INVESTIGATING THE EFFECTS OF FINANCIAL INNOVATIONS ON THE DEMAND FOR MONEY IN MALAYSIA USING THE ARDL APPOACH TO COINTERGRATION

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Abstract

Money demand function plays a vital role in monetary policy formulation. Over the years, several countries have experienced growth in financial innovation which has implications for monetary policy. This paper estimates the relationship between financial innovation and money demand in Malaysia with a focus on payment instruments (PI), payment systems (PS) and payment channels (PC) using the ARDL approach to cointegration between 2008 Q1 to 2015 Q4. This paper adopts the bounds testing procedure developed by Pesaran et al. (2001) to test the stability of the long-run money demand and determine the short-run dynamics for Malaysia. The empirical evidence points to the fact that while innovation in the Malaysian financial system have not ruled out the existence of stable long run money demand relationships as attested to by QUSUM Test, they (except for PS) fail to pass the Bound Test meaning that there is no evidence for a long-run association between variables. Therefore, for PI and PC, we cannot proceed to the next step. For PS, the estimated coefficient for the error correction term is not significant which means that there is no adjustment towards long-run equilibrium. In other words, disequilibrium between money demand and independent variables is not corrected over time and it actually diverges rather than converge.

Keywords: Money demand, Financial innovations, Stability, ARDL, Cointegration
JEL classification: C13, C40, C51, E40, E44

1. Introduction

The demand for money function creates a platform to investigate the effectiveness of monetary policies which is crucial for macroeconomic stability. Money demand is an essential indicator of economic growth. The increasing money demand is an indication of growth of the economy, whereas decreasing money demand indicates that the economy is deteriorating. It is important to assume that money demand function is stable for the purpose of conducting monetary policy. This is a crucial assumption as money demand function is used to get inflation rate under control (Owoye and Onafowora, 2007). As discussed above, stable relationship between money and its determinants is a requirement for implementing monetary policy including monitoring and targeting of monetary aggregates. If this is the case (existing a steady and state relationship between money demand and its determinants), the central bank will be able to use monetary policy to affect important macroeconomic variables successfully (Baharumshah, et al. 2009).

In light of the recent growth in financial innovation spanning over the last few decades, there are mixed results with regards to the stability of money demand. Therefore, it has become increasingly important to study the stability of money demand as financial innovation can have potential impact on the demand for money through over estimation of the money demand. Prior to the mid-1970s (before introducing financial innovations) when most empirical results showed a stable money demand, a few variables such as the interest rate and output were sufficient to achieve a stable money demand (Goldfeld and Sichel,1990). With the introduction of the financial innovation, several studies such as Arrau and De Gregorio (1993), Ireland (1995), Attanasio et al (2002), Alvarez and Lippi (2009), Nagayasu (2012), Arrau et al (1995), Mannah-Blankson and Belyne (2004), Hafer and Kutan (2003) and Hye (2009) have attempted to analyze money demand with inclusion of financial innovation.

It is often difficult to measure financial innovation and there are many definitions that capture this definition in the literature. Financial innovations have emerged over time as individuals moved away from holding cash to assets and the use of ATMS, Debit cards, Internet banking, mobile banking, ect. There is still a limited amount of studies that have analyzed the relationship between financial innovation and money demand. Examples of these few studies are those for M. Azali and Kent Mathhews (2001) who model the effect of financial innovation on demand in Malaysia using error correction model and Eu Chye Tan (1997) who conclude that liberalization and innovation in the Malaysian financial system that have not ruled out the existence of stable long run money demand relationships as attested to by the presence of cointegrating vectors, but they render short run relationships unstable.

While most research has yielded great insight to the money demand literature, a vital question that is worth investigating is if the demand for money is still stable given the recent financial innovation developments in Malaysia. Given the limited number of studies on money demand in Malaysia, this paper contributes to the relevant literature by estimating the Malaysian money demand including financial innovation proxies in three different systems: payment instrument (credit card, charge card, debit card, e-money), payment system (RENTAS, Interbank GIRO, FPX and Debit Card) and payment channel (ATM, Mobile Banking, Internet Banking). This study hopes to shed some light on the relationship between these new innovations and money demand one by one. Also, this study is likely to inform policy makers and guide their decision making particularly in terms of monetary policy. The rest of the paper is structured as follows. A review of the theoretical and empirical literature is given in Section 2 followed by methodology including a brief overview of the conventional demand for money and econometric approach in Section 3. Then, Section 4 describes the situation of financial innovation in Malaysia. Section 5 presents the data, the model specification and the results of the estimation and it ends up with summary in section 6.

2. Literature review

There are numerous studies that have examined the stability of money demand particularly in developing countries. The results depend on the data frequency, stability test methods, and the development stage of a country. Some of the studies that used ARDL cointegrating technique for investigating the long run relationship between money demand and its determinants as follow.

Halicioglu and Ugur (2005) examined the stability of the narrow M1 (money demand function) in Turkey. In doing so, they used annual data from 1950 to 2002. They conducted stability test of M1 for Turkish by applying a cointegration procedure (along with CUSUM and CUSUMSQ stability tests) that was proposed by Pesaran et al. (2001). They proved that money demand function was stable and therefore, it could be used as an intermediate target of monetary policy. Using quarterly data for the period 1973-2000, Bahmani & Oskooee and Rehman (2005) estimate money demand for seven Asian countries including India, Indonesia, Malaysia, Pakistan, Philippines, Singapore and Thailand. They used ARDL approach and CUSUM and CUSUMSQ tests. The results indicated that even though real M1 or M2 are cointegrated with their determinants in some Asian countries, the estimated parameters are unstable.

Akinlo (2006) used quarterly data (1970:1–2002:4). They applied ARDL approach along with CUSUM and CUSUMSQ tests, to investigate if money demand (M2) for Nigeria is cointegrated and stable. The results indicated that M2 was cointegrated with income, interest rate and exchange rate and it was somewhat stable using CUSUM test. Using monthly data over the period 1994:12-2006:12, Samreth (2008) estimated the money demand function for Cambodia. They applied ARDL approach to analyse cointegration property. They showed that there was a cointegrating relationship between M1, Industrial Production Index, Consumer Price Index, and Nominal Exchange Rate in money demand function. A stable money demand function was confirmed using CUSUM and CUSUMSQ tests. Using ARDL approach, Long and Samreth (2008) examined if short and long run monetary models of exchange rate is valid for monetary exchange rate model of the Philippines. The results confirmed that there was both short and long run relationships between variables in the monetary exchange rate model of the Philippines. They also showed that the estimated parameters were stable.

Baharumshah, et al. (2009) studied M2 (the demand for broad money) in China. They applied ARDL approach to cointegration and used quarterly data over the period 1990:4 &2007:2. Bounds test indicated that there was a stable, long-run relationship between M2 and real income, inflation, foreign interest rates and stock prices. Using quarterly data during1990:1-2008:3, Achsani (2010) applied the vector error correction model (VECM) and autoregressive distributed lag (ARDL) approach to examine the M2 money demand for Indonesia. He showed that for the purpose of predicting stable money demand function of Indonesia, the ARDL model is more appropriate compared to VECM. Finally, using monthly data from 1991 to 1998, Claudia Bush (2001) investigated the determinants and the stability of money demand functions in Hungary and Poland by applying an error correction model. The findings indicated that long-run parameters were in line with economic theory. However, on the basis of these findings alone would be premature. She concluded that money demand functions could serve as a useful appropriateness of different strategies for mapping the monetary policy of the surveyed countries.

