PAYMENT TECHNOLOGIES AND MONEY DEMAND: EVIDENCE FROM DYNAMIC PANEL

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Abstract

The banking system has experienced rapid and significant technological changes in recent years, including automated teller machines (ATMs), automated clearing houses, point of sale systems, telephone transfers, automatic bill payer accounts, and credit cards. The total effect of these innovations on money demand has been the subject of some empirical research; however, the individual effect of most of these innovations has not been estimated. This article attempts to partially bridge the gap in the empirical literature by providing empirical evidence relating to the effect of ATMs on money demand in world scale. The demand for money is a very important for the conduct of monetary policy and measurement of the effectiveness of monetary policy. This study attempts to analyse if financial innovations has impacted the demand for money using a system (the original equation and the transformed one) GMM method. In this study, money demand dynamics are examined empirically by using the Blundell–Bond estimator which reinforces Arellano–Bond by making an additional assumption that first differences of instrument variables are uncorrelated with the fixed effects. It makes it possible to introduce more instruments that improve the efficiency considerably. We estimate the demand for money (M2) for a panel of 215 countries and territories from 2004 to 2013. The elasticity of the demand for real money to ATM is about 0.01 percent meaning that the sensitivity of money demand to ATM is low. In other words, money demand is not elastic with regard to ATM.

Keywords: Money demand, ATM, Financial innovation, Dynamic panel data model, GMM

JEL classification: C13, C40, C51, E40, E44

1. Introduction

Using new electronic technologies caused more than ever the expansion of e-commerce due to its high-speed and low-cost data transfer that needs the monetary instruments and proportionate payments. It means that the transfer of funds by paper-based method is a major obstacle to the trade. Therefore, electronic transfer of funds has been developed along with the development of e-commerce in a variety of forms. Electronic payment method provides security, convenience, speed, low cost and high efficiency. Electronic payment can be made by automatic teller machines (ATMs) and include electronic money (e-money), electronic cards (e-cards) and electronic check. The use of electronic money in a large scale has significant business, economic, political and social impacts.

The Keynesian money demand = (,) is enriched with innovation (r*) so that it can be represented implicitly as = (,, r*). Financial innovation is an opportunity for investors, who, on the market, decide which innovation is going to survive and evolve, and monetary authority, which looks at the demand for money and its stability as an explanatory variable together with consumption and investments, should consider these portfolio shifts and their (adverse) effects.

The objectives of the current paper is to estimate the demand for money in the presence of financial innovation using panel data from 215 countries in the world for the period 1961 to 2013. We shall use a systems based General Method of Moments (GMM) of Blundell and Bond (1998) for estimation. This has several advantages. Our paper is the first to use this method to estimate demand for money with panel data for all of the countries in the world. The rest of the paper is structured as follows. A review of the theoretical and empirical literature is given in Section 2 followed by methodology including a brief overview of the conventional demand for money and econometric approach in Section 3. Section 4 presents the results of the estimation and it ends up with summary in section 5.

2. Literature Review

There are 3 different outcomes out of the bulk of the major previous studies about the impact of payment technologies on the demand for money. The first category came to the conclusion that it has a negative effect on money demand while the second group conclude a positive impact and the third one produce mixed results or no significant impact.

First, we begin with the studies with negative effect. Boeschoten (1992) find out that the use of ATMs, cheques and POS terminals significantly reduces cash holdings (based on microeconomic analysis of payment habits in the Netherlands). Attanasio et al. (1998) sum up that the demand for money of households who holds an ATM card is much more elastic to interest rate than that of households who do not (based on time-series and cross-sectional data during 1989 – 1995 in Italy). Rinaldi (2001) states that the development of card payments (including ATM cards) will reduce the demand for money in Belgium. Snellman et al. (2001) and Drehmann et al. (2002) come up with the result that the number of POS terminals and ATMs has significantly negative effects on money demand (based on panels of European countries). Attanasio et al. (2002) finds that the interest rate elasticity of money demand is sensibly higher for individuals who have access to ATMs than those lacking. Therefore, ATM users hold significantly lower cash balances than non-users (based on data from Central and in Southern Italy). Stix (2003) proves that if the share of individuals who use the ATM frequently is high compared to infrequent ATM users, then a negative effect on cash demand was likely to occur. Markose and Loke (2003) believe that high ATM density as well as low user costs may reduce cash demand. Duca and Van Hoose (2004) show that money demand is inversely related to the improvements in transaction technology (such as ATM) that lower transaction costs. Columba (2009) come to the conclusion that technological innovation has a negative effect on currency in circulation, whereas their effect on M1 is positive.

