THE EFFECT OF FINANCIAL INNOVATION ON THE FORECASTING PERFORMANCE OF MONEY DEMAND IN JAPAN IN THE CONTEXT OF ARIMA MODEL DURING 1990-2015

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Abstract: This paper studies the effect of financial variables on the forecasting accuracy of the demand for money in Japan using annual data from 1990 to 2015 using ARIMA model. We use broad money to total reserves ratio (MRR) and growth in net domestic credit to GDP (GDC) as financial variables to proxy the effect of financial variables due to insufficient data on more relevant financial variables such as ATM (automatic teller machine) and EFTPOS (electronic funds transfer at point of sale). In doing so, we use a traditional money demand specification with GDP and interest rate as the conventional determinants of money demand. Data are all in real term (constant 2010 US Dollar) retrieved from the World Bank. The result indicates that the forecast from ARIMA model without accounting for financial innovation outperforms the forecast from ARIMA model with the inclusion of financial innovation (proxied by GDC and MRR).

Keywords: Japan, money demand, ARIMA model, financial innovation, external shock

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.
Trade and commerce have been transformed since the introducing of new advanced information technology and technical innovations. Low-cost and high-speed data transfer because of these advancements has created an outstanding platform for e-commerce to grow rapidly which in turn helped to improve the efficiency and boost the competitiveness and economic growth.

Forecasting of money demand as a policy instrument, is considered essential to 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. In recent years, the Central Banks over the world have found it difficult to forecast accurately the amount of notes and coins demanded. As a result, this paper seeks to develop a models which is suitable for forecasting currency trends and assess its forecasting ability with and without financial innovation. Currency demand equations based on economic theory is used to identify the conventional determinants of the real demand for money and considering them as exogenous variables in time series ARIMA model.

The rest of the article is structured as follows. First, we provide a brief review of the previous works on the estimation of money demand with the inclusion of financial innovation. In methodology, we describe background, the modelling technique and the data used in the estimation. Next, the estimation results and interpretation of the model estimation will be presented, and finally summary and conclusions will be provided.

2. Literature review

In empirical work however, income and interest rates both are considered as the main determinants of money demand. In recent years, researchers started to include financial innovation in the money demand function due to its role in in reducing transaction costs. Excluding financial innovation could lead to serious misspecification and an unstable money demand (Arrau et al., 1995; Goldfeld and Sichel, 1990).

Melnik and Yashiv (1994) describe financial innovation as the “introduction of new liquid assets that partially replace traditional money in agent’s portfolios, technological progress in banking services that reduces the costs of transactions and changes in the regulatory environment that facilitate transactions.” Frame and White (2004) express financial innovation as something new that fulfils participant’s demands through reduced costs, reduced risks and improved products. Arrau et al. (1995) see financial innovation as a permanent change to the money demand that is caused by technological processes and not by interest rates and GDP) and Arrau and De Gregorio (1991) describe it to include deregulation as well.
Researchers have to use various proxies to measure financial innovation as it is difficult to measure it directly. Lippi and Secchi (2009), Fischer (2007), Sichei and Kamau (2012) and Attanansio et al. (2002) are among those who used ATM concentration as proxy. In order to take shifts in money demand into account, dummy variable was used by Hafer and Kutan (2003). Bank concentration was considered by Nagayasu (2012) while growth in private sector credit as a percent of GDP was used by Michalopoulos et al. (2009). Arrau et al. (1995) used a time trend and a stochastic trend that follows a random walk and Hye (2009) and Mannah-Blankson and Belyne (2004) used M2/M1 for capturing financial innovation. Most of these studies however, indicate that financial innovation has had a negative effect on the demand for money justifying the importance of inclusion of this factor in the money demand specification.

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.

3. Methodology

Background

In order to model the demand for money, we use the Auto-Regressive Moving Average (ARIMA) technique developed by Box and Jenkins (1970) which are independent of any particular economic theory, and the forecasts from the models are based only on the past behaviour of the money demand using the properties of a stationary time series to forecast its future movement. However, in the estimation process, we include some exogenous inputs as well.

