INVESTIGATING THE EFFECT OF FINANCIAL INNOVATIONS ON THE DEMAND FOR MONEY IN AUSTRALIA USING DOLS AND FMOLS AND COMPARING THEIR PREDICTIVE POWERS

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Abstract

In this paper we apply two different estimation methods, namely DOLS and FMOLS to estimate real demand for money in Australia with the inclusion of financial innovations. We use a conventional money demand function that was enriched with a proxy for financial innovations. This sum of the number of cheques, credit cards, charge cards, ATM and direct entry payment was included in the regression model to proxy the effect of financial innovations on the money demand. The results indicate that the estimated coefficient of TPI using DOLS is not significant yet it is highly significant using FMOLS and it bears positive sign so that 1 percent increase in TPI leads to the increase of money demand by 0.24 percent. Also, using "Root Mean Squared Error" as the benchmark for predictive power, we conclude that FMOLS is superior to DOLD when it comes to forecasting.

Keywords: financial innovations, money demand, dynamic OLS, fully modified OLS, forecast

JEL classification: E41, E42, E52

1. Introduction

It is the payments mechanism of an economy that allows smooth functioning of its financial and real sectors. An efficient payments system is the one that offers real time settlement of financial transactions and facilitate the exchange of goods and services in a speedy, secure and reliable manner.

Huge cost savings can be achieved by migrating from paper-based payments to electronic payments. Improved efficiency of the payment system due to these innovations will enhance the efficiency to the entire economy. Manual processing of cash and cheques requires a huge amount of resources while electronic payments does not. Electronic payment help improve productivity levels and lower the cost of doing business. Moreover, extended financial services to the unbanked communities as a result of using electronic payments will enable them to benefit from lower cost of financial services. More intensive use of electronic payments plays a vital role in achieving higher economic growth and improving the competitiveness of the economy.

Several empirical studies have included financial innovation in the money demand specification due to the growth in financial innovation over the last few years. A money demand function that does not include financial innovation will face the misspecification of the money demand through over estimation, commonly referred to as "missing money" (Arrau and De Gregorio, 1991). Some of the issues such as autocorrelated errors, persistent over prediction and implausible parameter estimates can be solved by including financial innovation in the money demand specification which is all backed by empirical evidence (Arrau et al, 1995). Furthermore, the failure of cointegration of the money demand could be explained by non-stationary processes such as financial innovation, so that accounting for financial innovation will eliminate the periods of "missing money" (Arrau and De Gregorio, 1991). Arrau and De Gregorio (1993), Ireland (1995), Attanasio et al (2002), Alvarez and Lippi (2009) and Nagayasu (2012) are examples of the studies that have accounted for financial innovation in the money demand specification.

The objectives of the current paper is to estimate the demand for money in the presence of financial innovations using annual data from Australia for the period 1995 to 2016. We shall use Dynamic OLS (DOLS) and Fully Modified OLS (FMOLS) as superior methods to the OLS for many reasons. Then, we do forecasts based on these two methods and finally, we compare these two forecast to find out which of them outperform the other.

Plan of the paper is to provide a review of literature in section 2. An overview of financial innovations in Australia is given in section 3. Theoretical background and measurement of variables is mentioned in section 4. Results and discussion of results are reported in section 5. Lastly section 6 is reserved for the main conclusions.

2. Literature review

There are numerous studies that have examined the cointegration property of money demand. Some of the studies that investigated the long run relationship between money demand and its determinants as follow.

Halicioglu and Ugur (2005) examine the stability of the narrow M1 (money demand function) in Turkey. In doing so, they use annual data from 1950 to 2002. They conduct stability test of M1 for Turkish by applying a cointegration procedure. They demonstrate that there is a long-run relationship between the narrow M1 money aggregate and its determinants: national income, interest rate and exchange rates.

Using quarterly data for the period 1973-2000, Bahmani & Oskooee and Rehman (2005) estimate money demand for seven Asian countries including India, Indonesia, Malaysia, Pakistan, Philippines, Singapore and Thailand. The results indicated that real M1 or M2 are cointegrated with their determinants in some Asian countries.

Akinlo (2006) use quarterly data (1970:1–2002:4). They apply ARDL approach to investigate if money demand (M2) for Nigeria is cointegrated and stable. The results indicate that M2 is cointegrated with income, interest rate and exchange rate.

Using monthly data over the period 1994:12-2006:12, Samreth (2008) estimate the money demand function for Cambodia. They apply ARDL approach to analyse cointegration property. They show that there is a cointegrating relationship between M1, Industrial Production Index, Consumer Price Index, and Nominal Exchange Rate in money demand function. Using ARDL approach, Long and Samreth (2008) examine if short and long run monetary models of exchange rate is valid for monetary exchange rate model of the Philippines. The results confirm that there is both short and long run relationships between variables in the monetary exchange rate model of the Philippines.

Baharumshah, et al. (2009) study M2 (the demand for broad money) in China. They apply ARDL approach to cointegration and use quarterly data over the period 1990:4 &2007:2. Bounds test indicate that there is a stable, long-run relationship between M2 and real income, inflation, foreign interest rates and stock prices.

However, most of these studies failed to account for financial innovation in the money demand specification except for Ndirangu and Nyamongo (2015) who employ the ARDL approach to cointegration for Kenya and use the currency outside banks/time deposit ratio as a proxy for financial development. The results also suggest that there is a long run relationship between money demand and its determinants with inclusion of mobile money.

