COMPARING THE FORECASTS OF THE DEMAND FOR MONEY IN MALAYSIA WITH THE INCLUSION OF FINANCIAL INNOVATION USING DIFFERENT ESTIMATION METHODS

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Abstract

In this paper, we compare the forecasting performance of multivariate models (ARDL/VECM/DOLS/FMOLS) versus univariate models (ARIMA/ETS) for the purpose of forecasting the real demand for money in Malaysia using monthly data during 2010Q1-2018Q4. This study overcomes the issue of misspecification by incorporating financial innovation in the money demand function using separate measures of payment instruments (credit card, charge card, debit card, e-money), payment channels (Real Time Electronics Transfer of Funds and Securities or RENTAS, Interbank GIRO, Financial Process Exchange or FPX and direct debit) and payment channels (Automated Teller Machines or ATM, mobile banking) to capture the effect of financial innovations. The multivariate models which are categorized into structural models (relying on a structural relationship between money demand and other variables) are also cointegration based models meaning that variables have long-run associationship and move together in the long-run while non-structural (non-cointegration) based techniques (ARIMA and ETS model) do not rely on such a structural relationship. We conclude that structural models are better for longer term forecasting. Non-structural models (notably ARIMA) have better forecasting performance for short term horizons such as one year than they do for long term horizons. However, our findings indicate that even for short term horizons, structural models do better than non-structural models but the gap between forecasting accuracy for these two kinds of models is much narrower in the short term horizon compared to long term horizon. The results also indicate that FMOLS has the most predictive power among cointegration/structural/multivariate based models for both short (12-months) and long-time (60-months) horizons. In the context of this model (FMOLS), financial innovation have positive yet small impact on money demand in Malaysia. Finally, we do out-of-sample forecast using FMOLS.

Keywords: Malaysia, Money Demand, Financial Innovations, Multivariate, Univariate, Cointegration

JEL classification: E41, E42, E52

1. Introduction

In the new environment of modern commerce and technological progress, traditional means of payment is no longer satisfying the need for more convenient, quicker, and more secure means of payment. The evolving commercial models pushed the payment systems constantly to catch up with the requirements of these models and transform into highly sophisticated modern electronic payment instruments. New payment standards were set by the fast growth of digital commerce which has had an impact on the evolution of current electronic payment instruments that in turn has reduced transactional and financial risks. Modern payment systems are crucial in our daily life and in the well-functioning of the economy. A set of instruments, and interbank funds transfer clearing systems that guarantee the circulation of money create the foundation of modern payment systems.

Since the introducing of new payment technologies, this traditional money demand relationships have changed causing traditional money demand function instable. High auto correlated errors, implausible parameter estimates and persistent over prediction can also be attributed to the ignorance of the rapid growth in financial innovation. Therefore, in specifying money demand function, we need to be aware of the importance of including innovation variations in the money demand function. In order to highlight our findings and compare it with other recent studies that used similar method, we discuss some of the most recent studies.

Investigation of the stability of money demand has received a lot of attention due to its importance for the successful implementation of monetary policy. The most prominent of these studies include Meltzer (1963), Darrat (1985), Adam (1992), Hoffman et al (1995) and in recent years Bahmani-Oskooee (2001), Hamori (2008), Bahmani-Oskooee and Gelan (2009).

Stability of money demand enables monetary authorities to control inflation effectively through adjusting the money supply while instability of money demand is a hinder for the proper monitoring of prices. A stable money demand is an indication of how effective the use of monetary aggregates is, in the conduct of monetary policy. Therefore, we need to make sure we have an answer to this important question. For monetary policy to be efficient, it needs to have predictable effect on the macroeconomic variables. The necessary condition for this is a stable money demand function. Whether or not a money demand is stable makes a difference between efficient and inefficient monetary policy.

The demand for money function creates a platform to investigate the effectiveness of monetary policies which is crucial for macroeconomic stability provided that this money demand is stable. Owoye and Onafowora (2007) point out that in order to control inflation rate, we need a stable money demand function. Baharomshah et al. (2009) state that if a steady and state relationship between money demand and its determinants (including financial innovation) exists, then the central bank will be able to use monetary policy to affect important macroeconomic variables successfully which in part plays a vital role in stimulating economic growth and stability.

Prior to the mid-1970s, stability of money demand was ensured with the inclusion of only interest rate and output (Goldfeld and Sichel, 1990). However, there has been mixed results in regards to the stability of money demand after the introduction of recent financial innovations over the last few decades. Therefore, researchers such as Arrau and De Gregorio (1993), Arrau et al (1995), Ireland (1995), Attanasio et al (2002), Hafer and Kutan (2003), Mannah-Blankson and Belyne (2004), Hye (2009), Alvarez and Lippi (2009) and Nagayasu (2012) began to include financial innovation in the money demand specification to achieve stability and to avoid some of the issues faced by traditional money demand specification such as autocorrelated errors, persistent over prediction and implausible parameter estimates (Arrau et al, 1995). Ignoring these innovations could lead to misspecification of the money demand through over estimation, or so called "missing money" (Arrau and De Gregorio, 1991). Besides, the failure of co-integration of the money demand can be attributed to the exclusion of financial innovation in the money demand function.

Forecasting of money demand as a basis on policy instrument, is considered essential for decision making of the central bank (Choi & Oh, 2003). Monetary authority need the forecast of money demand to choose appropriate monetary policy actions to maintain price stability and sustain long run economic growth. The problem with producing an accurate money demand forecast is that is to find a suitable estimation method for money demand that yields the most accurate forecast. That justifies why we need to compare the performance of money demand forecasting obtained from different estimation methods. Controlling inflation can be done at its optimum level only if the most accurate forecast of money demand is obtained which in turn depends on applying the most appropriate estimation method. In implement more appropriate rules and regulation to achieve the targets set by the policy makers, they need accurate pictures of current economics which is only possible by applying those methods with lower forecast error criterion (the most important of all, Root Mean Square Error or simply RMSE). Various methods ranging from univariate (such as exponential smoothing), to multivariate regression model (such as VECM) models have been used in estimating and forecasting economic and financial variables.

Many researchers have been trying to establish a model with the lowest out-of-the-sample forecast error. We will evaluate in-sample forecasting performance of estimated money demand function in Malaysia by comparing cointegration based method with non cointegration based method to test this hypothesis that cointegration property of the model improves the forecasting performance. First, we construct multivariate and univariate time series forecasting models using econometric methods that includes both the conventional (traditional) determinants of money demand (GDP and interest rate) in addition to financial variables to proxy the effect of financial innovation on the demand for money. Second, we produce both short-term (1-year) and longer term out of sample forecasts (5-years) using the estimation methods that provides the most accurate in sample forecast). The benchmark for choosing the method with the best forecasting performance is mainly Root Mean Square Error (RMSE) but other criteria such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Theil's U Statistic will also be considered.

Based on these steps, we can define 3 general objectives as below: a) Determining which forecast (either dynamic or static) is superior for each model, b) Comparing in-sample forecasts from all of the models to determine which model provides the most accurate forecast, c) Determining if non contegration model performs better in short-time horizon (1-year) or in long-time horizon (5-year) when it comes to forecasting, d) Doing out-of-sample forecast using the model with the best in-sample forecasting performance, and e) Estimating the models using the best (selected) estimator and comparing the estimated coefficients of the financial variable when the models include different sets of these variables (PI, PS and PC) to determine the impact of financial innovation on the demand for money in Malaysia.

After a brief introduction, we provide a literature review. Then, methodology will be provided with detail explanation of the background of the method used in this research and the money demand specification. It is followed by estimating the models using different sets of financial variables along with evaluating and comparing the forecasts based on these estimates. Summary and conclusion ends up the paper.

2. Literature review

Williams (1997) used cointegration and error correction model to forecasting the demand for currency in Jamaica describing the adjustment path for currency demand relative to the consumer price index (CPI), the weighted average deposit rate, the exchange rate as well as consumer imports comprising food and nondurable items. He used monthly data from 1990:12 to 1996:12. His finding indicates that in the short run, the main basis for holding cash balances is for transactions. The ECM term was negative and highly significant indicating the existence of a long run relationship between currency demand and the various macroeconomic variables. Appropriateness of model specification and lagged data availability for variables is considered an issue in a structural specification. Therefore, ARMA model is preferred for the purpose of forecasting currency demand.

Anderson-Reid (2008) estimated the effect of the non-cash means of payment (debit and credit cards in particular) on the demand for currency in Jamaica by applying the error correction method. The performance of this ECM model was compared to that of a short-run model and a univariate Autoregressive Integrated Moving Average (ARIMA) model to analyse the power and ability of the model for forecasting purpose. ECM model included currency in circulation, consumer goods imports, the consumer price index (CPI), the 3-month Treasury bill rate and the exchange rate. ATM volume, EFTPOS volume and the number of debit cards and credit cards were also included. The model was of the logarithm functional form that included M (currency in circulation), P (the price level), NOND (consumer goods imports) and TBlL (the interest rate on 3-month Treasury bill). ATM volume, EFTPOS volume and the number of debit and credit cards in circulation are denoted by ATMV, POSV and Card, respectively. All of the variables are in logarithms except for the interest rate variable that is in levels. Consequently, estimates of the coefficients are actually the elasticity as the model is in log functional form.

Hoffman and Rasche (1996) compare the forecasting performance of a co-integrated system with that of a non-cointegrated VAR system. They consider eight years out-sample forecast horizon for the US economy and conclude that only at longer forecast horizon, co-integrated system performs better than the non-cointegrated VAR system.

Using simulated and real data from the UK, Canada, Germany, France and Japan and interest rate data from the US and Taiwan, Lin and Tsay (1996) conclude the forecast performance of ECM for simulated data is superior while that for real data is mixed (due to deficiency in forecast error measure).

Cassino and Misich (1997) used ARIMA model to forecast the demand for currency in New Zealand and conclude that the error correction model's out-of-sample forecasts over this period are inferior to the forecasts from ARIMA.

Deng and Liu (1999) deal with the demand for money, including narrow money (M1) and broad money (M2) in China using data from the first quarter of 1990 to the fourth quarter of1994. They obtained forecasts over different horizons. Based on the cointegration and error - correction model that merges the short - run and long - run equations. They find that both the fitted values and predictive values for M1 and M2 are satisfactory. Finally, they give forecasts for M2 from the first quarter of 1995 to the second quarter of 1996.

Using annual data from 1867 to 1966 (for model specification) and annual data from 1966 to 2000 (for out-of sample forecast evaluation) for the United States, Wang and Bessler (2004) conclude that ECM is as the best model for three to four year ahead forecast.

Jansen and Wang (2006) compare the forecasting performance of the co-integration based ECM between the equity yield on the S&P 500 index and the bond yield with that of univariate models and found ECM superior to the univariate models for longer-horizon forecasts.

3. Methodology

3.1. Background

After collecting the required data (monthly data during 2010M1-2018M12, 108 time-series observations) for Malaysia, we will do a comparison between forecasting power of the 5 estimation methods (ARDL, VECM, DOLS, FMOLS, ARIMA and Exponential Smoothing) for short-time (one year or 12 months) in both static and dynamic forecasts, separately. Financial variables included in the model are credit card, charge card, debit card and e-money which makes payment instruments. Next, the same process will be done for a longer period (5 years) to determine how forecasting performances of the different methods varies over different time horizon. After this, we will turn to models that include payment systems (RENTAS, Interbank GIRO and FPX & Direct Debit) and finally to models that include payment channels (ATM and mobile banking). Internet Banking is excluded in this model as the data for the mentioned duration is not available. The current study overcomes the issue of misspecification by incorporating financial innovation in the money demand function 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) to capture the effect of financial innovations.

Before proceeding to estimation, we need to make sure that the all of the variables (including dependent variable) are non-stationary but when we convert them to first-differenced, they become stationary. In order to do so, we conduct unit root test using the Augmented Dickey-Fuller (ADF) test statistic. Then, we need to find out whether or not these variables cointegrated. Using Johansen Cointegration Test, we conclude that the variables are cointegrated or they have long-run associationship.

The objectives of this analysis is to estimate the demand for money in the presence of financial innovations for the purpose of forecasting money demand in future. We shall use Dynamic OLS (DOLS) and Fully Modified OLS (FMOLS) as superior methods to the OLS for many reasons. Finally, we will do forecasting based on these estimation method. "Root Mean Squared Error" is selected as the benchmark (among other measures) to evaluate the forecasting performance of these methods.

Engle and Granger (1987) state that "co-integration implies the existence of an error correction model (ECM) and ARDL model that links the long-run equilibrium relationship implied by co-integration with the short run dynamic adjustment mechanism that describes how the variables react when they move out of long-run equilibrium." In other words, ECM and ARDL has the advantage of containing both long-run levels and short-run first differences of non-stationary variables.

