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INVESTIGATING THE EFFECT OF FINANCIAL INNOVATION ON MONEY DEMAND USING PMG ESTIMATOR

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Abstract. This paper has investigated the relationship between financial innovation and money demand in 4 different income groups each consisting 25, 38, 43 and 33 countries between 2004 and 2015, using panel data estimation technique (PMG). The number of automated teller machines (ATMs) and the number of commercial bank branch (CBBs) were chosen to proxy the effect of financial innovation using a traditional money demand function consisting of income (GDP) and the opportunity cost of money (interest rate). It aims to study the results according to long run without financial innovations, long run with financial innovations, short run without financial innovations, and short run with financial innovations. These results suggest that financial innovation plays a crucial role in determining money demand in both the long run and the short run. There is some evidence of stability, with all of the error correction terms negative and significant, though the speed of adjustment varies across the different income groups.

Keywords: Money demand, financial innovation, PMG estimator, stability, Panel data

1. Introduction

Huge cost savings can be achieved by migrating from paper-based payments to electronic payments such as ATMs. 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. Regarding the importance of money demand for monetary policy and in general for macroeconomics, various estimation techniques have been introduced to measure the effect of these innovation on the demand for money.

The Pooled Mean group (PMG) estimator by Pesaran et al. (1999) is often used in cases where non stationarity may be an issue. It is considered a suitable estimator for data with large time series and cross sections in order to generate long run and short- run estimates without the need for stationarity and cointegration tests (with only assumptions for the existence of cointegration) giving it an edge compared to FMOLS and DOLS estimation methods. PMG estimator allows for homogeneity in the long run coefficients and heterogeneity in the short run which makes it more flexible compared to FMOLS and DOLS. The PMG also allows for the adjustment dynamic between the long run and short run that other panel data methods such as the DOLS and FMOLS do not account for (Bangake and Eggoh, 2012).

The PMG (within an ARDL structure) allows for the identical long run coefficients while the short run coefficients and error variances are allowed to differ across groups. Mean Group (MG) estimator on the other hand, assume that the slope coefficients and error variances are identical thereby, estimates N separate regressions and calculate the coefficient mean. However, as Asteriou and Hall (2007) and Pesaran et al. (1999) argue, for panel data with shorter time series, PMG is preferred to the MG since MG produces biased estimates with smaller time dimensions. PMG is also superior to the traditional panel data methods such as GMM for panel data with long time dimension as PMG yields consistent parameters while GMM does not.

This paper aimes to investigate the relationship between financial innovation and money demand in 4 different income groups each consisting 25, 38, 43 and 33 countries between 2004 and 2015, using panel data estimation technique (PMG). Plan of the paper is to provide a review of literature in section 2. Theoretical background, model specification and measurement of variables is mentioned in section 3. Results and discussion of results are reported in section 4. Lastly section 5 is reserved for the main conclusions.

2. Literature review

As a result of the growth in financial innovation over the last few years, several empirical studies have started including financial innovation in the money demand specification. Exclusion of financial innovation in the money demand function could lead to misspecification of the money demand through over estimation, commonly referred to as “missing money” (Arrau and De Gregorio, 1991). Empirical evidence suggests that financial innovation ought to be included in the money demand function to help solve some of the issues faced by money demand specification such as auto correlated errors, persistent over prediction and implausible parameter estimates (Arrau et al, 1995). In addition, non-stationary processes such as financial innovation, could explain the failure of cointegration of the money demand but once financial innovation is accounted for, periods of “missing money” are eliminated (Arrau and De Gregorio, 1991). Some of the studies that have accounted for financial innovation in the money demand specification include Arrau and De Gregorio (1993), Ireland (1995), Attanasio et al (2002), Alvarez and Lippi (2009) and Nagayasu (2012).

There are few cross country studies that have used panel data methods to analyse the money demand function with the inclusion of financial innovations. The most recent of these studies include Snellman et al. (2001) who conclude the expansion of using electronic payment instruments reduces the demand for money (based on panel data for 10 European countries during 1987-1996). Based on a panel data analysis, Rinaldi (2001) states that the development of card payments (including ATM cards) will reduce the demand for money in Belgium. 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).