3. Payment system in Australia

The ‘payments system’ refers to arrangements which allow consumers, businesses and other organisations to transfer funds usually held in an account at a financial institution to one another. It includes the payment instruments – cash, cards, cheques and electronic funds transfers which customers use to make payments – and the usually unseen arrangements that ensure that funds move from accounts at one financial institution to another. Types of retail payment instruments include:

Cheques: A cheque is a paper based payment instrument. It is a form of written order directing a bank to pay money to the beneficiary.

Credit Cards: A credit card enables its holder to buy goods and services with a credit line given by credit card issuer and the amount will be settled at a later date.

Charge Cards: The functionality of a charge card is similar to a credit card. However, charge card holders must settle their outstanding amount in full by the due date every month.

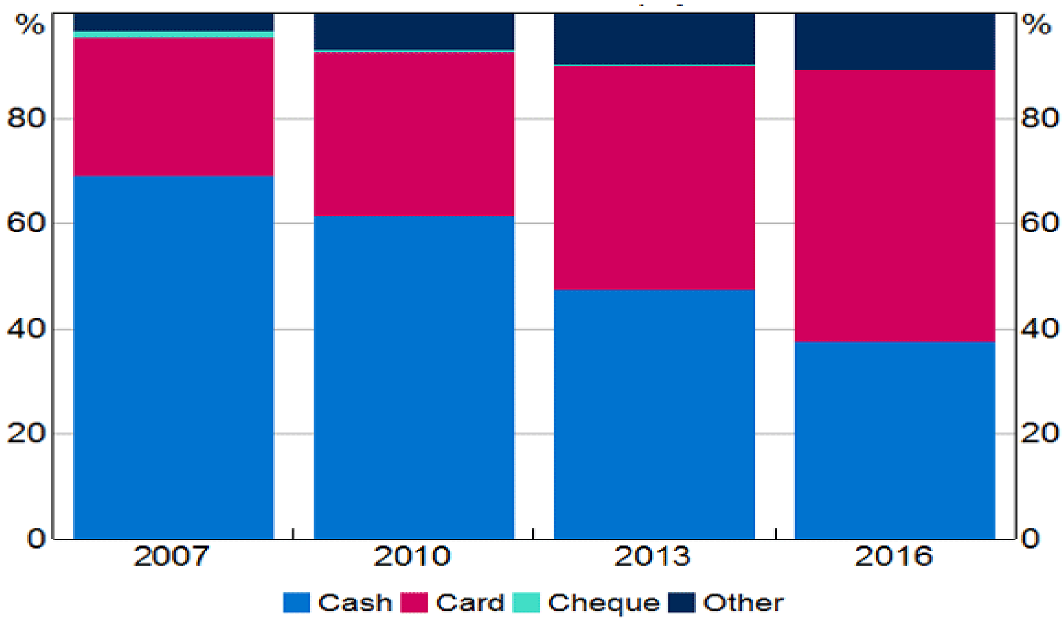
Debit Cards: A debit card (such as those used at ATMs) is a payment card where the transaction amount is deducted directly from the cardholder's bank account upon authorisation.

Direct entry: It is a convenient, safe and reliable way to send and receive payments. It is an electronic payment system typically used by businesses to send or collect regular payments from large numbers of their employees or customers.

Cash

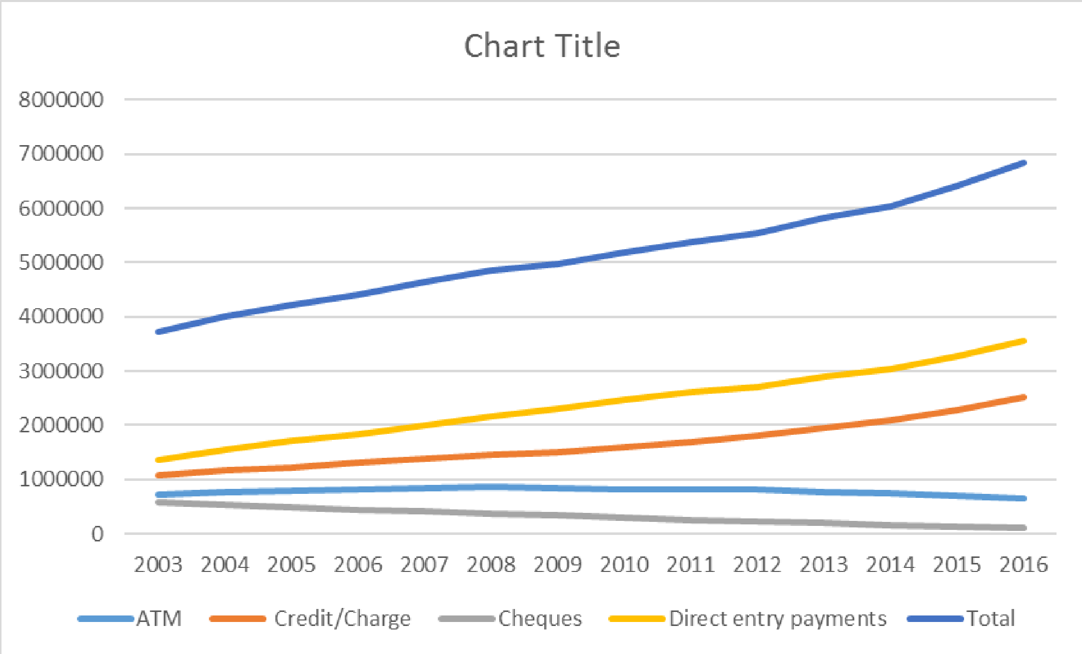
The use of cash as a payment method remains widespread. One of the most comprehensive sources of data on individual cash payments is the Reserve Bank's Consumer Payments Survey. This study was first undertaken in 2007 and was repeated in 2010, 2013 and 2016. The results indicate that consumers used cash for most of their low-value transactions, and overall, cash payments accounted for 37 per cent of the number and 18 per cent of the value of all consumer payments in 2016. The latest survey shows continued substitution away from cash use and towards electronic methods. The most common way consumers withdraw cash is through ATMs, which accounted for 69 per cent of the total number of cash withdrawals and 55 per cent of the value of withdrawals in 2016.