A stationary time series tends to return to its mean value after an increase or decrease. A non-stationary series will only change in response to an external shock. The auto-regressive / moving average modelling is carried out on the differenced series to make a non-stationary series to a stationary one.

Autoregressive model

The autoregressive model of order $p$ denoted by AR($p$) is written as:

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t$$

where, $c$ is a constant, $\varphi_1, \ldots, \varphi_p$ are parameters, and $\varepsilon_t$ (the random variable) is white noise.

If $|\varphi_1| \geq 1$, then processes in the AR(1) model are not stationary. Therefore, for the model to remain stationary, Some constraints on the values of the parameters are necessary.
Moving-average model

The moving average model of order $q$ which is denoted by MA($q$) is written as:

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

where $\mu$ is the expectation of $X_t$, the $\varepsilon_t$, $\varepsilon_{t-1}$, $\ldots$ are white noise error terms and the $\theta_1, \ldots, \theta_q$ are the parameters of the model.

ARMA model

The model with $p$ autoregressive terms and $q$ moving-average terms is denoted by ARMA($p$, $q$) which encompasses the AR($p$) and MA($q$) models:

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \phi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

Peter Whittle was the first one to describe the general ARMA model using Laurent series and Fourier analysis and statistical inference (Hannan, 1980). Box and Jenkins (1970) developed an iterative (Box–Jenkins) method for estimating this model and for low-order polynomials in particular (Hannan & Deistler, 1988).

The error terms $\varepsilon_t$ are generally assumed to be independent identically distributed random variables (i.i.d.) sampled from a normal distribution with zero mean: $\varepsilon_t \sim N(0, \sigma^2)$ where $\sigma^2$ is the variance.

The models can also be specified in terms of the lag operator $L$. Therefore, we can rewrite the AR($p$) model as:

$$\varepsilon_t = (1 - \sum_{i=1}^{p} \phi_i L^i)X_t = \varphi(L)X_t$$

Where the polynomial is represented by $\varphi$

$$\varphi(L) = 1 - \sum_{i=1}^{p} \phi_i L^i$$

The MA($q$) model can be rewritten as:

$$X_t = (1 + \sum_{i=1}^{q} \theta_i L^i)\varepsilon_t = \theta(L)\varepsilon_t$$

Again, the polynomial is represented by $\theta$

$$\theta(L) = 1 + \sum_{i=1}^{q} \theta_i L^i$$

Consequently, we rewrite the combined ARMA($p$, $q$) model as:

$$(1 - \sum_{i=1}^{p} \phi_i L^i)X_t = (1 + \sum_{i=1}^{q} \theta_i L^i)\varepsilon_t$$

or more briefly,

$$\varphi(L)X_t = \theta(L)\varepsilon_t$$

or

$$\frac{\varphi(L)}{\theta(L)}X_t = \varepsilon_t$$

Box et al. (1994) use a different convention for the autoregression coefficients by allowing all the polynomials involving the lag operator to appear in a similar form throughout and rewrite the ARMA model as:

$$(1 - \sum_{i=0}^{p} \phi_i L^i)X_t = (1 + \sum_{i=0}^{q} \theta_i L^i)\varepsilon_t$$

To get a more sophisticated formulation, we set $\Phi_0 = \theta_0 = 1$

$$\sum_{i=0}^{p} \phi_i L^i X_t = \sum_{i=0}^{q} \theta_i L^i \varepsilon_t$$

Brockwell & Davis (2016) recommend using AICc for finding appropriate values of $p$ and $q$ in the ARMA($p$, $q$) model. We adopt this approach in this paper. Although they can be determined by plotting the partial autocorrelation functions for an estimate of $p$ and $q$ as well.
OLS cannot be used to estimate ARMA models. Instead, we need to find the smallest values of $p$ and $q$ which provide an acceptable fit to the data. ARMA is suitable when a system is a function of a series of unobserved shocks (the MA or moving average part) as well as its own behaviour. For the case of money demand, it is affected not only by its past values, but also is affected by exogenous shocks (such as GDP, interest rate and technology innovations).