Nautz and Rondolf (2011) investigate the money demand for a panel of the Euro Area countries while Hamdi et al. (2014) investigates the money demand function for the Gulf Cooperation Council countries with regard to financial innovations. Elizabeth Kasekende (2016) suggest that financial innovation has a significant effect on the demand for money in Sub-Saharan Africa. It is negatively related to money demand in both the long run and the short run regardless of the estimation method used. Most importantly, the coefficients of the traditional money demand determinants appear to be sensitive to the addition of financial innovation, with most results showing a decline in coefficients. This may imply that the exclusion of this variable could indeed lead to biased or misleading estimates of the money demand equation.

3. Methodology

3.1. Background

Suppose that given data on time periods, t = 1, 2, …, T and groups I = 1, 2, …, N, we wish to estimate an ARDL (p, q, q, …, q) model,

$$\boldsymbol{Y}_{it} = \sum_{j=1}^{p} \lambda_{ij} \boldsymbol{Y}_{i,t-j} + \sum_{j=0}^{q} \delta'_{ij} \boldsymbol{X}_{i,t-j} + \mu_i + \varepsilon_{it} \qquad (1)$$

where $\boldsymbol{X}_{it}$ (k * 1) is a vector of explanatory variables (regressors) for group $\boldsymbol{i}$, μ_i represent the fixed effects, the coefficients of the lagged dependent variables, λ_{ij} , are scalars, and δ_{ij} are k * 1 coefficient vectors. $\boldsymbol{T}$ must be large enough such that we can estimate the model for each group separately. For notational convenience we shall use a common T and p across groups and a common q across groups and regressors, but this is not necessary. Similarly, time trends or other types of fixed regressors such as seasonal summies can be included in (1) but to keep the notations simple we do not allow for such effects. It is convenient to work with the following re-parameterization of (1):

$$\Delta \boldsymbol{Y}_{it} = \Phi_i \boldsymbol{Y}_{i,t-1} + \beta' \boldsymbol{X}_{it} + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta \boldsymbol{Y}_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij}^{*\prime} \Delta \boldsymbol{X}_{i,t-j} + \mu_i + \varepsilon_{it} \qquad (2)$$

$$\boldsymbol{i} = 1, 2, \ldots, \boldsymbol{N}, \ \boldsymbol{t} = 1, 2, \ldots, \boldsymbol{T}, \text{ where } \Phi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij}), \ \beta_i = + \sum_{j=0}^{q} \delta_{ij} \qquad (3)$$

$$\lambda_{ij}^{*} = - \sum_{m=j+1}^{p} \lambda_{im}, \ \boldsymbol{j} = 1, 2, \ldots, \boldsymbol{p}-1, \text{ and } \delta_{ij}^{*} = - \sum_{m=j+1}^{q} \delta_{im}, \ \boldsymbol{j} = 1, 2, \ldots, \boldsymbol{q}-1$$

If we stack the time-series observations for each group, equation (2) can be written as

$$\Delta \boldsymbol{y_i} = \Phi_i \boldsymbol{y}_{\boldsymbol{i},-1} + \boldsymbol{X_i}\beta_i + \sum_{\boldsymbol{j}=1}^{\boldsymbol{p}-1} \lambda_{\boldsymbol{ij}}^{*} \Delta \boldsymbol{y}_{\boldsymbol{i},-\boldsymbol{j}} + \sum_{\boldsymbol{j}=0}^{\boldsymbol{q}-1} \Delta \boldsymbol{X}_{\boldsymbol{i},-\boldsymbol{j}} \delta_{\boldsymbol{ij}}^{*} + \mu_i \boldsymbol{t} + \varepsilon_i \qquad (4)$$

$\boldsymbol{i} = 1, 2, \ldots, \boldsymbol{N}$, where $\boldsymbol{y_i} = (\boldsymbol{y}_{\boldsymbol{i}1}, \ldots, \boldsymbol{y_{iT}})'$ is a $\boldsymbol{T} * 1$ vector of the observations on the dependent variable of the $\boldsymbol{i}$-th group, $\boldsymbol{X_i} = (\boldsymbol{x}_{\boldsymbol{i}1}, \ldots, \boldsymbol{x_{iT}})'$ a $\boldsymbol{T} * k$ matrix of observations on the regressors that vary both across groups and time periods, $\boldsymbol{t} = (1, \ldots, 1)'$ a $\boldsymbol{T} * 1$ vector of ones, $\boldsymbol{y}_{\boldsymbol{i},-\boldsymbol{j}}$ and $\boldsymbol{X}_{\boldsymbol{i},-\boldsymbol{j}}$ are $\boldsymbol{j}$ period lagged values of $\boldsymbol{y_i}$ and $\boldsymbol{X_i}$, $\Delta \boldsymbol{y_i} = \boldsymbol{y_i} - \boldsymbol{y}_{\boldsymbol{i},-1}$, $\Delta \boldsymbol{X_i} = \boldsymbol{X_i} - \boldsymbol{X}_{\boldsymbol{i},-1}$, $\Delta \boldsymbol{y}_{\boldsymbol{i},-\boldsymbol{j}}$ and $\Delta \boldsymbol{X}_{\boldsymbol{i},-\boldsymbol{j}}$ are $\boldsymbol{j}$ period lagged values of $\Delta \boldsymbol{y_i}$ and $\Delta \boldsymbol{X_i}$, and $\varepsilon_i = (\varepsilon_{\boldsymbol{i}1}, \ldots, \varepsilon_{\boldsymbol{iT}})'$.