However, most of these studies failed to account for financial innovation in the money demand specification except for Ndirangu and Nyamongo (2015) who employed the ARDL approach to cointegration for Kenya and used the currency outside banks/time deposit ratio as a proxy for financial development. The current study overcomes this limitation by incorporating financial innovation in the money demand specification using separate measures of payment instruments (credit card, charge card, debit card, e-money), payment channels (RENTAS, Interbank GIRO, FPX and direct debit) and payment channels (ATM, mobile banking, Internet banking) to capture the effect of financial innovations. Prior to the empirical analysis, it is useful to know the main features of the conventional demand for money function that is done in the next section.

The purpose of this paper can be summarized as follow. 1) To examine the empirical relationship between M2 nominal monetary aggregates, nominal income, nominal interest rate and financial innovation using ARDL cointegration model. 2) To determine the stability of M2 money demand function. 3) To examine the long-run stability of the nominal money demand function.

3. Methodology

3.1. Theoretical approach: conventional demand for money function

We start the empirical estimation of money demand functions with introducing the long-run, log linear function that is of the form

$$\text{Log}\left(\frac{M_t^*}{P_t}\right) = \alpha + \beta_1 \log Y_t + \beta_2 R_t + \varepsilon_t$$

Desired stock of nominal money is denoted by M^*, P is the price index that we use to convert nominal balances to real balances, Y is the scale variable, and R is the opportunity cost variable.

The conventional money demand $M^d = (Y_t, R_t)$ is misspecified and leads to the bias that gets into the estimated coefficients. Therefore, it has to be enriched with financial innovation (r*) so that it can be represented implicitly as $M^d = (Y_t, R_t, r^*)$.

3.2. Econometric approach: autoregressive distributed lag (ARDL) models

3.2.1. Definitions

ARDL model was introduced by Pesaran et al. (2001) in order to incorporate I(0) and I(1) variables in same estimation. If the variables are all stationary I(0) then OLS is suitable and if they are all non-stationary I(1) then VECM (Johanson Approach) is recommended. Conventional OLS is not appropriate if at least one variable is I(1). As non-stationary variables change in time so OLS estimates show high t values by mistake as they become inflated due to common time component. In econometric it is called spurious results where R square of the model becomes higher than the Durban Watson Statistic. ARDL is considered a solution to this problem that can handle I(1) variables. Using ARDL model, this section addresses the key question of whether long-run money demand of Malaysia can be influenced by the impact of financial innovation and what are the possible explanations for such strong impacts of financial innovation on the demand for money in this country from 2008 Q1-2015 Q2. Eviews offers powerful time-saving tools for estimating and examining the properties of Autoregressive Distributed Lag (ARDL) models. ARDLs are standard least squares regressions that contain lags of both the dependent variable and independent variables as regressors (Greene, 2008).

ARDL models have become popular method in econometrics as it is able to examine long-run and cointegrating relationships among variables (Pesaran and Shin, 1999). In this section we chose the Autoregressive Distributed Lag (ARDL) modelling approach developed by Pesaran and Pesaran (1997), Pesaran and Smith (1998), and Pesaran et al. (2001). The ARDL has become popular due to a number of advantages compared to other single equation cointegration procedures. It is able to estimate the long and short-run parameters of the model simultaneously yet avoid the problems posed by non-stationary data. Also, there is no need to determine the order of the integration amongst the variables in advance. Other approaches, however, do require that the variables have the same order of integration. In addition, it is statistically much more significant approach for the determination of the cointegration relationship in small samples, while allowing different optimal lags of variables. We show that some proxies for financial innovation do have a positive long run impact on money demand in this sample while others don't. There has been no general consensus over the last several decades about the link between financial innovation and money demand. There is no way to say for sure if this relationship is positive or negative. Recent empirical studies offer contradictory evidence. As a result, the current verdict on the financial innovation-money demand relationship has remained inconclusive.

3.2.2. Background

Specification: An ARDL is a least squares regression containing lags of the dependent and explanatory variables. ARDLs are usually denoted with the notation ARDL ($p, q_1, \dots, q_k$), where p is the number of lags of the dependent variable, q_1 is the number of lags of the first explanatory variable, and q_k is the number of lags of the kth explanatory variable. An ARDL model may be written as:

$$y_t = \alpha + \sum_{i=1}^{p} \gamma_i y_{t-i} + \sum_{j=1}^{k} \sum_{i=0}^{q_j} X'_{j,t-i} \beta_{j,i} + \epsilon_i$$

Some of the explanatory variables, x_j , may have no lagged terms in the model (q_j=0). These variables are called static or fixed regressors. Explanatory variables with at least one lagged term are called dynamic regressors.

To specify an ARDL model, you must determine how many lags of each variable should be included (i.e. specify p and $q_1, \dots, q_k$). Fortunately simple model selection procedures are available for determining these lag lengths. Since an ARDL model can be estimated via least squares regression, standard Akaike, Schwarz and Hannan-Quinn information criteria may be used for model selection. Alternatively, one could employ the adjusted R^2 from the various least squares regressions.

4. Financial innovations in Malaysia

4.1. Innovations in payment systems in Malaysia

4.1.1. Migration from paper to electronic payments

Migrating from paper-based payments to electronic payments would improve the overall efficiency of the payment system, and provide meaningful cost savings and efficiency to the entire economy. By driving the displacement of cash and cheques through more intensive use of electronic payments, resources involved in manual processing can be redeployed and cost related to cash and cheque handling can be considerably reduced. Electronic payment, which is a more expedient and efficient means of payment, provide the opportunity to improve productivity levels and lower the cost of doing business. Studies have shown that shifting from paper based to a more electronic based payment system can generate an annual savings up to 1% of GDP. Moreover, electronic payments can also enhance financial inclusion by extending financial services to the unbanked communities. In so doing, such communities would be brought into the formal financial system and into the economic mainstream. This would enable them to enjoy lower cost of financial services and better means of savings. The shift to electronic payments is an area in which the quantum leap forward can be made and is essential to the quest to achieve higher economic growth and improve the competitiveness of the economy.

4.1.2. Driving towards electronic payments

Accelerating the country's migration to electronic payments (e-payments) to quicken the pace for the country to realise the resulting cost savings and benefits has become a part of the Bank's agenda to increase the efficiency of the nation's payment systems. To underscore the importance of e-payments and to drive this agenda forward, the Bank has released its Financial Sector Blueprint 2011-2020, which charts the future direction of the financial system over the next ten years. Electronic payment for greater economic efficiency is one of the nine focus areas under the Blueprint to drive Malaysia's transition to a high value-added, high-income economy with adequate safeguards to preserve financial stability. The Bank will work towards accelerating the migration to electronic payments. In the next ten years, the Bank targets to increase the number of e-payment transactions per capita from 44 transactions to 200 transactions, and reduce cheques by more than half from 207 million to 100 million per year. Measures to achieve this aim will include providing the right price signals to encourage the switch from paper-based payments to e-payments, and facilitating wider outreach of e-payments infrastructure, such as point-of-sale terminals and mobile phone banking.