**Autoregressive–moving-average model with exogenous inputs model (ARMAX model)**

The notation ARMAX($p, q, b$) refers to a model that contains the AR($p$) and MA($q$) models and a linear combination of the last $b$ terms of a known and external time series $d_t$:

$$X_t = \varepsilon_t + \sum_{i=1}^{p} \phi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \sum_{i=1}^{b} \eta_i d_{t-i}$$

Where the parameters of the exogenous input are denoted by $\eta_1, \ldots, \eta_b$. The estimated parameters refer to the regression:

$$X_t - m_t = \varepsilon_t + \sum_{i=1}^{p} \phi_i (X_{t-i} - m_{t-i}) + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

where $m_t$ incorporates all exogenous (or independent) variables:

$$m_t = c + \sum_{i=0}^{b} \eta_i d_{t-i}$$

**Autoregressive integrated moving average**

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.
Suppose a time series of data is denoted by \( X_t \) (\( X_t \) are real numbers) where \( t \) is an integer index then an ARMA\((p',q)\) model is expressed as:
\[
X_t - \alpha_1 X_{t-1} - \ldots - \alpha_p X_{t-p'} = \epsilon_t + \theta_1 \epsilon_{t-1} + \ldots + \theta_q \epsilon_{t-q}
\]
or
\[
(1 - \sum_{i=1}^{p} \alpha_i L^i) X_t = (1 + \sum_{i=1}^{q} \theta_i L^i) \epsilon_t
\]
where the parameters of the autoregressive part of the model is denoted by \( \alpha_i \), the lag operator is denoted by \( L \), the parameters of the moving average part is denoted by \( \theta_i \) and the \( \epsilon_t \) are error terms which are assumed to be independent, identically distributed variables sampled from a normal distribution with zero mean.

Then we rewrite the polynomial \((1 - \sum_{i=1}^{p} \alpha_i L^i)\) which has a unit root (a factor \((1 - L)\)) of multiplicity \( d \) as:
\[
(1 - \sum_{i=1}^{p} \alpha_i L^i) = (1 - \sum_{i=1}^{p'-d} \varphi_i L^i) \ (1 - L)^d
\]
This polynomial can be expressed by an ARIMA\((p,d,q)\) process with \( p=p'-d \):
\[
(1 - \sum_{i=1}^{p} \varphi_i L^i) \ (1 - L)^d X_t = (1 + \sum_{i=1}^{q} \theta_i L^i) \ \epsilon_t
\]
That is a particular case of an ARMA\((p+d,q)\) process having the autoregressive polynomial with \( d \) unit roots. The general form of the above equation is:
\[
(1 - \sum_{i=1}^{p} \varphi_i L^i) \ (1 - L)^d X_t = \delta + (1 + \sum_{i=1}^{q} \theta_i L^i) \ \epsilon_t
\]
This is an ARIMA\((p,d,q)\) process with drift \( \delta/(1 - \Sigma \varphi_i) \).

Choosing the order

The Akaike information criterion (AIC) is normally used to determine the order of a non-seasonal ARIMA model.
\[
\text{AIC} = -2\log(L) + 2(p + q + k + 1)
\]
where the likelihood of the data is represented by \( L \), the order of the autoregressive part is represented by \( p \) and the order of the moving average part is represented by \( q \). Finally, the number of parameters in the model being fitted to the data is represented by the parameter \( k \). For AIC, if \( k = 1 \) then \( c \neq 0 \) and if \( k = 0 \) then \( c = 0 \).

for ARIMA models, we correct the AIC as
\[
\text{AIC}_c = \text{AIC} + (2(p + q + k + 1) (p + q + k + 2)) / (T - p - q - k - 2)
\]
And the Bayesian Information Criterion is
\[
\text{BIC} = \text{AIC} + (\log(T) - 2) (p + q + k + 1)
\]
A good model should have a minimize values of AIC, AICc or BIC. For example. A model with lower AIC value, the better it will suit the data. AICc can only be used to compare ARIMA models with the same orders of differencing, otherwise, RMSE is used for this purpose.
Forecasts using ARIMA models

The ARIMA model is actually a "flow" of a non-stationary and a wide-sense stationary models. The non-stationary:
\[ Y_t = (1 - L)^d X_t \]
And the wide-sense stationary:
\[ (1 - \sum_{i=1}^{p} \varphi_i L^i ) Y_t = \left( 1 + \sum_{i=1}^{q} \theta_i L^i \right) \varepsilon_t \]
We may use a generalization of the method of autoregressive forecasting to forecast the process \( Y_t \).