Figure 1: Consumer payment methods (percent of number of payments)



Source: RBA calculations, based on data from Colmar Brunton, Ipsos and Roy Morgan Research

Figure 2: Trend of the number of transactions by financial payment instruments in Australia



Source: Reserve Bank of Australia

In figure 2, from bottom to the top are cheques, ATM, credit/charge card, direct entry payments and the total. It can be easily seen from the above figure that the number of transactions for cheques and ATM slightly declines while that of credit/charge cards and direct entry payments increases over time. However, the total number of transactions is on the rise.

Non-cash payments

Non-cash payments account for most of the value of payments in the Australian economy. On average, in 2016 non-cash payments worth around $230 billion were made each business day, equivalent to around 14 per cent of annual GDP.

Over 70 per cent of the value of non-cash transactions is accounted for by a small number of high-value payments made through Australia's real-time gross settlement (RTGS) system. Most of the value of these payments relates to the settlement of foreign exchange and securities markets transactions.

The migration of large business payments to the RTGS system saw a decline in the importance of the cheque as a payment instrument. In 2016, around 5 cheques were written per person in Australia, down from 22 cheques per person 10 years earlier. A significant share of cheque use is related to commercial payments, and financial institution ('bank') cheques for certain transactions such as property settlements.

In contrast to the declining importance of cheques, the use of electronic payment instruments at the retail level has been growing rapidly. In 2016, transactions (both purchases and cash withdrawals) undertaken using either credit or debit cards averaged about 305 per person, an increase of 59 per cent on the level of five years earlier.

For many years, Australian governments and businesses have made extensive use of Direct Entry credits for social security and salary payments. Consumers and businesses also establish direct debits for bill payments. Direct Entry payments are an important part of the payments landscape. These payments continue to account for the bulk of the value of non-cash retail payments (i.e. non-RTGS transactions).

Role of the Reserve Bank

A safe and efficient payments system is essential to support the day-to-day business of the Australian economy and to settle transactions in its financial markets. Accordingly, the Reserve Bank of Australia has important regulatory responsibilities for the payments system and plays a key role in its operations.

The Payments System Board (PSB) of the Reserve Bank oversees the payments system in Australia. It is responsible for promoting the safety and efficiency of the payments system and through the Payment Systems (Regulation) Act 1998 and the Payment Systems and Netting Act 1998, the Reserve Bank has one of the clearest and strongest mandates in the world in relation to payments systems.

The Bank consults closely with participants in the payments industry. The Bank is represented on a number of industry committees responsible for the day-to-day management of payments clearing systems and Bank staff regularly meet with industry representatives and other regulators.

Efficiency of the payments system

Australia was among the first countries in the world to make efficiency of payment systems a statutory objective of the central bank. In pursuit of this mandate, the Reserve Bank has encouraged a reduction in cheque-clearing times and the take-up of direct debits as a means of bill payment, and taken a number of steps to improve the competitiveness and efficiency of card systems. Initially the latter focus was on credit card systems. In 2001, the Bank designated the Bankcard, MasterCard and Visa credit card systems as payment systems under the Payment Systems (Regulation) Act. Designation is the first step in the possible establishment of standards and/or an access regime for a payment system. After extensive consultation, the Bank determined Standards for the designated schemes which lowered interchange fees and removed restrictions on merchants charging customers for the use of credit cards, and imposed an Access Regime which facilitates entry by new players (Reserve Bank of Australia).

4. Methodology

Background

Unit root

The theory behind ARMA estimation is based on stationary time series. A series is said to be (weakly or covariance) stationary if the mean and autocovariances of the series do not depend on time. Any series that is not stationary is said to be nonstationary. A common example of a nonstationary series is the random walk:

$$y_t = y_{t-1} + \varepsilon_t \quad (1)$$

Where ε is a stationary random disturbance term. The series y has a constant forecast value, conditional on t, and the variance is increasing over time. The random walk is a difference stationary series since the first difference of y is stationary:

$$y_t - y_{t-1} = (1\text{-}L)\, y_t = \varepsilon_t (2)$$

A difference stationary series is said to be integrated and is denoted as I(d) where d is the order of integration. The order of integration is the number of unit roots contained in the series, or the number of differencing operations it takes to make the series stationary. For the random walk above, there is one unit root, so it is an I(1) series. Similarly, a stationary series is I(0). Standard inference procedures do not apply to regressions which contain an integrated dependent variable or integrated regressors. Therefore, it is important to check whether a series is stationary or not before using it in a regression. The formal method to test the stationarity of a series is the unit root test.