Table 1: Key Performance Indicators

Target by 2020	
E-payment transactions per capita	200
Debit card transactions per capita	30
No. of EFTPOS terminals per 1,000 inhabitant	25
Number of cheques cleared	100 million

Source: Bank Negara Malaysia

4.1.3. Electronic payments on the rise (initiatives and achievements)

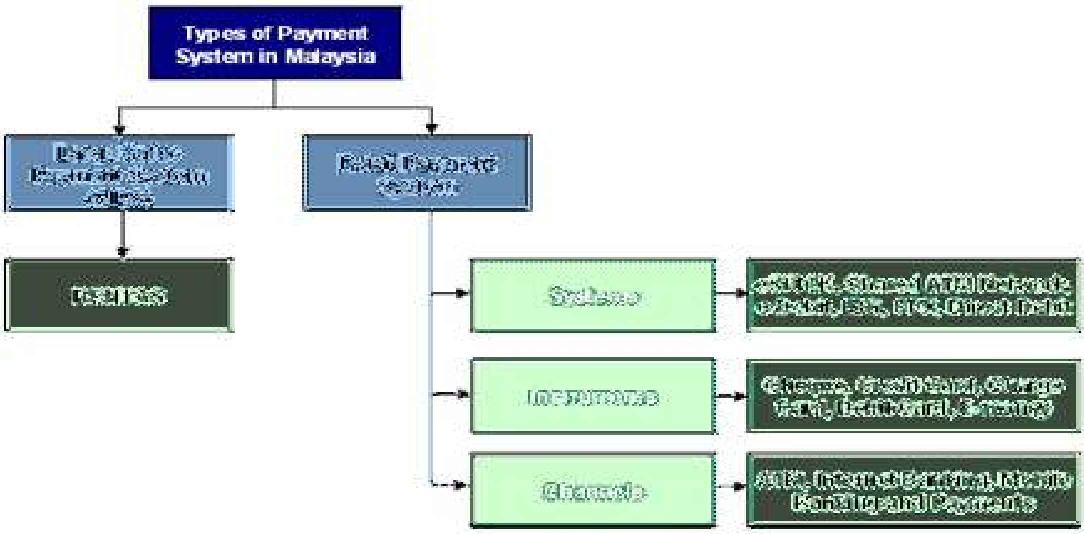
Through the collaboration between the Bank and the payments industry, efforts were made to improve and widen the access to the payments infrastructure, identify and remove barriers to greater adoption of electronic payments, and provide the necessary support to ensure the smooth transition to electronic payments. Whilst steps were taken to increase the offering and acceptance of all electronic payment services, particular focus was given in recent years to improving the infrastructure to promote greater use of Internet banking services, positioning the debit card as a convenient substitute for cash and as a more cost efficient payment instrument, as well as facilitating the Government to play a lead role in the migration to electronic payments. These efforts have resulted in many payments which were traditionally made by cash and cheques, being made electronically with plastic cards or through electronic channels. This is demonstrated by the increase in the number of electronic payment transactions made per capita to 56 transactions in 2012 as compared to 14.3 in 2003, and that more than 80% of retail payment transactions are conducted electronically. While the transition to electronic payments will be gradual and may span several years, efforts would be intensified to encourage the public to use electronic payment methods, with more initiatives to be undertaken in the years to come in tandem with advancements in technology.

4.2. Malaysian payment systems

4.2.1. Large value payment system

Payment systems are a vital part of the financial infrastructure of a country. In Malaysia, the large value payment system, RENTAS (Real Time Electronics Transfer of Funds and Securities), which is operated by the Malaysian Electronic Clearing Corporation Sdn. Bhd. (MyClear), a payment subsidiary owned by Bank Negara Malaysia, enables the transfer and settlement of high-value interbank payments and securities. Its failure could contribute to systemic crisis and transmit financial shocks to the financial system. The efficient functioning of RENTAS allows transactions to be completed safely and in a timely manner contributing to overall economic performance. Safe and efficient payment systems are fundamental to promote financial stability, facilitating Bank Negara Malaysia in the conduct of its monetary policy by allowing greater use of market-based instruments to achieve its objectives, while enhancing the efficiency of the financial system and the economy as a whole. Given its importance, the promotion of a secure, safe and efficient payment system is one the main pillars of the Bank.

Figure 1: Payment Systems in Malaysia



Source: Bank Negara Malaysia

4.2.2. Types of retail payment system

In general, the retail payments in Malaysia can be divided into three - Retail Payment Systems, Retail Payment Instruments and Retail Payment Channels. Types of retail payment systems includes: 1) National Electronic Cheque Information Clearing System (eSPICK), 2) Shared ATM Network, Interbank GIRO, 3) Financial Process Exchange, and 4). Types of retail payment instruments includes: 1) Cheques, 2) Credit cards, 3)Charge cards, 4) Debit cards, and 5) E-money. Types of retail payment channels includes: 1) Internet banking, 2) Mobile banking, 3) Mobile payment. InterBank GIRO: The Interbank GIRO (IBG) refers to a payment system that provides funds transfer services amongst its participating financial institutions. Direct Debit: Direct debit, which is operated by MyClear Sdn Bhd, is an interbank collection service for regular and recurring payments enabling automated collection directly from a customer's bank account at multiple banks with a single authorization. Financial Process Exchange: Financial Process Exchange (FPX) is an Internet-based multi-bank payment platform that leverages on the Internet banking services of banking institutions to offer online payment for electronic commerce (e-commerce) transactions.

4.2.3. Types of retail payment instruments

Cheques: A cheque is a paper based payment instrument. It is a form of written order directing a bank to pay money to the beneficiary. Credit Cards: A credit card enables its holder to buy goods and services with a credit line given by credit card issuer and the amount will be settled at a later date. Charge Cards: The functionality of a charge card is similar to a credit card. However, charge card holders must settle their outstanding amount in full by the due date every month. Debit Cards: A debit card is a payment card where the transaction amount is deducted directly from the cardholder's bank account upon authorisation. E-money: E-money is a payment instrument that contains monetary value that has been paid in advance by the user. E-money users can use their e-money to purchase goods and services from merchants. When users pay using e-money, the amount will be automatically deducted from their e-money balance. E-money comes in different forms and can be broadly categorised as card-based and network-based, which are currently accessible via the internet and mobile phones.

4.2.4. Types of retail payment channels

Internet Banking: Internet banking provides a fast and convenient way of performing common banking transactions, such as transferring funds from the customers' saving account to their current account, or even to a third party's account. If you have a computer with Internet access, a web browser and a registered account for Internet banking service from your banking institution, you'll be able to do your banking and payments from the comforts of your home, office, or virtually anywhere else in the world.

Mobile Banking: Mobile banking is similar to Internet banking in that it provides a fast and convenient way of performing common banking transactions. To enjoy the benefits of mobile banking, all you need is a mobile phone that is equipped with the features required by your bank that provides this service. Once you obtained a registered account for mobile banking from your banking institution, you'll be able to do your banking transactions from anywhere that has your mobile telecommunication network coverage.

Mobile Payment: Mobile payment allows you to make payments to selected merchants by using your mobile phones. Bill payments and purchase of goods and services are among the cashless transactions that can be made. To enjoy the benefits of mobile payments, you have to register and open an account with mobile payment service providers. Non-bank mobile payment services are provided using an e-money account (Bank Negara Malaysia).