To estimate the model, we adopt a likelihood approach and initially assume that the disturbances $\varepsilon_{\boldsymbol{it}}$ are normally distributed, though this assumption is not required for the asymptotic results. The likelihood of panel data model can be written as the product of the likelihoods for each group. Since the parameters of interest are long-run effects and adjustment coefficients, we directly work with the concentrated log-likelihood function. Given normality we have

$$\boldsymbol{l_T}(\varphi) = -\frac{\boldsymbol{T}}{2} \sum_{\boldsymbol{i}=1}^{\boldsymbol{N}} \boldsymbol{ln} 2\pi\sigma_i^2 - \frac{1}{2} \sum_{\boldsymbol{i}=1}^{\boldsymbol{N}} \boldsymbol{ln} 2\pi\sigma_i^2 \quad \frac{1}{\sigma_i^2} (\Delta \boldsymbol{y_i} - \Phi_i \varepsilon_i(\theta))' \boldsymbol{H_i} (\Delta \boldsymbol{y_i} - \Phi_i \varepsilon_i(\theta)) \qquad (5)$$

where $\boldsymbol{H_i} = \mathrm{I}_{\boldsymbol{T}} - \boldsymbol{W_i}(\boldsymbol{W_i'}\boldsymbol{W_i})^{-1}\boldsymbol{W_i'}$, $\varphi = (\theta', \Phi', \sigma')'$, $\Phi = (\Phi_1, \Phi_2, \ldots, \Phi_{\boldsymbol{N}})'$, and $\sigma = (\sigma_1^2, \sigma_2^2, \ldots, \sigma_{\boldsymbol{N}}^2)'$.

The pooled mean group estimator: The maximum likelihood (ML) estimation of the long-run coefficients, θ, and the group-specific error-correction coefficients, Φ_i, can be computed by maximizing (5) with respect to φ. These ML estimators will be referred to as the "pooled mean group" (PMG) estimators in order to highlight both the pooling implied by the homogeneity restrictions on the long-run coefficients and other short-run parameters of the model.

The PMG estimators can be computed by the familiar Newton-Raphson algorithm which makes use of both the first and the second serivatives. Alternatively, they can be computed by a "back-substitution" algorithm that only makes use of the first derivatives of (5). In this case, setting the first derivatives of the concentrated log-likelihood function with respect to φ to 0 yields the following relations in $\hat{\theta}$, $\hat{\Phi}_i$, and $\hat{\sigma}_i^2$ which need to be solved iteratively.

$$\hat{\theta} = -\left\{\sum_{\boldsymbol{i}=1}^{\boldsymbol{N}} \frac{\hat{\Phi}_i^2}{\hat{\sigma}_i^2} \boldsymbol{X_i'}\boldsymbol{H_i}\boldsymbol{X_i}\right\}^{-1} \left\{\sum_{\boldsymbol{i}=1}^{\boldsymbol{N}} \frac{\hat{\Phi}_i}{\hat{\sigma}_i^2} \boldsymbol{X_i'}\boldsymbol{H_i}(\Delta \boldsymbol{y_i} - \hat{\Phi}_i \boldsymbol{y}_{\boldsymbol{i},-1})\right\} \qquad (6)$$

$$\hat{\Phi}_i = (\hat{\varepsilon}_i' \boldsymbol{H}_i \hat{\varepsilon}_i)^{-1} \hat{\varepsilon}_i' \boldsymbol{H}_i \, \Delta \boldsymbol{y}_i \ , \boldsymbol{i} = 1, 2, \ldots, \boldsymbol{N} \tag{7}$$

