability of transitioning from high to low NPLs was about 9 per cent.

Markov Switching Structural VAR (MSSVAR) testing was conducted to explore the determinants of credit risk in Bulgaria and Romania in the aftermath of the Global Financial Crisis 2008-09 (Karoglou *et al.*, 2015). For Bulgaria, loan growth, high unemployment and low construction activity-induced high credit risk in the long run. There was no evidence of the Greek crisis's impact on Bulgarian NPLs. About 16.4% of the disequilibria of a shock in the previous month was adjusted back to the long-run equilibrium in the current month.

On the other hand, Romanian credit risk was affected by the Greek crisis, loan growth, the unemployment rate and money supply M2 in the long run. Approximately 30% of the disequilibria of a shock in the previous month adjusted to the current month's long-run equilibrium.

The MSSVAR framework is a combination of MS and time-varying structural VAR. Following an autoregressive process:

$$y_t = \sum_{i=1}^p \phi(s_t) Y_{t-i} + \varepsilon(s_t)$$

where s_t is the unobservable state variable following the Markov process with transition probability and assuming $\varepsilon(s_t) \sim NID(0, \sigma_{s_t}^2)$. The probability suggested if the unobservable state variable at time t in regime i, there is a probability $p_{j|i}$ will move to regime j at time t + 1, $\Pr(s_{t+1} = j|s_t = i) = p_{j|i}$. In the MSVAR framework, the VAR parameters are allowed to vary across regimes: the intercept (or mean), the autoregressive coefficients, or the variance-covariance matrix and all parameters are allowed to be statedependent. For the time-varying SVAR in the MSSVAR framework, the time variation of the parameters is driven by exogenous shocks that alter the mean or the volatility dynamics of the stochastic process.

The time-varying SVAR involves identifying the number and timing of shocks using a two-step procedure⁶ proposed by Karoglou (2010) and estimating the impact of the structural shocks using a structural VAR model based on the same model-consistent restrictions imposed in the case of the MSSVAR. In the estimated model, the regimedependent impulse responses trace credit risk responsiveness to each variable's shocks. As such, the MSSVAR was proposed to allow structural changes and investigate credit risk response to shocks originating from a set of explanatory variables under a different regime.

In Bulgaria, there were two regimes: low (booming period, until October 2008) volatility and high (bust period, the remaining period) volatility. None of the variables impacted credit risk in the low regime, while these variables appeared significant in the high regime, except for the Greek crisis variable. Two regimes were identified in Romania, low (until September 2008) and high (the remaining period) volatility regime. The positive impact of loan growth on credit risk was more significant in the high regime than the low regime. The unemployment rate was positive and significant in the high regime only, while the money supply negatively affected credit risk in the high regime. The Greek crisis variable's role in Romanian credit risk was positive but marginally significant in the high regime.

⁶ The nominating stage is an algorithm-based procedure that uses one or more statistical tests to identify the possible break dates in the data. The awarding stage describes the process used in deciding whether a nominated breakdate is indeed a break date.

The non-linear time series method, however, has its limitations. Firstly, it is sensitive to sample size and the frequency of observations. Secondly, the diverging dynamic can be difficult to interpret, specifically in a regime-switching model that allows multiple regimes. Further, Haldane and Madouros (2012) suggested that the complexity may generate a robustness problem. The complex dynamics intervening in the shocks due to the regime switches can lead to considerable error bands with low significance.

2.4 Summary

In Malaysia, household debt has ballooned since the global financial crisis. As an open economy, Malaysia is influenced by its external environment. Moreover, commodity price shocks, particularly oil, have led to significant export activity losses for commodity exporters such as Malaysia. Hence, this study considered the external and domestic environment in determining the factors of credit risk. It was also noteworthy to investigate a differential impact of the indicators across the different NPL categories f Malaysian. A few indicators were identified as risk factors highlighting increased vulnerability rather than factors that forecast the next default timing.

As per the reviewed theory and empirical evidence, Hyman Minsky's theory (1992) highlighted the importance of credit risk management as over-indebtedness eventually deteriorates banks' loan portfolios (Foos *et al.* 2010), causing financial instability. Several factors affect credit activities, underpinned by Okun's Law, which hypothesises that a recovering economy improves unemployment; therefore, loan quality, whereas a rise in interest rates tends to worsen it. The reviewed literature inspired the choice of the variables included in the transmission in the longer term. The variables characterised the external environment, domestic economic condition, and the effect of monetary policy on loan repayment obligations.

The Malaysian studies have mostly analysed the determinants of banks' aggregate NPLs, either for conventional or Islamic banks, based on a set of domestic macro and microeconomic indicators using linear statistical modelling techniques. Motivated by the reviewed literature, it was decided that the non-linear modelling approach better explains the association between NPLs and their determinants to adjust to different economic conditions. This study attempted to reveal the existence of a non-linear relationship between NPLs and the tested variables. Figure 2.2 summarises the main focus of the



Figure 2.2 Conceptual Framework

CHAPTER 3: DATA AND METHODOLOGY

This chapter describes the data and methodological approaches used in this research. The first two sections detail the data and unit root tests. Section 3.3 explains the long-run relationship, followed by a linear modelling approach and diagnostic tests in Sections 3.4 and 3.5, respectively. Then, the following section presents a nonlinear modelling technique. The seventh section in this chapter formulates the general hypotheses and illustrate a summary of the research design. This chapter's last two sections present an elementary investigation of interest variables, including a simple descriptive analysis and unit root.

3.1 Data

The study employed monthly data from 2006 to 2018 to analyse Malaysian household NPLs and NPLs for economic purposes.

Monthly data captures the business cycle as the economy does not change drastically weekly and daily. Moreover, most economic data is published monthly. The study period coincided with the US, Greek and European financial crises between 2008-2011 and commodity price shocks since 2014.

To determine the differential impact of economic indicators from different categories of NPLs, household NPLs, and NPLs (in RM million) on the purchase of residential properties (PRNPL), purchase of transport vehicles (PVNPL), personal uses (PUNPL) and credit cards (CCNPL) serve as an endogenous variable. They were examined individually, corresponding to the chosen determinants, which had economic relevance. The determinants and the expected sign of coefficients are shown in Table 3.1.

Explanatory Variables	Description/Unit	Unit of measurement	Expected sign with NPLs
Household	Interpolated median household income adjusted	RM	Negative
Income Adjusted for the Inflation rate (INC)	for inflation		
Crude oil price (OIL)	Crude Oil (petroleum), the simple average of three spot prices; Dated Brent, West Texas Intermediate, and the Dubai Fateh	RM Per Barrel	Negative
Overnight Policy Rate (OPR)	The target rate for the day-to-day liquidity operations of the BNM. (Note 1)	Per cent	Positive
Unemployment rate (UNE)	The total of the labour force that is unemployed but actively seeking employment and willing to work	Per cent	Positive
Stock Market index (KLCI)	The closing price of the FTSE KLCI index	RM	Negative
Outstanding Loans by loan categories (TLR)	Total loans in Malaysian Banking system/in ratio	Ratio	Positive
CCTLR	Credit card outstanding loans	RM	
PUTLR	Personal uses outstanding loans	RM	
PRTLR	Purchase of residential properties outstanding loans	RM	
VETLR	Purchase of transport vehicles outstanding loans	RM	
OTHERTLR1	Total outstanding household loans excluding credit card loans	RM	Positive
OTHERTLR2	Total outstanding household loans excluding personal loans	RM	
OTHERTLR3	Total outstanding household loans excluding residential properties loans	RM	
OTHERTLR4	Total outstanding household loans excluding vehicle loans	RM	

Table 3.1: The expected sign of relationship

Source: Monthly Statistical Bulletin, BNM (2018); Department of Statistics Malaysia, (2018); Indexmundi.com. (Note 1) An interest rate at a depository institution lends immediately available funds in the central bank to another depository institution overnight.

3.2 Tests for Unit Root

A time-series process is non-stationary if the mean or the variance or both properties

vary over time. Since most applied techniques are based on the assumption that a data

series is stationary, it is essential to examine whether it is stationary. Autocorrelation functions, Ljung Box Q statistics, and the unit root testing are widely applied to achieve this.

In general, the Augmented Dickey-Fuller (ADF) and Phillips Perron (PP) unit root tests have low power. Low power refers to unit root tests which cannot distinguish accurately stationary processes from nonstationary processes and vice-versa) Furthermore, the size (i.e., reject I(1) too much when is true) problem (Schwert 1987, 1989, Stock 1991, Campbell and Perron 1991, Diebold and Senhadji, 1996).

Further, the ADF test that includes a constant and trend in the test regression has less power than tests that only include a constant; PP tests are more size distorted than ADF tests. Although the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test has been widely used in literature to 'confirm' the ADF and PP tests results, Maddala and Kim (1998) found that the KPSS test is also overwhelmed by the low power and size distortion. However, evidence has also shown that the KPSS test performed more efficient or consistently compared to the conventional ADF and PP unit root tests (Chen (2002); Nusair (2003)).

3.2.1 Augmented Dickey-Fuller (ADF) Test

The augmented Dickey-Fuller test (ADF) extends the Dickey-Fuller (DF) test, a commonly used unit root test that adds the lagged dependent variables; error terms are not correlated. Let y_t be a time series process. The test equation of a unit root includes a constant and deterministic trend. The ADF test equation is

$$\Delta y_t = \mu + \beta t + \gamma y_{t-1} + \sum_{i=1}^p \beta_i \Delta y_{t-i} + \varepsilon_t$$

Equation 3.1
where μ is a constant, β denotes the coefficient on a time trend, p is the lag order of the autoregressive process, and ε is the error term.

Test H_0 : $\gamma = 0$ (i.e. the series needs to be differenced to make it stationary) against H_1 : $\gamma < 0$ (i.e. the series is stationary and does not need to be differenced), the test statistics refers to

$$DF = \frac{\hat{\gamma}}{SE(\hat{\gamma})} \sim \tau \text{ distribution}^7$$

and H_0 is rejected if computed DF > the Mackinnon critical value and the series y_t is integrated of order 0 and hence stationary. Otherwise, differencing is needed.

In choosing the suitable lag length for the unit root test, the value that minimises the information criteria, such as the Akaike Information Criteria (AIC)

$$AIC = n \sum \hat{\varepsilon_t}^2 + 2m$$

Equation 3.2

and the Schwarz Bayesian information criteria (BIC)

$$BIC = n \sum \hat{\varepsilon}_t^2 + m \ln n$$

Equation 3.3

where $\hat{\varepsilon}_t$ The residuals of the unit root test regression and *m* are the parameters in the test regression, including the constant. The Schwert (1987, 1989) criteria, which are

 $^{^7}$ The empirical τ distribution was further developed by several other researchers, including McKinnon

defined as the integer part of $[(12N/100)^{0.25}]$ with N refers to the sample size, is also one of the popular information criteria.

3.2.2 Phillips-Perron (PP) Test

The Phillips-Perron (PP) unit root test examines the same null hypothesis as the ADF test. They differ mainly in how they deal with serial correlation and heteroskedasticity in the errors. One advantage of the PP test over the ADF test is that the PP test is robust to general forms of heteroskedasticity in the error term. Another advantage is that the user does not have to specify a lag length for the test regression. The PP test equation is:

$$\Delta y_t = \mu + \beta t + \gamma y_{t-1} + \varepsilon_t$$

Equation 3.4

where ε_t is I(0) and maybe heteroscedastic. The PP test corrects serial correlation and heteroscedasticity in the error term in the test equation by modifying the test statistic:

$$Z_{\alpha} = t_{\alpha} \left(\frac{\gamma_{0}}{f_{0}}\right)^{\frac{1}{2}} - \frac{T(f_{0} - \gamma_{0})(se(\hat{\alpha}))}{2f_{0}^{\frac{1}{2}}s}$$

where $\hat{\alpha}$ is the estimate, t_{α} is the *t ratio* of α , $se(\hat{\alpha})$ is the standard coefficient error, *s* is the standard error of the test regression, γ_0 is a consistent estimate of the error variance in the ADF test equation and f_0 is an estimator of the residual spectrum at frequency zero.

3.2.3 Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

The KPSS test is another unit root test that differs from the ADF test. The model equation with time trend t,

$$y_t = \mu + \beta t + \varphi \sum_{i=1}^t \varepsilon_{t-i}$$

Equation 3.5

is tested under $H_0: \varphi = 0$ (i.e., trend stationary) against $H_1: \varphi \neq 0$ (i.e., the trend is not stationary) where μ is constant, u_t is a stationary process, and the past error $\varepsilon_{t-i} \sim i.i.d$ (0, 1). Test statistic is based on the LM statistic. H_0 is rejected if the computed LM > KPSS asymptotic critical value, the series y_t is then said not trend stationary.

3.3 Long-Run Relationships

Economic and financial time series are often nonstationary. Thus, such nonstationary variables' estimates will lead to spurious regression, and their economic interpretation will not be meaningful. Inclusion of transformed data by differencing in the ordinary least square regression may incur long-run information loss.

If the unit root tests find that a series has a unit root, the appropriate route, in this case, is to transform the data by differencing the variables before their inclusion in the regression model, but this incurs a loss of crucial long-run information. If a long-run relationship exists, regression involving the level form can proceed without generating spurious results.

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t$$

Equation 3.6

Consider two I(1) time series of interest y_t . x_t . These series are said cointegrated if there is a linear combination of βx_t . The resulting combination is I(0). Economic theory often suggests that there should be the presence of cointegration between some financial or economic variables. The intuition behind cointegration is that economic forces will restore the equilibrium relationship whenever these series wander too far apart from the equilibrium, implying similar stochastic trends (Brooks, 2014).

3.4 Linear Econometric Framework: Autoregressive Distributed Lags (ARDL)

To assess the long and short-run effects of sets of chosen variables, an Autoregressive Distributed Lag (ARDL) contains the lagged dependent variable, Y_t and both current values and lagged values of one or more explanatory variables, X_t *I*s employed for the cointegration, long- and short-run analyses. In its basic form, ARDL $(p, q_1, ..., q_k)$ can be written as:

$$Y_{t} = \beta_{0} + \sum_{i=1}^{p} \beta_{p} Y_{t-p} + \sum_{j=1}^{k} \sum_{i=0}^{q_{j}} a_{j,i} X_{j,t-i} + \varepsilon_{t}$$

Equation 3.7

where p is the number of lags of the dependent variable, Y_t , q is the number of lags of the explanatory variable, X_t and ε_t is a random disturbance term. Some explanatory variables may be static, i.e. no lagged terms, while dynamic explanatory variables contain at least one lagged term. Estimates with least square regression, the optimum lag length p and q in the model can be determined using standard the Akaike Information Criterion (AIC) and Schwarz Bayesian Criteria (SIC). The ARDL technique estimates $(p + 1)^k$ Regression where p is the maximum number of lags and k is the number of variables in Equation 3.7.

An ARDL model estimates the short and long-run relationships between the dependent and the explanatory variables. The long-run relationship indicates that the state of the system remains stable over a period and has no tendency of changing drastically

i.e. $y_{t-1} = y_t, x_{t-1} = x_t$. Hence, the first differenced variables will be zero in the long run if there is equilibrium. The estimated long-run parameter compute as:

$$\theta_j = \frac{\sum_{i=1}^{q_j} a_{j,i}}{1 - \sum_{i=1}^{p} \beta_i}$$

Equation 3.8

Conventional methods for estimating cointegrating relationships available in the literature are residual-based (Eagle & Granger, 1987) and maximum likelihood-based (Johansen 1991, 1995). The traditional cointegration method requires all the variables to be of the same integration of order one. If any of the variables is in I (1), estimation using an ordinary least square (OLS) estimator will lead to a spurious result, while if the variables are all in I (1), the vector error correction (VEC) model is preferred⁸.

The OLS based autoregressive distributed lag (ARDL) approach to cointegration has become popular in recent years. THE ARDL approach (Pesaran & Pesaran (1997); Pesaran *et al.* (2001)) offers advantages that do not require the **same integration order in all the variables under study, is free from autocorrelation problems and is robust for small sample sizes**. The ARDL method integrates the short-run impact of the given variables with a long-run equilibrium using an error correction term without dropping long-run information (Pesaran & Shin, 1999).

Further, it is based on a single equation framework rather than a system equation, such as the vector autoregression (VAR) model, so the number of parameters to be estimated is reduced. Unlike the Johansen approach, several lags' restrictions can be applied to each

⁸ Restricted Vector autoregression

variable separately. The ARDL approach also does not require pre-testing for the order of integration of the variables used in the model.

The cointegrating regression form of the ARDL model is obtained by first differenced of Equation 3.7, and the error correction term is obtained by substituting the long-run estimates from Equation 3.8. An error correction term is defined by *ECT* in Equation 3.9, and the negative sign of the error correction term shows that the model moves towards the stable position in the long run. The coefficient λ _reveals the speed Y of return to equilibrium after a shock in X.

$$\Delta Y_t = -\sum_{i=1}^{p-1} \beta_i \Delta Y_{t-1} + \sum_{j=1}^k \sum_{i=0}^{q_t-1} \alpha_{j,i} \Delta X_{j,t-i} - \lambda ECT_{t-1} + \varepsilon_t$$

Equation 3.9

where $ECT_t = Y_t - \beta_0 - \sum_{j=1}^k X'_{j,t}\theta_j$. Statistically, the *ECT* is a residual from the long-run cointegration model. According to Pesaran *et al.* (2001), one may assess whether the ARDL model contains the level (or long run) relationship between the variables using the ARDL Bounds Cointegration Test model

$$\Delta y_t = -\sum_{i=1}^{p-1} \beta_i \Delta Y_{t-1} + \sum_{j=1}^k \sum_{i=0}^{q_t-1} \alpha_{j,i} \Delta X_{j,t-i} - \rho Y_{t-1} - \beta_0 - \sum_{j=1}^k \pi_j X_{j,t-1} + \varepsilon_t$$

Equation 3.10

As hypothesised $H_0: \pi_1 = \pi_2 = \cdots \pi_k = 0$ vs $H_1:$ at least one π is not equal to 0, two sets of critical values for the cases where all regressors are I(0) and the cases where all the regressors are I(1) are computed for a given significance level. The null hypothesis is rejected if the calculated F statistics exceed the upper bound critical values. If the Fstatistic falls into the bound, the test becomes inconclusive (the variables composed of level and first difference integrated series for possible cointegration). The null hypothesis is not rejected if the calculated F statistic is below the lower bound critical value. No evidence of rejecting the null hypothesis indicates no cointegration, i.e., no long-run relationship exists between the variables. Under the case of inclusive conclusion, a possible remedial action is to examine the error correction term following (Banerjee *et al.*, 1998; Kremers *et al.*, 1992).

3.5 Diagnostic Tests

To ascertain the model's adequacy, a series of diagnostic tests were carried out to test the residuals for the existence of; autocorrelation, heteroscedasticity and normality. Additionally, the stability test was carried out by the cumulative sum of recursive residuals method (CUSUM), proposed by Brown *et al.* (1975), to check the stability of long- and short-run coefficient estimates⁹. Laurenceson & Chai (2003) mentioned that as long as the functionality test or the stability test was validated, the serial correlation would not distort the estimation. Further, heteroscedasticity and non-normality would be expected if the estimated model comprised variables with different integration orders.

3.5.1 Test for Parameter Stability: Cumulative sum of recursive residuals (CUSUM)

The existence of cointegration does not necessarily imply that the estimated coefficients are stable. Pesaran and Pesaran (1997) suggested applying the cumulative sum of recursive residuals (CUSUM), proposed by Brown *et al.* (1975), to the residuals of the estimated model to assess parameter constancy. These techniques can detect

⁹ The CUSUM test uses the cumulative sum of recursive residuals based on the first observations and is updated recursively and plotted against break point. The test is more suitable for detecting systematic changes in the regression coefficients.

systematic changes in the regression coefficients or structural instability in the parameters of the models

As per hypothesis H_0 : All coefficients were stable. The residuals were updated recursively plotted against the 5% critical bound for breakpoints. If the null hypothesis is not rejected, there is evidence of coefficients' stability and indicates an absence of a structural break in the estimated model. Unlike the Chow test that requires breakpoints to be specified, CUSUM does not require prior knowledge of the structural break's exact date. Naiya and Manap (2013) and Fuinhas and Marques (2012) recommended increasing the sample size or including a dummy variable if the coefficients were unstable.