5. Estimating nominal money demand for FPX and direct debit using ARDL

"ARDL" stands for "Autoregressive-Distributed Lag". Regression models of this type have been in use for decades, but in more recent times they have been shown to provide a very valuable vehicle for testing the presence of long-run relationships between economic time-series. ARDL models can be used to test for cointegration, and estimate long-run and short-run dynamics, even when the variables in question may include a mixture of stationary and non-stationary time-series. In its basic form, an ARDL regression model looks like this:

$$y_t = \beta_0 + \beta_1 y_{t-1} + ... + \beta_p y_{t-p} + \alpha_0 x_t + \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + ... + \alpha_q x_{t-q} + \varepsilon_t$$

where ε_t is a random "disturbance" term. The model is "autoregressive", in the sense that y_t is "explained (in part) by lagged values of itself. It also has a "distributed lag" component, in the form of successive lags of the "x" explanatory variable. Sometimes, the current value of x_t itself is excluded from the distributed lag part of the model's structure. Let's describe the model above as being one that is ARDL(p,q), for obvious reasons. Given the presence of lagged values of the dependent variable as regressors, OLS estimation of an ARDL model will yield biased coefficient estimates. If the disturbance term, ε_t, is autocorrelated, the OLS will also be an inconsistent estimator, and in this case Instrumental Variables estimation was generally used in applications of this model. First, recall that the basic form of an ARDL regression model is:

$$y_t = \beta_0 + \beta_1 y_{t-1} + ... + \beta_p y_{t-p} + \alpha_0 x_t + \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + ... + \alpha_q x_{t-q} + \varepsilon_t \quad (1)$$

where ε_t is a random "disturbance" term, which we'll assume is "well-behaved" in the usual sense. In particular, it will be serially independent.

We're going to modify this model somewhat for our purposes here. Specifically, we'll work with a mixture of differences and levels of the data. The reasons for this will become apparent as we go along. Let's suppose that we have a set of time-series variables, and we want to model the relationship between them, taking into account any unit roots and/or cointegration associated with the data. First, note that there are three straightforward situations that we're going to put to one side, because they can be dealt with in standard ways: 1) We know that all of the series are I(0), and hence stationary. In this case, we can simply model the data in their levels, using OLS estimation, for example. 2) We know that all of the series are integrated of the same order (e.g., I(1)), but they are not cointegrated. In this case, we can just (appropriately) difference each series, and estimate a standard regression model using OLS. 3) We know that all of the series are integrated of the same order, and they are cointegrated. In this case, we can estimate two types of models: (i) An OLS regression model using the levels of the data. This will provide the long-run equilibrating relationship between the variables. (ii) An error-correction model (ECM), estimated by OLS. This model will represent the short-run dynamics of the relationship between the variables. 4) Now, let's return to the more complicated situation mentioned above. Some of the variables in question may be stationary, some may be I(1) or even fractionally integrated, and there is also the possibility of cointegration among some of the I(1) variables. In other words, things just aren't as "clear cut" as in the three situations noted above.

Therefore, if we want to model the data appropriately and extract both long-run and short-run relationships, we have to use the ARDL model. The ARDL / Bounds Testing methodology of Pesaran and Shin (1999) and Pesaran et al. (2001) has a number of features that many researchers feel give it some advantages over conventional cointegration testing. For instance: 1) It can be used with a mixture of I(0) and I(1) data. 2) It involves just a single-equation set-up, making it simple to implement and interpret. 3) Different variables can be assigned different lag-lengths as they enter the model.

Here are the basic steps that we're going to follow: doing unit root test to make sure none of the variables are I(2), formulating a model with lagged difference and one lagged level of the variables, finding the optimum lag using AIC/SC critarion and estimating the model using this optimum lag, making sure that the errors of this model are serially uncorrelated, making sure that the model is dynamically stable, performing Bound Test to see if there is evidence of a long-run relationship between variables, estimating the long-run model and obtaining the error correction term if the outcome of the previous step is positive, estimating lagged model using this error correction term. In other words, estimate the long-run equilibrium relationship between the variables, making sure that the errors of this model are serially uncorrelated and that the model is dynamically stable, using the results of the model estimated in previous step to measure short-run dynamics effects (testing the causality running from independent variable to dependent variable one by one) and estimating the long-run equilibrating relationship between the variables (or simply long-run coefficients).

We can see from the form of the generic ARDL model given in equation (1) above, that such models are characterised by having lags of the dependent variable, as well as lags (and perhaps the current value) of other variables, as the regressors. Let's suppose that there are three variables that we're interested in modelling: a dependent variable, y, and two other explanatory variables, x_1 and x_2. More generally, there will be (k + 1) variables - a dependent variable, and k other variables. Before we start, let's recall what a conventional ECM for cointegrated data looks like. It would be of the form:

$$\Delta y_t = \beta_0 + \Sigma\beta_i\Delta y_{t-i} + \Sigma\gamma_1\Delta x_{1t-j} + \Sigma\delta_k\Delta x_{2t-k} + \varphi z_{t-1} + e_t \qquad (2)$$

Here, z, the "error-correction term", is the OLS residuals series from the long-run "cointegrating regression",

$$y_t = \alpha_0 + \alpha_1 x_{1t} + \alpha_2 x_{2t} + v_t \qquad (3)$$

The ranges of summation in (2) are from 1 to p, 0 to q_1, and 0 to q_2 respectively. Now, back to our own analysis:

Step 1: We can use the ADF test to check that none of the series we're working with are I(2).
Step 2: Formulate the following model:

$$\Delta y_t = \beta_0 + \Sigma\beta_i\Delta y_{t-i} + \Sigma\gamma_1\Delta x_{1t-j} + \Sigma\delta_k\Delta x_{2t-k} + \theta_0 y_{t-1} + \theta_1 x_{1t-1} + \theta_2 x_{2t-1} + e_t \quad (4)$$

Notice that this is almost like a traditional ECM. The difference is that we've now replaced the error-correction term, z_{t-1} with the terms y_{t-1}, x_{1t-1}, and x_{2t-1}. From (3), we can see that the lagged residuals series would be $z_{t-1} = (y_{t-1} - \alpha_0 - \alpha_1 x_{1t-1} - \alpha_2 x_{2t-1})$, where the α's are the OLS estimates of the α's. So, what we're doing in equation (4) is including the same lagged levels as we do in a regular ECM, but we're not restricting their coefficients. This is why we might call equation (4) an "unrestricted ECM", or an "unconstrained ECM". Pesaran et al. (2001) call this a "conditional ECM". Step 3: The ranges of summation in the various terms in (4) are from 1 to p, 0 to q1, and 0 to q2 respectively. We need to select the appropriate values for the maximum lags, p, q1, and q2. Also, note that the "zero lags" on Δx_1 and Δx_2 may not necessarily be needed. Usually, these maximum lags are determined by using one or more of the "information criteria" - AIC, SC (BIC), HQ, etc. These criteria are based on a high log-likelihood value, with a "penalty" for including more lags to achieve this. The form of the penalty varies from one criterion to another. Each criterion starts with 2 lags, and then penalizes, so the smaller the value of an information criterion the better the result. the Schwarz (Bayes) criterion (SC) is generally used, as it's a consistent model-selector. Some care has to be taken not to "over-select" the maximum lags, and one should usually pay some attention to the (apparent) significance of the coefficients in the model as well. Step 4: A key assumption in the ARDL / Bounds Testing methodology of Pesaran et al. (2001) is that the errors of equation (4) must be serially independent. As those authors note (p.308), this requirement may also be influential in our final choice of the maximum lags for the variables in the model. Once an apparently suitable version of (4) has been estimated, we should use the LM test to test the null hypothesis that the errors are serially independent, against the alternative hypothesis that the errors are (either) AR(m) or MA(m), for m = 1, 2, 3,...., etc. Step 5: We have a model with an autoregressive structure, so we have to be sure that the model is "dynamically stable". What we need to do is to check that cumulative sum appearing graphically as the Center line lie strictly between two dotted lines (Lower control limit and Upper control limit). The value of cumulative sum should not exceed these two threshold values to be considered stable. Step 6: Now we're ready to perform the "Bounds Testing" Here's equation (4), again:

$$\Delta y_t = \beta_0 + \Sigma\beta_i\Delta y_{t-i} + \Sigma\gamma_1\Delta x_{1t-j} + \Sigma\delta_k\Delta x_{2t-k} + \theta_0 y_{t-1} + \theta_1 x_{1t-1} + \theta_2 x_{2t-1} + e_t \quad (4)$$