There is a variety of powerful tools for testing a series (or the first or second difference of the series) for the presence of a unit root. In addition to Augmented Dickey-Fuller (1979) and Phillips-Perron (1988) tests, the GLS-detrended Dickey-Fuller (Elliot, Rothenberg, and Stock, 1996), Kwiatkowski, Phillips, Schmidt, and Shin (KPSS, 1992), Elliott, Rothenberg, and Stock Point Optimal (ERS, 1996), and Ng and Perron (NP, 2001) unit root tests are available as a view of a series. In this paper, however, we use Augmented Dickey-Fuller test for this purpose. The following discussion outlines the basics features of unit root tests. Consider a simple AR(1) process:

$$y_t = \rho y_{t-1} + x_t'\delta + \varepsilon_t \quad (3)$$

Where x_t are optional exogenous regressors which may consist of constant, or a constant and trend, ρ and δ are parameters to be estimated, and the ε_t are assumed to be white noise. If $|\rho| \geq 1$, y is a nonstationary series and the variance of y increases with time and approaches infinity. If $|\rho|< 1$, y is a (trend-)stationary series. Thus, the hypothesis of (trend-)stationarity can be evaluated by testing whether the absolute value of ρ is strictly less than one.

The unit root tests use the null hypothesis H_0: ρ = 1 against the one-sided alternative H_1: ρ < 1. In some cases, the null is tested against a point alternative. In contrast, the KPSS Lagrange Multiplier test evaluates the null of H_0: ρ < 1 against the alternative H_1: ρ = 1.

The Augmented Dickey-Fuller (ADF) test

The standard DF test is carried out by estimating Equation (3) after subtracting y_{t-1} from both sides of the equation:

$$\Delta y_t = \alpha y_{t-1} + x_t'\delta + \varepsilon_t \quad (4)$$

Where α = ρ -1. The null and alternative hypotheses may be written as,

$$H_0: \alpha = 0$$

$$H_1: \alpha < 0 \ (5)$$

and evaluated using the conventional t-ratio for α:

$$t_\alpha = \hat{\alpha} / (\mathrm{se}(\hat{\alpha})) \ (6)$$

where $\hat{\alpha}$ is the estimate of α , and se($\hat{\alpha}$)is the coefficient standard error.

Dickey and Fuller (1979) show that under the null hypothesis of a unit root, this statistic does not follow the conventional Student's t-distribution, and they derive asymptotic results and simulate critical values for various test and sample sizes. More recently, MacKinnon (1991, 1996) implements a much larger set of simulations than those tabulated by Dickey and Fuller. In addition, MacKinnon estimates response surfaces for the simulation results, permitting the calculation of Dickey-Fuller critical values and p-values for arbitrary sample sizes. The more recent MacKinnon critical value calculations are used in constructing test output.

The simple Dickey-Fuller unit root test described above is valid only if the series is an AR(1) process. If the series is correlated at higher order lags, the assumption of white noise disturbances ε_t is violated. The Augmented Dickey-Fuller (ADF) test constructs a parametric correction for higher-order correlation by assuming that the y series follows an AR(p) process and adding p lagged difference terms of the dependent variable y to the right-hand side of the test regression:

$$\Delta y_t = \alpha y_{t-1} + x_t'\delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \ldots + \beta_p \Delta y_{t-p} + v_t \quad (7)$$

This augmented specification is then used to test (5) using the t-ratio (6). An important result obtained by Fuller is that the asymptotic distribution of the t-ratio for α is independent of the number of lagged first differences included in the ADF regression. Moreover, while the assumption that y follows an autoregressive (AR) process may seem restrictive, Said and Dickey (1984) demonstrate that the ADF test is asymptotically valid in the presence of a moving average (MA) component, provided that sufficient lagged difference terms are included in the test regression.

One will face two practical issues in performing an ADF test. First, you must choose whether to include exogenous variables in the test regression. You have the choice of including a constant, a constant and a linear time trend, or neither in the test regression. One approach would be to run the test with both a constant and a linear trend since the other two cases are just special cases of this more general specification. However, including irrelevant regressors in the regression will reduce the power of the test to reject the null of a unit root. The standard recommendation is to choose a specification that is a plausible description of the data under both the null and alternative hypotheses. See Hamilton (1994, p. 501) for discussion. However, we chose to include only constant.

Second, you will have to specify the number of lagged difference terms (which we will term the "lag length") to be added to the test regression (0 yields the standard DF test; integers greater than 0 correspond to ADF tests). The usual (though not particularly useful) advice is to include a number of lags sufficient to remove serial correlation in the residuals. EViews provides both automatic and manual lag length selection options. Here, we selected automatic lag length.

Cointegration

Cointegration is statistical property of a collection of time series variables (X_1, X_2, …, X_k). First of all, these series have to be integrated of order 1. Next, if a linear combination of these series is integrated of order zero, then the collection is cointegrated. If X,Y,Z are integrated of order 1, and there exist coefficients a,b,c such that aX+bY+cZ is integrated of order 0, then X,Y, and Z are cointegrated. Cointegration is an important property in time-series analysis. Time series are characterised by having trends either deterministic or stochastic that are also called unit root processes, or processes integrated of order 1 or I(1). Unit root processes have non-standard statistical properties. Therefore, conventional econometric theory methods cannot be used in these cases. In other words, the series are cointegrated if they are individually integrated but linear combination of them has a lower order of integration. In general, it is the case where the individual series are first-order integrated (I(1)) but a vector of coefficients exists to form a stationary linear combination of them (I(0)). We use cointegration test in order to test if there is a statistically significant connection between two series. This cointegration test is called the Johansen test that allows for more than one cointegrating relationship, while the Engle–Granger method allows for only one cointegrating relationship.