ARDL. Pesaran et al. (1999) define another property of this method as capable of examine long-run and cointegrating relationships among variables. This gives ARDL an advantage age over 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. Having the same order of integration for variables is a requirement for other approaches. 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. Using ARDL (p,q) technique, Pesaran et al. (1999) incorporated the dynamic heterogeneous panel regression into the error correction model. The advantage of VECM over VAR (which you estimate ignoring VECM) is that it produces more efficient estimates. Another advantage of VECM is that it has a good interpretation with long term and short term equations. If data is non stationary, forecasting with VAR is not possible due to violating stationarity assumption which adds to the benefit of using VECM.

An autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average (ARMA) model fitted to time series data to improve forecasting ability. This model is used when series are non-stationarity so it can be eliminated by applying the "integrated" part of the model that is differencing step. In order to make the model fit the data as well as possible, three features of this kind of model is used: The AR part (regressing the dependent variable on its own lagged values) denoted by p (the order of the autoregressive model), The MA part (a linear combination of error terms whose values occurred contemporaneously and at various times in the past) denoted by q (the order of the moving-average model) and the "integrated" part (replacing data values with the difference between their values and the previous values) denoted by d , the degree of differencing (Hyndman and Athanasopoulos, 2015).

When two out of the three terms are zeros, the model is reduced to a based one. For example, ARIMA (1,0,0) which refers to a general form (ARIMA(p,d,q)) is actually AR(1), ARIMA(0,1,0) is I(1), and ARIMA(0,0,1) is MA(1). Box–Jenkins suggested an approach to estimate ARIMA models.

“Exponential smoothing is a time series forecasting method for univariate data. Time series methods like the Box-Jenkins ARIMA family of methods develop a model where the prediction is a weighted linear sum of recent past observations or lags. Exponential smoothing forecasting methods are similar in that a prediction is a weighted sum of past observations, but the model explicitly uses an exponentially decreasing weight for past observations” (Brownlee, 2018).[1]

For the purpose of forecast evaluation, first we choose “Root Mean Squared Error” (RMSE) as benchmark. This statistic refers to the gap between forecasted money demand and actual money demand in logarithm form. Smaller RMSE means better forecasting or more predictive power.

3.2. Specification

The general form of the theory of money demand can be represented as below:

$$\frac{M_t}{P_t} = \Phi(R_t, Y_t)$$

where M_t is the demand of nominal money balances, P_t is the price index that is used to convert nominal balances to real balances, Y_t is the scale variable relating to activity in the real sector of the economy (here, GDP as the best proxy for such a variable), and R_t is the opportunity cost of holding money (here, the interest rate as the best proxy). We start the

[1] https://machinelearningmastery.com/exponential-smoothing-for-time-series-forecasting-in-python/

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 $M^d = (Y_t, R_t, r^*)$, (Serletis, 2007) that is:

$$\text{Log}\left(\frac{M_t^*}{P_t}\right) = \alpha + \beta_1 \log Y_t + \beta_2 R_t + \beta_3 r_t^* + \varepsilon_t$$

The coefficient of interest β_3 which represents the effect of financial innovation on money demand is expected to be negative according to most of the literature on financial innovation (see Arrau et al (1995), Lippi and Secchi (2009) and Attanasio et al (2002)) although a few studies such as Hye (2009) and Mannah-Blankson and Belyne (2004) do indicate a positive relationship. The coefficients on income β_1 and the Treasury bill rate β_2 are expected to be positive and negative respectively as money demand theory predicts. The data are monthly, from 2010(M1) to 2018(M12).

In estimating the effect of financial innovation on the demand for money, we estimate a semi log-linear specification of the form:

$$\text{Log MOD} = \beta_0 + \beta_1 \text{Log GDP} + \beta_2 \text{ RIR} + \beta_3 \text{Log (Financial Innovation)} + e_t$$

The conventional theory of demand for money is the basis for this specification. We use a traditional specification of the conventional demand for money using ARDL model where MOD denotes real demand for money, GDP denotes real gross domestic product, RIR is the real interest rate (3-months treasury bill), Financial Innovation is the proxy for capturing the effect of financial innovations on the demand for money, and e_t is the error term. Data is collected from the official website of the Bank Negara Malaysia (BNM). Consumer Price Index (CPI) was used to convert nominal data to real data. Real interest rate (RIR) was calculated using the formula: (1+ (NIR)) / (1+ (IFR)) where NIR is the nominal interest rate and IFR is the inflation rate.

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) Direct Debit and Financial Process Exchange.

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, and 3) Mobile payment.

The first regression includes CRC (the nominal value of credit cards transactions), CHC (the nominal value of charge cards transactions), DEC (the nominal value of debit cards transactions) and EMO (the nominal value of E-money transactions).

The second regression includes REN (the nominal value of RENTAS transactions), IBG (the nominal value of Interbank GIRO transactions) and FDD (the nominal value of FPX and Direct Debit transactions).

The third regression includes ATM (the nominal value of ATM transactions), MOB (the nominal value of Mobile Banking transactions). IB (the nominal value of Internet Banking transactions) is excluded in the regression as the data are not available.

The data are monthly, from 2010(M1) to 2018(M12) for all of the models and were retrieved from the official website of Bank Negara Malaysia. They are all in million Ringgits (real terms), and in logarithm form except for interest rate (RIR).

The study follows a traditional money demand specification by Holly (1999), Rinaldi (2001), Anderson-Reid (2008), Hamori (2008), Hataiseree (2010), Rauf and Khan (2012), Oyelami and Yinusa (2013), Kasekende (2016), ect.

4. Empirical findings

We compare the predictive power of the models in 3 ways: First, we do a comparison between static and dynamic forecasts for each model. Second, we compare the forecasting accuracy of dynamic forecasts of different models to determine which model provides superior dynamic forecast. Third, we do the same as for static forecasting and select the model with the best forecasting performance. Fourth, based on the forecasting evaluations, we decide which forecast (static or dynamic) is superior. All of the forecasts are done in short-time dimension (1-year or 12-months) and long-time dimension (5-years or 60 months) to determine how forecasting performances varies over time

After collecting the required data (monthly data during 2010M1-2018M12, 108 time-series observations) for Malaysia, we will do a comparison between forecasting power of the 5 estimation methods (ARDL, VECM, DOLS, FMOLS and ARIMA) for long time (5 year or 60 months) in both static and dynamic forecasts, separately. Financial variables included in the model are credit card, charge card, debit card and e-money which makes payment instruments.

Next, the same process will be done for a short period (1 years or 12 months) to determine how forecasting performances of the different methods varies over different time horizon. After this, we will turn to models that include payment systems (RENTAS, Interbank GIRO and FPX & Direct Debit). Finally we target models that include payment channels (ATM and mobile banking). Internet Banking is excluded in this model as the data for the mentioned duration is not available.

The current study overcomes the issue of misspecification by incorporating financial innovation in the money demand function using separate measures of payment instruments (credit card, charge card, debit card, e-money), payment systems (RENTAS, Interbank GIRO, FPX and direct debit) and payment channels (ATM, mobile banking) to capture the effect of financial innovations.

4.1. Payment Instruments (PI)

4.1.1. Unit root tests (Augmented Dickey-Fuller test statistic)

Unit root tests show that these series are non-stationary in levels, but become stationary after first differencing.

Table 1: Unit root tests (Probabilities)

Variables	Level (Prob.)	First Differenced (Prob.)
LMOD	0.3861	0.0000
LGDP	0.4759	0.0001
RIR	0.3702	0.0000
LCRC	0.2203	0.0000
LCHC	0.4212	0.0000
LDEC	0.9029	0.0000
LEMO	0.8269	0.0000

Table 2 provides another way of looking at the test of the stationarity of variables by applying ADF test. Test results indicate that series are integrated of order one over the sample period as all of the series are non-stationary in the level but after first differencing, they become stationary regardless of the lag length or the information criteria.

Table 2: Unit root tests (t-Statistic)

Variables	ADF Test Statistic	10% Critical Value	5% Critical Value	1% Critical Value	Test Result
Log level of each series					
LMOD	-2.383298	-3.151673	-3.452358	-4.046072	Fail to reject
LGDP	-2.214722	-3.154273	-3.456805	-4.055416	Fail to reject
RIR	-0.793189	-1.614713	-1.943912	-2.587172	Fail to reject
LCRC	-2.747966	-3.154562	-3.457301	-4.056461	Fail to reject
LCHC	-1.71412	-2.581596	-2.8892	-3.493747	Fail to reject
LDEC	-0.405447	-2.405447	-2.8922	-3.500669	Fail to reject
LEMO	-0.755846	-2.581595	-2.8892	-3.493747	Fail to reject
Log difference of each series					
LMOD	-10.45483	-3.151911	-3.452764	-4.046925	Reject
LGDP	-28.80087	-3.153989	-3.456319	-4.054393	Reject
RIR	-12.87554	-3.152153	-3.453179	-4.047795	Reject
LCRC	-11.802256	-3.154562	-3.457301	-4.056461	Reject
LCHC	-12.42993	-2.581596	-2.8892	-3.493747	Reject
LDEC	-8.063768	-2.583192	-2.8922	-3.500669	Reject
LEMO	-10.68131	-2.581596	-2.8892	-3.493747	Reject

4.1.2. Optimum lag selection for the autoregressive model to be estimated by DOLS and FMOLS

According to Table 3, we choose the number of lags with corresponding minimum AIC/SC, that is, 1. It means that in estimating the model, we have to include only one lag of the dependent variable. Therefore, we proceed to cointegration test (and later estimation) using 1 lag.

Table 3: VAR Lag Order Selection Criteria

Lag	LogL	LR	PPE	AIC	SC	HQ
0	79.86506	NA	0.009752	-1.792388	-1.764236	-1.781046
1	301.2423	4326918*	6.51e-05*	-6.800960*	-6.744657*	-6.778277*
2	301.5404	0.575977	6.62e-05	-6.785009	-6.700555	-6.750985
3	301.6077	0.128393	6.76e-05	-6.763811	-6.651204	-6.718444
4	303.3378	3.263576	6.65e-05	-6.780404	-6.639646	-6.723696
5	304.7621	2.654405	6.59e-05	-6.790047	-6.621138	-6.721998
6	305.6683	1.668330	6.60e-05	-6.787916	-6.590856	-6.708526
7	305.8089	0.255502	6.73e-05	-6.768383	-6.543171	-6.677651
8	305.8213	0.022428	6.89e-05	-6.745940	-6.492576	-8.643866

* indicates lag order selected by the criterion. **LR**: sequential modified LR test statistic (each test at 5% level); **FPE**: Final prediction error; **AIC**: Akaike information criterion; **SC**: Schwarz information criterion; **HQ**: Hannan-Quinn information criterion.

It is clear from Table (4-2) that all of the criterias refer to 1 lag as the optimum number of lags.

4.1.3. Optimum lag selection for VECM

Before estimating VECM, we need to know how many lags should be included in the model. VAR Lag Order Selection Criteria leads us to the optimum number of lags. Too many lags lead to loss of degree of freedom. That is why, instead of choosing 8 lags according to AIC, 1 lag is chosen according to SC.

Table 4: VAR Lag Order Selection Criteria

Lag	LogL	LR	PPE	AIC	SC	HQ
0	547.9099	NA	1.08e-14	-12.29341	-12.09635	-12.21402
1	1032.613	881.2792	5.43e-19	-22.19576	-20.61927*	-21.56063*
2	1091.500	97.69897	4.42e-19	-22.42047	-19.46455	-21.22960
3	1147.179	83.51830*	4.00e-19*	-22.57226	-18.23692	-20.82566
4	1187.691	54.32274	5.38e-19	-22.37935	-16.66458	-20.07701
5	1239.189	60.86076	6.07e-19	-22.43611	-15.34192	-19.57804
6	1292.897	54.92928	7.24e-19	-22.54312	-14.06951	-19.12932
7	1334.137	35.61601	1.33e-18	-22.36675	-12.51371	-18.39721
8	1426.916	65.36713	9.52e-19	-23.36173*	-12.12926	-18.83645

4.1.4. Unrestricted Cointegration Rank test or (test of the existence of long-run associationship)

The last step before proceeding to estimations, is to make sure that the variables used in the model are cointegrated or they have a long-run associationship. For this purpose, we use two tests namely, Trace test and Max-eigenvaue test. According to Table 5, Trace test indicates 2 cointegration equation at the 0.05 level.

Table 5: Trace test

Hypothesized No.of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical value	Prob.**
None*	0.547684	198.2924	125.6154	0.0000
At most 1*	0.387305	116.5750	95.75366	0.0009
At most 2	0.240351	66.11652	69.81889	0.0952
At most 3	0.165011	37.80198	47.85613	0.3107
At most 4	0.111606	19.22730	29.79707	0.4767
At most 5	0.062145	7.038262	15.49471	0.5732
At most 6	0.004164	0.429747	3.841466	0.5121

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Table 6: Max-eigenvalue test

Hypothesized No.of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical value	Prob.**
None*	0.547684	81.71748	46.23142	0.0000
At most 1*	0.387305	50.45843	40.07757	0.0024
At most 2	0.240351	28-31454	33.87687	0.1994
At most 3	0.165011	18.57467	27.58434	0.4481
At most 4	0.111606	12.18904	21.13162	0.5291
At most 5	0.062145	6.608515	14.26460	0.5364
At most 6	0.004164	0.429747	3.841466	0.5121

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Max-eigenvaue test also indicates 2 cointegration equation at the 0.05 level Therefore, there is strong evidence of existence of cointegration among variables. In other words, the variables have long run association.