All that we're going to do is preform an "F-test" of the hypothesis, H_0: $\theta_0 = \theta_1 = \theta_2 = 0$; against the alternative that H_0 is not true. As in conventional cointegration testing, we're testing for the absence of a long-run equilibrium relationship between the variables. This absence coincides with zero coefficients for y_{t-i}, x_{1t-1} and x_{2t-1} in equation (4). A rejection of H_0 implies that we have a long-run relationship. There is a practical difficulty that has to be addressed when we conduct the F-test. The distribution of the test statistic is totally non-standard (and also depends on a "nuisance parameter", the cointegrating rank of the system) even in the asymptotic case where we have an infinitely large sample size. (This is somewhat akin to the situation with the Wald test when we test for Granger non-causality in the presence of non-stationary data. In that case, the problem is resolved by using the Toda-Yamamoto (1995) procedure, to ensure that the Wald test statistic is asymptotically chi-square). Exact critical values for the F-test aren't available for an arbitrary mix of I(0) and I(1) variables. However, Pesaran et al. (2001) supply bounds on the critical values for the asymptotic distribution of the F-statistic. For various situations (e.g., different numbers of variables, (k + 1)), they give lower and upper bounds on the critical values. In each case, the lower bound is based on the assumption that all of the variables are I(0), and the upper bound is based on the assumption that all of the variables are I(1). In fact, the truth may be somewhere in between these two polar extremes. If the computed F-statistic falls below the lower bound we would conclude that the variables are I(0), so no cointegration is possible, by definition. If the F-statistic exceeds the upper bound, we conclude that we have cointegration. Finally, if the F-statistic falls between the bounds, the test is inconclusive.

This reminds us of the old Durbin-Watson test for serial independence. As a cross-check, we should also perform a "Bounds t-test" of H_0 : θ = 0, against H_1: θ < 0. If the t-statistic for y_{t-1} in equation (10) is greater than the "I(1) bound" tabulated by Pesaran et al. (2001; pp.303-304), this would support the conclusion that there is a long-run relationship between the variables. If the t-statistic is less than the "I(0) bound", we'd conclude that the data are all stationary. Step 7: Assuming that the bounds test leads to the conclusion of cointegration, we can meaningfully estimate the long-run equilibrium relationship between the variables:

$$y_t = \alpha_0 + \alpha_1 x_{1t} + \alpha_2 x_{2t} + v_t \quad (5)$$

as well as the usual ECM:

$$\Delta y_t = \beta_0 + \Sigma\beta_i \Delta y_{t-i} + \Sigma\gamma_1 \Delta x_{1t-j} + \Sigma\delta_k \Delta x_{2t-k} + \varphi z_{t-1} + e_t \quad (6)$$

where $z_{t-1} = (y_{t-i} - \alpha_0 - \alpha_1 x_{1t-1} - \alpha_2 x_{2t-1})$, and the a's are the OLS estimates of the α's in (5).

Step 8: We can "extract" long-run effects from the unrestricted ECM. Looking back at equation (4), and noting that at a long-run equilibrium, $\Delta y_t = 0$, $\Delta x_{1t} = \Delta x_{2t} = 0$, we see that the long-run coefficients for x_1 and x_2 are $-(\theta_1/\theta_0)$ and $-(\theta_2/\theta_0)$ respectively. Step 9 involve obtaining long-run coefficients and step 10 involves testing short-run causality.

The empirical model

In estimating the effect of financial innovation (technology payments) proxied by the value of transactions of payment instruments on the demand for money, we estimate a semi log-linear specification of the form:

$$\text{Log LMOD} = \beta_0 + \beta_1 \text{Log LGDP} + \beta_2 \text{ INR} + \beta_3 \text{Log (LCRC)} + \beta_4 \text{Log (LCHC)} + \beta_5 \text{Log (LDEC)} + \beta_6 \text{Log (LEMO)} + e_t$$

We use a traditional specification of the conventional demand for money using ARDL, where MOD denotes currency in circulation, GDP denotes nominal gross domestic product, INR is the interest rate, CRC is the nominal value of credit cards transactions, CHC is the nominal value of charge cards transactions, DEC is the nominal value of debit cards transactions, EMO is the nominal value of E-money transactions (all in million Ringgits, and in logarithm form) and e_t is the error term. The data are quarterly, from 2008(Q1) to 2015(Q4). In terms of the notation that was introduced earlier, we have (k + 1) = 7 variables, so k = 6 when it comes to the bounds testing.

Table 2: Probability of the estimated coefficients of the level and the difference of the variables for payment instrument model

Level	LMOD	LGDP	INR	LCRC	LCHC	LDEC	LEMO
Prob	0.3867	0.4495	0.0293	0.4384	0.2949	0.3506	0.8635
FirstD	D(LMOD)	D(LGDP)	D(INR)	D(LCRC)	D(LCHC)	D(LDEC)	D(LEMO)
Prob	0.0081	0.0017	0.0002	0.0489	0.0001	0.0006	0.0000

To complete step 1, we need to check that neither of our time-series are I(2). Applying the ADF test to the levels and the first-differences of the series, the p-values are shown in table above. Clearly, neither series is I(2). All of the series except INR are I(1). INR is I(0). This is a great illustration of how the ARDL / Bounds Testing methodology can help. In order for standard cointegration testing (such as that of Engle and Granger, or Johansen) to make any sense, we must be really sure that all of the series are integrated of the same order. In this instance, we might not be feeling totally sure that this is the case. Step 2 is straightforward. We need to formulate an unrestricted ECM with different lags. Step 3 is to check AIC and SIC criterion and choose the one with lowest value of AIC and SIC. However, regarding the limited number of our observations which is only 32, estimating the model with more than 2 lags is not possible so we estimate using 2 lags as below: D(LMOD) C D(LMOD(-2)) D(LGDP(-1)) D(LGDP(-2)) D(INR(-1)) D(INR(-2)) D(LCRC(-1)) D(LCRC(-2)) D(LCHC(-1)) D(LCHC(-2)) D(LDEC(-1)) D(LDEC(-2)) D(LEMO(-1)) D(LEMO(-2)) LMOD(-1) LGDP(-1) INR(-1) LCRC(-1) LCHC(-1) LDEC(-1) LEMO(-1)