3.5.2 Test for Serial Correlation: Breusch-Godfrey test

Serial correlation does not affect the unbiasedness but rather the efficiency of the regression estimators, therefore, invalidating the significance test. The Breusch Godfrey test assumes covariance $(\varepsilon_i, \varepsilon_j) = 0$ for all *i* and *j* (different lags), otherwise the series is said to be serially correlated. The test hypothesises H_0 : $\rho = 0$ (No serial correlation) versus H_1 : $\rho \neq 0$ (Has serial correlation up to order p)

The simplest form of the Breusch Godfrey test tested on residuals is:

$$\varepsilon_t = \varepsilon_{t-1}\rho + v_t, v_t \sim N(0, \sigma_v^2)$$

Equation 3.11

This study tested for serial correlation up to lag 2.

3.5.3 Test for Heteroscedasticity

The White test for heteroscedasticity tests if the residuals have constant variances, i.e., Variance $(\varepsilon_t) = \sigma^2$, for all t. The test is hypothesised as H_0 : Constancy of residuals variances (Homoscedasticity) versus H_1 : Non-constancy of residuals variances (Heteroscedasticity). If heteroscedasticity is found, the estimation will no longer have a minimum variance, unbiased estimator.

3.6 Nonlinear Econometric Framework

The sample period covers different crisis episodes (Refer to Figure 1.1). At stress, the relationship between the economic or financial variables may be nonlinear (Foglia, 2008). In a different setting, the nonlinear modelling technique can serve as cross-validation of the results' robustness. Dufrénot and Mignon (2012) highlighted that there is always market friction. Hence, conventional methodologies, such as VECM, the bounds test that imply a constant adjustment speed to long-run equilibrium after a shock, do not hold. The methodology assumes the explanatory variable's impact is similar over time.

The development of the asymmetric ARDL or non-linear ARDL (NARDL) models are new techniques to capture the long and short-run asymmetries among variables while detecting the asymmetries in the dynamic relationship. The technique was advanced by Shin *et al.* (2014) and is an asymmetric expansion of the above linear ARDL model. Similar to the linear ARDL, the validity of the NARDL model depends on the CUSUM test. The autocorrelation problem does not distort the estimation while heteroscedasticity and nonnormality are expected if the estimated model comprises variables with different integration orders (Laurenceson and Chai, 2003)

Following Pesaran & Shin (1999), Shin *et al.* (2011), the following nonlinear asymmetric cointegration regression is proposed:

$$y_t = \beta^+ x_t^+ + \beta^- x_t^- + \varepsilon_t$$

Equation 3.12

where β^+ and β^- are the associated long-run parameters while:

$$x_t = x_0 + x_t^+ + x_t^-$$

Equation 3.13

the $q \ge 1$ vector of regressors decomposed to x_t^+ and x_t^- , the partial sum process of positive and negative changes in x_t

$$x_{t}^{+} = \sum_{j=1}^{t} \Delta x_{j}^{+} = \sum_{j=1}^{t} \max(\Delta x_{j}, 0) \text{ and } x_{t}^{-} = \sum_{j=1}^{t} \Delta x_{j}^{-} = \sum_{j=1}^{t} \min(\Delta x_{j}, 0)$$
Equation 3.14

Linking Equation 3.12 to the general ARDL (p, q) as in Equation 3.7, the asymmetric error correction model is obtained by:

$$\Delta y_t = \rho y_{t-1} + \theta^+ x_{t-1}^+ + \theta^- x_{t-1}^- + \sum_{i=1}^{p-1} \varphi_i \Delta Y_{t-i} + \sum_{i=1}^q (\pi_i^+ \Delta x_{t-i}^+ + \pi_i^- \Delta x_{t-i}^-) + \varepsilon_t$$

where $\theta^- = -\rho/\beta^-$ and $\theta^+ = -\rho/\beta^+$

The long-run relationship between y_t , x_t^+ and x_t^- , is established referring to a joint null hypothesis $H_0: \rho = \theta^- = \theta^+$. The Wald test is deployed to examine the presence of longrun symmetry, testing $H_0: \theta = \theta^- = \theta^+$ while the presence of short-run symmetry is hypothesised as $H_0: \pi = \sum_{i=1}^q \pi_i^+ = \sum_{i=1}^q \pi_i^-$

If the short-run symmetry is not rejected, Equation 3.15 will be rewritten as:

$$\Delta y_{t} = \rho y_{t-1} + \theta^{+} x_{t-1}^{+} + \theta^{-} x_{t-1}^{-} + \sum_{i=1}^{p-1} \varphi_{i} \Delta Y_{t-i} + \sum_{i=1}^{q} \pi_{i} \Delta x_{t-i} + u_{t}$$

Equation 3.15a

with a linear relationship in the short run, while in the long-run symmetry is not rejected, Equation 3.15 can be rewritten as:

$$\Delta y_t = \rho y_{t-1} + \theta x_{t-1} + \sum_{i=1}^{p-1} \varphi_i \Delta Y_{t-i} + \sum_{i=1}^q (\pi_i^+ \Delta x_{t-i}^+ + \pi_i^- \Delta x_{t-i}^-) + v_t$$

Equation 3.15b

where the long-run relationship is presented linearly. However, if both the long and short symmetry are not rejected, linear (symmetry), the ARDL model will be used.

$$\Delta y_{t} = \rho y_{t-1} + \theta x_{t-1} + \sum_{i=1}^{p-1} \varphi_{i} \Delta Y_{t-i} + \sum_{i=1}^{q} (\pi_{i} \ \Delta x_{t-i}) + w_{t}$$

Equation 3.15c

3.7 Research Hypotheses

Under linear and nonlinear modelling approaches, this study investigated whether there was a long and short-run relationship between the endogenous variable, Malaysian banks household non-performing loans (NPLs) and the five chosen control indicators: the crude oil price, household income adjusted for inflation, the overnight policy rate, the unemployment rate and the stock market index. The study analyses separately the long and short-run effects of the five indicators on each NPL by four different economic purposes (credit cards, personal uses, purchase of properties and purchase of transport vehicle) for 2006- 2018. Figure 3.1 illustrates the research design.

The general hypotheses for the study were

Hypothesis 1: Each type of credit affects household NPLs differently.

Hypothesis 2: Types of debt and economic and financial determinants have a differential impact on NPLs depending on the loan categories.

Hypothesis 3 A non-linear econometric methodology is better at explaining relationships between the indicators and household NPLs driven by a different crisis period that suggest regime shift.



Figure 3.1: Research design

3.8 Descriptive Analysis

Table 3.2 tabulates the descriptive statistics of Non-performing loans (NPLs) by different types of loans and explanatory variables (global crude oil prices, Kuala Lumpur composite index, household income adjusted for the inflation rate, unemployment and the overnight policy rate) used in the study. At the same time, Figures 3.2 and 3.3 illustrate the trend of these variables of interest.





Source: Monthly Statistical Bulletin; BNM (2018). Note: The the x-axis denotes sample period of 2006 to 2018. (a) Top, the y-axis denotes household NPL (in Million, RM), (b) Top left, the y-axis denotes credit card NPLs (in Million, RM), (c) Top right, the y-axis denotes personal uses NPLs (in Million, RM), (d) Bottom left, the y-axis denotes transport vehicles NPLs, (e) Bottom right, the y-axis denotes NPLs for the purchase of properties



Figure 3.3: The economic and financial determinant of Malaysian NPLs Source: Monthly Statistical Bulletin, BNM (2018); DOSM (2018); Index Mundi.com. *Note: x-axis denotes sample period of 2006 to 2018. (a) Top left y-axis: household income adjusted for inflation, (b) Top right, y-axis: the crude oil price, (c) Bottom left, y-axis: OPR, (d) Bottom right, y-axis: unemployment rate, (e) Bottom centre, y-axis: KLCI*

Throughout the sample period, credit card NPLs ranged from 0.63% to 1.53% of total loans. They recorded the lowest deviation (0.02%), meanwhile personal uses NPLs marked a minimum ratio of 0.36% and a maximum ratio of 1.79%, with the second-lowest deviation (1.126%) from the mean. Followed by the second-highest deviation (0.11%) from the mean purchase of transport vehicles NPLs ratio varied between 2.29% and 7.83%.

In contrast, the purchase of properties NPLs ratio showed the highest deviation (0.47%) from the mean, with NPL ratio values fluctuating between 9.24% and 27.16%. The variations hypothesised that different loan categories of NPLs responded differently towards the external environment and domestic market condition. In general, the NPLs for different loan categories have improved steadily since 2006. However, an upward trend in three categories NPLs indicated that the purchase of properties, personal uses

and credit card NPLs have been on the rise recently. On the other hand, the household NPLs range from 15.97% to 45.07% of total NPLs with a 0.76% deviation from the mean.

	Mean	Standard Deviation	Skewness	Minimum	Maximum
HOUSEHOLDNPL	12628.72	405.47	1.20	8551.62	24137.96
in ratio	23.58%	0.76%		15.97%	45.07%
CREDIT CARD NPL (CCNPL)	519.17	8.26	1.07	337.88	819.67
in ratio	0.97%	0.02%		0.63%	1.53%
PERSONAL USES NPL (PUNPL)	1354.31	24.18	0.36	959.90	2048.98
in ratio	2.53%	0.05%		1.79%	3.83%
PROPERTIES NPL (PRNPL)	7864.72	254.05	0.92	4949.43	14547.13
in ratio	14.68%	0.47%		9.24%	27.16%
VEHICLES NPL (VENPL)	2083.66	59.32	1.65	1226.13	4191.79
in ratio	3.89%	0.11%		2.29%	7.83%
HOUSEHOLD INCOME ADJUSTED FOR INFLATION (INCOME)	3484.95	61.53	0.32	2559.39	4848.06
CRUDE OIL PRICE (OIL)	264.89	4.94	0.08	129.99	430.78
OVERNIGHT POLICY RATE (OPR)	3.04	0.03	-1.30	2.00	3.50
UNEMPLOYMENT RATE (UNE)	3.25	0.02	0.13	2.79	3.79
KUALA LUMPUR COMPOSITE INDEX(KLCI)	1502.27	23.69	-0.71	863.61	1884.91

Table 3.2: Summary of descriptive statistics

Concerning the explanatory variables, global crude oil prices wandered up and down and hit the highest rate at RM430.78 per barrel in July 2008, while the lowest rate was in January 2016. Household income taking the inflation rate into account, showed slow and steady increases. The overnight policy rate (OPR), which could affect lending rates, had been adjusted several times to cushion the uncertainties in the global and domestic market conditions. As seen, the highest OPR marked 3.50% in February 1998, while the lowest OPR recorded 2.00% in 2009 February and remained for 12 months. Unemployment fluctuated slightly between 2.7% (lowest in 2014 Q3) and 4.5% (highest in 1999Q1). The Kuala Lumpur Composite Index (KLCI) closed at 1884.9, its highest, in 2014 June and went down to the lowest point for two quarters since the last quarter of 2018.

Table 3.3 shows how the tested economic and financial determinant variables were correlated before and after the decomposition in the sum of negative and positive changes. Generally, household income adjusted for the inflation rate, the OPR and KLCI were positive, negatively affecting crude oil and unemployment rates. The crude oil price, real income and the unemployment rate were related negatively; on the other hand, the crude oil price, KLCI and the OPR were related positively. There was a negative association between the OPR and unemployment rate, whereas the OPR and the tested variables were positively related. As expected, the unemployment rate and the stock market tended to have a negative relationship. The correlation statistics showed that the KLCI and real income were strongly correlated; this might indicate multicollinearity. In theory, multicollinearity inflates the regression coefficient's errors, but coefficients remain unbiased (Goldberger, 1991). Further, in most of the econometric analyses, multicollinearity issues could be ignored in an ARDL model as the degree of differencing of data tends to decompose model residuals and eliminate multicollinearity (Shabbir, 2019)

3.9 Unit Root and Stationarity Tests

The ARDL cointegration technique is preferable when dealing with a variable that is integrated of a different order, I(0), I(1) or a combination of them both. It is robust when a single long-run relationship exists between the underlying variables in a small sample size (Nkoro & Uko, 2016). Unit root and stationarity tests are conducted to ensure no series are I(2)¹⁰. The Augmented Dickey-Fuller (ADF) and Phillip Perron (PP) tests tested for unit root with constant and trending each series. The automatic selection method chose the optimal lag length by minimising the Schwarz Information Criterion (SIC). Natural logarithm (LN) transformations to avoid nonstationarity in variance were performed on all the tested series (except the overnight policy and unemployment rates) before the unit root tests were carried out.

For comparison, the Phillip Perron test corrects any serial correlation and heteroscedasticity in the error term. In contrast, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test tested the trend stationary for each series. The unit root and stationarity tests are shown in Table 3.4, and there is some contradiction of results between tests. The null hypothesis was rejected at a 5% significance level using the KPSS test for some tested series. However, most test results indicated that all the series were stationary after taking the first differencing.

¹⁰ Detailed discussion in Pesaran et al. (2010)

Correlation	INCOME	OIL	OPR	UNE	KLCI	INCOME-	INCOME+	OIL-	OIL+	OPR-	OPR+	UNE-	UNE+	KLCI-	KLCI+
INCOME	1.0000														
OIL	-0.1745	1.0000													
OPR	0.1294	0.0810	1.0000								-				
UNE	-0.1153	-0.4415	-0.4107	1.0000											
KLCI	0.8102	0.1926	0.0956	-0.4438	1.0000										
INCOME-	-0.7396	0.0175	0.3535	-0.0633	-0.5950	1.0000									
INCOME+	0.9973	-0.1619	0.0804	-0.0989	0.8076	-0.7866	1.0000								
OIL-	-0.9526	0.2221	0.0982	-0.0155	-0.7568	0.8804	-0.9691	1.0000							
OIL+	0.9439	-0.0428	-0.0856	-0.0657	0.8111	-0.8989	0.9631	-0.9836	1.0000						
OPR-	-0.6982	0.0403	0.5300	0.0616	-0.6903	0.8695	-0.7346	0.8297	-0.8427	1.0000					
OPR+	0.9127	0.0114	0.1018	-0.3695	0.8790	-0.7643	0.9199	-0.9023	0.9266	-0.7896	1.0000				
UNE-	-0.9541	0.0516	-0.0036	0.2533	-0.8713	0.8316	-0.9652	0.9582	-0.9723	0.8286	-0.9747	1.0000			
UNE+	0.9512	-0.1851	-0.1188	0.0368	0.7677	-0.8779	0.9676	-0.9944	0.9848	-0.8375	0.8966	-0.9574	1.0000		
KLCI-	-0.9030	0.0996	0.1904	0.0528	-0.7521	0.9345	-0.9295	0.9712	-0.9768	0.8870	-0.9027	0.9552	-0.9710	1.0000	
KLCI+	0.9246	-0.0058	-0.1042	-0.1892	0.8809	-0.8738	0.9427	-0.9554	0.9779	-0.8722	0.9478	-0.9829	0.9589	-0.9744	1.0000

Table 3.3: Correlation Matrix

	Level:		Level:			First difference	e:		Level:		F	first difference		Lev	vel:	Fi differe	irst nce:
		ADF			ADF			Рр			рр		KP	KPSS KPS		PSS	
Null Hypothesis:	Has a unit root		Has a unit root		Has a unit root		Has a unit root			Is stationary		Is stationary					
	t-stat	prob	lag length	t-stat	Prob	lag length	t-stat	prob	Band width	t-stat	prob	bandw idth	LM stat	bandw idth	LM stat	bandw idth	
LNINCOME	-1.9221	0.6378	1	-7.0532	<0.0001**	0	-1.8782	0.6611	6	-7.6821	<0.0001**	4	0.2325***	10	0.0009	6	
LNOIL	-3.0969	0.1111	1	-8.1052	<0.0001**	0	-2.8151	0.1942	3	-8.4335	<0.0001** *	2	0.1930**	9	0.0378	2	
OPR	-2.4385	0.3584	2	-9.5474	<0.0001** *	0	-2.0625	0.5621	6	-9.7106	<0.0001**	4	0.1579**	10	0.0560	6	
UNE	-2.3370	0.4112	0	-12.3279	<0.0001** *	0	-2.4440	0.3556	4	-12.3279	<0.0001**	2	0.1859**	10	0.0608	2	
LNKLCI	-1.8101	0.6949	1	-10.2438	<0.0001** *	0	-2.2727	0.4459	6	-10.8324	<0.0001**	5	0.1426*	9	0.0411	6	
LNHOUSEH OLDNPL	0.0480	0.9965	1	-14.5988	<0.0001** *	0	-0.0585	0.9952	5	-14.4095	<0.0001** *	6	0.37476***	10	0.1045	5	
LNCCNPL	-2.7047	0.2364	0	-11.9451	<0.0001**	0	-2.9581	0.1479	5	-11.9516	<0.0001**	3	0.2157**	9	0.0288	2	
LNPUNPL	-0.3557	0.9883	1	-14.8710	<0.0001** *	0	-0.2683	0.9909	4	-15.2418	<0.0001** *	2	0.3177***	10	0.0821	7	
LNPRNPL	0.3042	0.9985	0	-13.2854	<0.0001**	0	0.1267	0.9973	7	-13.2730	<0.0001** *	7	0.3110***	10	0.1626**	7	
LNVENPL	-2.0615	0.5623	3	-5.6351	<0.0001** *	2	-1.5985	0.7890	4	-15.8215	<0.0001** *	6	0.2154**	10	0.1513**	3	
LNCCTLR	-2.2085	0.4809	12	-2.6820	0.0029***	11	-3.4392	0.0500	10	-10.46072	<0.0001**	5	0.3004***	10	0.2098**	5	
LNPUTLR	-1.7611	0.7189	0	-13.3603	<0.0001** *	0	-1.7675	0.7159	1	-13.36032	<0.0001**	0	0.3537***	10	0.1618**	0	

Table 3.4: Unit Root and Stationarity Tests

'Table 3.4: continued'

LNPRTLR	-1.1361	0.9187	0	-11.6325	<0.0001**	0	-1.1636	0.9136	3	-11.63913	<0.0001**	3	0.3747***	3	0.0668	3
					*						*					
LNVETLR	-2.3791	0.3890	0	-12.2555	<0.0001** *	0	-2.3653	0.3962	2	-12.38928	<0.0001** *	8	0.2507***	10	0.0524	7
OTHERTLR_1	-2.2894	0.4368	0	-11.6456	0.0000***	0	-2.3929	0.3818	3	-11.6456	0.0000***	0	0.1980**	10	0.0558	0
OTHERTLR_2	-2.0067	0.5928	0	-12.1228	0.0000***	0	-2.1003	0.5412	4	-12.1207	0.0000***	3	0.2478***	10	0.0597	3
OTHERTLR_3	-0.6215	0.9761	0	-11.5857	0.0000***	0	-0.6853	0.9719	4	-11.5734	0.0000***	3	0.3486***	10	0.0776	3
OTHERTLR_4	-2.6699	0.2507	0	-11.3272	0.0000***	0	-2.9754	0.1426	5	-11.3506	0.0000***	4	0.1396*	9	0.0361	4

Note: Asterisks ***, **, * indicate statistically significant at 1%, 5% and 10%. Critical value based on MacKinnon (1996) for the ADF test and PP test Critical value based on Kwiatkowski-Phillips-Schmidt-Shin (1992) for the KPSS test.

CHAPTER 4: HOUSEHOLD NON-PERFORMING LOANS AND HOUSEHOLD CREDITS

Based on the underpinning theories and past empirical studies, this chapter relates the research questions, presents and interprets the econometric modelling findings to the scope of the study. Using monthly data from 2006 January to 2018 December, this study analysed the ex-post credit risk in NPLs. The Asian Financial Crisis, Global Financial Crisis, Euro sovereign debt crisis, and commodity prices declined during the study period.

In this direction, the study attempted to reveal the effect of credit facilities (credit cards, personal uses, purchase of residential properties and transport vehicles) on Malaysian banks' household NPLs. These are the four major types of household debt. Hence it was expected that these four categories would be most likely to be affected by shocks or economic headwinds. There were several crisis episodes throughout the sample period. In the following chapter, the study employs a nonlinear modelling technique for analysis as a nonlinear model may capture the asymmetrical impacts of household credit on household NPLs.

4.1 **ARDL** framework

The unit root and stationary test results in Section 3.9 showed that none of the series was I(2) and validated that ARDL was an appropriate modelling method. On the other hand, the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) were used to obtain the optimal lag length based on the first differenced variables. The SIC tends to choose lower order of lags as this method is more concerned with over parameters. In determining the factors that explain household debt impairment, the AIC, in contrast, predicted the best order of lag and was more relevant in choosing the optimum lag since the relationship between these variables should be dynamic.

In this study, the analysis of household NPLs was distinguished by four types of credit facilities separately, and those were credit cards (CCTLR), personal uses (PUTLR), purchase of residential properties (PRTLR) and purchase of transport vehicles (VETLR). The control variables used were household income adjusted for inflation (INCOME), the crude oil price (OIL), the overnight policy rate (OPR), the unemployment rate (UNE) and the stock market index (Kuala Lumpur composite index (KLCI)).