4.1.5. Five-years/sixty-months (2014M1-2018M12) in-sample forecast

We forecast the demand for money (MOD) in logarithm form for 5 years ahead using DOLS, FMOLS, ARDL, VECM and ARIMA models. The data contains monthly series from 2010M1 to 2018M12. Out of this data, we take a sample from 2010M1 to 2013M12 for estimation and use the estimated parameters to forecast MOD (using the methods) for the period 2014M1-2018M12 which is 5 years (60 months). The conventional determinants of money demand, (gross domestic product and interest rate) along with financial variables will be included in the models and the forecast will be done. Then, we compare the actual values with the dynamic/static forecasted values to determine the predictive power of the two models as follow: 1) The actual values will be compared with the dynamic and static forecasted values for each model, 2) The actual values will be compared with the dynamic forecasted values for all the models together 3) The actual values will be compared with the static forecasted values for all the models together, 4) We will determine which forecast (either dynamic or static) has more predictive power for a specific model, 5) We will determine which model has the best forecasting power when it comes to dynamic forecasting, and 6) We will determine which model has the best forecasting power when it comes to static forecasting

The difference between dynamic and static forecasts arises because of their estimation procedure. While the value of the previous forecasted value of the dependent variable is used to compute the next one by dynamic forecast, static forecast uses the actual value for each subsequent forecast.

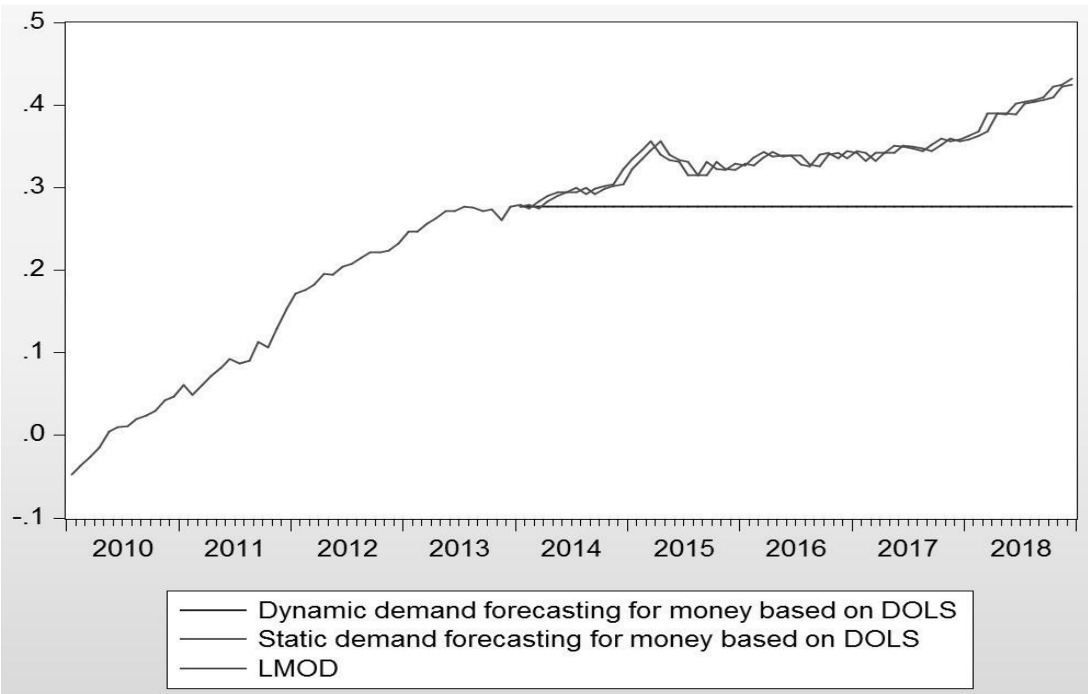
Table 7: DOLS estimation output

Variable	Coefficient	Std. Error	!t-Statistic	Prob.
LMOD(-1)	1.000000	2.59E-13	3.86E+12	0.0000
LGDP	-1.66E-13	6.61E-14	-2.505841	0.0227
RIR	-1.25E-14	1.12E-14	-1.120482	0.2781
LCRC	2.41E-13	1.23E-13	1.952236	0.0676
LCHC	-3.79E-14	1.09E-13	-0.348359	0..318
LDEC	-1.74E-13	8.77E-14	-1.987295	0.0632
LEMO	-4.70E-14	4.62E-14	-1.016535	0.3236
R-squared	1.000000		Mean dependent var	0.153620
Adjusted R-squared	1.000000		S.D.dependent var	0.096501
S.E. of regression	6.43E-15		Sum squared resid	7.04E-28
Long-run variance	7.79E-29			

Note: Fixed leads and lags specification (lead=1, lag=1). Long-run variance estimate (Bartlett kernel, Newey-West fixed bandwidth.

Here, we estimated the model including payment instruments using DOLS with one lag of the dependent variable as indicated by VAR Lag Order Selection Criteria in Table 3.

Figure 1: Comparing dynamic and static forecasts based on DOLS estimation



According to Figure 1, while static forecast closely follows the actual values of the dependent variable, dynamic forecast divert from the actual value from the starting point of forecasting (2019M1) and it distances most from the actual value at the end of forecasting period (2023M12) meaning that the gap between actual values and forecasted values for dynamic forecast is much wider than that of static forecast. Nest, we turn to FMOLS to determine how these two forecasts behave based on this method.

Table 8: FMOLS estimation output

Variable	Coefficient	Std.Error	t-Statistic	Prob.
LMOD(-1)	0.930718	0.045930	20.26403	0.0000
LGDP	-0.021579	0.010383	-2.078286	0.0443
RIR	0.006232	0.001709	3.647252	0.0008
LCRC	0.047669	0.016448	2.898245	0.0061
LCHC	0.013137	0.013061	1.005820	0.3207
LDEC	0.014671	0.015574	0.941995	0.3520
LEMO	-0.015067	0.009497	-1.586457	0.1207
R-squared	0.995167		Mean dependent var	0.149722
Adjusted R-squared	0.994423		S.D.dependent var	0.099019
S.E. of regression	0.007395		Sum squared resid	0.002133
Long-run variance	1.91E-05			

Note: Fixed leads and lags specification (lead=1, lag=1). Long-run variance estimate (Bartlett kernel, Newey-West fixed bandwidth

Figure 2: Comparing dynamic and static forecasts based on FMOLS estimation

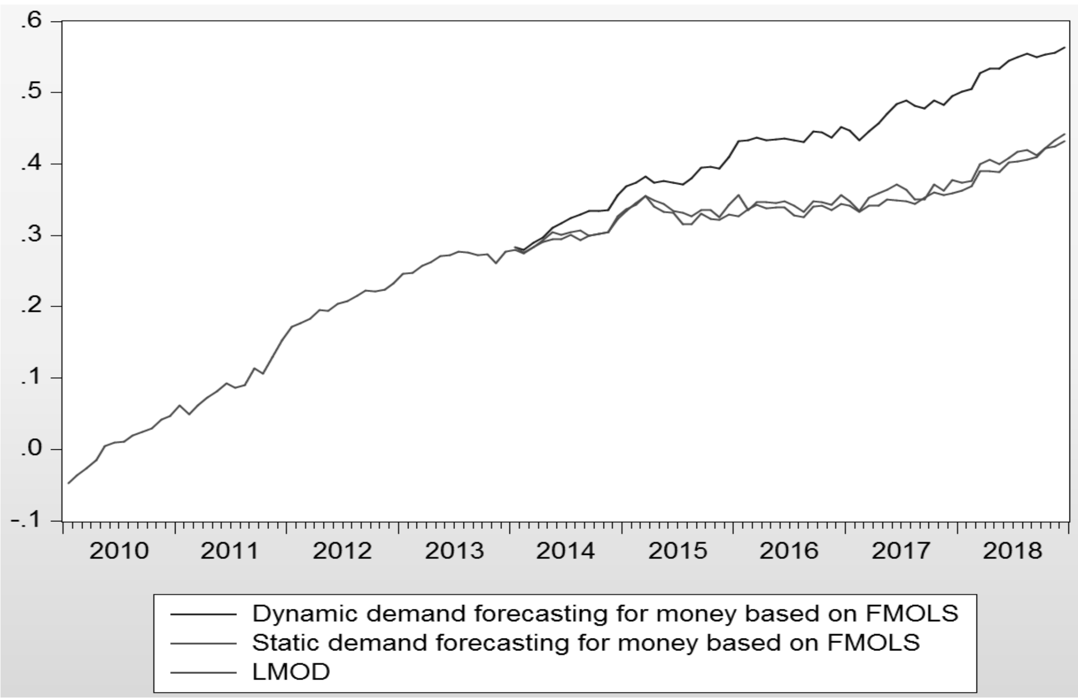


Figure 2 offers another way of looking at this comparison. While static forecast closely follows the actual values, dynamic forecast gets further distant (moves further from actual values) as times goes by. Now, we obtain forecasts based on the estimated coefficients from ARDL method.

Table 9: ARDL estimation output

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LMOD(-1)	0.297882	0.146440	2.034160	0.0519
LMOD(-2)	0.238265	0.159840	1.490643	0.1476
LGDP	0.097817	0.090585	1.079839	0.2898
LGDP(-1)	-0.261708	0.150252	-1.741796	0.0929
LGDP(-2)	-0.137040	0.150713	-0.909281	0.3712
LGDP(-3)	0.266963	0.095006	2.809947	0.0091
RIR	0.008358	0.002552	3.275579	0.0029
RIR(-1)	0.007048	0.002722	2.589190	0.0153
RIR(-2)	0.009549	0.003076	3.104933	0.0044
LCRC	0.109198	0.039410	2.770798	0.0100
LCHC	0.000716	0.024714	0.028989	0.9771
LDEC	-0.020566	0.030028	-0.684907	0.4992
LDEC(-1)	0.084128	0.025018	3.362678	0.0023
LDEC(-2)	-0.014388	0.024626	-0.584274	0.5639
LDEC(-3)	0.028572	0.023337	1.224336	0.2314
LDEC(-4)	0.052678	0.020244	2.602148	0.0149
LEMO	-0.019713	0.015556	-1.267172	0.2159

R-squared	0.997954	Mean dependent var	0.157451
Adjusted R-squared	0.996741	S.D.dependent var	0.094093
S.E. of regression	0.005371	Akaike info criterion	-7.331166
Sum squared resid	0.000779	Schwarz criterion	-6.641820
Log likelihood	178.2856	Hannan-Quinn criter.	-7.075523
Durbin-Watson stat	2.016813		

Selected Model: ARDL(2, 3, 2, 0, 0, 4, 0). Model selection method: Akaike info criterion (AIC).

The best ARDL model is selected automatically by the software using Akaike info criterion (AIC). Software has chosen 2 lags of dependent variable (money demand), 3 lags of the first independent (explanatory) variable which is GDP, 2 lags of real interest rate (RIR), no lags of credit cards (CRC), no lags of charge cards (CHC), 4 lags of debit cards (DEC) and finally no lags of e-money (EMO) which gives the model the minimum AIC. This selected ARDL model is used to obtain dynamic and static forecasts for the purpose of comparison.

Figure 3: Comparing dynamic and static forecasts based on ARDL estimation

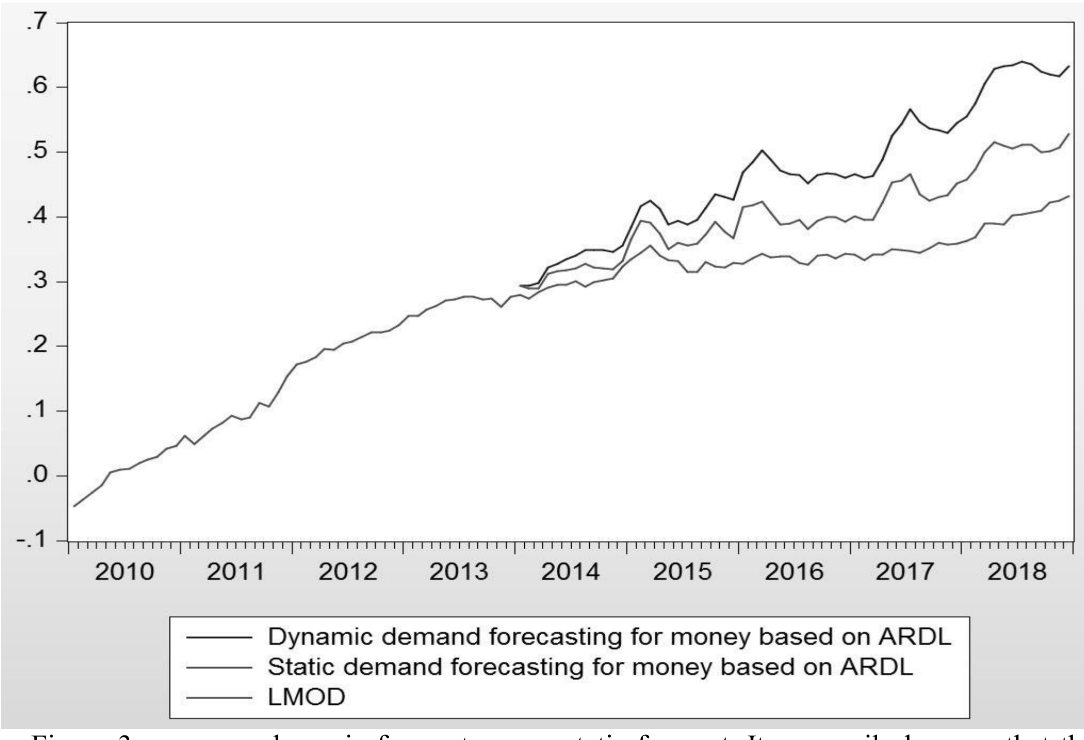


Figure 3 compares dynamic forecast versus static forecast. It can easily be seen that the static forecast is closer to actual values compared to dynamic forecast for the entire forecasting period. Table 10 summarized the results of forecasting measures.