We then, pay our attention to the studies with positive effect. Zilberfarb (1989) shows that the use of ATM reduces the transaction cost and therefore it increases demand deposits. Goodhart and Krueger (2001) state that people visit ATMs more often and withdraw small amounts of cash, which would increase the demand for small bank notes. Attanasio et al. (2002) say there are significant differences between individuals with an ATM card and those without. Most of the ATM transactions involve the withdrawal of cash (and very few deposits), it is quite likely that ATMs infra-structure influence the use of cash and money demand positively.

Finally, we focus on the studies with mixed or no significant effect. Boeschoten (1998) shows that ATMs lead to reduced cash demand by the public but increased inventories of currency held by the banking sector for ATM usage. Thus the total effect of ATMs on the total amount of currency outstanding is quite moderate (based on Dutch data during 1990–1994). Snellman, Vesala and Humphrey (2001) proves that ATMs leads to more cash withdrawal but less amount of cash and therefore, the total effect on cash demand is ambiguous. Drehmann et al. (2002) conclude their research with the results that ATMs seem to increase the demand for small notes, while the effects on large notes are unclear (based on annual data from 1980 to 1998 for 18 OECD countries).

3. Methodology

3.1. Theoretical approach

The general form of the theory of money demand includes the main determinants of the level of economic activity:

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

where the demand of nominal money balances is denoted by M_t, the price index is denoted by P_t that is used to convert nominal balances to real balances, the scale variable is denoted by that relates to activity in the real sector of the economy (proxied by GDP), and R_t is the opportunity cost of holding money that is proxied by the interest rate.

Scale Variables: We include the scale variable in the money demand function to measure transactions relating to economic activity. Transactions theories of money demand put emphasis on income as the relevant scale variable while in asset theories, wealth is considered as a relevant scale variable. The problem with asset theories is that it is not easy to measure wealth. Long time series on financial wealth have been collected and recorded only in few countries such as USA and UK. furthermore, these measures are not as comprehensive as the general measure of wealth that includes the value of human and nonhuman capital, proposed by Friedman's (1956) modern quantity theory. Measuring expected income was made possible by using Cagan's (1956) model of adaptive expectations. The adaptive expectations model for the unobserved expected level of income at time t, Y_t^e is:

$$Y_t^e - Y_{t-1}^e = \theta\,(Y_t^e - Y_{t-1}^e)$$

where $0 \leq \theta \leq 1$. By rearranging the above adaptive expectations model, we have:

$$Y_t^e = \theta Y_t + (1-\theta)\, Y_{t-1}^e$$

Y_t^e as shown in above formula implies that the expected level of income at time t is a weighted average of the current actual level of income and last period's expected value of income. The weights are the adjustment parameters θ and 1−θ. By continuous back-substitution, finally it yields the second presentation of the adaptive expectations model:

$$Y_t^e = \theta Y_t + (1-\theta) + \theta(1-\theta)^2 Y_{t-2} + \dots ,$$

This formulation indicates the unobserved expected level of income at time t is a weighted average of the current actual level of income and already known income levels of the past, Y_{t-1}, Y_{t-2}, and so on. θ, θ (1 − θ), $\theta(1-\theta)^2$, and so on that are the weighting scheme, represents a memory that is the influence of past income levels on the formation of expectations. For instance, if θ is close to zero, the weights decline slowly and the economic agent has a long memory. In other words information from the distant past considerably impacts the formation of expectations. Alternatively, If θ is close to one, the weights decline quickly and the agent has a short memory meaning that only information from the recent past impacts the formation of expectations. The problem with the adaptive expectations model is that it doesn't suppose enough rationality on the part of economic agents meaning that only current and past values of the variable in question are used by economic agents when it formulates expectations for the future. John Muth's (1961) rational expectations hypothesis is considered as an alternative hypothesis for the above analysis. Rational expectations imply that economic agents when forming their expectations for the future use all of the available information, including relevant economic theory. Lucas (1972, 1973), Sargent and Wallace (1975), and Barro (1976) made significant contributions to the concept of rational expectations. Using the rational expectations for empirical work requires quantifying the concepts of 'available information' and 'relevant economic theory.' This quantification is very helpful but it is not an easy task to do. It is because, we need to treat many issues, such as structural shifts in the income growth process for empirical work, see Barro (1977, 1978). In order to represent the scale variable in the money demand function, the level of current income is going to be used. Laidler (1993, pp. 98-99) mentions that the measurement of this variable is not problematic because, in spite of the fact that economists use gross national product series, net national product series and gross domestic product series to measure the scale variable, these variables move rather closely together over time and using one or the other makes no difference. Measure of transactions is a more comprehensive compared to the measure of income. We give an example for clarification purpose. Gross national product (GNP) does not include transactions in financial assets, sales of intermediate goods, transfers, and purchases of existing goods despite the fact that they all have impact on the demand for money. That is why economists have relied on the construction of scale variables on the basis of more general measures of transactions. It is not known yet to say for sure if these new data will make important improvements in the explanation of aggregate money demand. Recently, there have been attempts to disaggregate GNP into several scale variables to take into account this fact that all the transactions are not equally money intensive. For instance, Gregory Mankiw and Lawrence Summers (1986) state that consumption is a more suitable variable than GNP in order to estimate money demand functions and that the disaggregation of GNP into components that replicate the nature of international transactions is important for open economies. The fact that disaggregation of GNP improves the performance of money demand functions is not yet backed by empirical evidence.

Opportunity Costs: The opportunity cost of holding money is defined as the difference between the rate of return on assets alternative to money and the own rate on money. The question is that what is the best choice for the rate of return on alternative assets? Economists adopt a transactions approach and a narrow definition of money (short term interest rates, such as the Treasury bill rate, the commercial paper rate, or the saving deposit rate) is used for this purpose. By adopting asset approach, on the other hand, broader definition of money (longer-term rates of interest) is used. Now we turn our attention to the own rate on money. Most economists believe that it is actually zero meaning that the explicit rate of return on most forms of money (i.e., currency, demand deposits, etc.) is zero. This is questionable, because even if it is the case (the explicit return is zero), money earns an implicit rate of return (gifts, services, or reduced transactions fees) by maintaining a minimum level of deposits. The problem is that it is not easy to measure the implicit rate of return so many researchers have ignored it. See Benjamin Klein (1974) and Richard Startz (1979) for exceptions. However, some other variables might have impacts on the money demand function. For a discussion with further references see Goldfeld and Sichel (1990), Laidler (1993), and Subramanian Sriram (1999).

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

$$\text{Log}\left(\frac{\mathbf{M}_t^*}{\mathbf{P}_t}\right) = \alpha + \beta_1 \log \mathbf{Y}_t + \beta_2 \mathbf{R}_t + \varepsilon_t$$

Desired stock of nominal money is denoted by $\mathbf{M}^*$, 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 $\mathbf{M}^d = (\mathbf{Y}_t,)$ 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 $\mathbf{M}^d = (\mathbf{Y}_t,, r^*)$.

3.2. The empirical model

The standard specification, based on the quantity theory of money that is the conventional money demand function, used in many empirical works in several country specific models is as below that has a semi log-linear specification. We proxy the effect of financial innovation (technology payments) on the demand for money by the number of automated teller machines (ATMS):

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

In order to estimate a demand for real balance of money, we use the amount of currency in circulation. The currency in circulation in real term is denoted by M2, real gross domestic product is denoted by GDP, R refers to the interest rate, the number of automated teller machines is denoted by ATM, and the error term is denoted by e_t with t spanning from 2004 to 2013. The official website of the World Bank is the source of data.

3.3. Econometric approach

This study analyse some possible approaches ranging from simple (static pooled ordinary least squares to more complex dynamic panel models. In order to reach the preferred econometric estimator, we have to make a number of decision as follow: 1) should we use a pooled estimator, or effects-based models aiming at taking into account cross-sectional variation/heterogeneity; 2) if we decide that the preferred model should be dynamic (including lagged adjustments); 3) after deciding on a dynamic model, then we decide what the preferred estimator is; 4) the next step is that if we can use the estimates for forecasting purpose; and 5) if we can use the data for estimating such a model. Figure below shows the decision making process aimed at reaching the preferred estimator.