Empirical Model

Most of the previous empirical work on money aggregates have been dedicated to their potential use in monetary policy, testing the stability of money aggregate demand functions, and to identify structural relationships based on economic theory. The purpose of this study however is to forecast future movements of the money demand, we apply a forecasting technique that do not rely on a structural relationship between money and its determinants (namely GDP, interest rate and proxies for technology innovation). However, we describe the general form of the conventional money demand function to introduce the determinants of the money demand to be included in ARIMA model only as exogenous variables.

The general form of the theory of money demand can be represented as below (Serletis, 2007):
\[ \frac{M_t}{P_t} = \Phi(R_t, Y_t) \]
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 or IR as the best proxy). Definitions of the variables according to the World Bank are as follow.

"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. GDP is in constant 2011 international dollars (PPP, purchasing power parity). 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 2011 international dollars ,PPP) 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.
Growth in domestic credit provided by financial sector and broad money to total reserves ratio are not explicitly included in the money demand function. In the context of an ARIMA model, we consider them as external shocks to the system. Growth in domestic credit provided by financial sector is denoted by GDC and Broad money to total reserves ratio is denoted by MRR in the estimation results.

Domestic credit provided by the financial sector includes all credit to various sectors on a gross basis, with the exception of credit to the central government, which is net. The financial sector includes monetary authorities and deposit money banks, as well as other financial corporations where data are available (including corporations that do not accept transferable deposits but do incur such liabilities as time and savings deposits). Examples of other financial corporations are finance and leasing companies, money lenders, insurance corporations, pension funds, and foreign exchange companies.

Total reserves comprise holdings of monetary gold, special drawing rights, reserves of IMF members held by the IMF, and holdings of foreign exchange under the control of monetary authorities. The gold component of these reserves is valued at year-end (December 31) London prices.

The data are annually, from 1990 to 2015. The data are all in real term. The official website of the World Bank was used to retrieve the data.

Estimation

Now, we forecast the demand for money (MD) for 5 years ahead using ARIMA model. The data contains series from 1990 to 2015. Out of this data, we take a sample from 1990 to 2010 for estimation and use the estimated parameters to forecast MD for the period 2011-2015 which is 5 years and then, we compare the actual values with the forecasted values to determine the predictive power of the model. First, the conventional determinants of money demand, (gross domestic product and interest rate) will be included in the ARIMA model as exogenous variables or external shocks and the forecast will be done.

Table 1: AIC value for the ARIMA model with GDP and IR

<table>
<thead>
<tr>
<th>Automatic ARIMA Forecasting</th>
<th>Selected dependent variable: DLOG(MD)</th>
</tr>
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<tbody>
<tr>
<td>Date: 01/12/18 Time: 14:44</td>
<td>Sample: 1990 2010</td>
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<tr>
<td>Included observations: 20</td>
<td>Forecast length: 5</td>
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<tr>
<td>Number of estimated ARMA models: 25</td>
<td></td>
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<tr>
<td>Number of non-converged estimations: 0</td>
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<tr>
<td>AIC value: -2.95440746167</td>
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</table>
It is obvious from table 1 that the software has converted the variable to the logarithm form and it has taken first differenced. It means that the money demand has become stationary by taking one difference. 25 ARIMA models have been estimated. A model with the lowest AIC value (-2.9544) has been selected as the best one, that is, ARIMA(0,0)(0,0).

Figure 1: Comparison of the actual values with the forecasted values in an ARIMA model including GDP and IR

Figure 1 Compares the actual values and the forecasted values in an ARIMA model for the selected model, that is, ARIMA(0,0)(0,0). It indicates the amount of deviation of the forecasted value from the actual value during the 5-years forecast period. The lower the gap, the better the model is.
Figure 2: Forecasts based on ARIMA model with different order of p, d, q (including GDP and IR)

Figure 2 shows different estimated ARIMA models and the red line indicates the one that suits the data best with the lowest AIC value.
Table 2: Choosing the best ARIMA model (including GDP and IR) based on AIC values

<table>
<thead>
<tr>
<th>Model</th>
<th>Logl.</th>
<th>AIC*</th>
<th>BIC</th>
<th>HQ</th>
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Table 2 shows AIC, BIC and HQ values for different ARIMA models. It is clear that all of these value are minimum for ARIMA(0,0)(0,0).