Table 10: Forecast measures based on static forecast using different methods

Forecast Measures/Methods	DOLS	FMOLS	ARDL
RMSE	0.0080	0.0102	0.0694
MAE	0.0063	0.0082	0.0613
MAPE	1.8611	2.4025	17.344
TIC	0.0117	0.0147	0.0922
BP	0.1036	0.6195	0.7803
VP	0.0154	0.0237	0.1679
CP	0.8809	0.3566	0.0516
TUC	1.0000	1.2453	8.0760
SM	1.8732	2.3588	15.691

RMSE: Root Mean Squared Error; **MAE**: Mean Absolute Error; **MAPE**: Mean Abs. Percent Error; **TIC**: Theil inequality Coefficient; **BP**: Bias Proportion; **VP**: Variance Proportion; **CP**: Covariance Proportion; **TUC**: Theil U2 Coefficient; **SM**: Symmetric MAPE.

So far the two important conclusions are that 1) Static forecast is superior to dynamic forecast for all of the methods and 2) DOLS has the best forecasting performance with regard to static forecast (closely followed by FMOLS).

Next, we are eager to find out how these forecasts behave under VECM estimation. Therefore, we proceed to derive long-run (cointegration equations) and short-run (error corrections) estimates as follow.

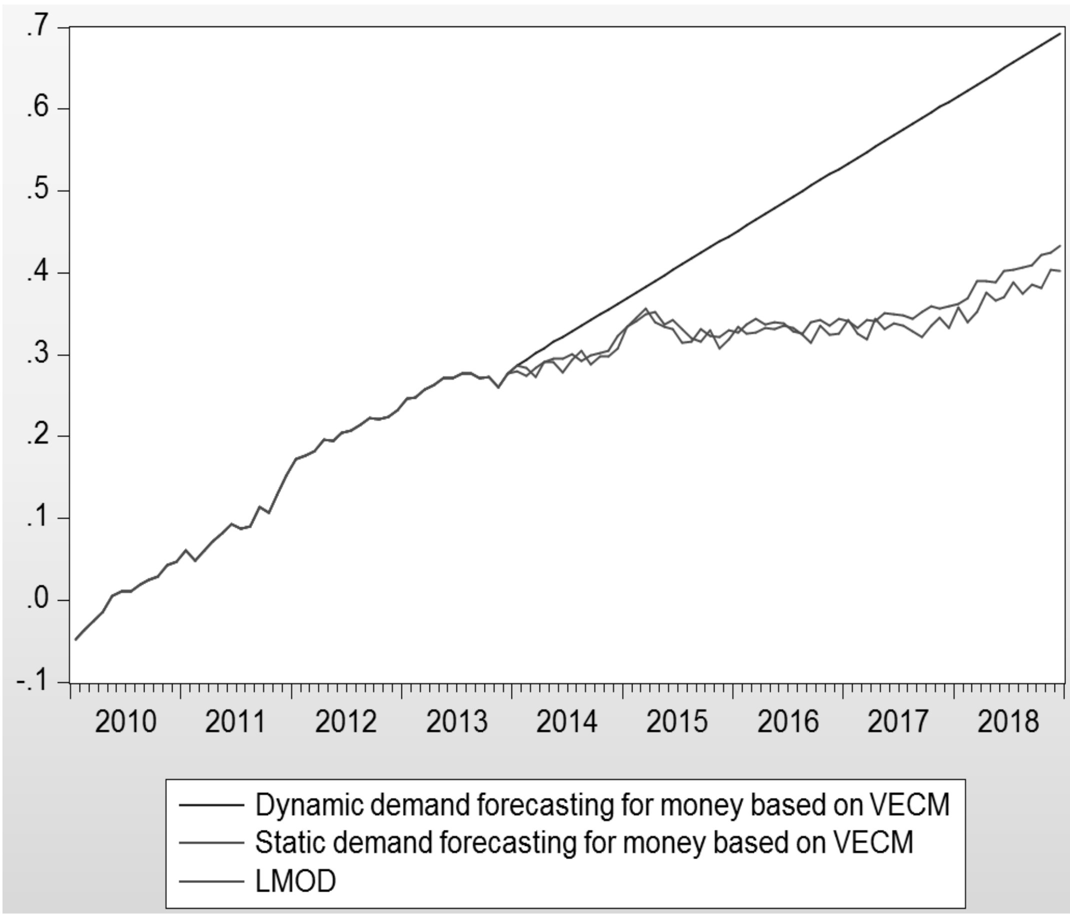
Table 11: VECM estimation output (Cointegration equation)

Cointegrating Eq:	CointEq1	CointEq2
LMOD(-1)	1.000000	0.000000
LGDP(-1)	0.000000	1.000000
RIR(-1)	-0.001125	-0.053485
	(0.00761)	(0.01465)
	[-0.14791]	[-3.65045]
LCRC(-1}	-0.019909	-0.447805
	(0.08088)	(0.15575)
	[-0.24616]	[-2.87518]
LCHC(-1)	-0.434430	0.381156
	(0.05416)	(0.10430)
	[-8.02078]	[3.65433]
LDEC(-1}	-0.073478	-0.300029
	(0.02909)	(0.05603)
	[-2.52558]	[-5.35522]
LEM0(-1)	-0.103097	0.127227
	(0.03531)	(0.06800)
	[-2.91965]	[1.87100]
c	-0.592166	-3.013661

Table 12: VECM estimation output (Error corrections)

Error Correction:	D(LMOD)	D(LGDP)	D(RIR)	D(LCRC)	D(LCHC)	D(LDEC)	D(LEMO)
CointEq1	0.121669	-0.320621	18.55386	1.239785	2.410860	0.369553	1.296330
	(0.10613)	(0.14551)	(4.72210)	(0.69572)	(0.56256)	(0.71949)	(0.96413)
	[1.14639]	[-2.20348]	[3.92916]	[1.78202]	[4.28555]	[0.51363]	[1.34455]
CointEq2	-0.002695	-0.229032	7.713456	0.954660	0.023648	0.557209	-0.163906
	(0.05278)	(0.07236)	(2.34839)	(0.34599)	(0.27977)	(0.35782)	(0.47948)
	[-0.05105]	[-3.16503]	[3.28457]	[2.75918]	[0.08453]	[1.55724]	[-0.34184]
D(LMOD(-1))	-0.262062	0.032883	-7.878064	0.299714	-1.988323	-0.330265	-3.866799
	(0.18870)	(0.25871)	(8.39581)	(1.23698)	(1.00021)	(1.27925)	(1.71421)
	[-1.38876]	[0.12711]	[-0.93833]	[0.24230]	[-1.98790]	[-0.25817]	[-2.25573]
D(LGDP(-1))	-0.104868	0.652408	-5.847686	0.125169	0.952055	-0.789085	0.124432
	(0.10311)	(0.14136)	(4.58751)	(0.67589)	(0.54652)	(0.69899)	(0.93665)
	[-1.01708]	[4.61523]	[-1.27470]	[0.18519]	[1.74203]	[-1.12890]	[0.13285]
D(RIR(-1))	0.002656	-0.016223	-0.372039	0.067253	0.006253	0.063908	-0.013054
	(0.00294)	(0.00402)	(0.13060)	(0.01924)	(0.01556)	(0.01990)	(0.02667)
	[0.90493]	[-4.03115]	[-2.84862]	[3.49512]	[0.40189]	[3.21151]	[-0.48955]
D(LCRC(-1))	0.027704	-0.062216	-1.541274	0.303438	0.161772	0.578834	0.415485
	(0.02897)	(0.03971)	(1.28873)	(0.18987)	(0.15353)	(0.19636)	(0.26313)
	[0.95648]	[-1.56673]	[-1.19596]	[1.59812]	[1.05369]	[2.94782]	[1.57903]
D(LCHC(-1))	0.000176	0.037257	3.833641	-0.317018	-0.136928	-0.380162	0.421174
	(0.02359)	(0.03234)	(1.04956)	(0.15463)	(0.12504)	(0.15992)	(0.21429)
	[0.00745]	[1.15200]	[3.65260]	[-2.05010]	[-1.09509]	[-2.37721]	[1.96540]
D(LDEC(-1))	0.024303	-0.196857	3.886109	-0.323921	-0.008500	-0.720520	-0.425430
	(0.03589)	(0.04920)	(1.59670)	(0.23525)	(0.19022)	(0.24328)	(0.32601)
	[0.67720]	[-4.00111]	[2.43384]	[-1.37695]	[-0.04469]	[-2.96164]	[-1.30498]
D(LEMO(-1))	0.010797	-0.017842	0.375014	0.087029	-0.072407	-0.026883	-0.323613
	(0.01545)	(0.02119)	(0.68758)	(0.10130)	(0.08191)	(0.10476)	(0.14039)
	[0.69868]	[-0.84211]	[0.54541]	[0.85910]	[-0.88396]	[-0.25660]	[-2.30516]
C	0.008368	0.005196	-0.028106	0.012654	0.022936	0.045914	0.049877
	(0.00201)	(0.00275)	(0.08932)	(0.01316)	(0.01064)	(0.01361)	(0.01824)
	[4.16815]	[1.88799]	[-0.31467]	[0.96158]	[2.15546]	[3.37368]	[2.73493]

Figure 4: Comparing dynamic and static forecasts based on VECM Estimation



Again, superiority of static forecast to dynamic forecast is proven by looking at Figure 4. The last two method we are going to investigate are ARIMA and ETS Smoothing models which are non-structural and non-cointegration based models that are specially designed for the purpose of forecasting. This kind of model does not rely on any structural functions or specifications. In another words, we aim at comparing the forecasting performance of cointegration based technique with another forecasting technique which do not impose co-integration restrictions (ARIMA and ETS Smoothing). Since the purpose of this study is mainly to forecast future movements of the money demand, we examine and compare the forecasting technique that rely on a structural relationship between money and other real variables (DOLS, FMOLS, ARDL and VECM) with that of a model that does not (ARIMA). Therefore, we first proceed to Automatic ARIMA forecasting.