Johansen cointegration test

VAR-based cointegration tests use the methodology developed in Johansen (1991, 1995). Consider a VAR of order p:

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + \mathrm{B}x_t + \varepsilon_t \quad (8)$$

Where y_t is a k-vector of non-stationary I(1) variables, x_t is a d-vector of deterministic variables, and ε_t is a vector of innovations. We may rewrite this VAR as,

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma \Delta\, y_{t-i} + \mathrm{B}x_t + \varepsilon_t \quad (9)$$

where:

$$\Pi = \sum_{i=1}^{p} A_i - I, \qquad \Gamma_i = - \sum_{j=i+1}^{p} A_j \qquad (10)$$

Granger's representation theorem asserts that if the coefficient matrix Π has reduced rank r < k, then there exist k * r matrices α and β each with rank r such that $\Pi = \alpha\beta'$ and $\beta' y_t$ is I(0). r is the number of cointegrating relations (the cointegrating rank) and each column of β is the cointegrating vector. As explained below, the elements of α are known as the adjustment parameters in the VEC model. Johansen's method is to estimate the Π matrix from an unrestricted VAR and to test whether we can reject the restrictions implied by the reduced rank of Π.

Phillips and Hansen (1990) propose an estimator which employs a semi-parametric correction to eliminate the problems caused by the long run correlation between the cointegrating equation and stochastic regressors innovations. The resulting Fully Modified OLS (FMOLS) estimator is asymptotically unbiased and has fully efficient mixture normal asymptotics allowing for standard Wald tests using asymptotic Chi-square statistical inference.

Fully Modified OLS

The FMOLS estimator proposed by Phillips and Hansen (1990) employs preliminary estimates of the symmetric and one-sided long-run covariance matrices of the residuals.

Let α_{1t} be the residuals obtained after estimating Equation ($y_t = X_t'\beta + D_{1t}'\gamma_1 + u_{1t}$). The α_{2t} may be obtained indirectly as $\alpha_{2t} = \Delta\hat{\varepsilon}_{2t}$ from the levels regressions

$$x_t = \Gamma_{21}' D_{1t} + \Gamma_{22}' D_{2t} + \hat{\varepsilon}_{2t} \qquad (11)$$

or directly from the difference regressions

$$\Delta x_t = \Gamma_{21}' \Delta D_{1t} + \Gamma_{22}' \Delta D_{2t} + \alpha_{2t} \qquad (12)$$

Let Ω and Λ be the long-run covariance matrices computed using the residuals $\alpha_t = (\alpha_{1t}, \alpha_{21}')'$. Then we may define the modified data

$$y_t^{\dagger} = y_t - \hat{\omega}_{12}\, \Omega_{22}^{-1} \alpha_2 \quad (13)$$

and an estimated bias correction term

$$\lambda_{12}^{\dagger} = \lambda_{12} - \hat{\omega}_{12}\, \Omega_{22}^{-1} \Lambda_{22} \qquad (14)$$

The FMOLS estimator is given by

$$\theta = \begin{bmatrix} \beta \\ \hat{\gamma}_1 \end{bmatrix} = \left(\sum_{t=2}^{T} Z_t Z_t'\right)^{-1}\left(\sum_{t=2}^{T} Z_t y_t^{\dagger} - T \begin{bmatrix} \lambda_{12}^{\dagger\prime} \\ 0 \end{bmatrix}\right) \qquad (15)$$

where $Z_t = (X_t', D_t')'$. The key to FMOLS estimation is the construction of long-run covariance matrix estimators Ω and Λ. Before describing the options available for computing Ω and Λ, it will be useful to define the scalar estimator

$$\hat{\omega}_{1.2} = \hat{\omega}_{11} - \hat{\omega}_{12}\Omega_{22}^{-1}\hat{\omega}_{21} \qquad (16)$$

which may be interpreted as the estimated long-run variance of u_{1t} conditional on u_{2t}. We may, if desired, apply a degree-of-freedom correction to $\hat{\omega}_{1.2}$. Hansen (1992) shows that the Wald statistic for the null hypothesis Rθ = r

$$W = (R\theta = r)'(RV(\theta)R')^{-1}(R\theta = r) \qquad (17)$$

With

$$V(\theta) = \hat{\omega}_{1.2}\left(\sum_{t=2}^{T} Z_t Z_t'\right)^{-1} \qquad (18)$$

has an asymptotic $\mathcal{X}_g^2$-distribution, where g is the number of restrictions imposed by R.

Dynamic OLS

A simple approach to constructing an asymptotically efficient estimator that eliminates the feedback in the cointegrating system has been advocated by Saikkonen (1992) and Stock and Watson (1993). Termed Dynamic OLS (DOLS), the method involves augmenting the cointegrating regression with lags and leads of ΔX_t so that the resulting cointegrating equation error term is orthogonal to the entire history of the stochastic regressor innovations:

$$y_t = x_t'\beta + D_{1t}'\gamma_1 + \sum_{j=-q}^{r} \Delta x_{t+j}'\delta + v_{1t} \qquad (19)$$

Under the assumption that adding q lags and r leads of the differenced regressors soaks up all of the long-run correlation between u_{1t} and u_{2t}, least-squares estimates of θ = $(\beta', \gamma')'$. Using Equation (19) have the same asymptotic distribution as those obtained from FMOLS. An estimator of the asymptotic variance matrix of θ may be computed by computing the usual OLS coefficient covariance, but replacing the usual estimator for the residual variance of v_{1t} with an estimator of the long-run variance of the residuals.