$$\hat{\sigma}_i^2 = \boldsymbol{T}^{-1} (\Delta \boldsymbol{y}_i - \hat{\Phi}_i \hat{\varepsilon}_i)' \, \boldsymbol{H}_i (\Delta \boldsymbol{y}_i - \hat{\Phi}_i \hat{\varepsilon}_i) \, , \boldsymbol{i} = 1, 2, \ldots, \boldsymbol{N} \tag{8}$$

where $\hat{\varepsilon}_i = \boldsymbol{y}_{i,-1} - \boldsymbol{X}_i \hat{\theta}$. Starting with an initial estimate of θ, say $\hat{\theta}^{(0)}$, estimates of Φ_i and σ_i^2 can be computed using (7) and (8), which can then be substituted in (6) to obtain a new estimate of θ, say $\hat{\theta}^{(1)}$, and so on until convergence is achieved.

In order to derive the asymptotic distribution of the PMG estimators we distinguish between the cases of stationary and non-stationary regressors, $\boldsymbol{x}_{it}$. Although in principle the same algorithm can be used to compute the PMG estimators irrespective of whether the regressors are I(0) or I(1), the underlying asymptotic theories for those two cases are fundamentally different and their derivations require separate treatments (Pesaran et al. ,1999).

3.2. Model specification

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

$$\frac{\boldsymbol{M}_t}{\boldsymbol{P}_t} = \Phi(\boldsymbol{R}_t , \boldsymbol{Y}_t) \tag{9}$$

where $\boldsymbol{M}_t$ is the demand of nominal money balances, $\boldsymbol{P}_t$ is the price index that is used to convert nominal balances to real balances, $\boldsymbol{Y}_t$ 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 $\boldsymbol{R}_t$ is the opportunity cost of holding money denoted IR (by interest rate as the best proxy (Serletis, 2007). Following Hamori (2008) a traditional money demand specification is used where money demand is a function of income and the opportunity cost of holding money.

$$\boldsymbol{LMD}_{it} = \beta_{0i} + \beta_{1i} \boldsymbol{IR}_{it} + \beta_{2i} \boldsymbol{LGDP}_{it} + \mu_{it} \tag{10}$$

i = 1, 2, é , N t = 1, 2, é , T

Where LMD is the logarithm of real money, LGDP is the logarithm of GDP (scale variable) , and IR is the opportunity cost variable. The expected signs of the coefficients in Equation (10) are positive for GDP and negative for interest rate (i.e. $\beta_1 > 0$, and $\beta_2 < 0$). In addition, the properties of the error sequence (ε_t) are an integral part of the theory. If (ϵ) has a stochastic trend, then the deviation from the money market equilibrium will not be eliminated (Enders, p. 357). This theory assumes that the ε_t sequence is stationary.

Annual data for all the variables used in this study for 139 countries in total was retrieved from the World Bank databank over a period of 12 years (2004-2015). Then we categorized these countries into 4 different income groups as low income countries, lower middle income countries, higher middle income countries and high income countries (each consists of a balanced panel of 25, 38, 43 and 33 countries, respectively) according to the World Bank income categorization. A list of countries are shown in the Appendix, Table 1**.**

According to the money demand theory and empirical literature, M2 was selected as the dependent variable. Some researchers however, used M1 for money demand. Those include Rao and Kumar (2009), and Mark and Sul (2003), and Salisu et al. (2013) while Hamori et al. (2008) used both M1 and M2.

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 and is used to capture the opportunity cost of holding money. 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.

We expect a positive relation between income and the demand for money. However, researchers have found different magnitudes for the estimated coefficient of GDP (income). Hamori (2008) and Salisu (2013) for Sub-Saharan Africa, Fidrmuc (2009) for Central and Eastern European countries, Kumar et al. (2013) for OECD countries, and Hamdi et al. (2014) for Gulf cooperation council countries found it to be less than one while Mark and Sul (2003) for OECD countries, Nautz and Rondorf (2010), and Arnold and Roelands (2010) for the countries in the European Union found it to be equal or higher than one.

Interest rate is the true proxy for capturing the opportunity cost of holding money. However, as Tahir (1995), Sriram (2000) and Bahmani-Oskooee and Gelan (2009) argue, inflation is used instead due to the lack of well-regulated interest rates, shortage of data on interest rates and limited financial markets. Suliman and Dafaalla (2011) for Sudan and Bahmani-Oskooee and Gelan (2009) for several African countries and Salisu et al.(2013) are examples of researchers who used inflation.