Based on the ADRL technique $(p, q_0, q_1, q_2, q_3, q_4, q_5)$, the empirical models were as follows.

$\begin{aligned} \text{Model 1:} \\ D(LNHOUSEHOLDPL)_t \\ &= \beta_0^* + \rho LNHOUSEHOLDPL_{t-1} + \pi_0 LNCCTLR_{t-1} + \pi_1 LNINCOME_{t-1} \\ &+ \pi_2 LNOIL_{t-1} + \pi_3 OPR_{t-1} + \pi_4 UNE_{t-1} + \pi_5 LNKLCI_{t-1} \\ &+ \sum_{i=1}^{p-1} \gamma_i D(LNHOUSEHOLDNPL)_{t-i} \\ &+ \sum_{l_0=0}^{q_0-1} \theta_{1,l_1} D(LNCCTLR)_{t-l_0} + \sum_{l_1=0}^{q_1-1} \theta_{1,l_1} D(LNINCOME)_{t-l_1} \\ &+ \sum_{l_2=0}^{q_2-1} \theta_{2,l_2} D(LNOIL)_{t-l_2} + \sum_{l_3=0}^{q_3-1} \theta_{3,l_3} D(OPR)_{t-l_3} \\ &+ \sum_{l_4=0}^{q_4-1} \theta_{4,l_4} D(UNE)_{t-l_4} + \sum_{l_5=0}^{q_5-1} \theta_{5,l_5} D(LNKLCI)_{t-l_5} + \varepsilon_t \end{aligned}$

Equation 4.1a

Model 2: D(LNHOUSEHOLDPL)_t

$$\begin{split} &= \beta_0^* + \rho LNHOUSEHOLDPL_{t-1} + \pi_0 LNPUTLR_{t-1} + \pi_1 LNINCOME_{t-1} \\ &+ \pi_2 LNOIL_{t-1} + \pi_3 OPR_{t-1} + \pi_4 UNE_{t-1} + \pi_5 LNKLCI_{t-1} \\ &+ \sum_{\substack{i=1 \\ q_0 - 1}}^{p-1} \gamma_i D(LNHOUSEHOLDNPL)_{t-i} \\ &+ \sum_{\substack{l_0 = 0 \\ l_0 = 0}}^{q_0 - 1} \theta_{1,l_1} D(LNPUTLR)_{t-l_0} + \sum_{\substack{l_1 = 0 \\ l_1 = 0}}^{q_0 - 1} \theta_{1,l_1} D(LNINCOME)_{t-l_1} \\ &+ \sum_{\substack{l_0 = 0 \\ l_2 = 0}}^{q_2 - 1} \theta_{2,l_2} D(LNOIL)_{t-l_2} + \sum_{\substack{l_3 = 0 \\ l_3 = 0}}^{q_3 - 1} \theta_{3,l_3} D(OPR)_{t-l_3} \\ &+ \sum_{\substack{l_4 = 0 \\ l_4 = 0}}^{q_4 - 1} \theta_{4,l_4} D(UNE)_{t-l_4} + \sum_{\substack{l_5 = 0 \\ l_5 = 0}}^{q_5 - 1} \theta_{5,l_5} D(LNKLCI)_{t-l_5} + \varepsilon_t \end{split}$$

Equation 4.1b

Model 3: D(LNHOUSEHOLDPL)_t

$$= \beta_{0}^{*} + \rho LNHOUSEHOLDPL_{t-1} + \pi_{0}LNPRTLR_{t-1} + \pi_{1}LNINCOME_{t-1} + \pi_{2}LNOIL_{t-1} + \pi_{3}LNOPR_{t-1} + \pi_{4}LNUNE_{t-1} + \pi_{5}LNKLCI_{t-1} + \sum_{i=1}^{p-1} \gamma_{i}D(LNHOUSEHOLDNPL)_{t-i} + \sum_{l_{0}=0}^{q_{0}-1} \theta_{1,l_{1}}D(LNPRTLR)_{t-l_{0}} + \sum_{l_{1}=0}^{q_{1}-1} \theta_{1,l_{1}}D(LNINCOME)_{t-l_{1}} + \sum_{l_{2}=0}^{q_{2}-1} \theta_{2,l_{2}}D(LNOIL)_{t-l_{2}} + \sum_{l_{3}=0}^{q_{3}-1} \theta_{3,l_{3}}D(OPR)_{t-l_{3}} + \sum_{l_{4}=0}^{q_{4}-1} \theta_{4,l_{4}}D(UNE)_{t-l_{4}} + \sum_{l_{5}=0}^{q_{5}-1} \theta_{5,l_{5}}D(LNKLCI)_{t-l_{5}} + \varepsilon_{t}$$

Equation 4.1c

Model 4: D(LNHOUSEHOLDPL)_t

$$\begin{split} &= \beta_0^* + \rho LNHOUSEHOLDPL_{t-1} + \pi_0 LNVETLR_{t-1} + \pi_1 LNINCOME_{t-1} \\ &+ \pi_2 LNOIL_{t-1} + \pi_3 OPR_{t-1} + \pi_4 UNE_{t-1} + \pi_5 LNKLCI_{t-1} \\ &+ \sum_{\substack{l=1\\q_0-1}}^{p-1} \gamma_l D(LNHOUSEHOLDNPL)_{t-l} \\ &+ \sum_{\substack{l_0=0\\q_2-1}}^{q_0-1} \theta_{1,l_1} D(LNVETLR)_{t-l_0} + \sum_{\substack{l_1=0\\l_1=0}}^{q_1-1} \theta_{1,l_1} D(LNINCOME)_{t-l_1} \\ &+ \sum_{\substack{l_2=0\\q_2-1}}^{q_2-1} \theta_{2,l_2} D(LNOIL)_{t-l_2} + \sum_{\substack{l_3=0\\q_3-1}}^{q_3-1} \theta_{3,l_3} D(OPR)_{t-l_3} \\ &+ \sum_{\substack{l_4=0\\q_4-1}}^{q_4-1} \theta_{4,l_4} D(UNE)_{t-l_4} + \sum_{\substack{l_5=0\\q_5,l_5}}^{q_5-1} D(LNKLCI)_{t-l_5} + \varepsilon_t \end{split}$$

4.1.1 ARDL Bound Test

This study attempted to distinguish household lending's possible roles on household nonperforming loans (NPLs) in the long and short run, controlled by macroeconomic, financial, and monetary indicators: household income adjusted for inflation, the crude oil price, the overnight policy rate, the unemployment rate and the KLCI.

Based on the ARDL model, an equilibrating relationship was extracted using ARDL bounds cointegration. Besides, the speed for adjustment was estimated if cointegration existed (Pesaran and Shin, 1999; Pesaran *et al.*, 2001).

The findings of the bounds test are tabulated in Table 4.1. It was hypothesised as H_0 : (No cointegration) against H_1 : the existence of long-run cointegration.

Table 4.1: ARDL bound test for cointegration (Endogenous: household NPLs)

	Bound Test for Cointegration										
Null Hypothesis: No long-run relationship exists											
	Model 1	Model 2	Model 3	Model 4							
F-statistic	4.88***	6.89***	5.34***	6.38***							
		Critical Bound									
Significance level		I(0)	I(1)								
10%		1.99	2.94								
5%		2.27	3.28								
1%		2.88	3.99								

Note: Asterisks ***, **, * indicate statistically significant at 1%, 5% and 10%

The F statistic was above the upper bound; therefore, there was sufficient evidence to reject the null hypothesis at a 1% significance level and conclude that a long-run relationship existed between household NPLs, outstanding loans, household income

adjusted for inflation, the crude oil price, the overnight policy rate, the unemployment rate and the stock market index.

The results of the ARDL bounds test approach for cointegration presented earlier confirmed that a long-run relationship existed between household NPLs, household credit, and both the global and domestic economic condition, as well as the long-run relationship between NPLs by economic purpose (credit card, personal uses, purchase of properties and purchase of transport vehicles), global environment and domestic market indicators.

4.2 Long and short-run estimates

Once the long-run relationship among the variables was confirmed, it was plausible to identify a long-run equilibrium relationship. The speed of adjusting the endogenous variable to converge to the long-run equilibrium was unfolded in the error correction model of the ARDL representation. Each variable used is specified in Section 3.1.

Model 1: The impact of credit card outstanding loans on household NPLs

$D(LNHOUSEHOLDPL)_t$

$$= \sum_{i=1}^{p-1} \gamma_i D(LNHOUSEHOLDNPL)_{t-i} + \sum_{l_0=0}^{q_0-1} \theta_{1,l_1} D(LNCCTLR)_{t-l_0} \\ + \sum_{l_1=0}^{q_1-1} \theta_{1,l_1} D(LNINCOME)_{t-l_1} + \sum_{l_2=0}^{q_2-1} \theta_{2,l_2} D(LNOIL)_{t-l_2} \\ + \sum_{l_3=0}^{q_3-1} \theta_{3,l_3} D(OPR)_{t-l_3} + \sum_{l_4=0}^{q_4-1} \theta_{4,l_4} D(UNE)_{t-l_4} \\ + \sum_{l_5=0}^{q_5-1} \theta_{5,l_5} D(LNKLCI)_{t-l_5} + \lambda ECT_{t-1} + \varepsilon_t$$

Equation 4.2a

Model 2: The impact of personal loan outstanding loans on household NPLs

 $D(LNHOUSEHOLDPL)_t$

$$= \sum_{i=1}^{p-1} \gamma_{i} D(LNHOUSEHOLDNPL)_{t-i} + \sum_{l_{0}=0}^{q_{0}-1} \theta_{1,l_{1}} D(LNPUTLR)_{t-l_{0}} \\ + \sum_{l_{1}=0}^{q_{1}-1} \theta_{1,l_{1}} D(LNINCOME)_{t-l_{1}} + \sum_{l_{2}=0}^{q_{2}-1} \theta_{2,l_{2}} D(LNOIL)_{t-l_{2}} \\ + \sum_{l_{3}=0}^{q_{3}-1} \theta_{3,l_{3}} D(OPR)_{t-l_{3}} + \sum_{l_{4}=0}^{q_{4}-1} \theta_{4,l_{4}} D(UNE)_{t-l_{4}} \\ + \sum_{l_{5}=0}^{q_{5}-1} \theta_{5,l_{5}} D(LNKLCI)_{t-l_{5}} + \lambda ECT_{t-1} + \varepsilon_{t}$$

Equation 4.2b

Model 3: The impact of residential properties outstanding loans on household NPLs

$D(LNHOUSEHOLDPL)_t$

$$= \sum_{i=1}^{p-1} \gamma_i D(LNHOUSEHOLDNPL)_{t-i} + \sum_{l_0=0}^{q_0-1} \theta_{1,l_1} D(LNPRTLR)_{t-l_0} \\ + \sum_{l_1=0}^{q_1-1} \theta_{1,l_1} D(LNINCOME)_{t-l_1} + \sum_{l_2=0}^{q_2-1} \theta_{2,l_2} D(LNOIL)_{t-l_2} \\ + \sum_{l_3=0}^{q_3-1} \theta_{3,l_3} D(OPR)_{t-l_3} + \sum_{l_4=0}^{q_4-1} \theta_{4,l_4} D(UNE)_{t-l_4} \\ + \sum_{l_5=0}^{q_5-1} \theta_{5,l_5} D(LNKLCI)_{t-l_5} + \lambda ECT_{t-1} + \varepsilon_t$$

Equation 4.2c

Model 4: The impact of vehicles outstanding loans on household NPLs

$$D(LNHOUSEHOLDPL)_{t}$$

$$= \sum_{i=1}^{p-1} \gamma_{i} D(LNHOUSEHOLDNPL)_{t-i} + \sum_{l_{0}=0}^{q_{0}-1} \theta_{1,l_{1}} D(LNVETLR)_{t-l_{0}}$$

$$+ \sum_{l_{1}=0}^{q_{1}-1} \theta_{1,l_{1}} D(LNINCOME)_{t-l_{1}} + \sum_{l_{2}=0}^{q_{2}-1} \theta_{2,l_{2}} D(LNOIL)_{t-l_{2}}$$

$$+ \sum_{l_{3}=0}^{q_{3}-1} \theta_{3,l_{3}} D(OPR)_{t-l_{3}} + \sum_{l_{4}=0}^{q_{4}-1} \theta_{4,l_{4}} D(UNE)_{t-l_{4}}$$

$$+ \sum_{l_{5}=0}^{q_{5}-1} \theta_{5,l_{5}} D(LNKLCI)_{t-l_{5}} + \lambda ECT_{t-1} + \varepsilon_{t}$$

Equation 4.2d

where λ is the speed of adjustment parameter.

Using the ARDL approach, the empirical results of the long and the short-run estimates are presented in Table 4.2. In the third panel of Table 4.2, a negative and significant ECT_{t-1} term further confirmed that the variables converged in the long run after a deviation. Approximately 4.6-7.8% of disequilibria in the household NPLs from the previous month were corrected in the current month. Also, in Table 4.2, the diagnostic tests, as hypothesised in Section 3.5, showed that all the NPL models were free from serial correlation at a 1% significance level. Further, all the NPLs models did not reject constancy of error variances at a 5% significance level. The results of CUSUM and CUSUM squares (CUSUMSQ) in Appendix B indicated that the estimated models' parameters were stable throughout the sample period, as most of these residuals were within the 5% breakpoint critical bound.

In Model 1, the effect of outstanding credit card loans on household debt impairment was not significant; however, the control variables, namely, the overnight policy rate and KLCI, had explanatory power in the long run. One percentage point increase in the OPR was associated with a 31% increase in household arrears. In contrast, a 1% rise in the

KLCI led to decreased household NPLs, by 1.86%. On the contrary, there was a shortterm positive effect of credit card loans on household debt defaults. None of the control variables was significant in the short run.

Regarding the outstanding personal uses loans, Model 2 suggested a negative longterm relationship between personal uses loans and the household NPLs. A 1% increase in personal loan debt causes household's NPLs to decrease by 2.04%. Besides that, the KLCI affected household NPLs in the opposite direction, i.e. household NPLs reduced by 0.93% when the KLCI went up by 1%. In the short run, outstanding personal use loans positively affected household NPLs, while household debt defaults positively affected change in the KLCI.

Model 3 revealed significant evidence that properties loans could impact the household NPLs level positively. A 1% increase in properties debt was expected to increase household arrears by 0.7%. Further, household impairments were affected by the OPR and KLCI. Given a one percentage point increase in the OPR, household NPLs were expected to increase by 31%. In contrast, with a 1% increase in the KLCI, household debt default is expected to decrease by 1.36%. On the other hand, none of the variables showed significance in explaining the household arrears in the short run.

Similarly to Model 3, except that loans for purchasing transport vehicles were not the primary source of household default, household NPLs were mainly explained by the OPR and KLCI. Specifically, one percentage point positive change in the OPR led to a 43% rise in debt default, whereas a 1% rise in the KLCI reduced the level of household NPLs by 2.06%. The short-run dynamics of all tested variables were found not significant.

	Model 1			Model 2			Model 3			Model 4	
	Selected Mo (4, 3, 0, 0, 0, 0,	odel: ARDL 0, 2)		Selected Mc (3, 0, 0, 0, 0, 0,	odel: ARDL 0, 2)		Selected Mode 0, 0, 1, 5, 4)	el: ARDL (2,		Selected Mo (7, 0, 4, 7, 0	odel: ARDL 9, 5)
	•				Long run 1	Estimates				•	
	Coefficient s	Prob		Coefficient s	Prob		Coefficients	Prob		Coefficien ts	Prob
LNCCTLR	0.2503	0.8695	LNPUTLR	-2.0424	0.0051**	LNPRTLR	2.3825	0.0756*	LNVETLR	0.0344	0.9741
LNINCOME	1.1491	0.4765	LNINCOME	0.0788	0.8859	LNINCOME	-0.4961	0.4929	LNINCOME	1.1782	0.2399
LNOIL	-0.1337	0.5157	LNOIL	-0.0203	0.8820	LNOIL	-0.1349	0.3455	LNOIL	-0.1056	0.6166
OPR	0.3109	0.0711*	OPR	0.1271	0.3290	OPR	0.3148	0.0058***	OPR	0.4335	0.0002***
UNE	-0.3319	0.3313	UNE	-0.1409	0.5367	UNE	-0.2998	0.2475	UNE	-0.2638	0.4954
LNKLCI	-1.8595	0.0148**	LNKLCI	-0.9265	0.0776*	LNKLCI	-1.3610	0.0012***	LNKLCI	-2.0569	0.0027***
constant	15.2099	0.0001***	Constant	9.1865	0.0018***	Constant	26.9649	<0.0001* **	constant	14.8074	0.0047***
					Short-run	Estimates					
D(LNHOUSEHOL DNPL(-1))	-0.2718	0.0006***	D(LNHOUSEHOL DNPL(-1))	-0.2715	0.0012***	D(LNHOUSEHO LDNPL(-1))	-0.2453	0.0017***	D(LNHOUSEHOL DNPL(-1))	-0.2773	0.0011***
D(LNHOUSEHOL DNPL(-2))	-0.1405	0.0758*	D(LNHOUSEHOL DNPL(-2))	-0.2076	0.0125**	D(LNHOUSEHO LDNPL(-2))	-0.1844	0.0218**	D(LNHOUSEHOL DNPL(-2))	-0.2364	0.0052***
D(LNHOUSEHOL DNPL(-3))	0.1853	0.0126**	D(LNPUTLR)	-0.1404	0.4428	D(LNHOUSEHO LDNPL(-3))	0.1631	0.0309**	D(LNVETLR)	0.3832	0.2372
D(LNCCTLR)	0.0653	0.6215	D(LNINCOME)	0.4879	0.2133	D(LNPRTLR)	0.4712	0.1915	D(LNINCOME)	0.1809	0.6488
D(LNCCTLR(-1))	0.2981	0.0305**	D(LNOIL)	-0.0063	0.7908	D(LNINCOME)	-0.0953	0.7261	D(LNOIL)	-0.0168	0.4787
D(LNCCTLR(-2))	0.2539	0.0629*	D(OPR)	-0.0203	0.3701	D(LNOIL)	-0.0227	0.2928	D(OPR)	-0.0206	0.3664
D(LNINCOME)	0.1665	0.5272	D(UNE)	-0.0293	0.2978	D(OPR)	-0.0247	0.2037	D(UNE)	-0.0190	0.5094
D(LNOIL)	-0.0067	0.7647	D(LNKLCI)	-0.0552	0.3122	D(UNE)	-0.0198	0.4559	D(LNKLCI)	-0.0793	0.1430

Table 4.2: Cointegrating form and long-run estimates (Endogeneous: household NPLs)

'Table 4.2 continued.'

D(OPR)	-0.0057	0.7677	D(LNKLCI(-1))	0.1681	0.0030***	D(LNKLCI)	-0.0762	0.1075	D(LNKLCI(-1))	0.1749	0.0027**
D(UNE)	-0.0156	0.5549				D(LNKLCI(-1))	0.152	0.0032***	D(LNKLCI(-2))	0.0646	0.248
D(LNKLCI)	-0.0839	0.0759*				D(LNKLCI(-2))	0.0314	0.5365	D(LNKLCI(-3))	0.1034	0.0708 *
D(LNKLCI(-1))	0.1269	0.0133**				D(LNKLCI(-3))	0.1121	0.0319**			
sum of D(cctlr)	0.6173	0.0051***									
					•						
ECT(-1)	-0.0463	<0.0001** *	ECT(-1)	-0.0783	<0.0001** *	ECT(-1)	-0.0665	<0.0001** *	ECT(-1)	-0.0525	<0.0001** *
Serial correlation test		04612	Serial correlation test		0.9102	Serial correlation test		0.1063	Serial correlation test		0.2524
Heteroscedasticit y		0.1671	Heteroscedasticit y		0.0871*	Heteroscedasticit y		0.0545*	Heteroscedasticit y		0.0537*

Note: Asterisks ***, **, * indicate statistically significant at 1%, 5% and 10%; Tested for serial correlation up to lag 2

CHAPTER 5: THE ASYMMETRICAL IMPACT OF HOUSEHOLD CREDIT FACILITY ON HOUSEHOLD DEBT DEFAULT

Alter, Feng and Valckx (2018) suggested that household debt changes were found to be more important than levels. The present study attempted to study how household debt changes in a different direction could affect NPLs. There might be hidden nonlinearity characteristics, especially the sample period, covering several events, such as commodity price shocks and financial crises. The nonlinear ARDL (NARDL) methodology allows the decomposition of the tested variables into a positive and negative partial sum of processes to investigate nonlinearities. The estimation of the asymmetric model differentiates each household credit facility on household debt defaults.