Next, we repeat the process above by adding two more variables to proxy the financial innovation (Growth in domestic credit provided by financial sector (% of GDP) and broad money to total reserves ratio) and do the forecast accordingly.

Table 3: AIC value for the ARIMA model with GDP, IR, GDC and MRR
The software has again taken a log of the variable and a first differenced as well. Out of 25 ARIMA models, a model with the lowest AIC value (-3.7707) has been selected as the best one, that is, ARIMA(0,2)(0,0).

Figure 3: Comparison of the actual values with the forecasted values in an ARIMA model including GDP, IR, GDC and MRR

Figure 3 make a Comparison between the actual values and the forecasted values in an ARIMA model for the selected model, that is, ARIMA(2,0)(0,0). It indicates the amount of deviation of the forecasted value from the actual value during the 5-years forecast period is relatively large despite the fact that it is the best.
Figure 4: Forecasts based on ARIMA model with different order of p, d, q (including GDP, IR, GDC and MRR)

Figure 4 shows the best ARIMA model as the red line which is appearing at the bottom of the figure.
Table 4: Choosing the best ARIMA model (including GDP, IR, GDC and MRR) based on AIC values

<table>
<thead>
<tr>
<th>Model</th>
<th>LogL</th>
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Table 4 shows AIC, BIC and HQ values are all in line with the fact that ARIMA(2,0)(0,0) is the best model when we include conventional determinants of the money demand and the proxies for financial innovation.
Figure 5 compares the actual values and the forecasted values in the selected ARIMA model for the two cases. The first one (MD_F01) is the forecasted MD in an ARIMA model with GDP and IR (the conventional determinants of money demand) and the second one (MD_F02) is the forecasted MD in an ARIMA model with GDP and IR and also GDC and MRR (as proxies for financial innovation). It indicates the amount of deviation of the forecasted value from the actual value during the 5-years forecast period is significantly large for the second case, that is, the model that includes GDC and MRR.

4. Summary

Forecasting the demand for money has become increasingly difficult due to introducing innovation in the financial sector. As a result, it is necessary to develop a model for predicting the demand for money. In this paper, we have compared the forecasting performances of ARIMA model with and without these innovations. The money demand model had better out-of-sample forecasts (by comparing the actual and forecasted values) without the inclusion of financial innovation than the one with it.

Technology innovations may have a strong impact on the demand for money in recent years. However, finding suitable variables to represent these developments satisfactorily is proves to be difficult. The problem is that the data on ATM (automatic teller machine) and EFTPOS (electronic funds transfer at point of sale) is only available for recent periods. Therefore, we had to use other variables to proxy these innovations which are considered weaker and inferior compared to ATM and EFTPOS. That is probably why including these variables to measure the effect of financial innovation deteriorated the forecast power of the model. Collecting data on these new payments technologies remains a priority for any future analysis of money demand in Japan.
The main focus of this paper is to find a model that forecasts accurately out-of-sample, over a 5-year horizon. In doing so, we reduced the estimation period back to 2010, and compared the predicted values from ARIMA model (with and without financial innovation) with the actual values over the period 2011 - 2015. The results indicate that the forecast power of the ARIMA model is significantly reduced by the inclusion of financial innovation bearing in mind that the conventional determinants of money demand, (gross domestic product and interest rate) were considered as exogenous variables or external shocks in both estimates.

There are a number of other reasons why an ARIMA model outperforms the structural demand function for the purpose of forecasting. Firstly, financial innovation such as ATM cards affects money demand in the long run. Therefore, a structural demand function without the inclusion of suitable proxies for these innovations in payment technologies leads to the misspecification of the money demand function. Secondly, for short-term horizons, such as five years, a simple predictive model like an ARIMA is more suitable than a structural model as the latter is preferred only for longer-term currency forecasting.

References