4. Empirical results

The requirement for running an ARDL model is that the variables should be either I(1) or integrated of order one and some maybe I(0) but no variable is I(2). Therefore, we conduct panel unit root tests to make sure this requirement is met before proceeding to the next step. We have for different income groups and we conduct the test using 5 different test statistics as follow: (1) Levin, Lin & Chu t, (2) Breitung t-stat, (3) Im, Pesaran and Shin W-stat, (4) ADF - Fisher Chi-square, and (5) PP - Fisher Chi-square.

Table 1: Panel unit root test summary for low income countries

	(1)	(2)	(3)	(4)	(5)
LMD/ DLMD	0.0000/ 0.0000	0.8176/ 0.0000	0.1850/ 0.0054	0.2718/ 0.0001	0.0000/ 0.0000
IR/ DIR	0.0000/ 0.0000	0.0094/ 0.0000	0.0000/ 0.0000	0.0000/ 0.0000	0.0000/ 0.0000
LGDP/ DLGDP	0.0000/ 0.0000	0.9354/ 0.3222	0.0775/ 0.0309	0.0074/ 0.0011	0.2336/ 0.0000
LATM/ DLATM	0.9288/ 0.8046	0.9340/ 0.0002	0.9458/ 0.0426	0.8344/ 0.0014	0.0000/ 0.0000
LCBB/ DLCBB	0.0000/ 0.0000	0.9818/ 0.0431	0.7400/ 0.0247	0.6951/ 0.0006	0.6771/ 0.0000

Table 2: Panel unit root test summary for lower middle income countries

	(1)	(2)	(3)	(4)	(5)
LMD/ DLMD	0.0000/ 0.0000	0.8879/ 0.0006	0.0123/ 0.0226	0.0045/ 0.0003	0.0000/ 0.0000
IR/ DIR	0.0000/ 0.0000	0.0567/ 0.0000	0.0082/ 0.0000	0.0030/ 0.0000	0.0000/ 0.0000
LGDP/ DLGDP	0.0000/ 0.0000	0.0030/ 0.2384	0.2239/ 0.0344	0.0383/ 0.0005	0.0873/ 0.0000
LATM/ DLATM	0.0001/ 0.1097	0.6885/ 0.0000	0.6430/ 0.0019	0.2012/ 0.0000	0.0000/ 0.0000
LCBB/ DLCBB	0.0000/ 0.0000	1.0000/ 0.0009	0.5788/ 0.0064	0.5614/ 0.0000	0.0577/ 0.0000

Table 3: Panel unit root test summary for higher middle income countries

	(1)	(2)	(3)	(4)	(5)
LMD/ DLMD	0.0000/ 0.0000	0.9562/ 0.0000	0.0073/ 0.0039	0.0071/ 0.0000	0.0000/ 0.0000
IR/ DIR	0.0000/ 0.0000	0.0000/ 0.0000	0.0000/ 0.0000	0.0000/ 0.0000	0.0000/ 0.0000
LGDP/ DLGDP	0.0000/ 0.0000	0.9535/ 0.0006	0.1228/ 0.2330	0.0075/ 0.0852	0.1609/ 0.0000
LATM/ DLATM	0.0000/ 0.0000	0.6626/ 0.0672	0.0000/ 0.0000	0.0004/ 0.0000	0.0000/ 0.0000
LCBB/ DLCBB	0.0000/ 0.0000	0.5999/ 0.9643	0.1449/ 0.0211	0.0185/ 0.0001	0.0001/ 0.0000

Table 4: Panel unit root test summary for high income countries

	(1)	(2)	(3)	(4)	(5)
LMD/ DLMD	0.0000/ 0.0000	0.9664/ 0.0000	0.0000/ 0.0000	0.0006/ 0.0000	0.0000/ 0.0000
IR/ DIR	0.0000/ 0.0000	0.0838/ 0.0000	0.0000/ 0.0000	0.0000/ 0.0000	0.0000/ 0.0000
LGDP/ DLGDP	0.0000/ 0.0000	0.0998/ 0.0000	0.0035/ 0.2137	0.0004/ 0.1112	0.7396/ 0.0003
LATM/ DLATM	0.0000/ 0.0000	0.5418/ 0.0013	0.9469/ 0.0574	0.8463/ 0.0048	0.0166/ 0.0000
LCBB/ DLCBB	0.0000/ 0.0000	1.0000/ 0.2127	0.9686/ 0.0834	0.9256/ 0.0077	0.0604/ 0.0000

It is clear from Table 1 to Table 4 that all of the variables for all the income groups are either I(1) or I(0). Therefore we can proceed to the estimation of the regression model for each of the income groups.