Forecast evaluation

When constructing a forecast of future values of a variable, economic decision makers often have access to different forecasts; perhaps from different models they have created themselves or from forecasts obtained from external sources. When faced with competing forecasts of a single variable, it can be difficult to decide which single or composite forecast is "best". Fortunately, there are some tools for evaluating the quality of a forecast which can help one determine which single forecast to use, or whether constructing a composite forecast by averaging would be more appropriate.

Evaluation of the quality of a forecast requires comparing the forecast values to actual values of the target value over a forecast period. A standard procedure is to set aside some history of actual data for use as a comparison sample in which one will compare of the true and forecasted values. It is possible to use the comparison sample to: (1) construct a forecast evaluation statistic to provide a measure of forecast accuracy, and (2) perform Combination testing to determine whether a composite average of forecasts outperforms single forecasts.

There are four different measures of forecast accuracy; RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), and the Theil Inequality Coefficient. These statistics all provide a measure of the distance of the true from the forecasted values. Suppose the forecast sample is j = T+1, T+2,…, T+h, and denote the actual and forecasted value in period t as y_t and y_t, respectively (Eviews help). The forecast evaluation measures are defined as table below.

Table 1: The forecast evaluation measures

Measure	Statistics
Root Mean Squared Error	$\sqrt{\sum_{t=T+1}^{T+h}(\hat{y}_t - y_t)^2 / h}$
Mean Absolute Error	$\sum_{t=T+1}^{T+h}\lvert\hat{y}_t - y_t\rvert / h$
Mean Absolute Percentage Error	$100 \sum_{t=T+1}^{T+h}\left\lvert\frac{\hat{y}_t - y_t}{y_t}\right\rvert / h$
Theil Inequality Coefficient	$\frac{\sqrt{\sum_{t=T+1}^{T+h}(\hat{y}_t - y_t)^2 / h}}{\sqrt{\sum_{t=T+1}^{T+h}(\hat{y}_t)^2 / h} + \sqrt{\sum_{t=T+1}^{T+h}(y_t)^2 / h}}$

Empirical model

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

$$\frac{M_t}{P_t} = \Phi(R_t, Y_t) \quad (20)$$

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 or IR as the best proxy).

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

$$\text{Log}\left(\frac{MD_t^*}{P_t}\right) = \alpha + \beta_1 \log GDP_t + \beta_2 IR_t + \varepsilon_t \quad (21)$$

Desired stock of nominal money is denoted by MD^*, P is the price index that we use to convert nominal balances to real balances, GDP is the scale variable, and IR 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 (TPI) so that it can be represented implicitly as $M^d = (Y_t, R_t, r^*)$, (Serletis, 2007) that is:

$$\text{Log}\left(\frac{MD_t^*}{P_t}\right) = \alpha + \beta_1 \log GDP_t + \beta_2 IR_t + \beta_3 TPI_t + \varepsilon_t \quad (22)$$

TPI which stand for the total number of payment instruments is the sum of the number of cheques, credit cards, charge cards, ATMs and direct entry payments. The data are annually, from 1995 to 2016. The official website of the World Bank and the official website of Reserve Bank of Australia were used as the source of data.

GDP (at purchaser's prices) is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in constant 2010 U.S. dollars. Dollar figures for GDP are converted from domestic currencies using 2010 official exchange rates.

Real interest rate (expressed as percent) is the lending interest rate adjusted for inflation as measured by the GDP deflator.

Broad money (in constant 2010 U.S. dollars) is the sum of currency outside banks; demand deposits other than those of the central government; the time, savings, and foreign currency deposits of resident sectors other than the central government; bank and traveler's checks; and other securities such as certificates of deposit and commercial paper.

5. Estimation results

Given the data set, unit root ADF test was applied to determine the order of integration of the variables included in the model. The ADF test statistics reported in Table 1 indicate that the variables are integrated of order I(1) at level and of order I(0) at first-differenced. Therefore, the requirements is met and we can proceed to the cointegration test.

Table 2: Augmented Dickey-Fuller test statistic

Level	Prob.	First Differenced	Prob
LMD	0.8669	D(LMD)	0.0004
LGDP	0.0609	D(LGDP)	0.0147
IR	0.0801	D(IR)	0.0004
LTPI	0.4232	D(LTPI)	0.0203

The cointegration test is applied to identify the number of cointegrating vectors using the likelihood ratio test. From the test results reported in Table 2 the null hypothesis of no cointegrating relationship is rejected at 5 percent significance level. The likelihood ratio statistics identified all the three cointegrating vectors at 5 percent significance level and confirm the presence of relationship among the variables specified in the model.

Table 3: The cointegration test

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.961946	107.4673	47.85613	0.0000
At most 1 *	0.762914	45.36133	29.79707	0.0004
At most 2 *	0.607027	18.01403	15.49471	0.0204
At most 3	0.013994	0.267774	3.841466	0.6048

Trace test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.961946	62.10600	27.58434	0.0000
At most 1 *	0.762914	27.34730	21.13162	0.0059
At most 2 *	0.607027	17.74626	14.26460	0.0135
At most 3	0.013994	0.267774	3.841466	0.6048

Max-eigenvalue test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Nest, we proceed to the estimation of the regression model using DOLS.