5.1 NARDL framework

Following the general empirical specification, the asymmetrical impact of different types of credit was assessed together with the control variables as follows:

LNhouseholdNPL = f(credit type⁻, credit type⁺, LNINCOME, LNOIL, OPR, UNE, LNKLCI)

Each of the credit types was specified as:

Model 1: LNhouseholdNPL = f(LNCCTLR⁻, LNCCTLR⁺, LNINCOME, LNOIL, OPR, UNE, LNKLCI)

Model 2: *LNhouseholdNPL* = f(*LNPUTLR*⁻, *LNPUTLR*⁺, *LNINCOME*, *LNOIL*, *OPR*, *UNE*, *LNKLCI*)

Model 3: *LNhouseholdNPL* = f(*LNPRTLR*⁻, *LNPRTLR*⁺, *LNINCOME*, *LNOIL*, *OPR*, *UNE*, *LNKLCI*)

Model 4: LNhouseholdNPL = f(LNVETLR⁻, LNVETLR⁺, LNINCOME, LNOIL, OPR, UNE, LNKLCI) Similarly to the linear ARDL approach, firstly, the null hypotheses of the cointegrating relationship were tested. In each of the models, despite the outstanding loans being decomposed to positive and negative charges, the study employed the same critical values for the bounds test, as per Shin *et al.*'s (2014) recommendation, where the lower the value of k results, indicated more robust evidence of the long-run relationship.

Table 5.1 presents the results of the null hypothesis of no existence of cointegration modelled in a nonlinear framework, the evidence of non-rejection of the null hypothesis's long-run relationship between the examined variables at a 5% level of significance. Further, the results of the CUSUM and CUSUMSQ tests¹¹ suggested that the estimates were stable within 5% for each specified model, except for Model 3. For the case of properties loans, the estimates were shown as not stable according to the CUSUMSQ test. The dummy variable took the effect of the global financial crisis in 2008Q4-2009Q3, which was then included in Model 3, accounting for the possible structural change. Unsurprisingly, the inclusion of the dummy variable led to a more stable estimate; thus, the dummy variable was added in the final specification for Model 3.

	Model 1	Model 2	Model 3	Model 3	Model 4
				<u>(with Dummy)</u>	
PSS Fstat	5.26***	6.24**	9.154***	8.63***	5.98**
CUSUM/					
CUSMSQ	Stable/Stable	Stable/Stable	Stable/Fail	Stable/Stable	Stable/Stable
3.7 (ار باریان باریان از ۲		. 11	10 / 50 /	1 1 0 0 /

Table 5.1: ARDL Bound test, CUSUM and CUSUMSQ diagnostics

Note: Asterisks ***, **, * indicate statistically significant at 1%, 5% and 10%.

¹¹ See Appendix C

5.2 Asymmetrical long and short-run impact

Next, the Wald test, long run and short symmetry test were conducted, and the results are tabulated in Table 5.2. As suggested in Model 1, only short-run asymmetry was found between the credit card outstanding loans and the household NPLs. As for Model 2, no presence of long and short-run asymmetrical impact of personal loans debt on household NPLs was found. On the other hand, Model 3 exhibited asymmetry between outstanding loans for the purchase of residential properties and the household NPLs, in both the long and short run. For Model 4, there was evidence of the non-rejection of symmetry linkage between vehicles outstanding loans and household loan default in both the long and short run. Thus, suggesting potential nonlinearity behaviour in Models 1 and 3 while maintaining the symmetries in the long and short run for Models 2 and 4.

 Table 5.2: Asymmetry test

Wald Test	Model 1	Model 2	Model 3	Model 4
			(with Dummy)	
LR symmetry	0.8900	0.1155	0.0001***	0.1635
SR symmetry	0.0410**	0.6260	0.0334**	0.7915

Note: Asterisks ***, **, * indicate statistically significant at 1%, 5% and 10%.

The final models are presented in Table 5.3 and estimated following Equations 3.15, 3.15a, 3.15b and 3.15c, based on the symmetry test results in Table 5.2. The first panel of Table 5.3 indicates the bounds test results; the second panel focuses on the long-run coefficients, while the third panel shows the short-run estimates. The fourth panel tabulates the diagnostic test results.

In the long run, credit card debts were not significant in explaining household NPLs. As for the control variables, one percentage point change in the OPR affected household NPLs positively, by 52%. In the opposite direction, a 1% change in the KLCI led to a 2.4% decrease in household NPLs. In contrast, credit card debts affected household NPLs asymmetrically in the short run. Specifically, only negative changes in credit card outstanding loans were significant in explaining household loan default. A 1% reduction in credit card outstanding loans was expected to reduce household loan default by 1.26%.

In a linear (symmetry) specification, the estimated long-run coefficients indicated that a 1% change in personal loan debt resulted in a 2.04% decrease in household NPLs. A significant impact was found in the KLCI. When the KLCI increased by 1%, household NPLs were expected to reduce by 0.93%. In the short run, the result revealed that personal uses loans were not contributing to the level of household NPLs.

Regarding the impact of outstanding loans for the purchase of residential properties on household NPLs modelled by Equation 4, the findings implied that the primary source of debt, i.e. the residential property loans, behaved asymmetrically in both the long and short run. The negative changes in housing loans positively and significantly affected household loan defaults in the long run. A 1% decrease in residential loans improved household NPLs by 6.66%, while every 1% increase in residential loans accumulated 1.5% of the household NPLs. The OPR was estimated to be significant, where household NPLs increased by 10% when there was one percentage point change in the OPR. As for the short-run asymmetrical relationship, only negative changes of outstanding property loans were deemed significant, where household NPLs were expected to decrease by approximately 1.4%, given a 1% unfavourable change in property loans.

The relationship between transport vehicle outstanding loans and household NPLs was captured linearly (symmetrically) in the form of Equation 4c. Vehicle loans did not significantly affect household default loans; however, the; macroeconomic indicators, OPR and the KLCI explained the NPLs level. If the OPR was changed by one percentage point, household NPLs were expected to increase by 43%, whereas a percentage increase

in the KLCI resulted in a 2.06 % reduction in household NPLs. There was no significant evidence that vehicle loans could affect household loans default for the short-run estimates.

Table 5.3 shows that the diagnostic test results confirmed that all the final specified models were free from serial correlation issues at a 1% significance level. There was evidence of rejection for homoscedastic residuals at 1% for Model 3 and 10% for Models 1, 2, 3, respectively. The heteroskedasticity issues were expected under the ARDL approach due to the combination of different orders of integration of the variables used (Shrestha & Chowdhury (2005); Fosu & Magnus (2006)). On the other hand, Laurenceson & Chai (2003) mentioned that the ARDL framework results from the coefficients' absence of instability. Validated earlier in Table 5.1, the estimated parameters in these models were stable throughout the sample period, as most of these residuals were within the 5% breakpoint critical bounds.
Table 5.3: Asymmetrical long and short-run estimates

	Model 1			Model 2			Model 3			Model 4	
					Long-Ru	n Dynamics					
	Coefficients	Prob		Coefficients	Prob		Coefficients	Prob		Coefficients	Prob
LNCCTLR	2.3165	0.1725	LNPUTLR	-2.0424	0.0051**	LNPRTLR-	6.6604	<0.0001***	LNVETLR	0.0344	0.9741
						LNPRTLR+	1.4457	0.0001***			
LNINCOME	2.7710	0.1088	LNINCOME	0.0788	0.8859	LNINCOME	-0.1617	0.4449	LNINCOME	1.1782	0.2399
LNOIL	0.1051	0.4874	LNOIL	-0.0203	0.8820	LNOIL	0.0091	0.7978	LNOIL	-0.1056	0.6166
LNOPR	0.5228	<0.0001** *	LNOPR	0.1271	0.3290	LNOPR	0.1041	0.0067*	LNOPR	0.4335	0.0002***
LNUNE	-0.0723	0.7652	LNUNE	-0.1409	0.5367	LNUNE	-0.0194	0.7438	LNUNE	-0.2638	0.4954
LNKLCI	-2.3707	0.0014***	LNKLCI	-0.9265	0.0776*	LNKLCI	-0.1936	0.1264	LNKLCI	-2.0569	0.0027***
Constant	10.3455	0.0146**	Constant	9.1865	0.0018***	Constant	12.3433	<0.0001***	constant	14.8074	0.0047***
			1		Short Ru	n Estimates	l	l			
	Coefficients	Prob		Coefficients	Prob		Coefficients	Prob		Coefficients	Prob
С	0.6784	0.1024	С	0.7196	0.0307**	С	3.3330	<0.0001***	С	0.7749	0.0495**
LNHOUSEHO LDNPL(-1)	-0.0656	0.0008***	LNHOUSEHO LDNPL(-1)	-0.0783	0.0083***	LNHOUSEHO LDNPL(-1)	-0.2700	<0.0001***	LNHOUSEHO LDNPL(-1)	-0.0523	0.0077***
LNCCTLR(-1)	0.1519	0.1311	LNPUTLR(-1)	-0.1600	0.0941*	LNPRTLR_NE G(-1)	1.7985	<0.0001***	LNVETLR(-1)	0.0018	0.9742

'Table 5.3 continued.'

LNINCOME(-	0.1817	0.0492**	LNINCOME(-	0.0062	0.8805	LNPRTLR_P	0.3904	0.0009***	LNINCOME(-	0.0617	0.1722
1)			1)			OS(-1)			1)		
LNOIL(-1)	0.0069	0.4835	LNOIL(-1)	-0.0016	0.8799	LNINCOME(-	-0.0437	0.4521	LNOIL(-1)	-0.0055	0.6011
						1)					
OPR(-1)	0.0343	0.0011***	OPR(-1)	0.0100	0.2898	LNOIL(-1)	0.0025	0.7996	OPR(-1)	0.0227	0.0178**
UNE(-1)	-0.0047	0.7555	UNE(-1)	-0.0110	0.4878	OPR(-1)	0.0281	0.0034***	UNE(-1)	-0.0138	0.4185
LNKLCI(-1)	-0.1555	0.0001***	LNKLCI(-1)	-0.0726	0.0065***	UNE(-1)	-0.0052	0.7389	LNKLCI(-1)	-0.1076	0.0002***
D(LNHOUSE	-0.3155	0.0002***	D(LNHOUSE	-0.2715	0.0012***	LNKLCI(-1)	-0.0523	0.0987*	D(LNHOUSE	-0.2773	0.0011***
HOLDNPL(-			HOLDNPL(-						HOLDNPL(-		
1))			1))						1))		
D(LNHOUSE	-0.1456	0.0832*	D(LNHOUSE	-0.2076	0.0125**	D(LNHOUSE	-0.2298	0.0040***	D(LNHOUSE	-0.2364	0.0052***
HOLDNPL(-			HOLDNPL(-			HOLDNPL(-			HOLDNPL(-		
2))			2))			1))			2))		
D(LNHOUSE	0.1493	0.0604*	D(LNPUTLR)	-0.1404	0.4428	D(LNHOUSE	-0.2054	0.0087***	D(LNVETLR)	0.3832	0.2372
HOLDNPL(-			•			HOLDNPL(-					
3))						2))					
D(LNCCTLR_	0.4789	0.0735*	D(LNINCOM	0.4879	0.2133	D(LNPRTLR_	1.3616	0.0438**	D(LNINCOM	0.1809	0.6488
NEG)			<i>E)</i>			NEG)			E)		
	1	l.		1	1	1	1	1	1	1	

'Table 5.3 continued.'

D(LIVECILK_	0.7856	0.0025***	D(LNOIL)	-0.0063	0.7908	D(LNPRTLR_	0.2659	0.6580	D(LNOIL)	-0.0168	0.4787
NEG(-1))						POS)					
D(LNCCTLR_	-0.3216	0.2144	D(OPR)	-0.0203	0.3701	D(LNPRTLR_	-0.1375	0.8024	D(OPR)	-0.0206	0.3664
POS)						POS(-1))					
D(LNCCTLR_	-0.2914	0.2964	D(UNE)	-0.0293	0.2978	D(LNPRTLR_	-1.6806	0.0023	D(UNE)	-0.0190	0.5094
POS(-1))						POS(-2))					
D(LNCCTLR_	0.3506	0.1650	D(LNKLCI)	-0.0552	0.3122	D(LNINCOM	0.0540	0.8807	D(LNKLCI)	-0.0793	0.1430
POS(-2))						<i>E</i>)					
D(LNINCOM	0.3318	0.3925	D(LNKLCI(-	0.1681	0.0030***	D(LNOIL)	-0.0065	0.7579	D(LNKLCI(-	0.1749	0.0027***
<i>E)</i>			1))		•				1))		
D(LNOIL)	-0.0077	0.7398				D(OPR)	-0.0295	0.1739	D(LNKLCI(-	0.0646	0.2480
									2))		
D(OPR)	-0.0194	0.4043				D(OPR(-1))	-0.0452	0.0191**	D(LNKLCI(-	0.1034	0.0708*
					\mathcal{D}				3))		
D(UNE)	-0.0186	0.4944				D(UNE)	-0.0283	0.2838			
D(LNKLCI)	-0.0591	0.2476				D(LNKLCI)	-0.0475	0.3361			
D(LNKLCI(-	0.2024	0.0011***				D(LNKLCI(-	0.1235	0.0233**			
1))						1))					

'Table 5.3 continued.'

D(LNKLCI(-2))	0.0707	0.2298				D(LNKLCI(-2))	0.0416	0.4369			
D(LNKLCI(-3))	0.1556	0.0068***				D(LNKLCI(-3))	0.0787	0.1436			
D(LNKLCI(-4))	0.1441	0.0094***				D(LNKLCI(-4))	0.1275	0.0123*			
						DUMMY	0.0418	0.0002***			
Sum of	1.2645	0.0003***				Sum of	1.3616	0.0438**			
D(LNCCTLR) -						D(LNPRILK)-					
Sum of	-0.2623	0.5011				Sum of	-1.5522	0.1408			
D(LNCCTLR)+					•	D(LNPRTLR)+					
ECT(-1)	-0.0656	<0.0001**	ECT(-1)	-0.0783	<0.0001**	ECT(-1)	-0.2701	<0.0001**	ECT(-1)	-0.0525	<0.0001**
		*			*			*			*
Serial correlation		0.1004	Serial correlation		0.9102	Serial correlation		0.1090	Serial correlation		0.2524
Heteroscedasticity		0.0783*	Heteroscedasticity		0.0871*	Heteroscedasticity		0.0014***	Heteroscedasticity		0.0537*

Note: Asterisks ***, **, * indicate statistically significant at 1%, 5% and 10%; Tested for serial correlation up to lag 2

5.3 Discussion: The impact of each household credit on household NPLs

This section provides a discussion on the findings of research questions 1 and 3. The ARDL approach was used to gauge the linear long-run relationship between household credit and household loans default, while the NARDL approach was employed to explore the asymmetries.

High consumer debt usually leads to higher credit risk. Hyman Minsky's theory (1992) highlighted the importance of credit risk management as over-indebtedness eventually deteriorates loan portfolios (Foos *et al.*, 2010) and, in turn, financial instability. Each type of credit affected household NPLs differently, as hypothesised in Chapter 3.

Evidence from the ARDL and NARDL estimations indicated that credit card debt did not affect household NPLs in the long run. After considering nonlinearity in the models, credit card debt's impact on household NPLs was captured asymmetrically in the short run. Among consumer loan types, credit card debt has a shorter tenure. It is a revolving debt instead of amortised debt. An increase in credit card outstanding loans did not find significant evidence in affecting household NPLs, while evidence of low credit card loans led to a decrease in household NPLs was detected. At times of distress, consumers are more likely to default on credit card loans than other types of loans, especially mortgages (Chan *et al.*, 2016), resulting in a compensating effect; Hence, an increase in credit card debts has no impact on household NPLs. In the meantime, for financially constrained households, either the outstanding credit card debt is unmanageable as the lesser time to pay off the credit card debt (Madeira, 2019), or households choose to pay the minimum charges hence building NPLs. This observation supported the findings that low credit card debt reduces the household NPLs level in the short run. On the other hand, vehicle and personal loans have a slightly more extended maturity period. Further, consumers are more prone to default on unsecured loan types than secured ones (Mihai *et al.*, 2018). As far as personal loan debts are concerned, household NPLs did not respond asymmetrically either in the long or short run. Personal uses outstanding loans on household debt were better explained in a linear framework. A negative relationship between personal uses loan debt and household NPLs, intuitively suggested that a rise in these debts did not accumulate but reduced household NPLs, assuming consumers tend to pay off other debt using easy to access loans.

Similarly to personal loans, a linear specification better explains the dynamics between outstanding vehicle loans and household NPLs. Nonetheless, in the long run, vehicle debts did not contribute to the accumulation of household NPLs, in the targeted sample period. The increased number of bankruptcy cases could explain this, as easy access to personal loans had overtaken vehicle loans as the leading cause of insolvency (MDI, 2019) over the last five years. These loans surpassed mortgage loans insolvency, seen over the last ten years. Several stringent measures and guidelines have been introduced by BNM to promote responsible financing, particularly concerning housing and car loans (BNM, 2011, The Edge, 2011; Lim, 2012).

Property loan amortisation usually represents the most significant household debt service component in a more extended debt tenure period. As for the relationship between mortgage loans and household NPLs, both symmetrical and asymmetrical impacts were detected in the mortgage loan growth on household NPLs, in a positive direction. Both positive and negative long-run changes in loans for purchasing residential properties were significant in a nonlinear setting. An adverse change in these loans had a more significant impact on household NPLs. On a side note, the adjustment speed of household sustainability may not be similar when credit shocks occur. Considering the fully asymmetric model as per *Equation 3.15*, which is in only Model 3 in this section, the dynamic impact of positive or negative changes in housing loans outstanding in household NPLs level were plotted in Figure 5.1. A negative credit shock dominated the asymmetric effects in the model. The level of NPLs changed quickly to lower rather than to higher housing lending. Households were not immediately affected by the higher amount of housing lending; however, it responded cyclically to the positive change in outstanding housing loans in the first six months. Full adjustment to the new equilibrium was a relatively prolonged process. This study concurs with past studies where credit impacted the NPLs (Jakubík & Reininger, 2013; Salas & Saurina, 2002; Foos *et al.*, 2010). The present study found the existence of an asymmetric relationship in properties loan growth that was attributed to the formation of household NPL.

The linkage between short-run changes in property loans and household NPLs were found in the asymmetric model. The relationship was deemed significant and positive for the negative changes in mortgage loans, implying that low outstanding mortgage loans would bring less household loan default in the short-term horizon.

Further, negative changes in mortgage loans on the household were more pronounced when focusing on the asymmetrical long-run dynamics. This finding was justified in Reinhart and Rogoff's (2010) study, where banking stability depended on the lowest mortgage loan growth. Housing loans had by far been observed as the leading cause of household indebtedness. Hence, the results further confirmed that a decrease in mortgage loans could decrease household impairments. Shocks from the OPR and KLCI were more likely transferred to households regardings the control variables, leading to household credit insolvency and default. This finding was consistent across linear and nonlinear ARDL. It was aligned with the findings of Kalirai and Scheicher (2002), Jakubik and Reininger (2013) and Espinoza & Prasad (2010), where high stock market returns were associated with low levels of NPLs. Good performance in the stock market is usually followed by stable domestic economic conditions, which are less affected by global headwinds. This safety net maintains household sustainability via employment and the income channel. Hence the level of household NPLs is reduced.

Similarly to past literature, the monetary condition was crucial, as it worsened the borrowers' financial positions. A positive shock in the interest rate limits borrowers' ability to meet their debt obligations, leading to an increase in NPLs (Nkusu, 2011; Adebola *et al.*, 2011). Concerning the case of property debt, consistent with the findings of Louzis *et al.* (2012), it was less responsive to other macroeconomic variables with only OPR movements shown as being significant, with the least impact relatively, even though in an episode of external turbulence. This finding showed that the loans for residential property purchases were less sensitive to macroeconomic conditions as homeowners were less likely to default on their mortgages due to home equity.

On the other hand, in the existing literature, some oil-exporting countries have shown crude oil price shocks as one of the explanatory variables of aggregate nonperforming loans. However, the findings indicated that the crude oil price did not significantly influence household debt defaults. Thus, the relationship between the crude oil price and non-performing household loans might be indirect. The indirect effect of the crude oil price fluctuations on households might have been spilt through other economic factors. Hence there was no significant explanatory power of the crude oil price.