Table 13: Estimation method: ARMA Maximum Likelihood (BFGS)

Variable	Coefficient	Std. Error	!-Statistic	Prob.
c	0.197935	0.259290	0.763374	0.4508
LGDP	-0.084927	0.058439	-1.453246	0.1559
RIR	0.005972	0.002236	2.670612	0.0118
LCRC	0.073017	0.018964	3.850179	0.0005
LCHC	0.014008	0.023907	0.585939	0.5620
LDEC	0.002893	0.011127	0.259959	0.7966
LEMO	-0.023436	0.024089	-0.972908	0.3379
AR(1)	0.337635	0.527763	0.639748	0.5269
AR(2)	0.904038	0.418247	2.161496	0.0382
AR(3)	-0.213961	0.247987	-0.862794	0.3947
AR(4)	-0.441341	0.171205	-2.577857	0.0148
MA(1)	-1.148590	1242.783	-0.000924	0.9993
MA(2)	-0.682495	785.6358	-0.000869	0.9993
MA(3)	0.844255	2044.015	0.000413	0.9997
SIGMASQ	2.29E-05	0.011784	0.001944	0.9985
R-squared	0.658893		Mean dependent var	0.006906
Adjusted R-squared	0.509659		S.D.dependent var	0.008283
S.E. of regression	0.005800		Akaike info criterion	-7.030522
Sum squared resid	0.001076		Schwarz criterion	-6.440050
Log likelihood	180.2173		Hannan-Quinn criter.	-6.808324
F-statistic	4.415156		Durbin-Watson stat	1.979995
Prob(F-statistic)	0.000249			
Inverted AR Roots	.84+.34i		.84-.34i -.67+.28i	-.67-.28i
Inverted MA Roots	1.00+.08i		1.00-.08i -.84	

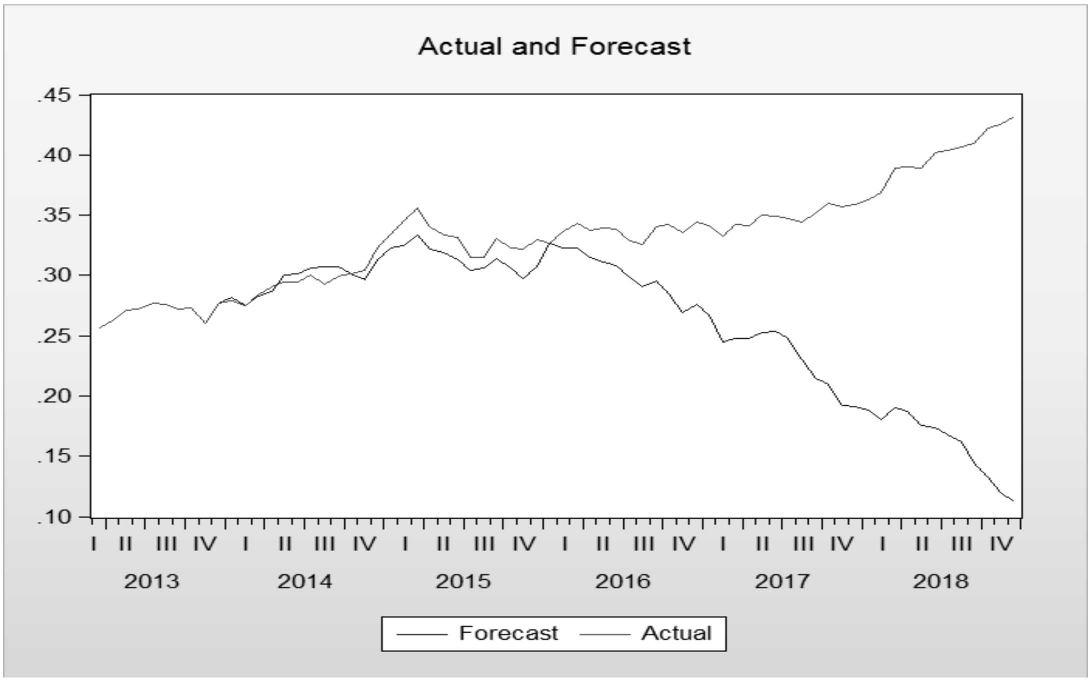
These estimates are based on a model that has the lowest AIC value which is ARDL (4,3)(0,0). In another words, an ARIMA model consisting of an autoregressive model of order 4 and a moving average model of order 3 provides the minimum AIC and therefore is chosen as the best ARIMA model.

Table 14: Model selection criteria table

Model	Logl	A1C*	BIC	HQ
(4,3)(0,0)	180.217278	-6.884053	-6.299303	-6.663075
(0,3)(0,0)	175.710100	-6.862921	-6.434104	-6.700870
(2,1)(0,0)	175.376312	-6.849013	-6.420196	-6.686962
(4,4)(0,0)	180.245767	-6.843574	-6.219840	-6.607864
(0,4)(0,0)	175.925835	-6.830243	-6.362443	-6.653461
(1,3)(0,0)	175.878002	-6.828250	-6.360450	-6.651468
(3,1)(0,0)	175.606033	-6.816918	-6.349118	-6.640136
(1,4)(0,0)	176.554772	-6.814782	-6.307999	-6.623268
(1,0)(0,0)	172.455835	-6.810660	-6.459810	-6.678073
(0,1)(0,0)	172.370306	-6.807096	-6.456246	-6.674509
(4,2)(0,0)	177.356625	-6.806526	-6.260759	-6.600280
(2,3)(0,0)	176.135487	-6.797312	-6.290528	-6.605798
(3,3)(0,0)	176.917228	-6.788218	-6.242451	-6.581972
(3,2)(0,0)	175.873895	-6.786412	-6.279629	-6.594898
(2,2)(0,0)	174.679236	-6.778302	-6.310501	-6.601519
(2,4)(0,0)	176.610278	-6.775428	-6.229661	-6.569182
(2,0)(0,0)	172.514331	-6.771430	-6.381597	-6.624112
(1,1)(0,0)	172.513491	-6.771395	-6.381562	-6.624077
(0,2)(0,0)	172.413293	-6.767221	-6.377387	-6.619902
(3,4)(0,0)	177.120998	-6.755042	-6.170291	-6.534064
(4,0)(0,0)	173.663002	-6.735958	-6.268158	-6.559176
(3,0)(0,0)	172.530423	-6.730434	-6.301617	-6.568384
(1,2)(0,0)	172.518080	-6.729920	-6.301103	-6.567869
(4,1)(0,0)	174.035300	-6.709804	-6.203021	-6.518290
(0,0)(0,0)	168.854722	-6.702280	-6.390413	-6.584425

25 ARIMA models have been estimated. A model with the lowest AIC value (-6.8840) has been selected as the best one, that is, ARIMA(4,3)(0,0). This one will be used for forecasting.

Figure 5: Comparing forecasts values and actual values based on ARIMA estimation



According to Figure 5, beginning with 2016, the gap between actual and forecasted values becomes unusually wide while it was quiet narrow during 2014-2015. We can probably conclude that ARIMA model is fairly good for a short time horizon (1 year, 2 at most) but its forecasting performance gets deteriorated by longer time horizon.

It is time to do forecasting in the context of ETS exponential smoothing. Exponential smoothing is a rule of thumb technique for smoothing time series data using the exponential window function. Exponential smoothing is a time series forecasting method for univariate data that can be extended to support data with a systematic trend or seasonal component. It is a powerful forecasting method that may be used as an alternative to the popular Box-Jenkins ARIMA family of methods.

Table 15: Model selection

Parameters	
Alpha:	0.851646
Beta:	0.000000
Phi:	0.980836
Initial Parameters	
Initial level:	-0.058142
Initial trend:	0.010834
Compact Log-likelihood	140.1318
Log-likelihood	164.9316
Akaike Information Criterion	-270.2637
Schwarz Criterion	-260.9077
Hannan-Quinn Criterion	-266.7280
Sum of Squared Residuals	0.002912
Root Mean Squared Error	0.007789
Average Mean Squared Error	0.000105

Model: A,AD,N - Additive Error, Additive-Dampened Trend, No Season (Auto E=', T= ', S='). Model selection:Akaike Information Criterion. Convergence achieved after 1 iteration.

We see that we have estimated an (A, AD, N) model using data from 2010M1 to 2013M12, and that the estimator converged, but with some parameters at boundary values. The next section of the table shows the smoothing parameters (α, β, φ) and initial parameters. Note the presence of the boundary zero values for β which indicate that the trend components do not change from their initial values.

Hyperparameters are: Alpha: Smoothing factor for the level, Beta: Smoothing factor for the trend, Trend Type: Additive or multiplicative, Dampen Type: Additive or multiplicative and Phi: Damping coefficient.

The top portion of the output, shows that the Akaike information criterion selected ETS model is an (M, N, M) specification, with level smoothing parameter estimate $\hat{\alpha}$ = 0.85, and the trend parameter $\hat{\beta}$ = 0 estimated on the boundary.

The bottom portion of the table output contains summary statistics for the estimation procedure. Most of these statistics are self-explanatory. The reported “Compact Log-likelihood” is simply the log-likelihood value absent inessential constants, and is provided to facilitate comparison with results obtained from other sources. The spool contains a multiple graph containing the actual and forecasted values of HS over the estimation and forecast period, along with the decomposition of the series into the level and trend components.

Figure 6: The structure of decomposing money demand into level and trend

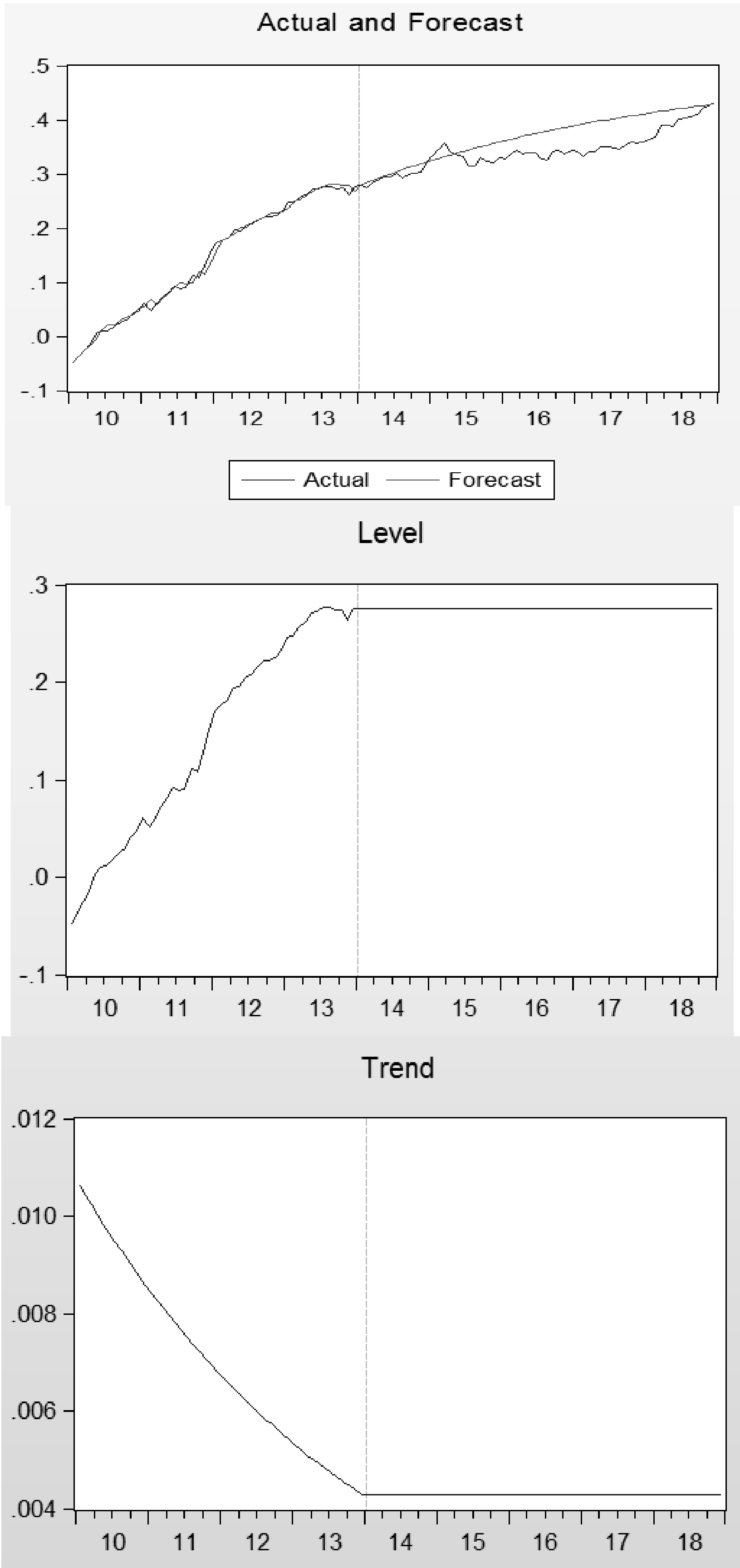


Figure 6 shows the structure of decomposing money demand (in logarithm form) into level and trend (there is no seasonality in this decomposition) and how to automatically split it into its components. These components are defined as follows: 1) Level: The average value in the money demand series, 2) Trend: The increasing or decreasing value in the money demand series, and 3) Seasonality: The repeating short-term cycle in the money demand series.

Decomposition provides a structured way of how to best capture each of these components in a given model. Automatic decomposition (as we used to decompose money demand in our analysis) requires that we need to specify whether the model is additive or multiplicative. This is to be decided according to Table 16 which is A, AD, N (Additive Error, Additive-Dampened Trend, No Season).

Additive decomposition is to create a time series (money demand) comprised of a linearly increasing trend and some random noise and decompose it as an additive model. This is so called Additive decomposition. Multiplicative decomposition is to arrange a quadratic time series (here, money demand) as a square of the time step and then decompose it assuming a multiplicative model.

An additive model is a model that the components are added together:

y(t) = Level + Trend + Seasonality

A multiplicative model is a model that the components are multiplied together:

y(t) = Level * Trend * Seasonality

Our chosen ETS display settings produced both the likelihood table which contains the actual likelihood and Akaike values for each specification, and the forecast comparison table, which presents a subset of the values displayed in the graph.