After discussing the possible econometric models, we will describe the initial modelling in order to select the preferred econometric model. It is important to use effects-based models to include the possibility of heterogeneity in the dataset. Based on statistical analysis, we decided that fixed effects were more appropriate. The reason for this is that static models lead to unjustly large parameter estimates and very high t-statistics. Therefore, dynamic specification is more appropriate. ECM or an ARDL model are as alternatives for dynamic models with the difference that in ECM, the long-run relationships are modelled explicitly while ARDL involves in modelling long-run relationships implicitly. We estimated ARDL due to the small number of time-series observations but it faces the challenge of identifying long-run elasticities explicitly. On the other hand, we estimated ECM, taking advantage of identifying long-run elasticities explicitly but again, it has the disadvantage that it is not very suitable for our short time-derived data. In other words, ARDL and ECM each have their own advantages and disadvantages with regard to our data set. At the end, we arrive at the final stage of choosing the best model. The question now is that model out of the two common dynamic panel data estimators is more appropriate. Based on its advantages, we decided that the Blundell–Bond estimator was the best.

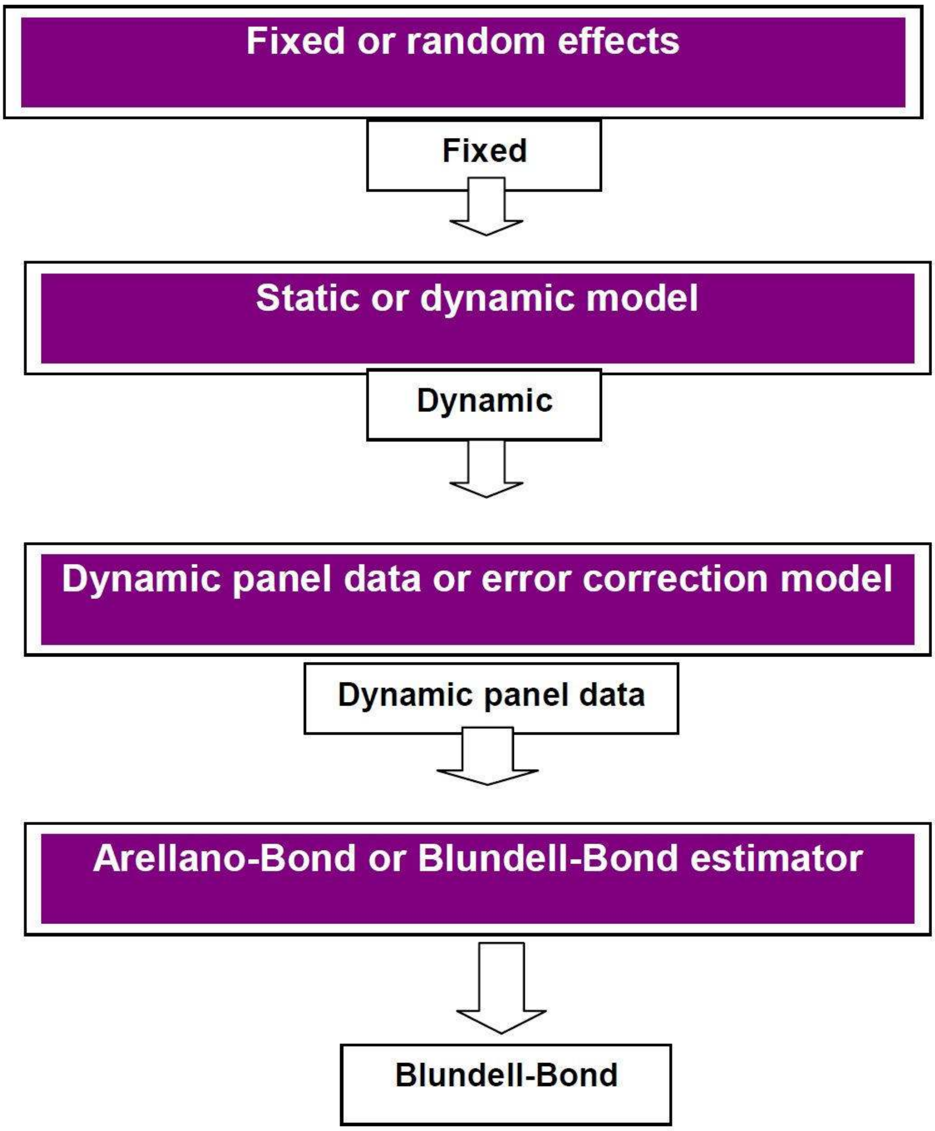
A model was estimated using the estimation Blundell & Bond technique. Arellano & Bond technique uses an estimator that is built to handle the endogenous nature of the lagged dependent variable that is very similar to the instrumental variables (IV) estimators that uses different variables as instruments or proxies for the lagged dependent variable. There should be no serial correlation in the residuals in order to meet the requirement of using these estimators; if there is serial correlation in the residuals, the instrumentation is not valid leading to inconsistent estimator. If the coefficient of the lagged dependent variable is large (in other words, if the time series is close to containing a unit root), the Arellano–Bond estimator will not be efficient (Baltagi, 2008). Blundell & Bond use a system of equations/GMM estimator that offers a solution to this problem. The Blundell–Bond also assumes that the initial observations have an insignificant impact on the observed observations. Based on these significant advantages, we chose the Blundell–Bond estimator as the best econometric technique for use in this study.