Besides, as in past studies, household income and the unemployment rate were expected to be determinants of non-performing loans. In contrast, the insignificance of household income adjusted for inflation and the unemployment rate found in this study showed incompatibility with the life cycle hypothesis. This observation posited that the non-performance of household loans was not primarily driven by income sources and long-term employment (current and future), as it was more likely built under household rational consumption behavioural factors. Another possible reason was that the households might use consumer credit facilities as wage substitution. Hence personal loans and credit card debts would affect the household default level.

CHAPTER 6: THE DETERMINANTS OF HOUSEHOLD NON-PERFORMING LOANS BY ECONOMIC PURPOSES

This chapter used the ARDL framework to capture the long- and short-run relationship between household NPLs for economic purposes and the relevant variables underpinned by theoretical and empirical evidence under a linearly specified modelling technique. One direction of this study was the comparative study of the effect of economic factors on NPLs for economic purposes. Another direction was to compare how the household debt portfolio affected each of the NPLs categories. Based on diagnostic testing, the importance of each determinant is discussed from the magnitude and significance of coefficients.

6.1 ARDL framework

The empirical study explored the spillovers of the global environment and domestic market indicators in influencing Malaysian banks' credit risk to uncover the potential long-run and short-run relationship between Malaysian banks NPLs and their determinants. Four common types of household NPLs were included in the analysis. ARDL modelling was employed and is specified as per the description in Section 3.4. Each of the variables used in the equation below was previously described in Section 3.1.

Credit card NPLs:

$D(LNCCNPL)_t$

 $= \beta_{0}^{*} + \rho LNCCNPL_{t-1} + \pi_{00}LNCCTLR_{t-1} + \pi_{01}LNOTHERTLR_{1t-1} + \pi_{1}LNINCOME_{t-1} + \pi_{2}LNOIL_{t-1} + \pi_{3}OPR_{t-1} + \pi_{4}UNE_{t-1} + \pi_{5}LNKLCI_{t-1} + \sum_{i=1}^{p-1} \gamma_{i}D(LNCCNPL)_{t-i} + \sum_{l_{00}=0}^{q_{00}-1} \theta_{00,l_{00}}D(LNCCTLR)_{t-l_{00}} + \sum_{l_{01}=0}^{q_{01}-1} \theta_{01,l_{01}}D(LNOTHERTLR_{1})_{t-l_{01}} + \sum_{l_{1}=0}^{q_{1}-1} \theta_{1,l_{1}}D(LNINCOME)_{t-l_{1}} + \sum_{l_{2}=0}^{q_{2}-1} \theta_{2,l_{2}}D(LNOIL)_{t-l_{2}} + \sum_{l_{3}=0}^{q_{3}-1} \theta_{3,l_{3}}D(OPR)_{t-l_{3}} + \sum_{l_{4}=0}^{q_{4}-1} \theta_{4,l_{4}}D(UNE)_{t-l_{4}} + \sum_{l_{5}=0}^{q_{5}-1} \theta_{5,l_{5}}D(LNKLCI)_{t-l_{5}} + \varepsilon_{t}$

Equation 6.1a

 $D(LNPUNPL)_t$

$$= \beta_{0}^{*} + \rho LNPUNPL_{t-1} + \pi_{00}LNPUTLR_{t-1} + \pi_{01}LNOTHERTLR_{2}_{t-1} + \pi_{1}LNINCOME_{t-1} + \pi_{2}LNOIL_{t-1} + \pi_{3}OPR_{t-1} + \pi_{4}UNE_{t-1} + \pi_{5}LNKLCI_{t-1} + \sum_{i=1}^{p-1} \gamma_{i}D(LNPUNPL)_{t-i} + \sum_{l_{00}=0}^{q_{00}-1} \theta_{00,l_{00}}D(LNPUTLR)_{t-l_{00}} + \sum_{l_{01}=0}^{q_{01}-1} \theta_{01,l_{01}}D(LNOTHERTLR_{2})_{t-l_{01}} + \sum_{l_{1}=0}^{q_{1}-1} \theta_{1,l_{1}}D(LNINCOME)_{t-l_{1}} + \sum_{l_{2}=0}^{q_{2}-1} \theta_{2,l_{2}}D(LNOIL)_{t-l_{2}} + \sum_{l_{3}=0}^{q_{3}-1} \theta_{3,l_{3}}D(OPR)_{t-l_{3}} + \sum_{l_{4}=0}^{q_{4}-1} \theta_{4,l_{4}}D(UNE)_{t-l_{4}} + \sum_{l_{5}=0}^{q_{5}-1} \theta_{5,l_{5}}D(LNKLCI)_{t-l_{5}} + \varepsilon_{t}$$

Equation 6.1b

 $D(LNPRNPL)_t$

$$= \beta_{0}^{*} + \rho LNPRNPL_{t-1} + \pi_{00}LNPRTLR_{t-1} + \pi_{01}LNOTHERTLR_{3}_{t-1} + \pi_{1}LNINCOME_{t-1} + \pi_{2}LNOIL_{t-1} + \pi_{3}OPR_{t-1} + \pi_{4}UNE_{t-1} + \pi_{5}LNKLCI_{t-1} + \sum_{i=1}^{p-1} \gamma_{i}D(LNPRNPL)_{t-i} + \sum_{l_{00}=0}^{q_{00}-1} \theta_{00,l_{00}}D(LNPRTLR)_{t-l_{00}} + \sum_{l_{01}=0}^{q_{01}-1} \theta_{2,l_{01}}D(LNOTHERTLR_{3})_{t-l_{01}} + \sum_{l_{1}=0}^{q_{1}-1} \theta_{1,l_{1}}D(LNINCOME)_{t-l_{1}} + \sum_{l_{2}=0}^{q_{2}-1} \theta_{2,l_{2}}D(LNOIL)_{t-l_{2}} + \sum_{l_{3}=0}^{q_{3}-1} \theta_{3,l_{3}}D(OPR)_{t-l_{3}} + \sum_{l_{4}=0}^{q_{4}-1} \theta_{4,l_{4}}D(UNE)_{t-l_{4}} + \sum_{l_{5}=0}^{q_{5}-1} \theta_{5,l_{5}}D(LNKLCI)_{t-l_{5}} + \varepsilon_{t}$$

Equation 6.1c

NPLs for the purchase of transport vehicles:

 $D(LNVENPL)_t$

$$= \beta_0^* + \rho LNVENPL_{t-1} + \pi_{00}LNVETLR_{t-1} + \pi_{01}LNOTHERTLR_4_{t-1} + \pi_1LNINCOME_{t-1} + \pi_2LNOIL_{t-1} + \pi_3OPR_{t-1} + \pi_4UNE_{t-1} + \pi_4UNE_{t-$$

$$\begin{aligned} \pi_{5}LNKLCI_{t-1} + \sum_{i=1}^{p-1} \gamma_{i}D(LNVENPL)_{t-i} + \\ \sum_{l_{00}=0}^{q_{00}-1} \theta_{00,l_{00}}D(LNVETLR)_{t-l_{00}} + \sum_{l_{01}=0}^{q_{01}-1} \theta_{2,l_{01}}D(LNOTHERTLR_{-}4)_{t-l_{01}} + \\ \sum_{l_{1}=0}^{q_{1}-1} \theta_{1,l_{1}}D(LNINCOME)_{t-l_{1}} + \sum_{l_{2}=0}^{q_{2}-1} \theta_{2,l_{2}}D(LNOIL)_{t-l_{2}} + \\ \sum_{l_{3}=0}^{q_{3}-1} \theta_{3,l_{3}}D(OPR)_{t-l_{3}} + \sum_{l_{4}=0}^{q_{4}-1} \theta_{4,l_{4}}D(UNE)_{t-l_{4}} + \\ \sum_{l_{e}=0}^{q_{5}-1} \theta_{5,l_{5}}D(LNKLCI)_{t-l_{5}} + \varepsilon_{t} \end{aligned}$$

Equation 6.1d

where Δ denotes the first difference operator and ε_t is the white noise residuals.

6.1.1 ARDL Bound Test

The ARDL bound test for cointegration is hypothesised as $H_0: \rho = \pi_1 = \pi_2 = \pi_3 = \pi_4 = \pi_5 = 0$ (No cointegration) against $H_1:$ at least one π 's not equal to zero (Existence of long-run cointegration). The results of the bounds test are shown in Table 6.1.

Table 6.1: ARDL bound test for cointegration (Endogenous: NPL categories)

Bound Test for Cointegratio	n			
Null Hypothesis: No long-ru	ın relationship e	exists		
		Dorgonal	Purchase of	Purchase of
Types of NPLs	Credit cards	Laga	<u>residential</u>	<u>transport</u>
		<u>Uses</u>	properties	<u>vehicles</u>
F-statistic	4.8528***	3.7305**	8.4654***	1.8230
		Critica	l Bound	
Significance level		I(0)	I(1)	
10%		2.08	3	
5%		2.39	3.38	
1%		3.06	4.15	

Note: Asterisks ***, **, * indicate statistically significant at 1%, 5% and 10%

The F-statistics was above the upper bound. Therefore, there was sufficient evidence to reject the null hypothesis at a 5 % significance level. In linearly estimated models, the results concluded that a long-run relationship existed between the NPLs, outstanding loans, household income adjusted for inflation, the crude oil price, the overnight policy rate, the unemployment rate and the KLCI, except for the vehicle NPLs category.

6.2 Differential impact of macroeconomic fundamentals on NPL categories

The long-run relationship among the variables was confirmed in Section 6.1.1, a longrun equilibrium relationship and the speed of adjustment of the endogenous variable (types of NPLs) to converge to the long-run equilibrium via the error correction model ARDL representation, as per below:

Model 1-Credit card NPLs:

$$\begin{split} D(LNCCNPL)_{t} &= \\ \sum_{i=1}^{p-1} \gamma_{i} D(LNCCNPL)_{t-i} + \sum_{l_{00}=0}^{q_{00}-1} \theta_{00,l_{00}} D(LNCCNPL)_{t-l_{00}} + \\ \sum_{l_{01}=0}^{q_{01}-1} \theta_{01,l_{01}} D(OTHERTLR_{-}1)_{t-l_{01}} + \sum_{l_{1}=0}^{q_{1}-1} \theta_{1,l_{1}} D(LNINCOME)_{t-l_{1}} + \\ \sum_{l_{2}=0}^{q_{2}-1} \theta_{2,l_{2}} D(LNOIL)_{t-l_{2}} + \sum_{l_{3}=0}^{q_{3}-1} \theta_{3,l_{3}} D(OPR)_{t-l_{3}} + \sum_{l_{4}=0}^{q_{4}-1} \theta_{4,l_{4}} D(UNE)_{t-l_{4}} + \\ \sum_{l_{5}=0}^{q_{5}-1} \theta_{5,l_{5}} D(LNKLCI)_{t-l_{5}} + +\lambda_{1} ECT_{t-1} + \varepsilon_{t} \end{split}$$

Equation 6.2a

Model 2-Personal Uses NPLs:

$$\begin{split} D(LNPUNPL)_{t} &= \\ \sum_{i=1}^{p-1} \gamma_{i} D(LNPUNPL)_{t-i} + \sum_{l_{00}=0}^{q_{00}-1} \theta_{00,l_{00}} D(LNPUNPL)_{t-l_{00}} + \\ \sum_{l_{01}=0}^{q_{01}-1} \theta_{01,l_{01}} D(OTHERTLR_{2})_{t-l_{01}} + \sum_{l_{1}=0}^{q_{1}-1} \theta_{1,l_{1}} D(LNINCOME)_{t-l_{1}} + \\ \sum_{l_{2}=0}^{q_{2}-1} \theta_{2,l_{2}} D(LNOIL)_{t-l_{2}} + \sum_{l_{3}=0}^{q_{3}-1} \theta_{3,l_{3}} D(OPR)_{t-l_{3}} + \sum_{l_{4}=0}^{q_{4}-1} \theta_{4,l_{4}} D(UNE)_{t-l_{4}} + \\ \sum_{l_{5}=0}^{q_{5}-1} \theta_{5,l_{5}} D(LNKLCI)_{t-l_{5}} + \lambda_{1} ECT_{t-1} + \varepsilon_{t} \end{split}$$

Equation 6.2b

Model 3-NPLs for purchase of residential properties:

$$\begin{split} D(LNPRNPL)_{t} &= \\ \sum_{i=1}^{p-1} \gamma_{i} D(LNPRNPL)_{t-i} + \sum_{l_{00}=0}^{q_{00}-1} \theta_{00,l_{00}} D(LNPRNPL)_{t-l_{00}} + \\ \sum_{l_{01}=0}^{q_{01}-1} \theta_{01,l_{01}} D(OTHERTLR_{-}3)_{t-l_{01}} + \sum_{l_{1}=0}^{q_{1}-1} \theta_{1,l_{1}} D(LNINCOME)_{t-l_{1}} + \\ \sum_{l_{2}=0}^{q_{2}-1} \theta_{2,l_{2}} D(LNOIL)_{t-l_{2}} + \sum_{l_{3}=0}^{q_{3}-1} \theta_{3,l_{3}} D(OPR)_{t-l_{3}} + \sum_{l_{4}=0}^{q_{4}-1} \theta_{4,l_{4}} D(UNE)_{t-l_{4}} + \\ \sum_{l_{r}=0}^{q_{5}-1} \theta_{5,l_{5}} D(LNKLCI)_{t-l_{5}} + \lambda_{1} ECT_{t-1} + \varepsilon_{t} \end{split}$$

Equation 6.2c

$$\begin{split} D(LNVENPL)_{t} &= \\ \sum_{i=1}^{p-1} \gamma_{i} D(LNVENPL)_{t-i} + \sum_{l_{00}=0}^{q_{00}-1} \theta_{00,l_{00}} D(LNVENPL)_{t-l_{00}} + \\ \sum_{l_{01}=0}^{q_{01}-1} \theta_{01,l_{01}} D(OTHERTLR_{-}4)_{t-l_{01}} + \sum_{l_{1}=0}^{q_{1}-1} \theta_{1,l_{1}} D(LNINCOME)_{t-l_{1}} + \\ \sum_{l_{2}=0}^{q_{2}-1} \theta_{2,l_{2}} D(LNOIL)_{t-l_{2}} + \sum_{l_{3}=0}^{q_{3}-1} \theta_{3,l_{3}} D(OPR)_{t-l_{3}} + \sum_{l_{4}=0}^{q_{4}-1} \theta_{4,l_{4}} D(UNE)_{t-l_{4}} + \\ \sum_{l_{5}=0}^{q_{5}-1} \theta_{5,l_{5}} D(LNKLCI)_{t-l_{5}} + \lambda_{1} ECT_{t-1} + \varepsilon_{t} \end{split}$$

Equation 6.2d

where λ is the speed of adjustment parameter.

Using the ARDL approach, the empirical results of the long and the short-run estimates are presented in Table 6.2. A negative and significant ECT_{t-1} term in the third panel further confirmed that the variables converged in the long run after a deviation. Approximately 7-15% of the disequilibria in the NPLs by purposes from the previous month were corrected in the current month. The diagnostic testing results are shown in the same panel, indicating that all the estimated model residuals were not serially correlated. The presence of heteroscedasticity was at the 10% significance level for vehicle-related NPLs model, at the 5% significance level for credit card and residential properties NPLs, and at the 1% level for the personal uses NPLs model. The CUSUM and CUSUMSQ plots in Appendix D showed that most residuals lay within the 5% critical values. This test determined the adequacy of these models.

Based on the linear specification, in the long run, as expected, the relationship between the crude oil price and stock market index, respectively, and credit card NPLs were negative. For a 1% change in the crude oil price and KLCI, credit card NPLs changed by 0.44% and 0.88% in the opposite direction. The effect of other household debts was found relatively significant compared to credit card debt. The OPR was not statistically significant in determining credit card NPLs, either in the long- or short run. Drops in the stock market index and increases in unemployment led to higher NPLs in the short run.

Looking at the personal uses NPLs model, which was specified linearly, none of the economic factors and outstanding loans explained this NPL category in the long run. However, a positive short-run effect of the crude oil price was expected. Personal uses NPLs increased by 0.16% for a 1% rise in the crude oil price in the short run.

From the ARDL model's findings, the evidence of the long-run relationship between the overnight policy rate and mortgage NPLs was found positive, given that a one percentage point change in the OPR led to changes in NPLs by 22.5%. On the other hand, the stock market index and household income adjusted for inflation significantly negatively explained the NPLs level. Mortgage NPLs decreased by 1.16% for a 1% increase in the stock market index, while mortgage NPL decreased by 1.76% for a 1% increase in inflation-adjusted household income. High residential property outstanding loans were the primary source of debt, forming more housing NPLs in the long run, compared to other forms of debt. The crude oil price and unemployment did not affect the level of residential property debt default.

For Model 4, while there was no long-run relationship detected between vehicle-related NPLs and the tested variable in the linear ADRL bounds test, this could be attributed to

the fact that the determinants may exhibit nonlinearities. An investigation is carried out in the next chapter.

	Model 1		-	Model 2		-	Model 3		-	Model 4	
	<u>Selected Mo</u> (2, 4, 0, 0, 5,	<u>del: ARDL</u> 0, 4, 0)		<u>Selected Model: ARDL</u> (3, 1, 6, 0, 5, 1, 0, 0)			<u>Selected Model: ARDL</u> (3, 0, 0, 0, 0, 1, 3, 4)			<u>Selected M</u> (4, 4, 2, 0, 0	
			·		Long run E	stimates			·		
	Coefficients	Prob		Coefficients	Prob		Coefficients	Prob		Coefficients	Prob
LNCCTLR	0.7039	0.5227	LNPUTLR	-0.9890	0.6307	LNPRTLR	5.9606	0.0068**	LNVETLR	2.5884	0.0911*
LNOTHER	8.9362	0.0030***	LNOTHER	-1.1581	0.9007	LNOTHER	1.2414	0.4252	LNOTHER	-0.0803	0.9882
LNINCOME	-0.7374	0.4195	LNINCOME	0.6606	0.4008	LNINCOME	-1.7606	0.0014***	LNINCOME	1.7308	0.1632
LNOIL	-0.4467	0.0043***	LNOIL	-0.5877	0.1507	LNOIL	-0.1317	0.2315	LNOIL	0.0853	0.7016
OPR	-0.0253	0.6791	OPR	0.2724	0.2256	OPR	0.2250	0.0087***	OPR	0.0520	0.6757
UNE	-0.3813	0.1121	UNE	-0.1195	0.7898	UNE	-0.2872	0.1655	UNE	-0.5248	0.1349
LNKLCI	-0.8816	0.0511*	LNKLCI	-0.3093	0.6502	LNKLCI	-1.1637	0.0009***	LNKLCI	-0.8050	0.1105
constant	30.5956	0.000***	Constant	2.9968	0.8766	Constant	41.6557	<0.0001** *	constant	5.6082	0.7127
			·		Short-run E	stimates			·		
D(CREDIT_CARD S_NPL(-1))	-0.1352	0.0685*	D(PERSONAL_USE S_NPL(-1))	-0.2893	0.0005***	D(PROPERTIES_ NPL(-1))	-0.2751	0.0004***	D(VEHICLES_NP L(-1))	-0.1548	0.0382**
D(LNLNCCTLR)	0.0614	0.7872	D(PERSONAL_USE S_NPL(-2))	-0.1682	0.0370**	D(PROPERTIES_ NPL(-2))	-0.1849	0.0196**	D(VEHICLES_NP L(-2))	-0.1509	0.0544*
D(LNLNCCTLR(- 1))	0.2451	0.2976	D(LNLNPUTLR)	1.0027	0.0141**	D(LNPRTLR)	0.5011	0.1949	D(VEHICLES_N PL(-3))	0.2693	0.0003***
D(LNLNCCTLR(- 2))	0.6087	0.0075***	D(LNOTHERTLR)	-0.8123	0.2484	D(LNOTHERTLR)	0.1745	0.6307	D(LNVETLR)	2.3779	0.0008***
D(LNLNCCTLR(- 3))	-0.5772	0.0115**	D(LNOTHERTLR(- 1))	0.0424	0.9475	D(LNINCOME)	-0.0188	0.942	D(LNVETLR(-1))	-1.0631	0.1861
D(LNOTHERTLR)	1.2132	0.066*	D(LNOTHERTLR(- 2))	-0.1253	0.8416	D(LNOIL)	-0.0095	0.6196	D(LNVETLR(-2))	-0.8867	0.1222
D(LNOTHERTLR(- 1))	0.0364	0.9555	D(LNOTHERTLR(- 3))	1.3199	0.0365**	D(OPR)	-0.0305	0.0879*	D(LNVETLR(-3))	1.6278	0.0049***

Table 6.2: Cointegrating form and long-run estimates (Endogenous: NPL by economic purposes)