Table 16: LL-based comparison table

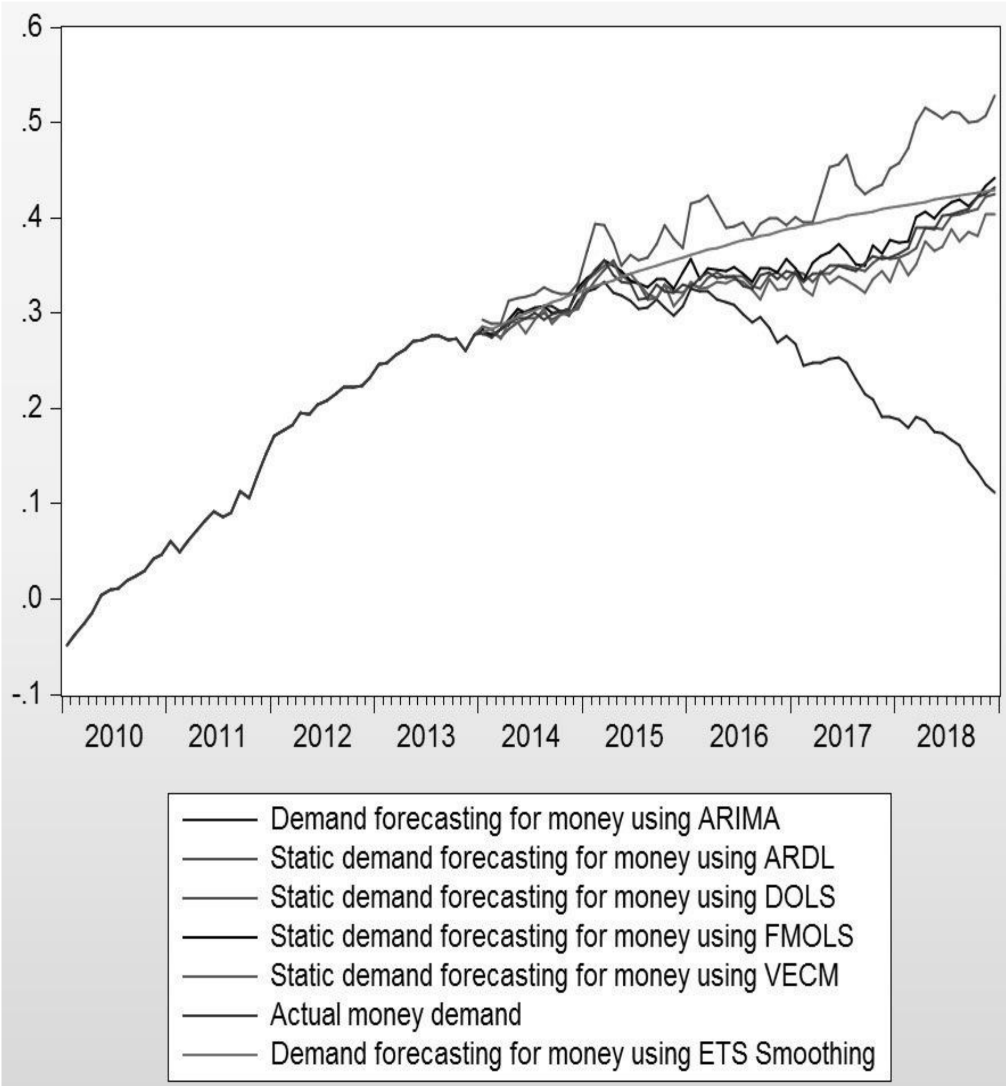
Model	Compact	Likelihood	AIC*	BIC	HQ	AMSE
A,AD,N	140.132	164.932	-270.264	-260.908	-266.728	0.00010
A,A,N	138.044	162.844	-268.089	-260.604	-265.260	0.00013
A,AD,A	150.252	175.052	-266.504	-234.694	-254.483	1.E+100
A,A,A	148.857	173.657	-265.714	-235.775	-254.400	0.00011
A,N,N	125.326	150.126	-246.652	-242 .910	-245.238	0.00033
A,N,A	129.762	154.561	-231.523	-205.326	-221.623	0.00029
M,A,A*	98.8532	123.653	-165.706	-135.767	-154.392	0.00032
M,AD,A	98.9392	123.739	-163.878	-132.068	-151.857	0.00029
M,A,N	85.7370	110.537	-163.474	-155.989	-160.645	0.00015
M,AD,N	85.8037	110.603	-161.607	-152.251	-158.072	0.00016
M,N,N	47.1637	71.9634	-90.3273	-86.5849	-88.9131	0.00047
M,N,A*	51.6077	76.4075	-75.2154	-49.0185	-65.3155	0.00169

2 models fail to converge. Model: M, AD, M – Multiplicative Error, Additive-Dampened Trend, Multiplicative Season (Auto E=, S=*). Model selection: Akaike Information Criterion

According to Table 16, 12 ETS smoothing models have been estimated. A model with the lowest AIC value (-270.264) has been selected as the best one, that is, A,AD,N.

Now, it is time to compare the static forecasts obtained from all of the model estimates along with forecasts from ARIMA and ETS Smoothing to determine which model provides the most accurate forecast among these estimators.

Figure 7: Comparing forecasts using different estimation methods



The models from strongest to weakest predictive powers are: 1) DOLS, 2) FMOLS, 3) VECM, 4) ETS Smoothing, 5) ARDL and 6) ARIMA. Therefore, we proceed to estimate the model including payment instruments using the model that provides the most accurate forecast which is DOLS. Then, we will obtain out-of-sample static forecast (as a superior forecast to dynamic forecast) for the period 2019M1-2023M12.

Table 17: DOLS estimation using selected model for ETS smoothing

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LMOD(-1)	1.000000	3.37E-14	2.97E+13	0.0000
LGDP	1.76E-13	3.09E-14	5.685733	0.0000
RIR	-5.04E-15	2.46E-15	-2.050229	0.0437
LCRC	-3.65E-13	6.59E-14	-5.533128	0.0000
LCHC	-1.70E-14	2.60E-14	-0.653064	0.5157
LDEC	-1.55E-14	1.25E-14	-1.240550	0.2185
LEMO	5.05E-14	1.48E-14	3.414925	0.0010
R-squared	1.000000	Mean dependent var	0.261371	
Adjusted R-squared	1.000000	S.D.dependent var	0.116142	
S.E. of regression	5.67E-15	Sum squared resid	2.48E-27	
Long-run variance	7.33E-29			

Figure 8: Actual money demand and static demand forecasting using DOLS for the period 2019M1-2023M12

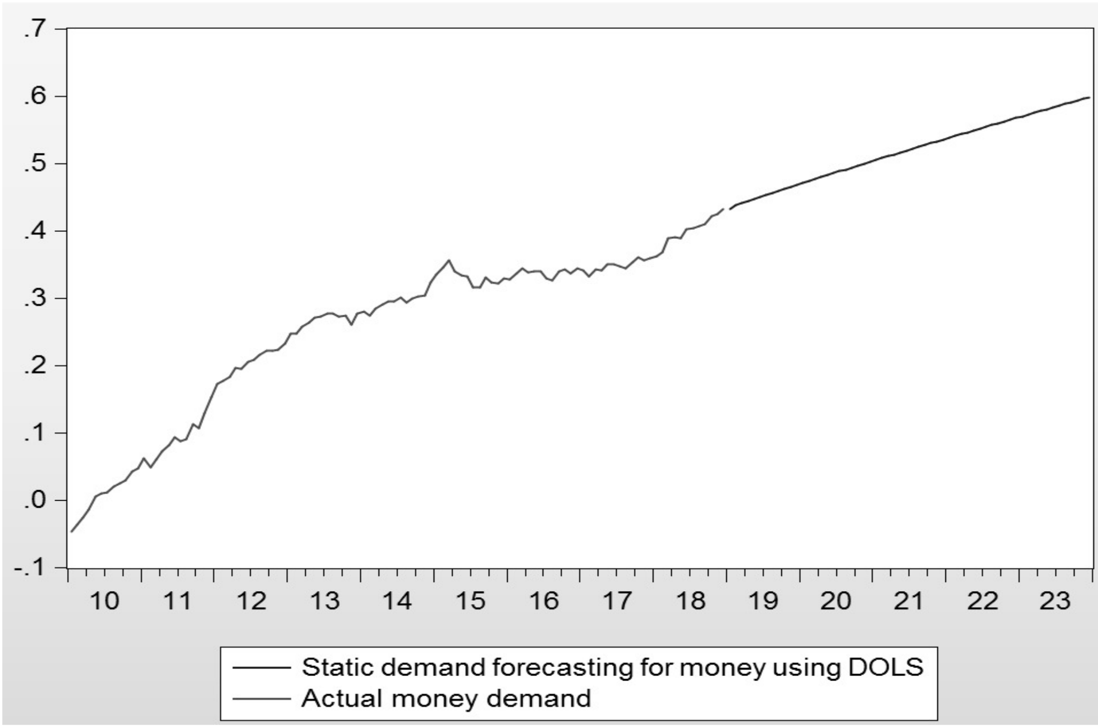


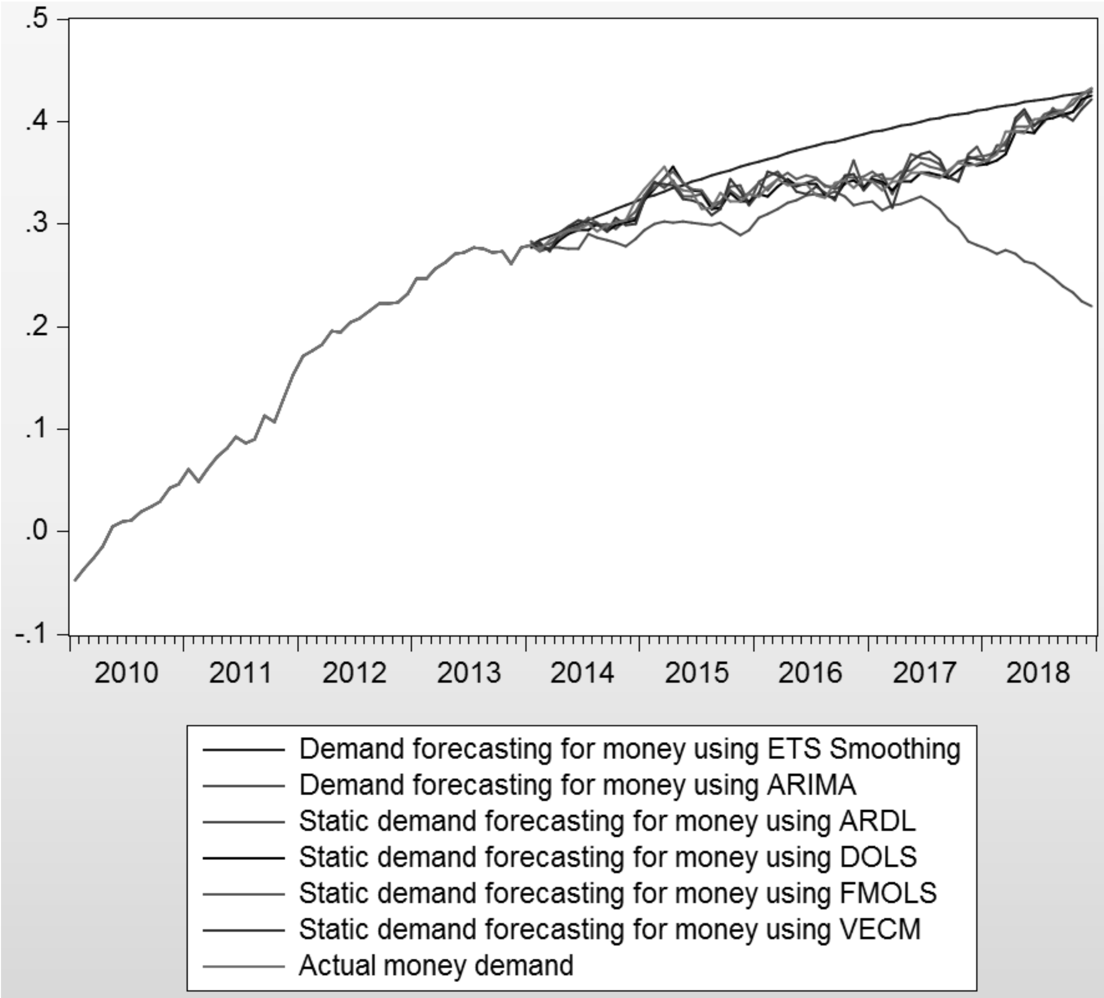
Figure 8 provides the final step in forecasting analysis for the models including payment instruments. The red line in this figure is the actual value of money demand up to 2018M12. After this point, static forecast will be done using the best fitted model for forecasting (DOLS method). It shows that money demand (in logarithm form) continues to growth at a steady rate during the forecast period.

4.2. Payment Systems (PS)

Now, we repeat the same process for model that include payment instruments. Payment instruments include: RENTAS (REN), Interbank GIRO (IBG) and FPX & Direct Debit (FDD)

Again, for all of the model estimates, static forecasts are superior to dynamic forecasts. In order to be compendious, we avoid repeating the same process for the models that include payment systems. We only confine ourselves to the final graphs and tables showing the comparison of static forecasts for all of the models and doing out-of sample forecast based on the chosen model which provides the most accurate forecast.

Figure 9: Comparing static forecasts using different estimation methods



According to Figure 9, DOLS, FMOLS, VECM, and ARDL are almost the same as to predictive power and they can be considered equally powerful for forecasting. Fifth best model is ETS Smoothing followed by ARIMA as the worth model for forecasting. Table 24 offers another way of looking at this comparison between DOLS, FMOLS and ARDL using different forecasting measures and RMSE as the most important of all and the benchmark to decide on the best model.