Table 4: DOLS estimation output

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LGDP	1.108354	0.043518	25.46887	0.0000
IR	-0.085649	0.027634	-3.099471	0.0362
LTPI	-0.147428	0.069665	-2.116245	0.1018
R-squared	0.995556	Mean dependent var		27.38284
Adjusted R-squared	0.983336	S.D. dependent var		0.319389
S.E. of regression	0.041230	Sum squared resid		0.006800
Long-run variance	0.000556			

For the purpose of forecast evaluation, we use data from 1995 to 2012 as our sample for estimation and use the estimated regression to do forecast for the period 2013 to 2016. It is obvious from table 4 that the estimated coefficients of GDP and IR (interest rate) are significant, meaning that these two variables can influence the dependent variable (money demand). The signs of the confidents are in line with underlying theory. For example, 1 percent increase in GDP leads to 1.10 percent increase in the demand for money. However, TPI (total number of payment instruments) does not have impact on money demand as the estimated coefficient of TPI is not significant. Then, we turn our attention to FMOLS estimation.

Table 5: FMOLS estimation output

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LGDP	0.861118	0.024015	35.85730	0.0000
IR	0.016756	0.017444	0.960555	0.3531
LTPI	0.240176	0.042061	5.710248	0.0001
R-squared	0.947189	Mean dependent var		27.35024
Adjusted R-squared	0.939645	S.D. dependent var		0.337204
S.E. of regression	0.082842	Sum squared resid		0.096079
Long-run variance	0.010104			

Again, for the same reason, data from 1995 to 2012 was used for estimation so that we can use the estimation result for forecasting dependent variable for the period 2013-2016. Here, the estimated coefficients of GDP and TPI are significant while that of IR is not. This is because, the sign of the coefficient of IR is positive (0.0167) which is not according to our expectation. In fact, it should be negative. That is why, it is not significant. In other words, it does not affect money demand. For TPI, for instance, 1 percent increase in TPI causes money demand to increase by 0.24 percent. For GDP, the magnitude is almost three times higher meaning that 1 percent increase in GDP will increase money demand by 0.86 percent. The sign of the estimated coefficient of GDP is also according to the economic theory. Now, it is time to do forecasts based on these two different estimation methods.

Figure 3: Forecasting dependent variable based on DOLS estimation

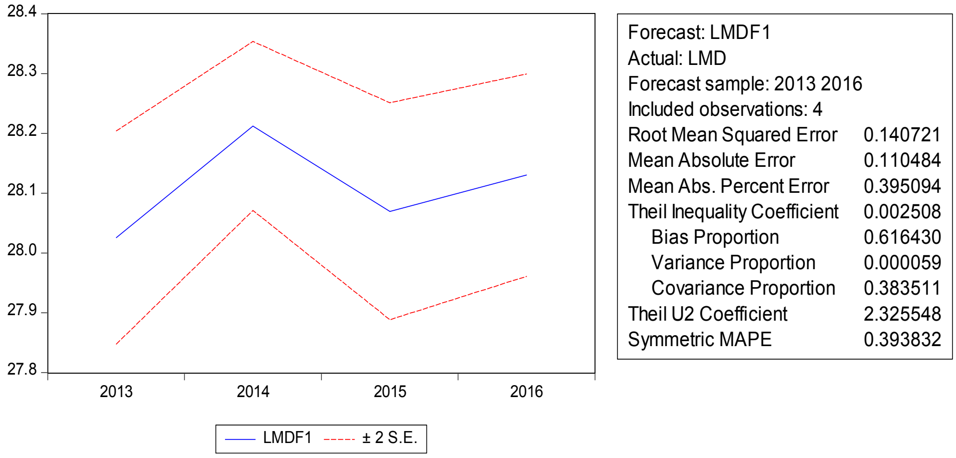
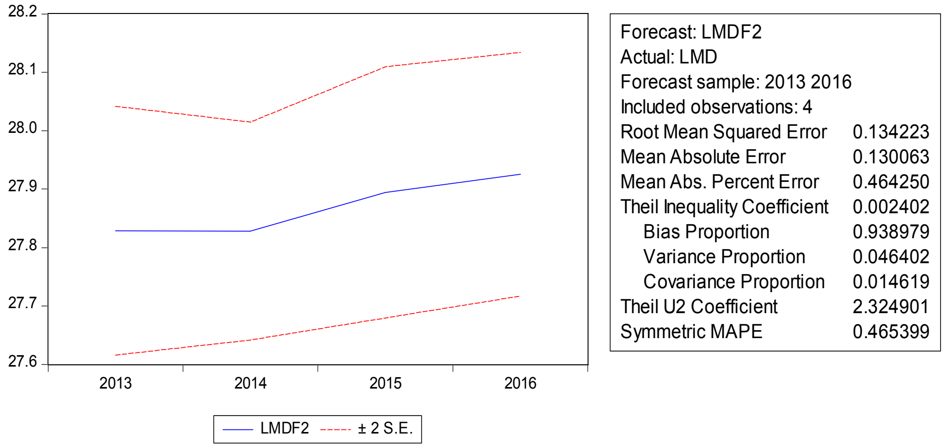