'Table 6.2 Continued'

D(LNINCOME)	0.1826	0.7033	D(LNOTHERTLR(- 4))	0.4539	0.4713	D(UNE)	-0.0273	0.2518	D(LNOTHERTLR)	-1.4125	0.1305
D(LNOIL)	-0.0188	0.5999	D(LNOTHERTLR(- 5))	-1.7849	0.0066***	D(UNE(-1))	0.0154	0.4595	D(LNOTHERTLR (-1))	1.8323	0.0722*
D(LNOIL(-1))	0.0406	0.3221	D(LNOTHERTLR(- 6))	0.9581	0.148	D(UNE(-2))	0.0540	0.0081***	D(LNINCOME)	0.6652	0.2861
D(LNOIL(-2))	-0.0713	0.0763*	D(LNINCOME)	0.0145	0.9748	D(LNKLCI)	-0.0828	0.0511*	D(LNOIL)	0.0049	0.9016
D(LNOIL(-3))	0.0470	0.2439	D(LNOIL)	-0.0264	0.4899	D(LNKLCI(-1))	0.0930	0.034**	D(OPR)	-0.0619	0.1025
D(LNOIL(-4))	0.0977	0.0119**	D(LNOIL(-1))	0.0354	0.3915	D(LNKLCI(-2))	0.0735	0.0875*	D(OPR(-1))	-0.0496	0.1476
D(OPR)	0.0218	0.5309	D(LNOIL(-2))	-0.0042	0.9172	D(LNKLCI(-3))	0.0909	0.0459**	D(OPR(-2))	0.1029	0.0028***
D(UNE)	0.0137	0.7580	D(LNOIL(-3))	0.0787	0.0518*				D(UNE)	-0.0914	0.0709*
D(UNE(-1))	0.0499	0.2498	D(LNOIL(-4))	0.0852	0.0316**				D(LNKLCI)	-0.1608	0.0763*
D(UNE(-2))	0.0720	0.0607*	D(OPR)	-0.0561	0.1179				D(LNKLCI(-1))	0.2734	0.0046***
D(UNE(-3))	0.1411	0.0005***	D(UNE)	-0.0162	0.7374						
D(LNKLCI)	-0.1760	0.0308**	D(LNKLCI)	0.0341	0.6783						
Sum of D(LNCCTLR)	0.3379	0.4599	Sum of D(LNOTHERTLR)	0.0519	0.9764	Sum of D(UNE)	0.0421	0.2771			
Sum of D(LNOTHERTLR)	1.2497	0.1654	Sum of D(LNOIL)	0.1687	0.0207**	Sum of D(LNLNKLCI)	0.1745	0.0275**			
Sum of D(LNOIL)	0.1139	0.1249									
Sum of D(UNE)	0.2766	0.0014***									
ECT(1)	0.1574	<0.0001** *	ECT(-1)	-0.0724	<0.0001** *	ECT(-1)	0.0768	<0.0001** *	ECT(-1)	-0.1022	0.0002
Serial correlation test	-0.13/4	0.8733	Serial correlation test		0.3507	Serial correlation test	-0.0700	0.3174	Serial correlation test		0.4876
Heteroscedasticity		0.0111**	Heteroscedasticity		0.0032***	Heteroscedasticity		0.0446**	Heteroscedasticity		0.0801*

Note: Asterisks ***, **, * indicate statistically significant at 1%, 5% and 10%; Tested for serial correlation up to lag 2

CHAPTER 7: A NONLINEAR ANALYSIS OF HOUSEHOLD NON-PERFORMING LOANS BY ECONOMIC PURPOSES

A linear and long-run dynamic model might be insufficient to explain the real relationship without a cointegration relationship (Katrakilidis & Trachanas, 2012; Fasianos *et al.*, 2017). Though the linear ARDL bounds test in Table 6.1 favoured the non-rejection of the null hypothesis for vehicle NPLs, the result of no cointegration could have been due to nonlinearity.

Moreover, most economic variables are nonlinear, as mentioned in Section 2.3.3, and household indebtedness is closely related to the business cycle (Mian *et al.*, 2017). As shown, a shock to household debt generated a boom-bust cycle in the real economy. Debt default had strong fluctuations over the business cycle, as seen from Table 1.3; households might react differently when different macroeconomic shocks occur (Madeira, 2018). hence, this study revealed the potential nonlinear relationship between NPLs by economic purpose and their determinants. This section deployed the asymmetric cointegration methodology and nonlinear modelling technique.

7.1 NARDL framework

The asymmetrical impact of economic variables was assessed together with outstanding loans. Each of the economic variables was decomposed into the partial sum of positive and negative change as follows:

Model 1: Credit card NPLs

LNCCNPL = f(LNCCTLR,LNOTHERTLR_1,LNINCOME⁻,LNINCOME⁺,LNOIL⁻,LNOIL⁺ OPR⁻,OPR⁺, UNE⁻,UNE⁺,LNKLCI⁻,LNKLCI⁺)

In Model 1's specification, LNCCNPL refers to credit card NPLs in natural logarithm form. LNCCTLR refers to credit card outstanding debt in natural logarithm form, *LNOTHERTLR*_1 denotes household total outstanding loans, except for credit card debt in natural logarithm form.

Model 2: Personal uses NPLs

LNPUNPL = f(LNPUTLR,LNOTHERTLR_2,LNINCOME⁻,LNINCOME⁺,LNOIL⁻,LNOIL⁺, OPR⁻,OPR⁺, UNE⁻,UNE⁺,LNKLCI⁻,LNKLCI⁺)

In Model 2's specification, LNPUNPL refers to personal uses NPLs in natural logarithm form. LNPUTLR refers to personal loan outstanding debt in natural logarithm form, *LNOTHERTLR*_2 denotes household total outstanding loans, except for personal loan debt in natural logarithm form.

Model 3: NPLs for purchase residential properties

LNPRNPL = f(LNPRTLR,LNOTHERTLR_3,LNINCOME⁻,LNINCOME⁺,LNOIL⁻,LNOIL⁺, OPR⁻,OPR⁺, UNE⁻,UNE⁺,LNKLCI⁻,LNKLCI⁺)

In Model 3's specification, LNPRNPL refers to residential properties NPLs in natural logarithm form. LNPRTLR refers to residential properties outstanding debt in natural logarithm form, *LNOTHERTLR*_3 denotes household total outstanding loans, except for residential properties debt in natural logarithm form.

Model 4: NPLs for the purchase of transport vehicles

LNVENPL= $f(LNVETLR, LNOTHERTLR_4, LNINCOME^-, LNINCOME^+, LNOIL^-, LNOIL^+,$

OPR⁻, *OPR*⁺, *UNE*⁻, *UNE*⁺, *LNKLCI*⁻, *LNKLCI*⁺)

Lastly, in Model 4's specification, LNVENPL refers to transport vehicle NPLs in natural logarithm form. LNVETLR refers to transport vehicle outstanding debt in the natural logarithm form, *LNOTHERTLR*_4 denotes household total outstanding loans, except for transport vehicle debt in the natural logarithm form.

where *LNINCOME*⁻ and *LNINCOME*⁺ are the partial-sum processes of the negative and positive changes in real household income in natural logarithm form, *LNOIL*⁻ and *LNOIL*⁺ are the partial-sum processes of the negative and positive changes in the crude oil price in natural logarithm form, *OPR*⁻ and *OPR*⁺ are the partial-sum processes of the negative and positive changes in the overnight policy rate, *UNE*⁻ and *UNE*⁺ are the partial-sum processes of the negative changes in the negative changes in the negative changes in the overnight policy rate, *UNE*⁻ and *UNE*⁺ are the partial-sum processes of the negative and positive changes in the negative changes in the negative changes in the unemployment rate in natural logarithm form. *LNKLCI*⁻ and *LNKLCI*⁺ are the partial-sum processes of the negative changes in the KLCI in natural logarithm form.

Similarly to the linear ARDL approach, the bounds test for cointegration was performed as the first step. Table 7.1 presents the results of the null hypothesis of no existence of cointegration. The non-rejection of the null hypothesis indicated a long-run nonlinear relationship between the examined variables at a 5% level of significance. Further, the CUSUM and CUSUMSQ tests suggested that the estimates were stable within 5% for each specified model (See Appendix E). For personal and property loans, a dummy variable was included to take account of possible structural change.

7.2 The long and short-run asymmetrical effect of the tested variables

In the second step, the long- and short-run asymmetry tests were conducted using the Wald test, and the results are tabulated in Table 7.2. As suggested, there was only short-run asymmetry of the OPR captured in the credit card NPL model. As for Model 2, the

short-run asymmetrical impact of the crude oil price and the OPR were found on the personal uses NPLs. On the other hand, Model 3 exhibited a long asymmetry relationship between the OPR, the unemployment rate and the housing NPLs. At the same time, the nonlinear effect of the OPR was detected in the short run only. For Model 4, there was evidence of an asymmetric linkage between vehicle loan defaults, household income adjusted for inflation, the OPR and the stock market index in the long run. In the short run, the asymmetrical impacts of the OPR and the unemployment rate were reported as significant. These findings further supported the nonlinearity characteristics that existed in each of the household NPLs category models.

Table 7.1: ARDL Bound test, CUSUM and CUSUMSQ diagnostics

	Model 1	Model 2 (with	Model 3 (with	Model 4				
		<u>dummy)</u>	Dummy)					
PSS F-statistic	5.1618***	3.7170**	6.5954***	5.9836**				
CUSUM/								
CUSMSQ	Stable/Stable	Stable/Stable	Stable/Stable	Stable/Stable				
No								

Note: Asterisks ***, **, * indicate statistically significant at 1%, 5% and 10%.

•	Model 1		Model 2(with dummy)		Model 3 (with dummy)		Model 4	
Waldtast				A	·			
wala lesi	LR	SR	LR	SR	LR	SR	LR	SR
LNINCOME	0.1660	0.7647	0.2178	0.2674	0.3465	0.5410	0.0002***	0.4663
LNOIL	0.3446	0.1427	0.1574	0.0883**	0.7056	0.3845	0.2674	0.2733
OPR	0.3906	0.0131**	0.3505	0.0009***	0.0196**	0.0561*	0.0224**	0.0452**
UNE	0.2560	0.3040	0.6848	0.2544	0.0156**	0.1352	0.4438	<0.0001***
LNKLCI	0.2436	0.8742	0.9058	0.7957	0.7673	0.5589	<0.0001***	0.2543

Note: Asterisks ***, **, * indicate statistically significant at 1%, 5% and 10%.

Next, the final models were estimated based on the asymmetry test results in Table 7.2. The long and short-run dynamics are presented in the first and second panels,

respectively, in Table 7.3, while the third panel reports the findings of diagnostic checking.

Table 7.3:	Cointegrat	ting form	and long-run	estimates (Endogen	ious: NPL by p	urposes)				
Model 1				Model 2			Model 3			Model 4	
					Long-1	Run Dynamics					
	Coefficients	Prob		Coefficients	Prob		Coefficients	Prob		Coefficients	Prob
LNCCTLR(-1)	1.7154	0.069*	LNPUTLR(-1)	0.0408	0.9852	LNPRTLR(-1)	6.2677	<0.0001* **	LNVETLR(-1)	6.3273	0.0636*
LNOTHERTLR (-1)	6.0638	0.0096***	LNOTHERTLR (-1)	3.0248	0.6879	LNOTHERTLR(-1)	0.6973	0.4473	LNOTHERTLR(- 1)	3.0409	0.5185
LNINCOME(- 1)	0.0309	0.9662	LNINCOME(- 1)	0.242	0.7547	LNINCOME(-1)	-1.4185	0.0001***	LNINCOME_NE G(-1)	-12.6925	0.2666
									LNINCOME_PO S(-1)	2.9133	0.0494**
LNOIL(-1)	-0.3633	0.0001***	LNOIL(-1)	-0.445	0.3292	LNOIL(-1)	-0.1578	0.0042***	LNOIL(-1)	0.2602	0.253
					C						
OPR(-1)	0.0309	0.5785	OPR(-1)	0.5872	0.1386	OPR_NEG(-1)	-0.0158	0.7824	OPR_NEG(-1)	-0.0745	0.6438
						OPR_POS(-1)	0.3182	0.1104	OPR_POS(-1)	1.3203	0.1593
UNE(-1)	-0.0054	0.9666	UNE(-1)	0.3638	0.3874	UNE_NEG(-1)	0.4269	0.0285***	UNE(-1)	0.4835	0.4001
						UNE_POS(-1)	-0.2952	0.0046***			
LNKLCI(-1)	-0.4516	0.0913*	LNKLCI(-1)	-0.0734	0.9235	LNKLCI(-1)	-0.0435	0.742	LNKLCI_NEG(- 1)	1.0427	0.19
									LNKLCI_POS(-1)	-0.9295	0.0449*
Constant	21.1326	<0.0001* **	Constant	7.4976	0.6331	Constant	30.9628	0.000***	constant	18.673	0.0054***

Table 7.3: Cointegrating form and long-run estimates (Endogenous: NPL by purposes)

'Table 7.3 C	ontinued'
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Table 7.3 Continued'											
Short Run Estimate											
	Coefficients	Prob		Coefficients	Prob		Coefficients	Prob		Coefficients	Prob
D(LNCCTLR)	0.1968	0.1024	D(PERSONA L_USES_NPL (-1))	-0.2985	0.0001***	D(PROPERTI ES_NPL(-1))	-0.2675	0.0002***	D(VEHICLES_N PL(-1))	-0.3781	0.0002***
D(LNOTHER TLR)	0.886	0.0008***	D(PERSONA L_USES_NPL (-2))	-0.2718	0.0006***	D(PROPERTI ES_NPL(-2))	-0.2117	0.006***	D(VEHICLES_N PL(-2))	-0.3327	0.0002***
D(LNINCOM E)	-0.8873	0.1311	D(LNPUTLR)	0.613	0.0456**	D(LNPRTLR)	0.6913	0.1823	D(LNVETLR)	1.4849	0.1002
D(LNOIL)	-0.0955	0.0492**	D(LNOTHER TLR)	-0.0606	0.925	D(LNOTHERT LR)	0.1526	0.7369	D(LNVETLR(-1))	-0.4916	0.5778
D(OPR_NEG)	-0.0016	0.4835	D(LNINCOM E)	-0.0316	0.951	D(LNINCOME)	-0.2095	0.5831	D(LNOTHERTLR)	0.8613	0.4468
D(OPR_POS)	-0.1529	0.0011***	D(LNOIL_NE G)	0.1071	0.0610*	D(LNOIL)	-0.0136	0.5698	D(LNOTHERTLR (-1))	1.4899	0.1937
D(OPR_POS(-1))	-0.0998	0.7555	D(LNOIL_PO S)	-0.202	0.0026***	D(LNOIL(-1))	-0.0268	0.2496	D(LNINCOME)	0.5758	0.4944
D(UNE)	0.1208	0.0001***	D(OPR_NEG)	0.0604	0.1559	D(OPR_NEG)	-0.0133	0.3303	D(LNINCOME(- 1))	1.394	0.0553**
D(LNKLCI)	-0.0485	0.0002***	D(OPR_POS)	-0.088	0.1302	D(OPR_POS)	-0.0375	0.3188	D(LNOIL)	-0.0176	0.6979
			D(OPR_POS(-1))	-0.1266	0.0221**	D(OPR_POS(- 1))	-0.0446	0.0180**	D(OPR_NEG)	-0.0642	0.2756
			D(UNE)	0.0155	0.7247	D(UNE)	-0.0451	0.0309**	D(OPR_POS)	-0.0537	0.4491
			D(LNKLCI)	0.0088	0.9157	D(UNE(-1))	-0.0283	0.3029	D(OPR_POS(-1))	-0.282	0.0001***

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			DUMMY	0.0351	0.0184**	D(LNKLCI)	-0.0809	0.0435**	D(UNE_NEG)	-0.2589	0.0024***
						DUMMY	0.0283	0.0093***	D(UNE_NEG(-1))	-0.2984	0.0001***
									D(UNE_POS)	0.0942	0.2462
								0	D(UNE_POS(-1))	0.1835	0.0307**
									D(LNKLCI)	-0.1253	0.2147
sum of D(OPR_POS)	-0.2592	0.0122**	Sum of D(OPR_POS)	-0.2146	0.0164**	sum of D(LNOIL)	-0.0403	0.0694*	sum of D(LNINCOME)	-0.3685	0.7706
						sum of D(OPR_POS)	-0.0819	0.0456**	sum of D(OPR_POS)	-0.164	0.0001***
						Sum of D(UNE)	-0.0734	0.0419**	sum of D(UNE_NEG)	-0.482	0.0001***
									sum of D(UNE_POS)	0.2016	0.0761***
ECT(-1)	-0.0305	0.0735*	ECT(-1)	-0.0641	<0.0001***	ECT(-1)	-0.1542	< 0.0001***	ECT(-1)	-0.164	<0.0001***
Serial correlation test		0.729	Serial correlation test	5	0.9102	Serial correlation test		0.0191**	Serial correlation test		0.2524
Heteroscedasticity		0.0077***	Heteroscedasticity		0.0871*	Heteroscedasticity		0.0516*	Heteroscedasticity		0.0537*

'Table 7.3 Continued'

Note: Asterisks ***, **, * indicate statistically significant at 1%, 5% and 10%; Tested for serial correlation up to lag 2

The long-run analysis of the asymmetric credit card NPLs model observed that: first, the outstanding loans were one of the primary sources of the credit card debt default. It was about four times greater than another type of household debt than the credit card outstanding debt.

Among the macroeconomic indicators, the crude oil price and stock market index had a significant long-run impact on credit card NPLs. For a 1% increase in the crude oil price and KLCI, credit card debt impairment was likely to be reduced by 0.36% and 0.45%, respectively. These variables also affected the level of default in the short run, in a smaller magnitude. Besides, unemployment and credit card NPLs were related linearly and positively in the short run. For short-run asymmetry, only positive changes in the OPR were significant, where a rise in the OPR reduced the credit card NPL level.

In the nonlinear ARDL estimated model, the long-run analysis findings were similar to those in the linearly specified model, i.e., none of the macroeconomic variables and types of outstanding loans affected the personal use NPLs. As for the short-run dynamics, personal loan NPLs did not react differently to crude oil price shocks. Short-term changes in crude oil prices led to lower NPLs for personal uses, with a more significant impact on positive crude oil price changes. Besides that, the short term positive changes in the OPR were more likely to reduce personal use NPLs.

Occupying the largest share of the household NPLs, the NPLs for purchasing residential properties were significantly affected by high-level outstanding housing loans. For the economic fundamentals' long-run impact, household income adjusted for inflation and the crude oil price were negatively related to housing NPLs. Residential property NPLs were expected to reduce by 1.45% for a 1% increase in real income, whereas residential properties debt default dropped by 0.16% for a 1% increase in the crude oil

price. For long term unemployment, household indebtedness reacted indifferently. Long term negative change in the unemployment rate tended to lower down the level of housing NPLs.

On the other hand, positive changes in the unemployment rate, in the long run, were found to reduce the default level, with almost 1.5 more substantial impacts captured from a negative change of the unemployment rate. In the short run, the crude oil price, KLCI and the unemployment rate were negatively related to the residential property NPLs. The short-run asymmetry impact of the OPR was found significant in which positive changes of the OPR tended to reduce property NPLs.

Regarding the determinants of the transport vehicle NPL model, the impact of outstanding vehicle loans was significant in the long run. Aside from macroeconomic determinants, there was a long-run asymmetry effect of household income adjusted for inflation on the vehicle NPLs. With a 1% increase in real income, vehicle NPLs were expected to increase by 2.9%. Vehicle debt defaults responded to long-run positive changes in the KLCI only. Every 1% increase in the KLCI reduced the vehicle NPL level. The short-run dynamics analysis indicated that positive changes in the OPR decreased vehicle NPLs. Besides that, short-term positive and negative changes in the unemployment rate tended to accumulate NPLs. However, a more considerable impact was found from negative changes.

The diagnostic test results confirmed that all the final specified models were free from serial correlation issues at a 1% significance level. There was evidence of rejection for homoscedastic residuals at 1% for Model 1 and 10 % for Models 2, 3 and 4. The issue of heteroskedasticity is usually encountered under the ARDL model due to combining

different integration orders used in the variables (Shrestha & Chowdhury, 2005; Fosu & Magnus, 2006).

However, as Laurenceson & Chai (2003) mentioned, the ARDL framework results are more of a concern due to the instability of the coefficients. For this study, as seen earlier in Table 7.1, the estimated coefficients in these models were stable throughout the sample period as most of these residuals were within the 5% breakpoint critical bounds.