3-4- Diagnostic testing

Diagnostic testing in panel data is not as advanced as diagnostic testing in cross -sectional or time-series analysis. However, only a few tests that is available to use which include: autocorrelation, and instrument validity. This is because when the cross-sectional element of the data is large (as is the case for this study); the estimated standard errors are asymptotically robust to heteroscedasticity and non-normality. In other words, even if the errors are non-normal and hetroscedastic, the estimated standard errors are not affected by these factors. Also, the squared correlation coefficient between actual and fitted results is used as the optimal measure of model fit. We discuss these diagnostic tests further below. Fortunately, the estimated regression passed all of these tests. Autocorrelation: Arellano & Bond developed a test for autocorrelation in dynamic panel data. The Arellano–Bond and the

Blundell–Bond estimators are both based on the assumption that there is no residual autocorrelation in the model. The Arellano–Bond test for autocorrelation is a statistical test for correlation in the first-differenced errors. There is autocorrelation in the first differences due to the construction of the model. Therefore, we expect that the null hypothesis of no autocorrelation will be rejected for the first differences. However, if null hypothesis of no autocorrelation at second or third differences is rejection, it means that the moment conditions are not valid and therefore, the estimator is not valid. Moment validity: The estimators mentioned above are valid only if the moment conditions are valid meaning that the instruments that have been used in the estimation must be uncorrelated with the error term and correlated with the lagged dependent variable. There is no way to test this assumption directly. Next best approach for testing the validity of the instruments is using the Sargan test. Only if the instruments are valid, the estimates of the parameters of interest are considered consistent so Sargan test is of special importance.

Figure 1: Econometric procedure selection



4. Results

The systems GMM estimator thus combines the standard set of equations in first differences with suitably lagged levels as instruments, with an additional set of equations in the levels with lagged first differences as instruments. Although the levels of Y_{it} are necessarily correlated with the individual-specific effects (η_i) given model (1) below, assuming that the first-differences DY_{it} are not correlated with η_i, and thus permitting lagged first-differences to be used as instruments in the levels equations.

$$Y_{it} = \alpha Y_{i,t-1} + \eta_i + v_{it} \qquad |\alpha| < 1$$

Results of the Monte Carlo simulation show that the system based GMM approach has better finite sample properties in terms of bias and root mean squared error than that of GMM estimator with first differences alone. It is argued by Blundell and Bond (1998) that the systems GMM estimator performs better than the simple GMM estimator because the instruments in the levels equation remain good predictors for the endogenous variables in this model even when the series are very persistent. Though it is argued that system based GMM approach uses more instruments than the standard GMM and many instruments problem could be serious, in the simulation results this is not found to be a limitation. In fact simulation results show that the systems GMM estimates are less biased even in moderate sample sizes of cross-section data, too.

Linear dynamic panel-data models include p lags of the dependent variable as covariates and contain unobserved panel-level effects, fixed or random. By construction, the unobserved panel-level effects are correlated with the lagged dependent variables, making standard estimators inconsistent. Arellano and Bond (1991) derived a consistent generalized method of moments (GMM) estimator for this model. The Arellano and Bond estimator can perform poorly if the autoregressive parameters are too large or the ratio of the variance of the panel-level effect to the variance of idiosyncratic error is too large. Building on the work of Arellano and Bover (1995), Blundell and Bond (1998) developed a system estimator that uses additional moment conditions; xtdpdsys implements this estimator. This estimator is designed for datasets with many panels and few periods. This method assumes that there is no autocorrelation in the idiosyncratic errors and requires the initial condition that the panel-level effects be uncorrelated with the first difference of the first observation of the dependent variable.