Figure 4: Forecasting dependent variable based on FMOLS estimation

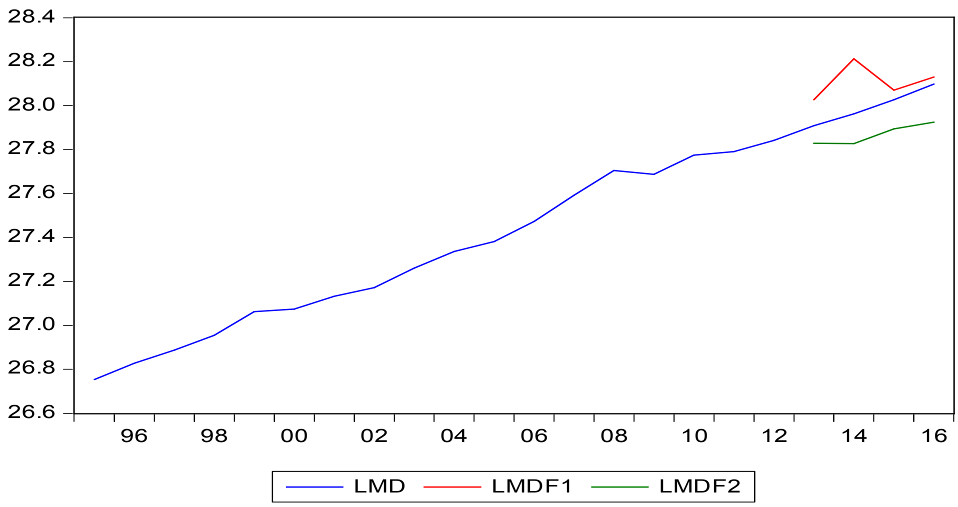


As can be seen, the forecasted dependent variable in both figures is passing through 95 percent confidence intervals or between two standard deviations. Now, we can compare the predictive power of these two estimation methods. Because all of data is known, we call it ex-post forecasting. Here, we focus on static forecasting, that is, a sequence of one-step ahead forecasts using the actual values not forecasted values of lagged dependent variable. First, we have to deal with forecasting error which is the gap between actual and forecasted dependent variable. The method with smaller forecasting error is superior.

For the purpose of forecast evaluation, first we choose "Root Mean Squared Error" (RMSE) as benchmark. This statistic refers to the gap between forecasted LMD and actual LMD. Smaller RMSE means better forecasting or more predictive power. By comparing the magnitude of this statistic for the two methods from figure 3 and figure 4 (0.1342 for FMOLS compared to 0.1407 for DOLS), we simply find out that FMOLS method is superior to DOLS for forecasting purpose. To see this better, we plot the forecasted LMD based on the two different estimation methods along with actual LMD.

It is clear that forecasted LMD using FMOLS is moving more closely to actual LMD compared to forecasted LMD using DOLS. Therefore, figure 5 is another evidence on the superiority of FMOLS over DMOLS. We may also consider Theil Inequality Coefficient (TIC) as another measure of the forecasting performance. If TIC = 0, there is a perfect fit meaning that forecasted LMD and actual LMD are the same. If TIC = 1, the predictive power of the model is worst. TIC is between 0 and 1. Again, TIC for FMOLS is less than that of DOLS certifying the fact that the forecasting performance of FMOLS is better than DOLS.

Figure 5: Comparison of the predictive power of the regression based on FMOLS and DOLS estimation



6. <u>Conclusion</u>

In this paper we applied two different estimation methods, namely DOLS and FMOLS to estimate real demand for money in Australia with the inclusion of financial innovations. We used a conventional money demand function that was enriched with a proxy for financial innovations. This sum of the number of cheques, credit cards, charge cards, ATM and direct entry payment was included in the regression model to proxy the effect of financial innovations on the money demand. Data (annually from 1995-2016) was collected from the official website of the World Bank and the official website of Reserve Bank of Australia. Our goal is to estimate the effect of financial innovations on the demand for money using two different methods (DOLS and FMOLS) and compare the predictive power of these methods.

DOLS and FMOLS are superior to the OLS for many reasons: (1) OLS estimates are super-consistent, but the t-statistic gotten without stationary or I(0) terms are only approximately normal. Even though, OLS is super-consistent , in the presence of "a large finite sample bias' convergence of OLS can be low in finite samples, (2) OLS estimates may suffer from serial correlation and heteroskedasticity since the omitted dynamics are captured by the residual so that inference using the normal tables will not be valid even asymptotically. Therefore, "t" statistics for the estimates OLS estimates are useless, (3) DOLS & FMOLS take care of endogeneity by adding the leads & lags. In addition, white heteroskedastic standard errors are used. FMOLS does the same using a nonparametric approach. FMOLS is a non-parametric approach used to dealing with serial correlation. Dynamic OLS (DOLS) is an alternative (parametric) approach in which lags and leads are introduced to cope with the problem irrespectively of the order of integration and the existence or absence of cointegration.

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. Also, there are 3 cointegrated equations. After making sure that the variables are cointegrated, we can proceed to DOLS and FMOLS which both are very efficient and sophisticated estimation methods. By doing this, we obtain long-run estimates.

In both methods, GDP coefficient is significant and bears the expected sign (positive sign). However, the magnitude of the GDP coefficient using DOLS is higher than that of FMOLS. However, our focus is on TPI which represents the impact of financial innovations on money demand. The estimated coefficient of TPI using DOLS is not significant yet it is highly significant using FMOLS and it bears positive sign so that 1 percent increase in TPI causes money demand to increase by 0.24 percent.

Finally, we did forecast based on these estimation method. According to table 1, there are four different measure to evaluate the forecasting performance. Out of these, we selected “Root Mean Squared Error” as the benchmark and concluded that FMOLS is superior to DOLD when it comes to forecasting. Also, FMOLS method produced significant TPI meaning that financial innovation did in fact impact on the money demand.

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