7.3 Discussions: The determinants of NPLs by economic purpose

As the present study hypothesised that macroeconomic determinants were nonhomogeneous across different loan types, an analysis was carried out to investigate the specific macroeconomic indicators related to the NPLs.

From a macroeconomic perspective, the long-run economic magnitude and significance of coefficients were explained and compared across different NPL categories in the ARDL and NARDL approaches

Most of the estimated coefficients had signs compatible with the available empirical evidence, as detailed in Chapter 2. The negative and significant error correction term confirmed cointegrating relationships between NPLs by economic purpose and the tested variables. Across the different NPLs for economic purposes, the short-term change of lagged NPLs on current NPLs was expected to be negative, as NPLs tend to decrease when they increased in the previous month due to write-offs. Regarding the effect of credit growth, Salas & Saurina (2002) and Foos *et al.* (2010) found that the relationship between credit growth and loan loss was significant and positive. Jakubík and Reininger (2013) also indicated that past credit growth was one factor that explained NPL changes.

In line with past literature, this study found that all the outstanding loan growth led to high NPLs in the long run, except for personal loans. Consumers tended to cover debt by taking out personal loans.

Focusing on the determinants of credit card NPLs, the crude oil price and stock market index appeared to be the explanatory variables besides outstanding household debt, excluding credit cards. When nonlinearity was taken into account, credit card debts were significant in affecting credit card NPLs. However, the effect of other debt was more significant when these debts were factored in. Borrowers with other loans (s) tended to default the credit card loans compared to those without (Argawal and Liu, 2003), especially mortgages. (Chan *et al.*, 2015). Further, the model had an asymmetric shortrun effect on the OPR, unemployment, and oil price.

As for personal uses NPLs, in a linear and nonlinear specification, none of the tested variables affected the NPLs, either in the long- or short run. Based on Franco Modigliani's life cycle hypothesis, household debt is accrued far-sighted, it is strongly dependent on household income and utility maximising smoothening their consumption over time (Mishkin 2010). Anecdotally, personal financing is commonly used for sustaining the luxury lifestyle of borrowers. Hence, household debt default is not sensitive to any macroeconomic indicators. It is more likely built under household rational consumption behavioural factors. Similar to the credit card NPLs, an asymmetric short-run effect of the OPR was found in the model.

Looking at the long-run determinants of NPLs for purchasing residential properties in the linear ARDL model, several factors significantly affected loan defaults. They are a high level of property debt, low household income adjusted for inflation, a higher OPR and a lower stock market index. For the asymmetrical impact of macroeconomic indicators, positive and negative unemployment shocks became significant in the long run, while positive changes in the OPR contributed to the level of NPLs.

Based on the examination of previous literature, high NPLs were often driven by economic factors. However, there was no cointegrating relationship between transport vehicle NPLs and their determinants within the tested sample period, using the linearly specified model. This result perhaps indicated that the relationship deviated over time due to various shocks or fluctuations. The F-statistic of the bounds test for cointegration validated the potential long-run asymmetrical relationship between the tested variables in the nonlinear specification. There was a strong demand for cars among consumers. The middle and bottom forty had a larger exposure to motor vehicle loans, whereby these groups were the most vulnerable to any adverse shocks (Siti *et al.*, 2018; Hansen & Neilson, 2017). From the findings of the nonlinear ARDL approach, outstanding vehicle loans, positive changes in household income adjusted for inflation, and positive changes in the KLCI were the main contributors to the nonperformance of such loans in the long run. In the short-term horizon, positive changes in the OPR were related to this NPL category.

The stock market index and crude oil price contributed more to credit card and vehicle loan default than other NPL categories. This result was consistent with Kalirai and Scheicher (2002), Jakubik and Reininger (2013) and Espinoza & Prasad (2010). A booming stock market is due to a positive outlook on firms' profitability that maintains employment and enables households and individuals to repay their loans.

Besides that, it was not surprising to observe that the crude oil price (global commodity price shock) negatively affected the credit card and housing NPLs in the long run. These findings were similar to the study conducted by the International Monetary fund (2015),

Idris and Nayan (2016), Kinda, Mlachila, and Ouedraogo (2016)). A decline in the oil price benefits oil importers through lower inflation. However, weak prices in Malaysia's commodity exports would dent the level of disposable income among the nation's households and the country's fiscal position, as a low oil price would impede economic activity. This phenomenon would increase the unemployment rate and constrain borrowers in meeting loan repayment obligations in the long run.

On the other hand, long term positive oil price shocks and a booming stock market tend to inflate prices while these prices are always sticky down. Such prolonged inflationary pressure could lead to lower demand due to the postponement of consumer consumption. Subsequently, the implementation of a loosened monetary policy would be expected to encourage demand and spending. This policy would imply that an interest rate cut will necessarily improve borrowers' repayment obligations. Consumers will benefit from any cutback of the OPR, especially for floating mortgage and credit card loans with the highest interest rates amongst all loan categories.

For collateral lending, such as houses whose values appreciate, lenders will pursue borrowers if they default in the long run. For these reasons, borrowers are expected to serve their loans, hence a reduction in nonperforming loans. Besides that, compared to credit card debt, the debt repayment amount is not affected by the stock market index caused by the direct spillover of domestic vulnerability or the indirect effect of the external environment, in either the long or short run. Firstly, a possible reason for this would be high levels of personal loan defaults caused by the use above capabilities mismatched with income sustainability, i.e. related to household rational consumption behaviour. Secondly, consumers might speed up repayments of other debt by taking out a personal loan. Hence the effect is muted. Changes in the OPR affect the borrowing costs for banks, which eventually leads to a chain effect. The coefficient sign of the OPR was in line with the past literature. However, the analysis showed that the OPR was not the main contributor in explaining the NPL categories in the long run, which contradicted the results of earlier studies (Khemraj & Pacha (2009); Dash & Kabra (2010)). The insignificant coefficient of interest rate policy obtained across all NPL models indicated that monetary policy did not contribute directly to high NPLs in the long run. However, the impact was transmitted by multiple channels. In general, increasing interest rates typically present a robust economic condition. A lower overnight policy rate revision indicates the early stages of a slowdown in the economy or a recession (Markus, Irene and Andreas, 2001). For all NPL categories, it was also observed that there was an asymmetrical effect between the NPL categories and the overnight policy rate in the short run, where a positive change of the OPR was found to be significant and negatively related to the NPL. A possible reason for this could be that the households could still sustain debt repayments during a short term rise in the OPR.

Occupational control was expected to affect loan arrears. Supported by Rinaldi & Sanchis-Arellano (2006), Campbell & Coco (2015) and Alfaro & Gallardo (2012), higher real income improved the availability of cash flow, which in turn reduced the probability of default, and this long-run relationship was evident, particularly in residential NPLs. In contrast, the long run asymmetrical relationship between vehicle NPLs and income was found to be positive. This asymmetric relationship could be caused by unobservable factors, such as the income of the household's car loan owner. While the household income data was not affected by the lower quintile of income, there was the possibility that some of the household members were vulnerable to any shock, therefore, increasing the chance of defaults.

As far as long-term unemployment is concerned, property loans reacted indifferently. A long term high in the unemployment rate was expected to reduce the housing loan NPLs, while a long term low in the unemployment rate had a more pronounced effect in reducing housing debt defaults. A household with debts is most likely to face liquidity problems during periods of high unemployment as it would be less capable of coping with debt payments. As pointed out by Loh *et al.* (2015) and Bahruddin & Masih (2018), long term employment promotes a favourable wealth position, therefore, inducing low loan defaults. The general impression is that long term unemployment adversely affects the credit market; the negative effect is compensated. In the long run, a weak labour market brings about a chain effect, including lower loan growth, as loan applications require proof of a steady income source. As the economy slows down, central banks will reduce the OPR to encourage spending to boost economic growth. Borrowers with loans with floating rates could either enjoy extra cash due to the cutback of the OPR or refinance their existing loans at a lower rate. As such, NPLs are reduced.

In contrast, the vehicle-related NPL model's expected short-run negative or positive unemployment changes brought more impaired loans. An adverse change in unemployment had a more significant impact. Credit card NPLs also reacts to short term unemployment in a positive but linear direction. This observation indicated that in any event where households have less capability to repay debt, borrowers rationally choose to default on unsecured loans over other loan categories or delay the repayment of vehicle loans. The insignificance of long-run household income adjusted for inflation and the effect of the unemployment rate on unsecured NPLs posits that non-performance of unsecured loans was not principally driven by income sources (current and future); but more attributable to other factors.

CHAPTER 8: CONCLUSION

This study has addressed household indebtedness and NPLs by providing new evidence concerning the sources of Malaysian household NPLs, summarised in the following section. The effects of household lending, namely credit cards, personal uses, purchase of residential properties, and purchase of transport vehicles, on household debt default were investigated using the ARDL and NARDL approaches, using the sample period from 2006 to 2018. Besides that, the factors of each of the NPLs by categories were determined.

8.1 Summary of Findings

There have been several studies concerning aggregate NPL analysis. In contrast, this study demonstrated enhanced evidence of the potential stress in four major household loan components on household deleverage. The impact of each type of household credit on household NPLs was found heterogeneous across the types of loans over the study period. This study examined the existence of an asymmetrical relationship between household credit and household NPLs. Upon investigation, a differential impact of credit on household sustainability was found. Credit card lending and indebtedness were explained in the asymmetry model, where lower credit card debt was more likely to reduce the level of household arrears in the short run. Next, the impact of personal loans on household NPLs was better captured linearly. In the long run, households tended to take personal loans to cover other debts, compensating for the high amount of household NPLs.

The leading household NPLs accounted for the possible structural break represented by the global financial crisis. The asymmetrical relationship of these loan movements was found evident with higher impact sources from negative changes. While most previous studies have suggested that past credit growth leads to higher NPLs, the hidden nonlinear relationship revealed that a low level of outstanding housing loans was expected to conserve the debt from becoming non-performing in the long-run horizon. Instead of holding back housing loan approvals, the authorities should focus on debt recovery or restructuring strategies to avoid such loans turning into bad debt. As explained by the linear model, outstanding loans for vehicles had no explanatory power to accumulate household NPLs.

Given that vehicle loans have a shorter loan tenure and vehicle values depreciate each successive year, vehicle loans did not contribute to household debt defaults in the long run. In line with other past studies, the OPR and KLCI were the main macroeconomic determinants of household NPLs compared to the other tested variables. The KLCI was shown as the leading indicator, reflected by domestic and global economic conditions, affecting debt and default dynamics.

Secondly, by narrowing the household NPLs into four major categories, the findings have provided additional insights into the economic determinants associated with the former movements and explained how the household debt portfolio affected each NPLs category. Motivated by the fact that macroeconomic variables may exhibit nonlinearities, the analysis of the determinants of the household NPLs assessed how changes in each of the tested economic factors in different directions could affect household NPLs. The findings showed important differences in the responses of households to positive or negative changes of the explanatory variables, and these determinants were found heterogeneous across different NPL categories. In the credit card NPL model, it was observed that if the credit card owner had other debt simultaneously, they tended to default on credit card debt. Moreover, credit card debt default was not impacted directly
by domestic factors. However, the risk of default was likely transmitted from global effects, including; the crude oil price and KLCI in the long run. On the other hand, There was no explanatory power of tested macroeconomic variables and debt portfolio on the nonperformance of personal loans in the long run. The personal use NPLs were likely to be explained by the concepts of micro-foundations.

NPLs related to the purchase of residential properties were described in an asymmetric specification. The former's movements were directly affected by both domestic and global factors. At the same time, monetary policy and the KLCI were not the main contributors. As expected, outstanding housing loans tended to increase housing NPLs. Further, linear ARDL modelling was insufficient to assess the relationship between vehicle NPLs and the tested variables. However, nonlinear ARDL modelling uncovered the dynamics. High outstanding debt for vehicles in the loan portfolio was related to high NPLs. Vehicle NPLs were significantly linked to income and stock market shocks.

8.2 Policy Implications

One of the challenges of being a standard open economy and a net exporter of oil is that Malaysia is likely to be affected by external shocks and domestic market conditions. Following a cyclical pattern, banks usually receive timely loan repayments during boom periods. However, when the pressure of international and domestic economic shocks are passed to firms and households, banks are exposed to credit risk. This exposure consequently translates into an inability to meet debt repayments and consequently the accumulation of NPLs. Given the risks involved, the long- and short-run results captured in this study might give necessary policy implications in lending practices and stress testing frameworks. Further, from an asymmetric perspective, this study has revealed important information concerning the responses of household NPLs to positive or negative changes of the explanatory variables.

Each type of credit carries different risks to a bank's balance sheet. This study's findings detected the credit risk by revealing the potential risk of bad household debt turning into non-performing loans to maintain financial stability. Firstly, policymakers could price loan default risk distinctly by deliberating an appropriate instrument for each credit facility's quantitative impact. Meanwhile, this study has given an insight into how the household debt portfolio affects each of the NPL categories. Banking institutions could create different incentive structures for each type of loan regarding the costs of bankruptcy or collateralised assets. Secondly, the findings have provided the basis for the future development of the macroprudential framework by understanding the transmission channel of global and domestic macroeconomic shocks to households. The central bank should continuously improve the regulatory policies to reduce the bad locks and minimise loan losses, considering domestic and global headwinds. With various possible changes in the prevalent market conditions, incorporating the significant macroeconomic control variables to the early warning system of household distress would enable policymakers to reduce or maintain the risk of household default more effectively and efficiently.

8.3 Future work

This study could be extended by exploring credit risks in different regimes or different phases of the economic cycle. Moreover, bank or household-specific microeconomic factors could be incorporated into such future studies. Given the presence of asymmetric cointegrations, the present study recommends that future studies examine the threshold values of the asymmetric adjustment to the involved variables.

REFERENCES

- Adebola, SS, Sulaiman, W., Yusoff, W. and Dahalan, J. (2011). An ARDL Approach to the determinants of non-performing loans in the Islamic banking system in Malaysia. Arabian Journal of Business and Management Review, 1(2), 20-30.
- Ahmad, F., and Bashir, T. (2013). The explanatory power of bank-specific variables as determinants of non-performing loans: Evidence from Pakistan banking sector. *World Applied Sciences Journal*, 22(9), 1220-1231.
- Ahmad, F., Abbas, Z., and Bashir, T. (2013). The explanatory power of macroeconomic variables as determinants of non-performing loans: Evidence from Pakistan. *World Applied Sciences Journal*, 22(2), 243-255.
- Ahmad, R., & Omar, N. (2013). Credit Card Debt Management: A Profile Study of Young Professionals. *Asia-Pacific Management Accounting Journal*, 8(1), 1-17.
- Alfaro, R. and Gallardo, N. (2012). The determinants of household debt default. Retrieved from http://repositorio.uahurtado.cl/bitstream/handle/11242/2009/353-1168-1-PB.pdf?sequence=1&isAllowed=y
- Alter, A., Feng, A., and Valckx, N. (2018). Understanding the macro-financial effects of household debt: A global perspective. IMF working paper 18/76
- Agarwal, S. and Liu, C. (2003). Determinants of Credit Card Delinquency and Bankruptcy: Macroeconomic Factors. *Journal of Economics and Finance*, 27 (1), 75-84
- Asari, F.F.A.H., Muhammad, N.A., Ahmad, W., Latif, N.I.A., Abdullah, N. and Jusoff, K. (2011). An Analysis of Non-Performing Loan, Interest Rate and Inflation Rate Using Stata Software. *World Applied Sciences Journal*, 12:41-48
- Asea, P.K. and Blomberg, B. (1997) Lending cycles. *Journal of Econometrics*, Elsevier, 83(1-2), 89-128
- Bahruddin, W. A., & Masih, A. (2018). Is the relation between lending interest rate and non-performing loans symmetric or asymmetric? Evidence from ARDL and NARDL. University Library of Munich, Germany.

- Banerjee, A., Dolado, J. & Mestre, R. (1998). Error-correction mechanism tests for cointegration in a single-equation framework. *Journal of time series analysis*, 19(3), 267-283.
- Bank Negara Malaysia (2011). Measures to promote responsible financing practice. Bank Negara Malaysia Press Statements.
- Bank Negara Malaysia. (2018). Monthly statistical bulletin, available at http://www.bnm.gov.my/index.php?ch=en_publicationandenandpub=msbarc (accessed 31 January 2018)
- Beck, R., Jakubik, P. and Piloiu, A. (2015), Key determinants of non-performing loans: New evidence from a global sample. *Open Economies Review*, 26(3), 525-550.
- Beck, R., P. Jakubík and A. Piloiu (2013). Non-performing loans: What matters in addition to the economic cycle? European Central Bank. Working Paper No. 1515.
- Bernanke, B., Gertler, M. and Gilchrist, S. (1998). *The financial accelerator in a quantitative business cycle framework*. In J. B. Taylor and M. Woodford, editors, Handbook of Macroeconomics, Amsterdam, Elsevier Science.
- Bianco, K. M (2008). The Subprime Lending Crisis: Causes and Effects of the Mortgage Meltdown. CCH, Wolters Kluwer Law and Business, 2008
- Bofondi, M. and Ropele, T. (2011). Macroeconomic determinants of bad loans: evidence from Italian banks.
- Bonfim, D. (2009). Credit risk drivers: Evaluating the contribution of firm-level information and macroeconomic dynamics. *Journal of Banking & Finance*,33(2), 281-299.
- Bonilla, C. A. O. (2011). Macroeconomic determinants of the Non-Performing Loans in Spain and Italy. The University of Leicester.
- Borio, C., Drehmann, M., and Tsatsaronis, K. (2014). Stress-testing macro stress testing: does it live up to expectations?. *Journal of Financial Stability*,12, 3-15.

- Brooks, C. (2014). *Introductory econometrics for finance*, New York: Cambridge university press.
- Brown, R. L., Durbin, J. and Evans, J. M. (1975), Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society*. Series B (Methodological), 149–192.
- Bucur, I.A. and Dragominascu, S.E. (2014) The Influence Of Macroeconomic Conditions On Credit Risk: Case Of Romanian Banking System. *Studies and Scientific Researches*. Economics Edition, No 19.
- Büyükkarabacak, B., and Valev, N. T. (2010). The role of household and business credit in banking crises. *Journal of Banking & Finance*, *34*(6):1247-1256.
- Callen, T., Khandelwal, P., Miyajima, K., and Santos, A. (2015). Oil prices, financial stability, and the use of countercyclical macroprudential policies in the GCC. *Prepared for the annual meeting of ministers of finance and central bank governors*.
- Calza, A., & Sousa, J. (2006). Output and inflation responses to credit shocks: are there threshold effects in the euro area?. *Studies in Nonlinear Dynamics & Econometrics*, 10(2). Retrieved from https://www.econstor.eu/bitstream/10419/152915/1/ecbwp0481.pdf
- Campbell, J. Y., and Cocco, J. F. (2015). A model of mortgage default. *The Journal of Finance*, 70(4), 1495-1554. Retrieved from https://www.nber.org/papers/w17516.pdf
- Caporale, G.M, Stefano Di Colli, Lopez, J.S. (2013). Bank Lending Procyclicality and Credit Quality During Financial Crises, Economics and Finance Working Paper Series, June 2013.
- Carling, K., Jacobson, T., Lindé, J., & Roszbach, K. (2007). Corporate credit risk modeling and the macroeconomy. *Journal of Banking & Finance*,31(3), 845-868.
- Castro, V. (2013). Macroeconomic determinants of the credit risk in the banking system: the case of the GIPSI, *Economic Modeling*, 31, 672-683.
- Chaibi, H., and Ftiti, Z. (2015). Credit risk determinants: Evidence from a cross-country study. *Research in international business and finance*,33, 1-16.

- Chan, S., Haughwout, A., Hayashi, A. and Van der Klaauw, W. (2016). Determinants of a mortgage default and consumer credit use: the effects of foreclosure laws and foreclosure delays. *Journal of Money*, Credit and Banking,48(2-3):393-413
- Chernykh, L., Davydov, D., & Sihvonen, J. (2019). Financial stability and public confidence in banks (No. 2/2019). Bank of Finland, Institute for Economies in Transition. Retrieved from https://www.econstor.eu/bitstream/10419/212910/1/bofit-dp2019-002.pdf
- Chiquier, L. (2006). Housing Finance in East Asia. East Asian Finance Flagship Book, World Bank., "To Build Sound and Accessible Housing Finance Systems," March 15-17.
- Cho, B.Y. (2013). Why do countries implement Basel II? An analysis of the global diffusion of Basel II implementation. The London School of Economics and Political Science
- Chowla, S., Quaglietti, L. and Łukasz, R. (2014). *How Have World Shocks Affected the UK Economy?* Bank of England Quarterly Bulletin, 2014 Q2
- Cohen, M. J. (2007). Consumer Credit, Household Financial Management, Sustainable Consumption, *International Journal of Consumer Studies*, 31(1)L 57–65.
- Crotty, J. (2009). Structural causes of the global financial crisis: a critical assessment of the new financial architecture. *Cambridge journal of economics*,33(4): 563-580.
- Dash, M.K and Kabra, G. (2010). The Determinants of Non-Performing Assets in Indian Commercial Bank: An Econometric Study. *Middle Eastern Finance and Economics*, 7, 94-106.
- Debelle, G. (2004). *Macroeconomic implications of rising household debt*. Working paper (153), BIS Retrieved from http://dx.doi.org/10.2139/ssrn.786385
- De Haas, R., Ferreira, D. and Taci, A. (2010). What determines the composition of banks' loan portfolios? Evidence from transition countries. *Journal of Banking & Finance.*,34(2): 388-398.