Table 3: Estimation output of step 3

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.502256	2.421808	-0.207389	0.8409
D(LMOD(-2))	0.063157	0.350249	0.180320	0.8614
D(LGDP(-1))	0.117270	0.136149	0.861332	0.4141
D(LGDP(-2))	-0.106425	0.143639	-0.740920	0.4799
D(INR(-1))	0.039280	0.020009	1.963081	0.0853
D(INR(-2))	-0.022100	0.017368	-1.272471	0.2389
D(LCRC(-1))	-0.158747	0.192825	-0.823268	0.4342
D(LCRC(-2))	0.097044	0.147745	0.656836	0.5297
D(LCHC(-1))	-0.060534	0.055468	-1.091345	0.3069
D(LCHC(-2))	-0.039376	0.042223	-0.932582	0.3783
D(LDEC(-1))	0.041053	0.091191	0.450190	0.6645
D(LDEC(-2))	-0.055927	0.071079	-0.786830	0.4541
D(LEMO(-1))	-0.024363	0.055608	-0.438114	0.6729
D(LEMO(-2))	0.009939	0.049861	0.199339	0.8470
LMOD(-1)	-0.156976	0.175879	-0.892519	0.3982
LGDP(-1)	0.006182	0.154409	0.040036	0.9690
INR(-1)	0.006189	0.019755	0.313262	0.7621
LCRC(-1)	0.236932	0.179591	1.319284	0.2236
LCHC(-1)	0.078937	0.071483	1.104275	0.3016
LDEC(-1)	-0.089274	0.044499	-2.006226	0.0797
LEMO(-1)	0.052048	0.066015	0.788433	0.4532

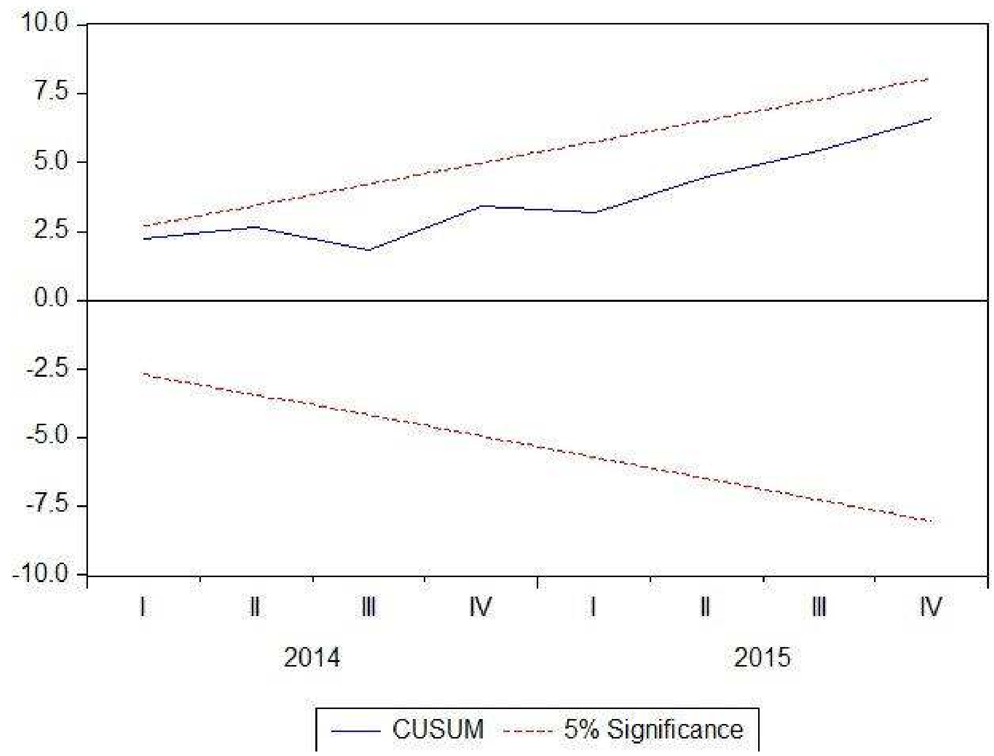
Step 4 involves checking that the errors of this model are serially independent.

Table 4: Breusch-Godfrey Serial Correlation LM Test

F-statistic	0.602625	Prob. F(2,6)	0.5774
Obs*R-squared	4.850939	Prob. Chi-Square(2)	0.0884

According to the result, we do not have a problem with serial correlation. Next, Step 5 involves checking the dynamic stability of this ARDL model. We use QUSUM Test for this purpose.

Figure 2: COSUM Test



It seems to be well as the plotted line is entirely between the two dotted lines meaning that money demand is stable. Step 6 is the Bounds Test itself. We want to test if the coefficients of laged dependent and independent variables are zero in our estimated model so we use Wald Test:

Table 5: Wald Test [Null Hypothesis: C(15)=C(16)=C(17)=C(18)=C(19)=C(20) =C(21)=0]

Test Statistic	Value	df	Probability
F-statistic	1.488594	(7, 8)	0.2936
Chi-square	10.42016	7	0.1660

Table CI (iii) on p.300 of Pesaran et al. (2001) is the relevant table for us to use here. We haven't constrained the intercept of our model, and there is no linear trend term included in the ECM. F-statistics should be compared with Pesaran critical value at 5 percent level with unrestricted intercept and no trend. According to Pesaran table, lower bound is 2.45 and upper bound is 3.61

Regarding the fact that F-statistics is less than the upper bound, we cannot reject the null hypothesis so the variables including dependent variables and independent variables do not have long-run relationship. In other words, they do not move together in the long-run. Therefore, it not recommended proceeding further. In spite of this, we move to the next step to obtain the coefficient of the error correction term to determine the speed of adjustment. In step 7, we estimate the long-run model to obtain the residuals:

Table 6: Estimation output of step 7

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	14.04408	2.018956	6.956107	0.0000
LGDP	-0.049057	0.181057	-0.270946	0.7887
INR	0.018856	0.021698	0.869043	0.3931
LCRC	-0.258364	0.184695	-1.398869	0.1741
LCHC	0.017069	0.082962	0.205745	0.8387
LDEC	0.245973	0.055295	4.448356	0.0002
LEMO	0.166434	0.084686	1.965308	0.0606

In step 8, after we estimate the levels model above by OLS, and construct the residuals series, (ect), we can fit a regular (restricted) ECM. However, the estimated model shows the evidence of serial correlation so we fit a model by omitting D(LMOD(-1)) and obtain:

Table 7: Estimation output of step 7

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.018654	0.004587	4.067030	0.0012
D(LMOD(-2))	0.522730	0.206935	2.526065	0.0242
D(LGDP(-1))	-0.017299	0.067030	-0.258086	0.8001
D(LGDP(-2))	-0.259048	0.100837	-2.568981	0.0223
D(INR(-1))	0.055257	0.017685	3.124493	0.0075
D(INR(-2))	-0.037984	0.012618	-3.010374	0.0094
D(LCRC(-1))	0.213378	0.069288	3.079597	0.0082
D(LCRC(-2))	0.396914	0.090306	4.395198	0.0006
D(LCHC(-1))	0.053683	0.033409	1.606846	0.1304
D(LCHC(-2))	-0.007567	0.031089	-0.243412	0.8112
D(LDEC(-1))	-0.098027	0.044063	-2.224716	0.0431
D(LDEC(-2))	-0.169954	0.042650	-3.984875	0.0014
D(LEMO(-1))	0.023012	0.034738	0.662433	0.5185
D(LEMO(-2))	0.065101	0.033026	1.971197	0.0688
ECT(-1)	-0.022732	0.104548	-0.217429	0.8310

