USING ARDL APPROACH TO COINTEHRATION FOR INVESTIGATING THE RELATIONSHIP BETWEEN PAYMENT TECHNOLOGIES AND MONEY DEMAND ON A WORLD SCALE

Payam MOHAMMAD ALIHA
Ph.D candidate, National University of Malaysia (UKM), Malaysia
payammaliha@gmail.com

Tamat SARMIDI
Associate Professor Dr. at Faculty of Economics and Management, Universiti Kebangsaan Malaysia (UKM), Malaysia
tamat@ukm.edu.my

Abu Hassan SHAAR
Professor Dr. at Faculty of Economics and Management, Universiti Kebangsaan Malaysia (UKM), Malaysia
ahassan@ukm.edu.my

Fathin FAIZAH SAID
Dr. at Faculty of Economics and Management, Universiti Kebangsaan Malaysia (UKM), Malaysia
fatin@ukm.edu.my

Abstract

This paper estimates the relationship between financial innovation and money demand in world countries with a focus on the number of automated teller machines (ATMs) using the ARDL approach to cointegration. In this study, we estimated a conventional money demand model with currency in circulation (M2) as dependent variable and gross domestic product (GDP, constant 2005 US$), interest rate (IRATE), the number of automated teller machines per 100,000 adults (ATM) to take into account for the effects of financial innovation as dependent variables. It covers 215 countries and territories over the period 2004-2013. 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 all of the countries as a whole. The empirical evidence points to the existence of long-run and cointegrating relationships between variables meaning all of these variables move together in the long run. The speed of adjustment toward long run equilibrium is - 0.4345 which means that the whole system gets back to long run equilibrium at the speed of 43.45 percent. The results confirm that in the short-run, ATM does not impact money demand.

Keywords: Money demand, Financial innovations, Stability, ARDL, Cointegration.
JEL classification: R21, R32

1. Introduction

Over the years, numerous empirical studies have attempted to investigate the stability of money demand given its importance for the successful implementation of monetary policy (see Bahmani-Oskooee and Gelan (2009), Hoffman et al (1995), Bahmani-Oskooee (2001), Adam (1992) and Darrat (1985). Most of the earlier studies in advanced economies including Brunner and Meltzer (1963) found that the demand for money is stable meaning that the monetary authority can effectively control inflation through adjusting the money supply while instability of the money demand hinders the proper monitoring of prices (Hamori, 2008). These results can be extended to developing countries when it comes to a stable money demand function. For instance studies by Suliman and Dafaalla (2011) for Sudan, Bahmani-Oskooee and Gelan (2009), Hamori (2008) for Africa, and Mwenga (1990) and Adam (1992) for Kenya and Dong W. Cho and William Miles for South Korea all found that money demand is stable with exclusion of financial innovation.

However, 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. Section 4 presents the results of the estimation and it ends up with summary in section 5.

2. Literature review

Regarding econometric modelling of the stability of money demand, several cointegration methods have been used over time. The first was the Engel and Granger (1987) cointegration method which uses a two-step procedure to determine a stationary linear combination. It was followed by Adam (1992) and Augustina et al (2010) who apply this method to determine cointegration of money demand and its determinants for Kenya and Nigeria respectively. Although this method has been commonly used in earlier studies, there are some limitations with this two-step procedure. The errors can be transferred from the first step to the second step. In addition, because one variable has to be on the left hand side and others on the right hand side as regressors, the variable that is selected for normalization can affect the outcome and any change in the ordering of the equation could lead to different results (Enders, 2010).

The Johansen andadam Juselius (1990) rank test method for cointegration that is an attempt to improve some of the limitations of the Engel and Granger method by allowing for multiple cointegrating vectors (Enders, 2010). Hoffman et al (1995), Bahmani-Oskooee and Bohl (2000), Sichei and Kamau (2012), Hafer and Kutan (2003), Mannah-Blankson and Belyne (2004), and Suliman and Dafaalla (2011) are examples of the studies that used the Johansen and Juselius rank test. However, mandatory testing for stationarity prior to the cointegration test is its weakness that means one needs to know the order of integration, of which various studies have mainly focused on I(1) variables. The autoregressive distributed Lag (ARDL) model proposed by Pesaran et al (2001) has an advantage over the Johansen and Juselius rank test as it is more flexible in terms of the order of intergration. Also, it is not necessary to test for stationarity for the ARDL method since both I(0) and I(1) variables can be used rather than using merely I(1) variables. In order to use ARDL method to cointegration to determine stability, we need to apply stability tests such as the (CUSUM)[1] and (CUSUMSQ)[2] tests after cointegration for determining stability of the coefficients (Bahmani-Oskooee and Gelan, 2009). This is because the estimated elasticities could remain unstable after co-integration of the variables. Studies by Bahmani-Oskooee and Gelan (2009), Kiptui (2014) and Ndirangu and Nyamongo (2015) have employed the ARDL approach to cointegration for Kenya However, they failed to account for financial innovation in the money demand specification except for Ndirangu and Nyamongo (2015) who use 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 real monetary aggregates, real income, real 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 real 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