- Demyanyk, Y., & Hasan, I. (2010). Financial crises and bank failures: A review of prediction methods. *Omega*,38(5), 315-324.
- Dinh, T. H. T. and Kleimeier, S. (2007). A credit scoring model for Vietnam's retail banking market. *International Review of Financial Analysis*,16(5): 471-495
- Drees, M. B., & Pazarbasioglu, C. (1998). *The Nordic Banking Crisis: Pitfalls in Financial Liberalization: Pitfalls in Financial Liberalization*. International monetary fund.
- Endut, R., Nurul Syuhada, Fathiah Ismail and Wan Mansor W. Mahmood (2013). Macroeconomic Implications on Non-Performing Loans in the Asian Pacific Region. World Applied Sciences Journal 23 (Enhancing Emerging Market Competitiveness in the Global Economy): 57-60,
- Espinoza, R.A. and Prasad, A. (2010). Non-performing loans in the GCC Banking System and their Macroeconomic Effects", *IMF Working Papers* 10/224, 2010.
- Fainstein, G. and Novikov I. (2011). The Comparative Analysis of Credit Risk Determinants In the Banking Sector of the Baltic States. *Review of Economics & Finance*
- Fasianos, A., Raza, H., & Kinsella, S. (2017). Exploring the link between household debt and income inequality: an asymmetric approach. *Applied Economics Letters*, 24(6), 404-409. Retrieved from <u>https://doi.org/10.1080/13504851.2016.1197360</u>
- Felix, A.T. and Claudine, T.N. (2008). *Bank Performance and Credit Risk Management* (Unpublished Masters Dissertation in Finance), University of Skovde
- Filip, B. F. (2014). Non-performing loans-dimension of the non-quality of bank lending/loans and their specific connections. *Theoretical and Applied Economics*, 18(5 (594), 127-146.
- Foglia, A. (2008) *Stress testing credit risk: a survey of authorities' approaches*. Bank of Italy, Working Paper, 37.
- Foos, D., Norden, L. and Weber, M. (2010). Loan growth and riskiness of banks. *Journal* of Banking and Finance. 34(12), 2929-2940

- Fosu, O.A.E. and Magnus, F.J. (2006). Bounds testing approach to cointegration an examination of foreign direct investment, trade and growth relationships. Am. J. Appl. Sci. 3, 2079–2085
- Funso, K, T., Kolade, A, R., and Ojo, O, M. (2012). Credit Risk and Commercial Banks 'Performance in Nigeria: A Panel Model Approach. *Australian Journal of Business and Management Research*, 2(2), 31-38.
- Falk, B. (1986). Further evidence on the asymmetric behaviour of economic time series over the business cycle. *The Journal of Political Economy*, pp.1096-1109
- Garr, D. K. (2013). Determinants of credit risk in the banking industry of Ghana. *Developing Country Studies*,3(11):64-77.
- Goldstein, M and D Xie (2009). *The impact of the financial crisis on emerging Asia*. Federal Reserve Bank of San Francisco. Asia Economic Policy Conference, October 18–20.
- Greenidge, K. and Grosvenor, T. (2010). Forecasting non-performing loans in Barbados. Journal of Business, Occasional Paper 89.
- Grosvenor, T. and Guy, K. (2013). A Regime Switching Approach to Analyzing Bank Non-Performing Loans in Barbados. CBB Working Paper No. WP/13/7.
- Gu, T. (2011). Procyclicality of the Basel II Credit Risk Measurements and the Improvements in Basel III, [Unpublished Master thesis], Aarhus School of Business, Aarhus University.
- Guy, K. and Lowe, S. (2011). Non-performing Loans and Bank Stability in Barbados. *Central Bank of Barbados Economic Review*, Vol.XXXVII, No.1.
- Hà, V.T.N*, Trien, K.L. and Diep, H. (2014). Macro Determinants on Non-performing Loans and Stress Testing of Vietnamese Commercial Banks' Credit Risk, VNU Journal of Science: Economics and Business, Vol. 30, No. 5E (2014),1-16
- Heitfield, E. and Sabarwal, T. (2004). What Drives Default and Prepayment on Subprime Auto Loans? *Journal of Real Estate Finance and Economics*, 29 (2004):457– 477.

- Hansen, A., & Nielsen, K. B. (2016). *Cars, automobility and development in Asia: wheels of change*. Taylor & Francis.
- Hou, Y. and Dickinson, D.(2007). The Non-Performing Loans: Some Bank-level Evidences, Research
- Hussain, M., Shahmoradi, A. and Turk, R. (2016). An overview of Islamic finance. Journal of International Commerce, Economics and Policy,7(01), 1650003
- Idris, I.T. and Nayan, S. (2016). The Joint Effects of Oil Price Volatility and Environmental Risks on Non-performing Loans: Evidence from Panel Data of Organization of the Petroleum Exporting Countries. *International Journal of Energy Economics and Policy*,6(3),522-528.
- IMF (2015). Oil Prices, Financial Stability, and the Use of Countercyclical Macroprudential Policies in the GCC, Annual Meeting of Ministers of Finance and Central Bank Governors
- Isaev, M. and Masih, A. (2017). Macroeconomic and bank-specific determinants of different categories of non-performing financing in Islamic banks: Evidence from Malaysia, University Library of Munich, Germany, Retrieved from https://mpra.ub.uni-muenchen.de/79719/1/MPRA paper 79719.pdf
- Ito, T., & Hashimoto, Y. (2007). Bank Restructuring in Asia: Crisis management in the aftermath of the Asian financial crisis and prospects for crisis prevention-Malaysia. *Trade and Industry*. Retrieved from <u>https://www.rieti.go.jp/jp/publications/dp/07e039.pdf</u>
- Jakubík, P. and Reininger, Th. (2013). Determinants of Non-performing Loans in Central, Eastern and Southeastern Europe, Oesterreichische Nationalbank, *Focus on European Economic Integration*, Q3/13, 48-66
- Janvisloo, M. A. and Muhammad, J. (2013). Non-Performing Loans Sensitivity to Macro Variables: Panel Evidence from Malaysian Commercial Banks. *American Journal of Economics*, 3(5c), 16-21
- Jickling, M. (2009). *Causes of the financial crisis*. Congressional Research Service (Vol. 29).

- Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica*, 59(6), 1551–1580.
- Johansen, S. (1995). *Likelihood-based Inference in Cointegrated Vector Auto-regressive Models*. Oxford University Press, Inc., New York.
- Jordà, Ò., Schularick, M., and & Taylor, A. M. (2016). The great mortgaging: housing finance, crises and business cycles. *Economic policy*,*31*(85), 107-152.
- Jordan, A. and Tucker C. (2013). Assessing the Impact of Non-performing Loans on Economic Growth in The Bahamas. Monetaria
- Kalirai, H. and Scheicher, M. (2002). *Macroeconomic Stress Testing: Preliminary Evidence for Austria*, Financial Stability Report 3 (Vienna: Austrian National Bank). http://www2.oenb.at/english/download/pdf/fsr 3e.pdf
- Kaminsky, G. L., & Reinhart, C. M. (1999). The twin crises: the causes of banking and balance-of-payments problems. *American economic review*, 89(3), 473-500.
- Karim, M. Z. A., Chan, S.G. & Hassan, S. (2010) Bank efficiency and non-performing loans: Evidence from Malaysia and Singapore, *Prague Economic Papers*, 2(2010), 118–3. Retrieved from https://econpapers.repec.org/article/prgjnlpep/v_3a2010_3ay_3a2010_3ai_3a2_ 3aid_3a367_3ap_3a118-132.htm
- Karoglou, M., Mouratidis, K., & Vogiazas, S. (2018). Estimating the Impact of Credit Risk Determinants in two Southeast European Countries: A Non-Linear Structural VAR Approach. *Review of Economic Analysis*, 10, 55-74.
- Katrakilidis, C. and Trachanas, E. (2012). What drives housing price dynamics in Greece: New evidence from asymmetric ARDL cointegration. *Economic Modelling*, 29(4), 1064-1069.
- Khemraj, T and Pasha S. (2009) "The determinants of non-performing loans: an econometric case study of Guyana." Presented at the Caribbean Centre for Banking and Finance Bi-annual Conference on Banking and Finance, St. Augustine, Trinidad.
- Klein, N. (2013). Non-Performing Loans in CESEE: Determinants and Impact on Macroeconomic Performance, IMF Working Paper WP/13/72

- Kokularupan, N (2005). Mortgage-backed securities markets: The experience of Malaysia, Cagamas Berhad, presentation at Asia Pacific Finance, available at https://center4affordablehousing.org/wp-content/uploads/2016/08/Malaysia-Experience-of-MBS-in-Housing.pdf
- Kremers, J. J., Ericsson, N. R. and Dolado, J. J. (1992). The power of cointegration tests. Oxford bulletin of economics and statistics, 54(3), 325-348.
- Kukk, M. (2016). How did household indebtedness hamper consumption during the recession? Evidence from microdata. *Journal of Comparative Economics*,44(3):764-786.
- Laurenceson, J and Chai, J. (2003). Financial Reform and Economic Development in China. Cheltenham, UK, Edward Elgar
- Lim, A (2012, February 28). Guideline on responsible financing: BNM and the automotive industry hold dialogue over the low loan approval rate issue. *Paultan.org.* Retrieved from http://paultan.org/2012/02/26/guideline-onresponsible-financing-bnm-and-automotive-industry-hold-dialogue-over-lowloan-approval-rate-issue/
- Loh, C. Y., Chai, Y. S., Chong, S. Y., Lee, B. S., and Tan, S. Y. (2015). Macroeconomic variables on banks' non-performing loans in Malaysia. (Undergraduate research project), UTAR
- Lokare S (2014). Re-emerging Stress in the Asset Quality of Indian Banks: Macro-Financial Linkages. Reserve Bank of India Working Paper 03/2014
- Lombardi, M. J., Mohanty, M. S., and Shim, I. (2017). The real effects of household debt in the short and long run. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2906555
- Louzis, D. P., Vouldis, A. T., and Metaxas, V. L. (2012). Macroeconomic and bankspecific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. Journal of Banking and Finance, 36(4), 1012-1027.

Macdonald, S.S and Timothy W. (2006). Management of Banking; 6th edition.

- Madeira, C. (2018). Explaining the cyclical volatility of consumer debt risk using a heterogeneous agents model: The case of Chile. *Journal of Financial Stability*, 39, 209-220.
- Madeira, C. (2019). The impact of interest rate ceilings on households' credit access: evidence from a 2013 Chilean legislation. *Journal of Banking and Finance*, 106, pp.166-179
- Makri, V., Tsaganos, A. & Bellas, A. (2014). Determinants of Non- Performing Loans: The Case of Eurozone. Panoeconomicus, 61 (2), 193-206
- MDI (2019). Bankruptcy Statistics December 2019, available at http://www.mdi.gov.my/index.php/about-us/resources/statistics/bankruptcy (accessed 7 May 2020)
- Meng, C. (2014). Consumer Loans in Cambodia: Implications on Banking Stability. University Library of Munich, Germany, available at https://mpra.ub.unimuenchen.de/54131/1/MPRA_paper_54131.pdf (accessed 25 June 2018)
- Messai, A.S. and Jouini, F. (2013). Micro and Macro Determinants of Non-performing Loan. International Journal of Economics and Financial Issues, 3(4): 852 - 860
- Mian, A. and Sufi, A. (2011). House prices, home equity-based borrowing, and the US household leverage crisis, *American Economic Review*,101(5): 2132-56.
- Mian, A., Sufi, A. and Verner, E. (2017). Household debt and business cycles worldwide. *The Quarterly Journal of Economics*, 132(4), 1755-1817.
- Mihai, I., Popa, R. and Banu, E. (2018). *The probability of default for private individuals using microeconomic data. What is the role played by macroprudential measures*?, In proceedings, 2nd Annual Workshop of ESCB Research Cluster 3, Bank of Greece and the European Central Bank: Financial stability, macroprudential regulation and micro-prudential supervision, available at https://www.ecb.europa.eu/pub/conferences/shared/pdf/20180906_2nd_annual_ ws/Mihai_Popa_Banu_paper.pdf (accessed 10 Apr 2020)
- Minsky, H. P. (1992). *The financial instability hypothesis*, The Jerome Levy Economics Institute, available at http://dx.doi.org/10.2139/ssrn.161024

- Miyajima, K. (2016). An empirical investigation of oil-macro-financial linkages in Saudi Arabia. IMF Working Paper No. 16/22, Retrieved from https://ssrn.com/abstract=2754926
- Moinescu, B. G. (2012). Determinants of nonperforming loans in Central and Eastern European Countries: Macroeconomic indicators and credit discipline. *Review of Economic and Business Studies*, (10), 47-58.
- Nakornthab, D. (2010). *Household Indebtedness and Its Implications for Financial Stability*, South-East Asian Central Banks, Research and Training Centre.
- Neftci, S.N. (1984). Are economic time series asymmetric over the business cycle?. *The Journal of Political Economy*, pp.307-328.
- Nkoro, E., & Uko, A. K. (2016). Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation. *Journal of Statistical and Econometric Methods*, 5(4), 63-91.
- Nkusu, M. (2011). Non-performing Loans and Macro financial Vulnerabilities in Advanced Economies. IMF Working Paper 11/161.
- Novikov, I. (2011) The Empirical Estimation of the Influence of Credit Risk Determinants in the Baltic States' Banking Sector. *Journal of Modern Accounting and Auditing*, January 2012, 8(1): 113-127
- Norden, L., & Stoian, A. (2014). Bank earnings management through loan loss provisions: a double-edged sword?.
- Pesaran, M. and Shin, Y. (1999). An Autoregressive Distributed Lag Modeling Approach to Cointegration Analysis. In S. Strom, (ed) Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium, Cambridge University Press, Cambridge.
- Pesaran, M.H. and Pesaran, B. (1997). Working with Microfit 4.0: Interactive Econometric Analysis, United Kingdom: Oxford University Press.
- Pesaran, M.H., Shin, Y. and Smith, R.J. (2001). Bounds Testing Approaches to the Analysis of Level Relationships. *Journal of Applied Econometrics*, 16(3), 289-326

- Pinho, C., Madaleno, M. (2009), "Time-Frequency Effects on Market Indices: World Comovements. "Paper presented at Paris December 2009 Finance International Meeting AFFI - EUROFIDAI.
- Podder J and Al-Mamun A (2004). Loan loss provisioning system in Bangladesh Banking—A critical analysis. *Journal of Managerial Auditing*, 19(6). 729-740.
- Poghosyan, T. and Hesse, H. (2009). Oil prices and bank profitability: Evidence from major oil-exporting countries in the Middle East and North Africa. *IMF Working Papers*, 09(WP/09/220), 1-22
- Pool, S., De Haan, L., & Jacobs, J. P. (2015). Loan loss provisioning, bank credit and the real economy. *Journal of Macroeconomics*, 45, 124-136.
- Quagliariello, M. (2007). Banks' Riskiness over the Business Cycle: A Panel Analysis on Italian Intermediaries, *Applied Financial Economics*. 17(2), 119-138
- Quagliariello, M (2004). Banks' Performance over the Business Cycle: A Panel Analysis on Italian Intermediaries, University of York, Department of Economics Discussion Papers 04/17
- Rajaraman, I.and Vasishtha, G. (2002). Non-performing loans of PSU banks: Some panel results. *Economic and Political Weekly*, 429-435.
- Reinhart, C. M., and Rogoff, K. S. (2010). Growth in a Time of Debt. *American economic* review, 100(2): 573-78.
- Rinaldi, L., & Sanchis-Arellano, A. (2006). Household debt sustainability: what explains household non-performing loans? An empirical analysis. Retrieved from https://www.econstor.eu/bitstream/10419/153004/1/ecbwp0570.pdf
- Salas, V. and Saurina, J. (2002). Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of Financial Services Research*,2(3): 203-224
- Sassi, S. and Gasmi, A. (2014). The effect of enterprise and household credit on economic growth: New evidence from European Union countries. *Journal of Macroeconomics*, 39:226-231.

- Samuelson, P A. & Nordhaus, WD. (2001). *Economics* (17th Edition). Boston: McGraw-Hill Irwin.
- Senawi and Mat Isa (2014). Gold Price as a Determinant of Non-Performing Loans: An Analysis of Malaysia. Global Business and Management Research: An International Journal Vol. 6, No. 4
- Shamsudheen, SV. and Mansur, M. (2015). Does the conventional benchmark prop up non-performing loans in Islamic banks? A case study of Malaysia with the ARDL Approach. In: MPRA Paper RePEc.
- Shrestha, M.B. and Chowdhury, K. (2005). ARDL Modelling Approach to Testing the Financial Liberalization Hypothesis. Economics Working Paper Series 2005, University of Wollongong.
- Siti, B., Borhan, H., Ling, L. S., Khairul, M., & Abd, M. (2018). Indebted to Debt: An Assessment of Debt Levels and Financial Buffers of Households.
- Skarica, B. (2013). Determinants of Non-Performing Loans In Central And Eastern European Countries. *Financial Theory and Practice*, 38 (1) 37-59.
- Sutherland, D., & Hoeller, P. (2012). Debt and macroeconomic stability: An overview of the literature and some empirics. *OECD Economics Department Working Papers*, 1006 (2012).
- Tan, T. H. (2009). Home owning motivation in Malaysia. University Library of Munich,
Germany.Retrievedfrom<u>https://mpra.ub.uni-</u>
muenchen.de/34906/1/Homeowning.pdf
- Tan, Y., & Floros, C. (2012). Bank Profitability and Inflation: The Case of China. *Journal* of Economic Studies, 39(6), 675-696.
- Tee, L.S (2016, Apr 02). Household debt on the rise. *The Star online*. Retrieved from https://www.thestar.com.my/business/business-news/2016/04/02/household-debt-on-the-rise/
- The Edge (2011, November 18). Bank Negara's measures to promote responsible financing practices, Retrieved from https://www.theedgemarkets.com/article/bank-negaras-measures-promote-responsible-financing-practices

- The Malay Mail Online (2015). Malaysia's soaring household debt feared as 'unsustainable', may trigger the crisis. Retrieved from <u>http://www.themalaymailonline.com/malaysia/article/malaysias-soaring-</u> household-debt-feared-unsustainable-may-trigger-crisis#sthash.JQPCiSdR.dpuf
- The Sun daily (2016, April 20). The majority of bankruptcy cases in the country are caused by vehicle purchases. Retrieved from https://www.thesundaily.my/archive/1773050-ESARCH362277
- T'ng, BH (2013). External Risks and Macro-Financial Linkages in the ASEAN-5 Economies, Bank Negara Malaysia Working Papers WP1/2013, December
- Villafuerte, M. & López-Murphy, P. (2010). Fiscal Policy in Oil-Producing Countries during the Recent Oil Price Cycle. IMF Working Paper 10/28.
- Vogiazas, S. D. and E. Nikolaidou (2011). Credit risk determinants in the Bulgarian banking system and the Greek twin crises. MIBES, South-East European Research Centre: 177-189.
- Vogiazas, S.D. (2015). Determinants of credit risk in the Bulgarian and the Romanian banking systems and the role of the Greek crisis (Doctoral dissertation). Retrieved from <u>http://etheses.whiterose.ac.uk/id/eprint/8394</u>
- Waweru, N.M. and Kalani, V. M. (2009). Commercial banking crises in Kenya: causes and remedies. *African Journal of Accounting, Economics, Finance and banking research*, 4(4): 12-32.

Westpac Institutional Bank (2016). https://www.westpac.co.nz/assets/Business/Economic-Updates/2016/Bulletins-2016/Household-debt-levels-now-higher-than-before-the-financial-crisis-April-2016.pdf

World Bank. (2000). *Making the transition work for everyone: poverty and inequality in Europe and Central Asia.* The World Bank.