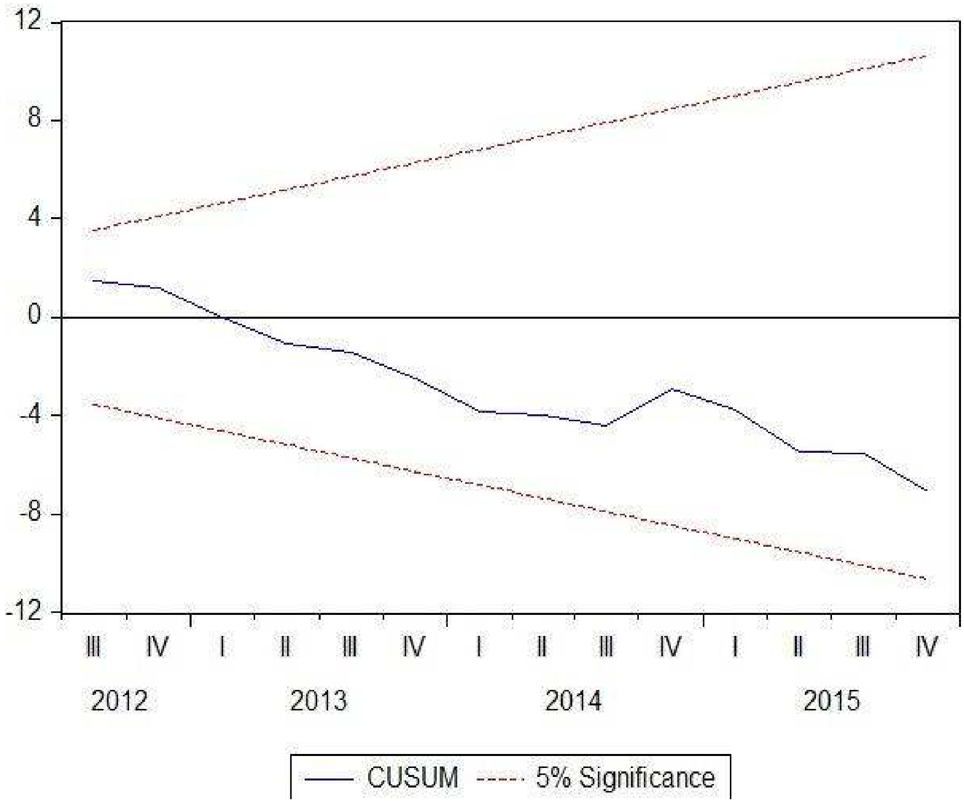
Now, we check again for the serial correlation and stability as below:

Table 8: Breusch-Godfrey Serial Correlation LM Test

F-statistic	0.033407	Prob. F(2,12)	0.9672
Obs*R-squared	0.160574	Prob. Chi-Square(2)	0.9229

According to LM Test, there is no evidence of serial correlation. Then we check for the stability:

Figure 3: COSUM Test



Fortunately, this final ECM is dynamically stable. Notice that the coefficient of the error-correction term, ECT(-1) which is one lagged ECT, is negative but not significant. If there was cointegration between MOD (money demand) and independent variables, we would expect a negative and significant one. The magnitude of this coefficient implies that nearly 2% of any disequilibrium between MOD and independent variables is corrected within one period (one quarter). Finally, the within-sample fit (in terms of the levels of MOD) is exceptionally good. In step7, long-run coefficients can be obtained from the estimated coefficients above by dividing the coefficients of the lagged independent variables by the coefficient of the lagged dependent variable, for example, an increase of 1 percent in EMO (E-money) will lead to an increase of 0.33 percent [-(0.052048/-0.156976)= -0.33157] in money demand:

Table 9: Long-run coefficients

Financial innovations variables	Long-run coefficients
CRC	1.5
CHC	0.5
DEC	-0.5
EMO	0.3

The last step involves testing short-run causality running from each of the independent variables to dependent variable. In doing so, we conduct Wald test:

Table 10: Short-run causality

Variables	F-statistic	Chi-square	Short-run causality
GDP	0.0669	0.0369	Yes
INR	0.0104	0.0016	Yes
CRC	0.0017	0.0000	Yes
CHC	0.2889	0.2570	No
DEC	0.0027	0.0001	Yes
EMO	0.1800	0.1432	No

After estimating money demand with the inclusion of payment instruments as a proxy for financial innovation, we did repeat the same process for estimating money demand with payment systems and payment channels. The model for payment systems is:

$$\text{Log LMD} = \beta_0 + \beta_1 \text{Log LGDP} + \beta_2 \text{ IR} + \beta_4 \text{Log (LRE)} + \beta_5 \text{Log (LIG)} + \beta_6 \text{Log (LFD)} + e_t$$

We use a traditional specification of the conventional demand for money using ARDL, where MD denotes currency in circulation, GDP denotes nominal gross domestic product, IR is the interest rate, RE is the nominal value of RENTAS transactions, IG is the nominal value of Interbank GIRO transactions, FD is the nominal value of FPX and Direct Debit transactions (all in million Ringgits, and in logarithm form) and e_t is the error term. The data are quarterly, from 2008(Q1) to 2015(Q4). The model for payment channels is:

$$\text{Log LMD} = \beta_0 + \beta_1 \text{Log LGDP} + \beta_2 \text{ IR} + \beta_4 \text{Log (LATM)} + \beta_5 \text{Log (LMB)} + \beta_6 \text{Log (LIB)} + e_t$$

Where We use a traditional specification of the conventional demand for money using ARDL, where MD denotes currency in circulation, GDP denotes nominal gross domestic product, IR is the interest rate, ATM is the nominal value of ATM transactions, MB is the nominal value of Mobile Banking transactions, IB is the nominal value of Internet Banking transactions (all in million Ringgits, and in logarithm form) and e_t is the error term. The data are quarterly, from 2008(Q1) to 2015(Q4). In table below, we sum up the results of the ARDL estimation of all of these three cases for comparison.

Table 11: Summary of the results

Tests	Breusch-Godfrey Serial Correlation LM Test (prob)	Normality Test (prob)	Heteroskedasticity Test: Breusch-Pagan-Godfrey (prob)	Stability Test (CUSUM Test)	Bound Test: Test of the Existence of long-run association	Adjustment toward long-run equilibrium (ECT and its prob)
PI	0.0884	0.6045	0.7604	stable	no	-0.0227 (0.8310)
PS	0.1964	0.8756	0.3912	stable	yes	-0.1841 (0.0954)
PC	0.0577	0.0350	0.9253	stable	no	-0.1454 (0.5298)

To test for short run causality, we use Wald Test to find out if the coefficients of the lagged variables are jointly equal to zero or not. For PI: There is short run causality running from GDP, interest rate, debit cards and E-money to money demand, however, there is no short run causality running from credit cards and charge cards to money demand. For PS: There is short run causality running from interest rate, RENTAS and FPX and Direct Debit to money demand, however, there is no short run causality running from GDP and Interbank GIRO to money demand. For PC: There is short run causality running from interest rate, ATM, Mobile Banking and Internet Banking to money demand, however, there is no short run causality running from GDP to money demand.

Table 12: Long-run coefficients

PI	PI	PS	PS	PC	PC
Variables	Long-run coefficients	Variables	Long-run coefficients	Variables	Long-run coefficients
GDP	0.03	GDP	0.21	GDP	1.02
INR	0.03	IR	0.06	IR	-0.03
CRC	1.50	RE	0.21	ATM	0.47
CHC	0.50	IG	-0.24	MB	-0.003
DEC	-0.56	FD	0.21	IB	-0.005
EMO	0.33				

According to the table that is obtained by dividing the coefficients of the lagged independent variables by the coefficient of the lagged dependent variable, for example, an increase of 1 percent in GDP will lead to an increase of 0.03 percent in money demand for PI.