$$\text{Log } M2_{it} = \beta_0 + \beta_1 \text{Log } GDP_{it} + \beta_2 R_{it} + \beta_3 \text{Log } (ATM_{it}) + e_{it}$$

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 $M^d = (Y_t, R_t, r^*)$. Conventional Demand for Money Function mentioned above is the basis for this specification. The amount of currency in circulation for the 215 countries at the end of December 2013 was used to estimate a demand for currency in circulation. We use a traditional specification of the conventional demand for money, where M2 denotes currency in circulation, GDP denotes real gross domestic product, R is the interest rate, ATM is the number of automated teller machines, and e_t is the error term. We then estimated a demand for M2 with panel regressions with fixed country effects with the goal of checking for cross-section payment technology heterogeneity with t spanning from 2004 to 2013. Data is collected from the official website of the World Bank. The number of ATMs or ATM volume may be positively or negatively related to the demand for currency. In one hand, individuals demand more money since it can be easily accessed. On the other hand, the existence of ATMs reduces the demand for money since individuals can minimize the opportunity cost of idle cash balances. Therefore, ATMs would have a negative impact on currency demand. The overall impact depends on the strengths of negative/positive sides.

[1] cumulative sum of recursive residuals
[2] cumulative sum of squares recursive residuals

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.

Based on Pesaran et al. (1999), the dynamic heterogeneous panel regression can be incorporated into the error correction model using the autoregressive distributed lag ARDL (p,q) technique and described as below (Loayza and Ranciere, 2006):

$$\Delta(y_i)_t = \sum_{j=1}^{p-1} \gamma_j^i \, \Delta(y_i)_{t-j} + \sum_{j=0}^{q-1} \delta_j^i \, \Delta(X_i)_{t-j} + \varphi^i[(y_i)_{t-j} - \{ \beta_0^i + \beta_1^i (X_i)_{t-j} \} \, \varepsilon_{it}$$

where y is the demand for money, X is a set of independent variables including the financial innovation proxy, γ is the short-run coefficients of lagged dependent and δ is the short-run coefficients of lagged independent variables, β are the long-run coefficients, and φ is the coefficient of speed of adjustment to the long-run equilibrium. The subscripts i and t represent country and time, respectively. The long-run money demand regression is placed in the square brackets. Δ is first-difference operator and p is the optimal lag length.

The F test is used to test the presence of long-run relationship. If there is long-run relationship, F test indicates which variable has to be normalized. The null hypothesis for no cointegration among variables in equation (1) is stated as H_0: $\delta_1 = \delta_2 = \delta_3 = 0$ against the alternative hypothesis H_0: $\delta_1 \neq \delta_2 \neq \delta_3 \neq 0$ for our case that includes three independent variables. The F-test having a non-standard distribution depends on (i) if variables of the model are I(0) or I(1), (ii) the number of regressors, and (iii) if the model includes an intercept and/or a trend. The test involves asymptotic critical value bounds, depending whether the variables are I(0) or I(1) or a mixture of both. Two sets of critical values are produced. One set is related to the I(1) series which is called upper bound critical values and the other refers to the I(0) series that is called lower bound critical values. If the F test statistic exceeds upper critical values, it means that there is long-run relationship between the variables regardless of the order of integration of the variables. If the test statistic is less than the upper critical value, the null hypothesis of no cointegration cannot be rejected and if it lies between the bounds, a decision cannot be made without knowing the order of integration of the underlying regressors.

We select the order of the lags in the ARDL model by using either the Akaike Information criterion (AIC) or the Schwarz criterion (SC), before estimation the model by OLS.