Table 24: Forecast measures based on static forecast using different methods

Forecast Measures/Methods	DOLS	FMOLS	ARDL
RMSE	0.0080	0.0216	0.0358
MAE	0.0063	0.0195	0.0307
MAPE	1.8611	5.6564	9.0115
TIC	0.0117	0.0305	0.0498
BP	0.1036	0.8062	0.7361
VP	0.0154	0.0487	0.0236
CP	0.8809	0.1449	0.2402
TUC	1.0000	2.5961	4.3840
SM	1.8732	5.4700	8.4999

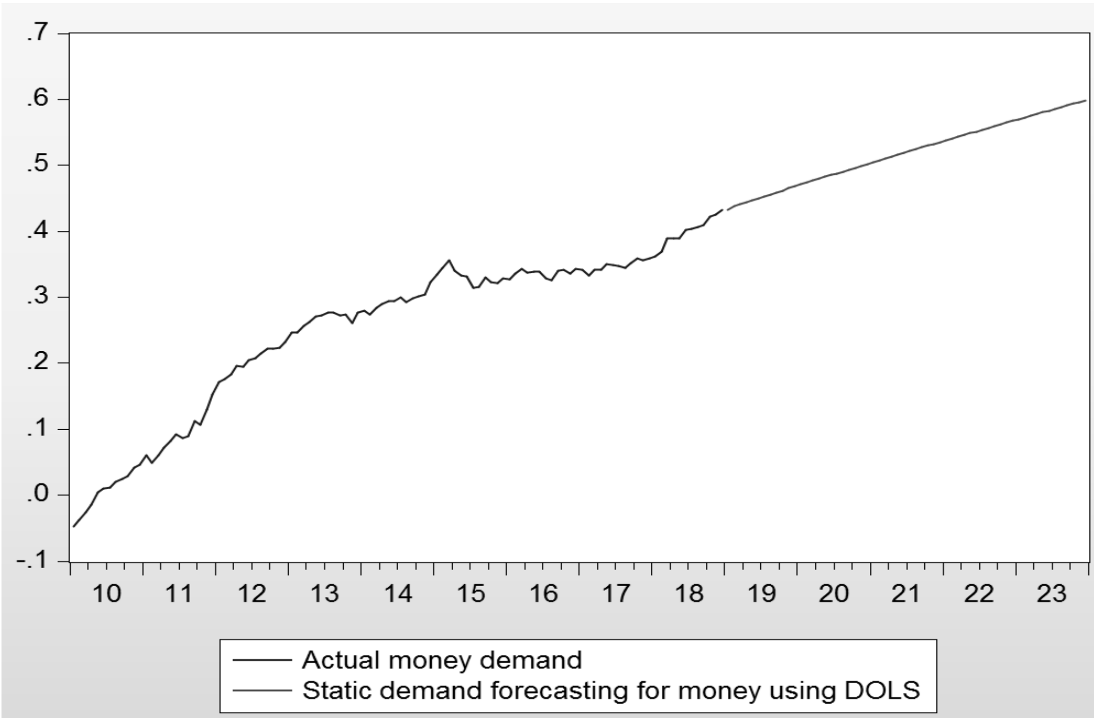
This table confirms the fact that DOLS is marginally superior to other methods so as before, we obtain forecast for out-of-sample period using the estimates from DOLS.

Table 25: DOLS estimation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LMOD(-1)	1.000000	4.32E-14	2.32E+13	0.0000
LGDP	2.87E-13	5.56E-14	5.160729	0.0000
RIR	4.76E-15	4.36E-15	1.092145	0.2780
LREN	-1.57E-13	3.15E-14	-5.005287	0.0000
LIBG	3.55E-15	1.75E-14	0.202947	0.8397
LFDD	-4.51E-14	1.53E-14	-2.944816	0.0042

R-squared	1.000000	Mean dependent var	0.261371
Adjusted R-squared	1.000000	S.D.dependent var	0.116142
S.E. of regression	9.31E-15	Sum squared resid	7.02E-27
Long-run variance	2.63E-28		

Figure 10: Actual money demand and static demand forecasting using DOLS for the period 2019M1-2023M12



4.3. Payment Channels (PC)

Now, we repeat the same process for model that include payment instruments. Payment instruments include: Automated Teller Machines (ATM) and Mobile Banking (MOB).

Figure 11: Comparing static forecasts using different estimation methods

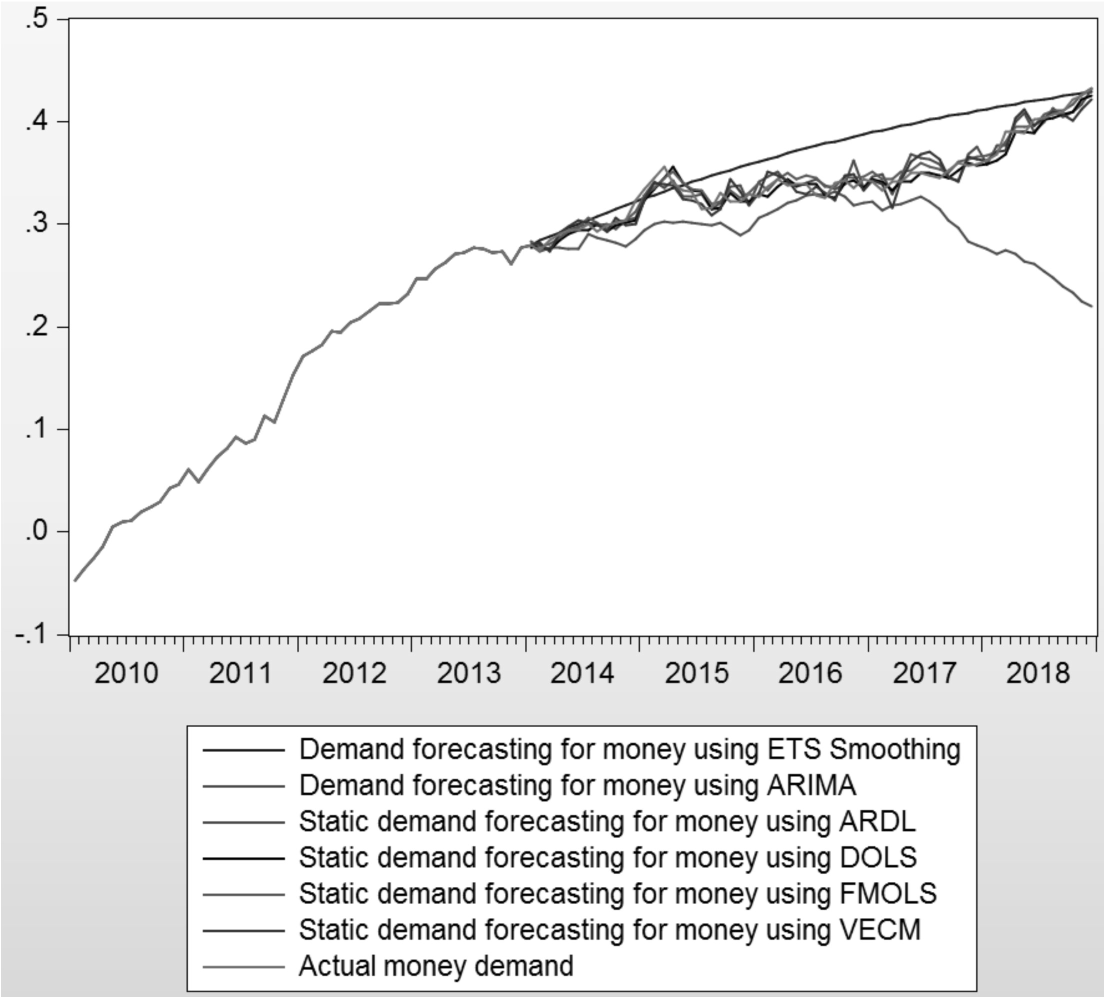


Figure 11 indicates that forecasts from FMOLS, DOLS, VECM and ARDL are all closely following the actual values of the dependent variable (money demand). ETS Smoothing and ARIMA provides the fifths and sixth best models to forecast money demand for the period 2019M1-2023M12.

Table 32: Forecast measures based on static forecast using different methods

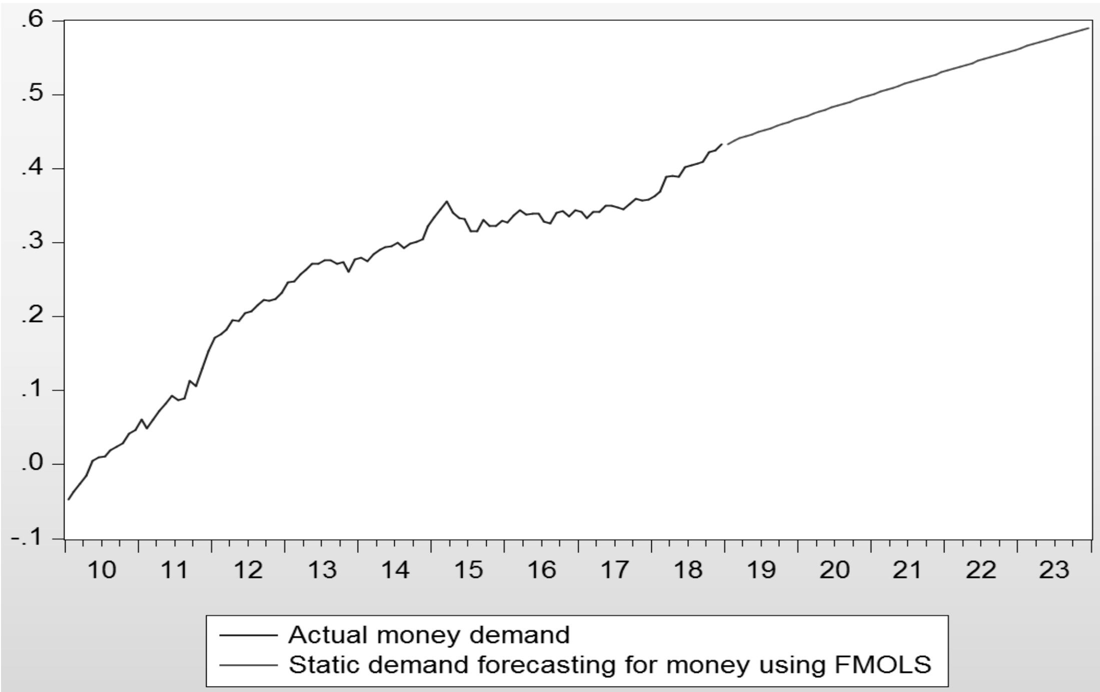
Forecast Measures/Methods	DOLS	FMOLS	ARDL
RMSE	0.0080	0.0073	0.0106
MAE	0.0063	0.0059	0.0088
MAPE	1.8611	1.7791	2.5658
TIC	0.0117	0.0105	0.0154
BP	0.1036	0.1773	0.0228
VP	0.0154	0.0010	0.0009
CP	0.8809	0.8215	0.9762
TUC	1.0000	0.9024	1.2978
SM	1.8732	1.7674	2.5509

Table 32 provides a closer and more precise way of comparing the predictive powers of the 3 models (DOLS, FMOLS and ARDL). According to this table, FMOLS has the best forecasting performance among these three models and definitely among all the estimated models. Therefore, we proceed further to do forecast based on the estimation of FMOLS model.

Table 33: FMOLS estimation using selected model for ETS smoothing

Variable	Coefficient	Std.Error	t-Statistic	Prob.
LMOD(-1)	0.911081	0.032921	27.67491	0.0000
LGDP	-0.005210	0.006278	-0.829929	0.4085
RIR	0.003240	0.000769	4.215760	0.0001
LATM	0.012916	0.007779	1.660327	0.1000
LMOB	0.003976	0.001963	2.026104	0.0454
R-squared	0.996871	Mean dependent var	0.258662	
Adjusted R-squared	0.996747	S.D.dependent var	0.118904	
S.E. of regression	0.006782	Sum squared resid	0.004645	
Long-run variance	3.63E-05			

Figure 12: Actual money demand and static demand forecasting using FMOLS for the period 2019M1-2023M12



4.4. Overall Conclusion

So far, the results indicate that DOLS method has the most predictive power when it includes PI and PS for 5-years forecasting ahead (2019M1-2023M12). However, its forecasting power is closely followed by FMOLS as the second best forecasting ability. When the model includes PC, FMOLS has the best forecasting performance.

We repeat the same process to do out-of-sample forecast for 1 year (12 months) ahead which is 2019. In this case, FMOLS proves to be superior as to forecasting accuracy when the model includes PI and PC. For the model including PS, it is ARDL that provides the most accurate forecast. Again, it is closely followed by FMOLS. Overall, we recognize FMOLS as the best estimator for forecasting purpose either in short horizon (1 year) or long horizon (5 years).