Table 13: Existence of short-run causality

PI	PI	PS	PS	PC	PC
Variables	Short-run causality	Variables	Short-run causality	Variables	Short-run causality
GDP	Yes	GDP	No	GDP	No
INR	Yes	IR	Yes	IR	Yes
CRC	No	RE	Yes	ATM	Yes
CHC	No	IG	No	MB	Yes
DEC	Yes	FD	Yes	IB	Yes
EMO	Yes				

6. Summary

Both long and short run nominal money demand functions of Malaysia with money defined as M2 have been estimated using ARDL approach to cointegration technique. The period under review is 2008Q1–2015Q4. While innovation in the Malaysian financial system have not ruled out the existence of stable long run money demand relationships as attested to by QUSUM Test, they (except for PS) fail to pass the Bound Test meaning that there is no evidence for a long-run association between variables. Asymptotic critical value bounds for the F-statistic are used as criteria to test the existence of a levels relationship. I(0) and I(1), that is, lower bound and upper bound for unrestricted intercept and no trend at the significance level of 0.050 are compared to F-statistic from Wald Test. F-statistic is less than the upper bound in two of the three cases (PI and PC) so we cannot reject the null hypothesis meaning that the variables (dependent variable and independent variables) do not have long-run association. In other words, these variables not move together in the long-run rather they diverge instead of converge. For PS, the estimated coefficient for the error correction term is not significant which means that there is no adjustment towards long-run equilibrium. In other words, disequilibrium between money demand and independent variables is not corrected over time and it actually diverges rather than converge.

Table 14: Data used in the regression analysis (RM million)

					PI				PS			PC		
Year	Quarters	M2	GDP	IR	credit card	charge card	debit card	e-money	RENTAS	Interbank GIRO	FPX and Direct Debit	ATM	Mobile Banking	Internet Banking
2008	1Q	843244.38	182202.00	3.37	15312.89	593.78	401.68	424.45	8397753.07	19746.29	179.17	55424.70	11.81	124766.17
	2Q	868007.30	195021.00	3.44	15798.05	678.57	459.11	504.95	9755270.44	21110.91	233.27	56269.89	15.66	187027.76
	3Q	883547.20	205404.00	3.43	17035.72	865.82	547.62	550.55	11075347.05	24254.73	290.45	63509.23	23.09	165952.46
	4Q	903429.71	187321.00	3.31	17142.51	921.81	549.99	587.13	9515799.34	24507.56	329.17	60177.32	20.99	146615.70
2009	1Q	921831.48	165315.00	2.38	16217.48	914.56	548.07	477.02	8489873.98	23449.34	370.08	61228.13	29.78	144879.71
	2Q	922616.86	169790.00	1.90	16709.52	885.41	606.93	535.08	9373649.41	26092.80	413.94	62065.58	29.97	162901.21
	3Q	950412.62	182766.00	1.96	17566.51	952.50	729.86	556.33	9541217.11	28260.27	541.20	66428.56	38.30	180987.85
	4Q	989342.89	194986.00	1.98	18827.11	1063.40	889.07	632.96	9854160.74	31045.17	680.99	66263.15	42.83	213275.78
2010	1Q	1002708.23	196650.00	2.11	19002.98	1029.92	1094.99	550.54	10178561.90	28689.20	788.07	68393.41	36.35	297068.72
	2Q	1007317.93	199372.00	2.59	19341.08	1200.16	1099.73	700.62	9659840.98	30247.86	985.25	69040.29	32.37	323274.16
	3Q	1028850.56	207460.00	2.83	19919.74	1199.17	1207.84	737.47	9739698.40	32314.77	1062.54	72322.42	25.78	
	4Q	1060153.58	217953.00	2.85	21546.32	1259.28	1301.23	719.73	9856452.68	35617.76	1248.02	76838.14	43.37	407242.62
2011	1Q	1088617.28	218298.00	2.83	21034.71	1265.33	1395.23	807.81	10192778.33	35806.28	1306.87	76570.35	69.91	419676.86
	2Q	1132071.24	224055.00	2.91	21765.71	1307.24	1481.07	872.25	12833859.95	38651.70	1187.08	79801.15	112.81	474165.17
	3Q	1162582.03	231335.00	2.98	22299.00	1366.95	1625.95	912.16	12338998.82	42875.08	1331.02	80172.01	220.62	494361.65
	4Q	1214390.28	238045.00	2.98	23697.30	1448.05	1753.58	885.05	11809959.73	48808.20	1625.97	80224.52	448.79	546004.30
2012	1Q	1254562.76	234956.00	3.00	22632.55	1553.75	1902.03	909.26	12131484.14	47602.93	1913.81	81538.45	770.77	704859.03
	2Q	1285864.19	239607.00	3.05	23055.52	1633.21	2058.97	1017.52	11322846.88	51149.86	2151.85	84411.98	971.38	681230.35
	3Q	1313763.72	245203.00	3.04	23419.33	1625.28	2247.50	1114.08	11676469.92	53173.69	2314.09	88885.29	1134.32	732025.18
	4Q	1330788.24	251485.00	3.05	24977.48	1646.27	2410.22	1203.06	11038616.65	59733.29	2690.03	80263.76	1360.17	860320.02
2013	1Q	1373101.64	241870.00	3.04	23638.75	1700.19	2561.20	1168.49	10912807.19	60742.76	2776.63	80508.77	1752.58	1168.49
	2Q	1400408.00	245107.00	2.99	24170.79	1778.08	2768.83	1214.19	12089176.05	66723.52	3040.15	81057.17	2098.81	881246.39
	3Q	1416222.29	258334.00	2.98	25163.99	1853.21	2953.03	1232.19	11695463.53	73598.32	3237.47	83647.53	2462.48	864208.93
	4Q	1436451.85	273510.00	2.98	26759.39	1891.58	3170.60	1303.93	11740296.74	84202.59	3569.92	85485.67	2928.85	883850.23
2014	1Q	1459864.10	266114.00	2.97	25138.84	1984.58	3344.62	1240.00	11645276.83	91777.52	3985.97	86009.55	3206.63	1032294.93
	2Q	1479547.48	272267.00	2.99	25911.22	2354.95	3539.42	1309.76	12710784.44	103982.45	4606.66	85762.55	3457.96	996441.76
	3Q	1492807.26	278828.00	3.19	26296.29	2106.33	3690.63	1352.09	12739841.26	112160.75	4991.51	98685.25	3963.34	1023451.51
	4Q	1544657.38	289371.00	3.35	28151.82	2115.71	4212.03	1382.41	12031491.62	124616.11	5403.54	99358.77	4049.55	1056082.59
2015	1Q	1583570.81	277207.00	3.21	28829.41	2075.14	5015.81	1384.23	11969318.05	142340.32	5479.19	102638.63	4545.26	1146949.01
	2Q	1575139.00	283244.00	2.95	26405.41	2158.52	4718.63	1391.43	13460472.23	153609.21	6806.44	100090.94	4595.18	1180157.02
	3Q	1574467.45	292580.00	3.17	27438.84	2218.48	4908.03	1509.74	13771048.99	164105.52	7279.95	101923.74	5301.21	1151928.81
	4Q	1589204.16	303849.00	3.11	30001.03	2448.47	5314.54	1709.60	14369655.05	176509.98	8347.63	108245.69	6123.27	

Source: Bank Negara Malaysia

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