Accordingly, 6 lags were chosen. The above equation can be estimated by three different estimators: the mean group (MG) model of Pesaran and Smith (1995), the pooled mean group (PMG) estimator developed by Pesaran et al. (1999), and the dynamic fixed effects estimator (DFE). All three estimators take into account the long-run equilibrium and the heterogeneity of the dynamic adjustment process (Demetriades and Law, 2006) and are computed by maximum likelihood guaranteed to have consistent and efficient estimates of the parameters in a long-run relationship if there is co-integration among variables with the same order of integration.

However, Pesaran and Shin (1999) state that panel ARDL can be used even with variables with different order of integration no matter if they are I (0) or I (1). In addition, the short-run and long-run effects both can be estimated simultaneously from a data set with large cross-section and time dimensions. Finally, the ARDL model produces consistent coefficients despite the possible presence of endogeneity because it includes lags of dependent and independent variables (Pesaran et al, 1999). Finally, the dynamic fixed effects estimator (DFE) that is applied here imposes restrictions on the slope coefficient and error variances to be equal across all countries in the long run. The DFE model further restricts the speed of adjustment coefficient and the short-run coefficient to be equal too. However, the model features country-specific intercepts.

We employ four different types of panel unit root tests: and (i) Levin, Lin and Chu, (ii) Im, Pesaran and Shin, (iii) ADF - Fisher Chi-square, and (iv) PP - Fisher Chi-square to determine the order of integration between all the series in our data-set. Though testing for the order of integration of variables is not important when applying the ARDL model as long as the variables of interest are I(0) and I(1), (Pesaran and Smith, 1995; Pesaran, 1997; Pesaran et al, 1999), these tests are carried out just to make sure that no series exceeds I(1) order of integration. The results indicate that financial innovation has a negative weakly significant impact in the long run and no impact in the short run on money demand according to the DFE estimator. To conclude this argument, financial innovation and money demand have been strange bedfellows. Most studies conclude that as a whole, financial innovation plays a significant role in demand for money.

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 k^{th} explanatory variable. An ARDL model may be written as:

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

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.

Post-Estimation Diagnostics: Long-run Relationships: Since an ARDL model estimates the dynamic relationship between a dependent variable and explanatory variables; it is possible to transform the model into a long-run representation, showing the long run response of the dependent variable to a change in the explanatory variables. The calculation of these estimated long-run coefficients is given by:

$$\theta_j = \frac{\sum_{i=1}^{q_j} \beta_{j,i}}{1 - \sum_{i=1}^{p} \gamma_i} \qquad (2)$$

The standard error of these long-run coefficients can be calculated from the standard errors of the original regression using the delta method.

Cointegrating Relationships: Traditional methods of estimating cointegrating relationships, such as Engle-Granger (1987) or Johansen's (1991, 1995) method, or single equation methods such as Fully Modified OLS, or Dynamic OLS either require all variables to be I(1), or require prior knowledge and specification of which variables are I(0) and which are I(1). To alleviate this problem, Pesaran and Shin (1999) showed that cointegrating systems can be estimated as ARDL models, with the advantage that the variables in the cointegrating relationship can be either I(0) or I(1), without needing to pre-specify which are I(0) or I(1). Pesaran and Shin also note that unlike other methods of estimating cointegrating relationships, the ARDL representation does not require symmetry of lag lengths; each variable can have a different number of lag terms. The cointegrating regression form of an ARDL model is obtained by transforming (1) into differences and substituting the long-run coefficients from (2):

$$\Delta y_t = -\sum_{i=1}^{p-1} \gamma_i^* \Delta y_{t-1} + \sum_{j=1}^{k} \sum_{i=0}^{q_j-1} \Delta X'_{j,t-i} \beta_{j,i}^* - \hat{\phi} EC_{t-1} + \epsilon_i \qquad (3)$$

where

$$EC_t = y_t - \alpha - \sum_{i=0}^{q_j} X'_{j,t} \hat{\theta}_j$$

$$\phi = 1 \quad \sum_{i=1}^{p} \hat{\gamma}_i \qquad (4)$$

$$\gamma_i^* = \sum_{m=i+1}^{p} \hat{\gamma}_m$$

$$\beta_{j,i}^* = \sum_{m=i+1}^{q_j} \beta_{j,m}$$

The standard error of the cointegrating relationship coefficients can be calculated from the standard errors of the original regression using the delta method.