Table 34: Overall assessment

FI/TH	1-YEAR	5-YEAR
PI	FMOLS	DOLS/FMOLS
PS	ARDL/FMOLS	DOLS/FMOLS
PC	FMOLS	FMOLS

According to the final results provided in Table 34, we conclude that FMOLS can be selected as the best model for either short time or long time horizon out-of-sample forecasting with minor consideration. Regarding this fact, we will estimate FMOLS model with the inclusion of financial variables (PI, PS and PC) and conduct test of serial correlation to rest assured that the estimated models are free from statistical issues.

4.5. Effects of financial innovation on the demand for money in the context of FMOLS model

Table 35: FMOLS estimation for model including PI

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LMOD(-1)	0.962852	0.014244	67.59780	0.0000
LGDP	-0.026839	0.004416	-6.077318	0.0000
RIR	0.004205	0.000618	6.803918	0.0000
LCRC	0.057116	0.008673	6.585661	0.0000
LCHC	0.004518	0.007350	0.614639	0.5402
LDEC	0.001361	0.005248	0.259349	0.7959
LEMO	-0.006367	0.006207	-1.025715	0.3075

R-squared	0.997219	Mean dependent var	0.258662
Adjusted R-squared	0.997050	S.D. dependent var	0.118904
S.E. of regression	0.006458	Sum squared resid	0.004129
Long-run variance	2.53E-05		

Note: Fixed leads and lags specification (lead=1, lag=1). Long-run variance estimate (Bartlett kernel, Newey-West fixed bandwidth. Endogeneity is being taken care of by adding the leads and lags. Since the omitted dynamics are captured by the residual in OLS estimation, serial correlation, heteroskedasticity is inheriting in this estimation while DOLS and FMOLS address these issues using a nonparametric approach.

Table 36: Test of serial correlation

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.110	-0.110	1.3134	0.252
		2	-0.019	-0.031	1.3526	0.509
		3	0.060	0.055	1.7493	0.626
		4	-0.132	-0.121	3.6956	0.449
		5	0.069	0.046	4.2362	0.516
		6	-0.036	-0.034	4.3834	0.625
		7	0.106	0.119	5.6832	0.577
		8	-0.018	-0.021	5.7207	0.678
		9	0.010	0.033	5.7336	0.766
		10	-0.091	-0.118	6.7264	0.751
		11	0.004	0.023	6.7281	0.821
		12	0.218	0.203	12.530	0.404
		13	0.012	0.086	12.548	0.483
		14	-0.097	-0.135	13.709	0.472
		15	-0.095	-0.142	14.844	0.463
		16	0.009	0.023	14.853	0.535
		17	0.071	0.131	15.502	0.559
		18	0.047	0.070	15.785	0.608
		19	-0.070	-0.159	16.437	0.628
		20	0.125	0.075	18.515	0.554
		21	-0.031	0.043	18.648	0.608
		22	-0.091	0.019	19.780	0.597
		23	0.094	0.033	20.996	0.581
		24	0.074	0.033	21.766	0.593
		25	0.071	0.030	22.474	0.608
		26	-0.147	-0.087	25.566	0.487
		27	-0.018	0.020	25.615	0.540
		28	-0.020	-0.021	25.676	0.591
		29	-0.076	-0.147	26.534	0.597
		30	0.000	-0.104	26.534	0.648
		31	-0.053	0.010	26.962	0.674
		32	-0.027	-0.059	27.078	0.714
		33	-0.039	-0.064	27.317	0.746
		34	0.001	0.008	27.317	0.785
		35	-0.016	0.005	27.357	0.818
		36	0.077	0.041	28.337	0.815

Table 37: FMOLS estimation for model including PS

Variable	Coefficient	Std.Error	t-Statistic	Prob.
LMOD(-1)	0.977759	0.013501	72.42025	0.0000
LGDP	-0 031158	0.010724	-2.905457	0.0045
RIR	0.003885	0.000718	5.411615	0.0000
LREN	0.019625	0.006053	3.242091	0.0016
LIBG	-0 007782	0.005006	-1.554453	0.1232
LFDD	0.009591	0.003688	2.600957	0.0107

R-squared	0.996727	Mean dependent var	0.258662
Adjusted R-squared	0.996563	S.D. dependent var	0.118904
S.E. of regression	0.006971	Sum squared resid	0.004859
Long-run variance	3.42E-05		

Table 38: Test of serial correlation

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.028	-0.028	0.0829	0.773
		2	-0.007	-0.008	0.0887	0.957
		3	0.192	0.192	4.1984	0.241
		4	-0.152	-0.148	6.8064	0.146
		5	-0.089	-0.097	7.7094	0.173
		6	-0.109	-0.158	9.0676	0.170
		7	-0.098	-0.050	10.176	0.179
		8	-0.031	-0.023	10.290	0.245
		9	0.040	0.069	10.477	0.313
		10	-0.087	-0.112	11.375	0.329
		11	-0.002	-0.046	11.375	0.412
		12	0.253	0.212	19.195	0.084
		13	0.056	0.115	19.581	0.106
		14	-0.100	-0.138	20.830	0.106
		15	0.049	-0.083	21.132	0.133
		16	-0.070	-0.065	21.761	0.151
		17	-0.092	0.006	22.855	0.154
		18	0.001	0.050	22.855	0.196
		19	-0.103	-0.059	24.241	0.187
		20	0.101	0.076	25.611	0.179
		21	0.047	-0.002	25.903	0.210
		22	-0.009	0.056	25.913	0.255
		23	0.095	0.061	27.165	0.249
		24	0.123	0.065	29.282	0.210
		25	0.067	0.028	29.908	0.228
		26	-0.057	-0.033	30.373	0.252
		27	-0.027	-0.031	30.474	0.293
		28	-0.047	-0.002	30.800	0.326
		29	-0.196	-0.148	36.525	0.159
		30	-0.020	0.014	36.587	0.189
		31	-0.095	-0.059	37.955	0.182
		32	-0.041	-0.034	38.218	0.208
		33	0.076	-0.015	39.118	0.214
		34	-0.038	-0.013	39.343	0.243
		35	0.029	-0.041	39.477	0.277
		36	0.142	0.061	42.770	0.203

Table 39: FMOLS estimation for model including PC

Variable	Coefficient	Std.Error	t-Statistic	Prob.
LMOD(-1)	0.911081	0.032921	27.67491	0.0000
LGDP	-0.005210	0.006278	-0.829929	0.4085
RIR	0.003240	0.000769	4.215760	0.0001
LATM	0.012916	0.007779	1.660327	0.1000
LMOB	0.003976	0.001963	2.026104	0.0454

R-squared	0.996871	Mean dependent var	0.258662
Adjusted R-squared	0.996747	S.D.dependent var	0.118904
S.E. of regression	0.006782	Sum squared resid	0.004645
Long-run variance	3.63E-05		

Table 40: Test of serial correlation

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.049	-0.049	0.2636	0.608
		2	0.036	0.033	0.4044	0.817
		3	0.219	0.223	5.7110	0.127
		4	-0.124	-0.108	7.4271	0.115
		5	-0.027	-0.059	7.5116	0.185
		6	0.020	-0.021	7.5593	0.272
		7	-0.052	0.003	7.8742	0.344
		8	0.035	0.042	8.0208	0.431
		9	0.110	0.113	9.4465	0.397
		10	-0.064	-0.055	9.9276	0.447
		11	0.025	-0.016	10.001	0.530
		12	0.262	0.248	18.391	0.104
		13	0.037	0.123	18.561	0.137
		14	-0.077	-0.128	19.300	0.154
		15	0.048	-0.095	19.593	0.188
		16	-0.075	-0.039	20.318	0.206
		17	-0.080	-0.010	21.141	0.220
		18	0.021	0.026	21.198	0.270
		19	-0.125	-0.103	23.268	0.226
		20	0.081	0.044	24.149	0.236
		21	0.040	-0.008	24.363	0.276
		22	-0.058	0.016	24.819	0.306
		23	0.050	0.017	25.161	0.342
		24	0.071	0.003	25.867	0.360
		25	0.013	-0.000	25.889	0.414
		26	-0.110	-0.105	27.630	0.377
		27	-0.055	-0.064	28.063	0.408
		28	-0.064	-0.021	28.669	0.429
		29	-0.172	-0.133	33.045	0.276
		30	-0.039	-0.047	33.273	0.311
		31	-0.118	-0.080	35.381	0.269
		32	-0.038	-0.039	35.600	0.303
		33	0.035	-0.018	35.789	0.339
		34	-0.076	-0.024	36.709	0.344
		35	-0.000	-0.011	36.709	0.390
		36	0.107	0.072	38.589	0.353

Table 41: Estimated coefficients of the model with the inclusion of financial variables in three different aspects using selected estimator (FMOLS)

Model	**PI**	**PS**	**PC**
Variable	**Coefficient (Prob.)**	**Coefficient (Prob.)**	**Coefficient (Prob.)**
LMOD(-1)	0.962852 (0.0000)	0.977759 (0.0000)	0.911081 (0.0000)
LGDP	-0.026839 (0.0000)	-0.031158 (0.0045)	-0.005210 (0.4085)
RIR	0.004205 (0.0000)	0.003885 (0.0000)	0.003240 (0.0001)
LCRC	0.057116 (0.0000)		
LCHC	0.004518 (0.0000)		
LDEC	0.001361 (0.5402)		
LEMO	-0.006367 (0.3075)		
LREN		0.019625 (0.0016)	
LIBG		-0.007782 (0.1232)	
LFDD		0.009591 (0.0107)	
LATM			0.012916 (0.1000)
LMOB			0.003976 (0.0454)

For the model including PI: CRC and CHC have positive and significant impact on money demand, yet the impact is small.

For the model including PS: REN and FDD have positive and significant impact on money demand, yet the impact is small.

For the model including PC: ATM and MOB have positive and significant impact on money demand, yet the impact is small.

5. Conclusion

Here, we used cointegration/structural based techniques (ARDL/VECM/DOLS/FMOLS) to investigate the effect of financial innovation on the demand for money. Non-stationary time series data may provide spurious regression analysis. That is why co-integration based techniques are so popular. Cointegration (also referred to as a long-run equilibrium relationship) provides a solution to this problem by transforming the linear combination of non-stationary time series into a stationary one. However, the models of this kind need a convenient framework (structural function based on economic theory) for estimation, testing and forecasting.

Appropriateness of model specification and lagged data availability for variables is considered an issue in a structural specification. Therefore, ARMA and ETS Smoothing models are considered as a good alternative to structural based models for the purpose of forecasting money demand for short term horizon.

First, we compared static and dynamic forecasts for each model consisting payment instruments. The results indicated that for all of the structural based models, static forecast is superior to dynamic forecast. Therefore, dynamic forecasts were ruled out and the comparison were made among static forecasts obtained from the models. Second, we compared the forecasting accuracy of dynamic forecasts of different models. All of the forecasts were done in short-time dimension (1-year or 12-months) and long-time dimension (5-years or 60 months) to determine how forecasting performances varies over time. While DOLS proved to be the best model for 5-years forecasting, FMOLS turned out to be the best for 1-year forecasting. We did the same analysis to determine the best model with regards to forecasting when they include payment systems and payment channels as financial variables. The overall result indicates that FMOLS is the model with the most predictive power for both short and long terms (with minor consideration). Then, this chosen model was used for out of sample forecasting (again for 1-year and 5 years-time horizons). Finally, we obtained and compared the estimated coefficients of the financial variables with the conclusion that those financial variable whose coefficients are significant, have positive yet small impact on money demand in Malaysia.

It seems from comparison graphs that cointegration/structural based models (DOLS, FMOLS, ARDL and VECM) do better in forecasting as compared to non-cointegration/structural based models (ARMA and Exponential Smoothing). However, the forecasting performance of these models are fairly good and comparable with structural based models but it gets deteriorated as we approach the end of the forecasting period meaning that non-structural based models do more accurate forecasting for a short time dimension than they does for long time dimension. Another fact is that while FMOLS has the most predictive power among cointegration/structural based models, Exponential Smoothing proves better than ARIMA for forecasting purpose.

This because, restrictions on the low-frequency dynamic behavior of multivariate time series as implied by cointgration, will produce superior long-horizon forecasts. Cointegraton enhances the accuracy of long-horizon forecasts relative to those from systems estimated in levels provided the univariate representations of all variables contain unit roots.

The Auto-Regressive Integrated Moving Average (ARIMA) technique developed by Box and Jenkins (1970) are independent of any particular economic theory and generates forecasts that are based purely on the past behaviour of money demand (in our case). In order to apply this technique, time series (money demand) should be stationary (the property of the variable to return to its mean value after an increase or decrease). If not, ARIMA uses variable in its first-differenced form.

We expect that innovations in payments technology will have a strong impact on money demand in the long term. Structural models such as ECM/VECM and other cointegration based models are most appropriate to reveal the impact of these innovation in the long term. Therefore, we conclude that structural models are better for longer term forecasting. ARIMA will probably have better performance for short term horizons such as one year. However, our findings indicate that even for short term horizons, structural models do better than non-structural models but the gap between forecasting accuracy for these two kinds of models is much narrower in the short term horizon compared to long term horizon.

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