Consider the dynamic panel-data model

$$\mathbf{y_{it}} = \sum_{j=1}^{p} \alpha_j \, \mathbf{y_{i,t-j}} + \beta_1 \mathbf{x_{it}} + \beta_2 \mathbf{w_{it}} + \mathbf{v_i} + \boldsymbol{\varepsilon_{it}}$$

where:

the α_j are p parameters to be estimated,

$\mathbf{x_{it}}$ is a 1 X $\mathbf{k_1}$ vector of strictly exogenous covariates,

β_1 is a $\mathbf{k_1}$ X 1 vector of parameters to be estimated,

$\mathbf{w_{it}}$ is a 1 X $\mathbf{k_2}$ vector of redetermined or endogenous covariates,

β_2 is a $\mathbf{k_1}$ X 1 vector of parameters to be estimated,

$\mathbf{v_i}$ are the panel-level effects (which may be correlated with the covariates), and

$\boldsymbol{\varepsilon_{it}}$ are i.i.d. over the whole sample with variance σ_ε^2.

The $\mathbf{v_i}$ and $\boldsymbol{\varepsilon_{it}}$ are assumed to be independent for each i over all t.

By construction, the lagged dependent variables are correlated with the unobserved panel-level effects, making standard estimators inconsistent. With many panels and few periods, the Arellano–Bond estimator is constructed by first-differencing to remove the panel-level effects and using instruments to form moment conditions.

Blundell and Bond (1998) show that the lagged-level instruments in the Arellano–Bond estimator become weak as the autoregressive process becomes too persistent or the ratio of the variance of the panel-level effects v_i to the variance of the idiosyncratic error ε_{it} becomes too large. Building on the work of Arellano and Bover (1995), Blundell and Bond (1998) proposed a system estimator that uses moment conditions in which lagged differences are used as instruments for the level equation in addition to the moment conditions of lagged levels as instruments for the differenced equation. The additional moment conditions are valid only if the initial condition E[$v_i \Delta y_{i2}$] = 0 holds for all i. Xtdpdsys fits dynamic panel-data estimators with the Arellano–Bover/Blundell–Bond system estimator.

That the system estimator produces a much higher estimate of the coefficient on lagged money demand agrees with the results in Blundell-Bond (1998) who that show the system estimator does not have downward bias that the Arellano-Bond estimator has when the true value is high.

STATA bond reports the Arellano-Bond test for serial correlation in the first-differenced errors. The moment conditions are valid only if there is no serial correlation in the idiosyncratic errors. Because the first difference of independently and identically distributed idiosyncratic errors are autocorrelated, rejecting the null hypothesis of no serial correlation at order one in the first-differenced errors does not imply that the model is misspecified. Rejecting the null hypothesis at higher orders implies that the moment conditions are not valid that in fact is not rejected. Also, according to Sargan test, instruments are valid.

Predetermined covariates: Sometimes we cannot assume strict exogeneity. A variable x_{it} is said to be strictly exogenous if E[$x_{it}\varepsilon_{is}$] = 0 for all t and s. If E[$x_{it}\varepsilon_{is}$] ≠ 0 for s < t but E[$x_{it}\varepsilon_{is}$] = 0 for all s ≥ t, the variable is said to be predetermined. Intuitively, if the error term at time t has some feedback on the subsequent realizations of x_{it}, x_{it} is a predetermined variable. However, we do not believe that unforecastable errors today might affect future changes in GDP, so we do not suspect that GDP is predetermined instead of strictly exogenous. Estimated coefficients using GMM method are as follow:

The estimate of the coefficient on the expected interest rate is positive and it is significant at 5% level. It says that if the real interest rate increases by one unit, the real amount of currency held increases by 0.003 percent meaning that money demand is not sensitive to the interest rate. The estimate of the coefficient on GDP says that when the level of GDP increases by one percent, the currency held increases by 0.11 percent. Its sign is positive as expected, and it is significant at 5% level. The most important result is the estimate of the coefficient on ATM numbers which is negative. If ATM increases by one percent, the currency held decreases by 0.01 percent. Since we use the data obtained by the whole economy, not a survey, it tells us the exact relationship between the number of ATM and the currency demand in the economy. Finally, according to the estimation results, elasticity of money demand to one lagged money demand is 0.89 percent. For models estimated by GMM, we may compute the first and second order serial correlation statistics proposed by Arellano and Bond (1991) as one method of testing for serial correlation. The test is actually two separate statistics, one for first order correlation and one for second. We expect the first order statistic to be significant (with a negative auto-correlation coefficient), and the second order statistic to be insignificant. In other words, there is first order autocorrelation while there is not second order autocorrelation.