Bounds Testing: Using the cointegrating relationship form in Equation (3), Pesaran, Shin and Smith (2001) describe a methodology for testing whether the ARDL model contains a level (or long-run) relationship between the independent variable and the regressors. The Bounds test procedure transforms (3) into the following representation:

$$\Delta y_t = -\sum_{i=1}^{p-1} \gamma_i^* \Delta y_{t-1} + \sum_{j=1}^{k} \sum_{i=0}^{q_j-1} \Delta X'_{j,t-i} \beta_{j,i}^* - \rho y_{t-1} - \alpha - \sum_{j=1}^{k} X'_{j,t-1} \delta_j + \epsilon_t \qquad (5)$$

The test for the existence of level relationships is then simply a test of

$$\rho = 0$$
$$\delta_1 = \delta_2 = \cdots = \delta_k = 0 \qquad (6)$$

The coefficient estimates used in the test may be obtained from a regression using (1), or can be estimated directly from a regression using (5).The test statistic based on Equation (5) has a different distribution under the null hypothesis (of no level relationships), depending on whether the regressors are all I(0) or all I(1). Further, under both cases the distribution is non-standard. Pesaran, Shin and Smith provide critical values for the cases where all regressors are I(0) and the cases where all regressors are I(1), and suggest using these critical values as bounds for the more typical cases where the regressors are a mixture of I(0) and I(1).

4. Estimation

According to unit root tests (refer to appendix), MD, GDP, IRATE and ATM have unit root [I(1)] at %5 significance level, however, they become stationary at first difference. Then, we estimate the standard ARDL model with 6 lags (and fixed effects) as below:

D(LMD) = -0.0295 + 0.0064*D(LMD(-1)) - 0.0302*D(LMD(-2)) + 0.1698*D(LMD(-3)) - 0.0623*D(LMD(-4)) - 0.0011*D(LMD(-5)) + 0.1316*D(LMD(-6)) + 1.1832e-12*D(GDP(-1)) + 4.7661e-13*D(GDP(-2)) + 8.1629e-15*D(GDP(-3)) - 1.4373e-13*D(GDP(-4)) - 9.7703e-14*D(GDP(-5)) - 1.2590e-12*D(GDP(-6)) + 0.0013*D(IRATE(-1)) + 0.0006*D(IRATE(-2)) + 0.0006*D(IRATE(-3)) + 0.0020*D(IRATE(-4)) + 0.0004*D(IRATE(-5)) - 0.0001*D(IRATE(-6)) + 0.0009*D(ATM(-1)) + 0.0003*D(ATM(-2)) + 0.0009*D(ATM(-3)) + 0.0006*D(ATM(-4)) - 7.6456e-05*D(ATM(-5)) - 0.0007*D(ATM(-6)) + 0.0023*LMD(-1) + 2.1280e-15*GDP(-1) + 0.0002*IRATE(-1) - 6.0507e-05*ATM(-1)

And obtain Akaike info criterion and Schwarz criterion. Then we repeat the estimation with 4 and 2 lags, other things remain unchanged and we put down AIC and SC values in the table below.

Table (1): Estimated Akaike info criterion and Schwarz criterion for the number of lags

Number of Lags	AIC	SC
6	-2.94	-1.23
4	-2.18	-1.02
2	-1.98	-1.00

From table, we see that the model with 6 lags has the lowest value of AIC and SC so it is the best model.

To test whether or not the variables move together in the long run, we run Wald Test as below:

Table (2): Wald Test

Test Statistic	Value	df	Probability
Null Hypothesis: C(26)=C(27)=C(28)=C(29)=0			-
F-statistic	9.671835	(4, 139)	0.0000
Chi-square	38.68734	4	0.0000

F-statistics should be compared with Pesaran critical value at %5 significance level corresponding to no intercept and no trend. Based on this comparison, we can reject null hypothesis which means that the coefficients are not equal to zero jointly. In other words, LMD(-1), GDP(-1), IRATE(-1) and ATM(-1) have long run association which means all of these variables move together in the long run. Next, we estimate the long run model as LS LMD C GDP IRATE ATM and obtain residual as below:

LMD = 22.5969 + 0000000000004.0*GDP + 0.0006*IRATE + 0.0089*ATM

We copy and paste it and rename it as ECT (Error Correction Term). Then we run the model with 6 lags with an added variable ECT(-1), that is, lagged ECT as following:

D(LMD) = 0.1077 - 0.2944*D(LMD(-1)) - 0.2098*D(LMD(-2)) + 0.0569*D(LMD(-3)) - 0.1322*D(LMD(-4)) - 0.1069*D(LMD(-5)) + 0.0572*D(LMD(-6)) + 1.2386e-12*D(GDP(-1)) + 2.0927e-12*D(GDP(-2)) + 2.0304e-12*D(GDP(-3)) + 1.9457e-12*D(GDP(-4)) + 1.1353e-12*D(GDP(-5)) + 5.8933e-13*D(GDP(-6)) + 0.0038*D(IRATE(-1)) + 0.0045*D(IRATE(-2)) + 0.0045*D(IRATE(-3)) + 0.0063*D(IRATE(-4)) + 0.0046*D(IRATE(-5)) + 0.0021*D(IRATE(-6)) - 0.0020*D(ATM(-1)) - 0.0034*D(ATM(-2)) - 0.0019*D(ATM(-3)) - 0.0014*D(ATM(-4)) - 0.0029*D(ATM(-5)) - 0.0034*D(ATM(-6)) - 0.4345*ECT(-1)

D(LMD(-1), ..., D(LATM(-6)) are all short run coefficients and ECT is the speed of adjustment toward long run equilibrium, meaning that the whole system gets back to long run equilibrium at the speed of 43.45 percent. In other words, the deviation of money demand from long run value is corrected in a bit more than two years. It should be negative and significant.

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.

Table (3): Wald Test

Test Statistic	Value	df	Probability
Null Hypothesis:			
C(8)=C(9)=C(10)=C(11)=C(12)=C(13)=0			
F-statistic	0.847067	(6, 142)	0.5357
Chi-square	5.082400	6	0.5333
C(14)=C(15)=C(16)=C(17)=C(18)=C(19)=0			
F-statistic	6.075407	(6, 142)	0.0000
Chi-square	36.45244	6	0.0000
C(20)=C(21)=C(22)=C(23)=C(24)=C(25)=0			
F-statistic	1.781310	(6, 142)	0.1070
Chi-square	10.68786	6	0.0985

According to the result, for GDP and ATM, we cannot reject the null hypothesis so there is no short run causality from GDP and ATM to LMD. However, we can reject null hypothesis for IRATE meaning that there is short run causality from interest rate.

5. Summary

In this study, we estimated a conventional money demand model (as described above) with currency in circulation (M2) as dependent variable and gross domestic product (GDP, constant 2005 US$), interest rate (IRATE), the number of automated teller machines per 100,000 adults (ATM) to take into account for the effects of financial innovation as dependent variables. It covers 215 countries and territories over the period 2004-2013.

ARDLs are standard least squares regressions which include lags of both the dependent variable and explanatory variables as regressors. It is a method of examining long-run and cointegrating relationships between variables. The requirement for this estimation is that variables should be integrated of order 1 and some maybe (not necessarily) of order zero so ARDL requirements for estimation are satisfied. The findings of this estimator is as follow: 1) Lagged variables, that is, MD(-1), GDP(-1), IRATE(-1) and ATM(-1) have long run association which means all of these variables move together in the long run, 2) The speed of adjustment toward long run equilibrium is - 0.4345. It should be negative and significant that it actually is. In other words, the whole system gets back to long run equilibrium at the speed of 43.45 percent, 3) There is no short run causality running from GDP and ATM to MD, and 4) There is short run causality running from IRATE to MD. Again, the results confirm that in the short-run, ATM does not impact money demand.

6. References

Bahmani-Oskooee, M. & Gelan, A. 2009. How Stable Is the Demand for Money in African Countries? Journal of Economic Studies 36(3): 216-235.

Hoffman, D. L., Rasche, R. H. & Tieslau, M. A. 1995. The Stability of Long-Run Money Demand in Five Industrial Countries. Journal of Monetary Economics 35(2): 317-339.

Bahmani-Oskooee, M. 2001. How Stable Is M2 Money Demand Function in Japan? Japan and the World Economy 13(4): 455-461.

Adam, C. 1992. On the Dynamic Specification of Money Demand in Kenya. Journal of African Economies 1(2): 233-270.