The statistics are calculated as:

$$m_j = \frac{\rho_j}{\sqrt{VAR(\rho_j)}}$$

$$\rho_j = \frac{1}{T-3-j}\sum_{t=4+j}^{T} \rho_{tj}$$

$$\rho_{tj} = E(\Delta\epsilon_{i,v}, \Delta\epsilon_{i,t-j})$$

Where ρ_j is the average j-th order autocovariance. (Note that this test is only available for equations estimated by GMM using first difference cross-section effects).

TABLE 1: STATA output of the Blundell-Bond estimation (Two-step results):

Variables	Coef.	Std. Err.	z	P>|z|	[95%Conf.	Interval]
Lmd(-1)	0.896889	0.0077811	115.27	0.000	0.8816383	0.9121396
lgdp	0.117268	0.0075553	15.52	0.000	0.1024598	0.1320761
irate	0.0029198	0.0000754	38.73	0.000	0.0027721	0.0030676
latm	-0.0109137	0.001865	-5.85	0.000	0.1024598	0.1320761
cons	-0.1471167	0.0201003	-7.32	0.000	0.1865126	-0.1077208

TABLE 2: Allerano-Bond test for zero autocorrelation in first-differenced errors (H_0: no autocorrelation)

Order	z	Prob>|z|
1	-5.1748	0.0000
2	-1.6693	0.0950

TABLE 3: Sargan test for over-identifying restrictions (H_0: over-identifying restrictions are valid)

Chi2 (440)	110.2809
Prob>chi2	0.3430

Also, according to Arellano-Bond Serial Correlation Test (with probability of 0.00 for first order and 0.08 for second order) and Sargan test of overidentifying restrictions (with probability of 0.26), the estimated model passed both authocorrolation and Sargan tests. Therefore, the instruments for differenced eqution (that is the second lag of money demand) and instruments for level equation (that is the fisrt lag of money demand) are valid. Heteroscedasticity would not be a problem as the panel data by itself is a solution to heteroscedasticity. The advantage gained on GMM is that is consistent even in the presence of heteroskedasticity. Also, we did not include period dummy variables to take into account for period fixed effects. We also note that the estimated coefficients of interest rate is very low meaning that demand for real money is not sensitive to the change in interest rate. One lagged dependent variable followed and GDP are considered variables with the biggest impact on money demand. Also, interest rate and ATM are considered predetermined variables and GDP is considered an endogenous variable. The reason for treating interest rate and ATM as predetermined variables is that predetermined is more common in economic theory than the extreme cases of being exogenous and endogenous as the first one implies that the independent variable is uncorrelated with current, past and future error terms and the second implies that it is correlated with contemporaneous errors which is highly unlikely in either cases so I supposed the variables are predetermined implying that the current period error term is uncorrelated with current and lagged values of the predetermined variable but may be correlated with future values that is the most common case which makes fully sense regarding the fact that interest rate and the number of ATMs are already decided in the previous year. Also, we know that GDP is endogenous by its nature. One lag dependent variable is included in the model. Furthermore, 1 lag of dependent variable and 2 lags of predetermined variables (interest rate and ATM) are used as instrument to address the issue of endogeneity. Finally, estimation output does pass Arellano-Bond test for zero autocorrelation in first-differenced errors and Sargan test of overidentifying restrictions as well while having significant and meaningful coefficients.

5. Summary

In this study, we estimated a conventional money demand model (as described above) with currency in circulation (M2) as dependent variable and gross domestic product (GDP, constant 2005 US$), interest rate (IRATE), the number of automated teller machines per 100,000 adults (ATM) to take into account for the effects of financial innovation as dependent variables. It covers 215 countries and territories over the period 1961-2013. The model is estimated using different estimation methods as follow: GMM, Cointegration, Vector Error Correction Model (VECM), Autoregressive Distributed Lag (ARDL), OLS (Panel Fixed Effects), and Panel Dummy Variables. Each of these methods/estimators have their own weaknesses and strengths, however, regarding the nature of our data, GMM was selected as the preferred model. The results of the other estimation methods should be treated with care as the limited time-series dimension of our data may not be enough to produce efficient and trustful estimates and they should be considered merely as by product of this study. Therefore, we chose GMM as the best estimator.