Darrat, A. F. 1985. The Demand for Money in a Developing Economy: The Case of Kenya. World Development 13(10): 1163-1170.

Meltzer, A. H. 1963. The Demand for Money: The Evidence from the Time Series. The Journal of Political Economy 219-246.

Hamori, S. 2008. Empirical Analysis of the Money Demand Function in Sub-Saharan Africa. Economics Bulletin 15(4): 1-15.

Suliman, S. Z. & Dafaalla, H. A. 2011. An Econometric Analysis of Money Demand Function in Sudan, 1960 to 2010. Journal of Economics and International Finance 3(16): 793.
Goldfeld, S. M. & Sichel, D. E. 1990. The Demand for Money. Handbook of monetary economics 1(299-356.
Arrau, P. & De Gregorio, J. 1993. Financial Innovation and Money Demand: Application to Chile and Mexico. The Review of Economics and Statistics 524-530.
Ireland, P. N. 1995. Endogenous Financial Innovation and the Demand for Money. Journal of Money, Credit, and Banking 27(1): 92-93.
Attanasio, O. P., Guiso, L. & Jappelli, T. 2002. The Demand for Money. Financial Innovation
Alvarez, F. & Lippi, F. 2009. Financial Innovation and the Transactions Demand for Cash. Econometrica 77(2): 363-402.
Nagayasu, J. 2012. Financial Innovation and Regional Money. Applied Economics 44(35): 4617-4629.
Arrau, P., De Gregorio, J., Reinhart, C. M. & Wickham, P. 1995. The Demand for Money in Developing Countries: Assessing the Role of Financial Innovation. Journal of Development Economics 46(2): 317-340.
Mannah-Blankson, T. & Belyne, F. 2004. The Impact of Financial Innovation on the Demand for Money in Ghana. Bank of Ghana Working Paper.
Hafer, R. & Kutan, A. M. 2003. Financial Innovation and the Demand for Money: Evidence from the Philippines. International Economic Journal 17(1): 17-27.
Hye, Q. M. A. 2009. Financial Innovation and Demand for Money in Pakistan. The Asian Economic Review 51(2): 219-228.
Engle, R. F. & Granger, C. W. 1987. Co-Integration and Error Correction: Representation, Estimation, and Testing. Econometrica: journal of the Econometric Society 251-276.
Enders, C. K. 2010. Applied Missing Data Analysis. Guilford Press.
Johansen, S. & Juselius, K. 1990. Maximum Likelihood Estimation and Inference on Cointegration—with Applications to the Demand for Money. Oxford Bulletin of Economics and statistics 52(2): 169-210.
Bahmani-Oskooee, M. & Bohl, M. T. 2000. German Monetary Unification and the Stability of the German M3 Money Demand Function. Economics Letters 66(2): 203-208.
Sichei, M. M. & Kamau, A. W. 2012. Demand for Money: Implications for the Conduct of Monetary Policy in Kenya. International Journal of Economics and Finance 4(8): 72.
Pesaran, M. H., Shin, Y. & Smith, R. J. 2001. Bounds Testing Approaches to the Analysis of Level Relationships. Journal of applied econometrics 16(3): 289-326.
Ndirangu, L. & Nyamongo, E. M. 2015. Financial Innovations and Their Implications for Monetary Policy in Kenya†. Journal of African Economies 24(suppl 1): i46-i71.
Serletis, A. 2007. The Demand for Money: Theoretical and Empirical Approaches. Springer Science & Business Media.
Greene, W. H. 2008. The Econometric Approach to Efficiency Analysis. The measurement of productive efficiency and productivity growth 92-250.
Pesaran, M. H., Shin, Y. & Smith, R. P. 1999. Pooled Mean Group Estimation of Dynamic Heterogeneous Panels. Journal of the American Statistical Association 94(446): 621-634.
Pesaran, M. H. & Pesaran, B. 1997. Working with Microfit 4.0: Interactive Econometric Analysis;[Windows Version]. Oxford University Press.
Pesaran, M. H. & Smith, R. P. 1998. Structural Analysis of Cointegrating Vars. Journal of Economic Surveys 12(5): 471-505.
Demetriades, P. & Hook Law, S. 2006. Finance, Institutions and Economic Development. International Journal of Finance and Economics 11(3): 245.