Generalised Method of Moment (GMM) proposed by Arellano and Bond (1991) is the commonly employed estimation procedure to estimate the parameters in a dynamic panel data model. In GMM based estimation, first differenced transformed series are used to adjust the unobserved individual specific heterogeneity in the series. But Blundell and Bond (1998) found that this has poor finite sample properties in terms of bias and precision, when the series are persistent and the instruments are weak predictors of the endogenous changes. Arellano and Bover (1995) and Blundell and Bond (1998) proposed a systems based approach to overcome these limitations in the dynamic panel data. This method uses extra moment conditions that rely on certain stationarity conditions of the initial observation.

We can summarize the results as follow: 1) GMM is an OLS procedure applied to a suitably transformed version of the model whose elements are uncorrelated therefore yielding more efficient estimates. 2) GDP and IR coefficients are all positive and significant. 3) ATM coefficient is negative and significant. 4) Lagged money demand is the most important determinant of the current money demand followed by GDP and ATM. We used lagged dependent and independent variables as instruments in the estimation. ATM is found to have a negative effect on the demand for real money; however, its impact on money demand is small meaning that 1 percent increase in ATM unit will lead to only 0.01 percent decrease in money demand. The coefficient of the interest rate is positive which is not what we expect from the theory, however, the magnitude of the coefficient is very close to zero implying that its effect on demand for money is negligible and the total effect of financial innovation/payment technologies advancements is channelled through income effect (GDP).

The finding of this study revealed that financial innovations have a negative effect on money demand. Introduction of new financial products due to innovations in the financial sector reduces the efficiency of the financial sector than in turn caused the complication of the environment in which monetary policy operates. This situation makes money demand sensitive to changes in monetary environment and so researches should keep an eye on variables that may affect money demand. The results of this study are primarily in line with theoretical and empirical studies that proved the macroeconomic impact of financial innovations on money demand. The implication of this finding for money demand is that financial innovation have to be included in the estimation of money demand, otherwise, the money demand function will be misspecified. There is a need for keeping an eye on the ever changing monetary aggregates that may cause structural changes on monetary developments. This is because, if financial innovations have impact on money demand, adjustment can be made to monetary aggregates in the presence of such monitoring. Central banks should conduct inflation targeting, economic growth enhancement along with enhancing efficiency and effectiveness in a changing financial and economic environment.

The study reveals some more implications as follow: 1) The low interest elasticity of the money demand indicates that the money market in most countries is not sufficiently developed. This is particularly true as most of the countries under investigation are actually underdeveloped countries. The money market in most countries lacks the depth and flexibility that results from a diversified participant. Another reason is that underdeveloped countries suffer from an unhealthy financial system. 2) Income level is a primary determinant of demand for money by economic agents. 3) Regarding the fact that financial innovations have an impact on the demand for money; there is room for monetary policy as a macroeconomic stabilization measure.

Financial innovation leads to the deepening of the money market and promoting the effectiveness of monetary policy through its significant impact on the demand for money. In the light of our findings based on GMM estimation, this research project suggests the following recommendations: 1) A policy should be made to attract more private participants and private sector funds to the money market to deepen the market thereby making the market more dynamic and open to monetary policy, 2) Recapitalization in the banking sector to pave the way for financial innovations and adopting a suitable monetary policy strategy to deal with the challenges posed, and 3) The central banks needs to monitor the financial landscape and be able to predict the consequences of financial innovations.

Further research need to be conducted to quantify the relationship between the change in money demand and the effectiveness of monetary policy to establish a link between financial innovation and effectiveness of monetary policy as this study is limited to determine the effect of financial innovation on the demand for money which is just one side of this two-sided relationship. This study targeted the impact of financial innovations/payment technologies on the demand for real money and did not investigate the effect of financial innovations on money multiplier and money velocity that can be a possible area for further research. Assessing the effect of financial innovation on currency in circulation also provide another potential area for research. Investigating the effect of financial innovations on economic growth can attract further research. They should be positively related to each other but the effect has not been quantified in any empirical research by far. There is also a need to examine if financial crisis in the economy are caused by innovations in the financial sector. Further research can be conducted on how monetary aggregates react to a monetary shock due to new innovative products.

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