Table 5: Financial innovation (ATM & CBB) and money demand (PMG estimates from balanced panel data 2004-2015) for low income countries

	Without ATM & CBB		With ATM & CBB	
	Coefficient	Probability	Coefficient	Probability
Long Run Estimates				
IR	0.003962	0.0000	0.000106	0.9604
GDP	0.933902	0.0000	0.921510	0.0000
ATM			0.110760	0.0000
CBB			0.281284	0.0000
Short Run Estimates				
D.IR	0.001393	0.2764	0.003095	0.0508
D.GDP	1.290419	0.0000	0.777986	0.0390
D.ATM			-0.023091	0.3128
D.CBB			0.109021	0.0454
Error correction term	-0.149173	0.0080	-0.111781	0.1069
No. of Observations	**300**	**300**	**300**	**300**
No. of Countries	**25**	**25**	**25**	**25**

Table 6: Financial innovation (ATM & CBB) and money demand (PMG estimates from balanced panel data 2004-2015) for lower middle income countries

	Without ATM & CBB		With ATM & CBB	
	Coefficient	Probability	Coefficient	Probability
Long Run Estimates				
IR	0.017506	0.0000	0.029910	0.0000
GDP	0.963595	0.0000	0.975905	0.0000
ATM			-0.009048	0.6252
CBB			-0.094189	0.0000
Short Run Estimates				
D.IR	0.262320	0.3132	0.265109	0.3151
D.GDP	0.789061	0.0002	0.374069	0.1472
D.ATM			0.008534	0.8561
D.CBB			0.253743	0.0176
Error correction term	-0.172531	0.0000	-0.180259	0.0000
No. of Observations	**456**	**456**	**456**	**456**
No. of Countries	**38**	**38**	**38**	**38**

Table 7: Financial innovation (ATM & CBB) and money demand (PMG estimates from balanced panel data 2004-2015) for higher middle income countries

	Without ATM & CBB		With ATM & CBB	
	Coefficient	Probability	Coefficient	Probability
Long Run Estimates				
IR	-0.004075	0.2062	0.004612	0.0001
GDP	0.981848	0.0000	0.928395	0.0000
ATM			0.228301	0.0000
CBB			0.139996	0.0000
Short Run Estimates				
D.IR	0.003867	0.0000	0.002426	0.0006
D.GDP	0.637775	0.0000	0.390974	0.0183
D.ATM			0.045331	0.5153
D.CBB			-0.044970	0.8032
Error correction term	-0.158541	0.0003	-0.180259	0.0000
No. of Observations	**516**	**516**	**516**	**516**
No. of Countries	**43**	**43**	**43**	**43**

Table 8: Financial innovation (ATM & CBB) and money demand (PMG estimates from balanced panel data 2004-2015) for high income countries

	Without ATM & CBB		With ATM & CBB	
	Coefficient	Probability	Coefficient	Probability
Long Run Estimates				
IR	0.026144	0.0000	0.041501	0.0000
GDP	0.987634	0.0000	1.033344	0.0000
ATM			-0.033733	0.2953
CBB			-0.297778	0.0000
Short Run Estimates				
D.IR	0.003184	0.3465	-0.002479	0.2722
D.GDP	0.985046	0.0055	0.592686	0.0010
D.ATM			0.450283	0.3110
D.CBB			0.276789	0.0797
Error correction term	-0.111159	0.0020	-0.180259	0.0000
No. of Observations	**396**	**396**	**396**	**396**
No. of Countries	**33**	**33**	**33**	**33**

Three sets of results are discussed in this section starting with the results for the low income countries using the pooled mean group (PMG) estimation procedure depicted in Table 5. The data consists of a balanced panel of 25 countries over the period 2004-2015 which provides 300 observations. This is followed by the results for lower middle income countries, higher middle income countries and high income countries in tables 6 to 8 using the same estimation procedures (PMG). These tables (5-8) depict the results without and with financial innovations (ATM and CBB). It is decided that a maximum lag length of 1 has the smallest AIC and BIC values implying that it is the optimum lag length for the regressions. Therefore, we estimate an ARDL (1,1,1,1,1) representing one lagged of all of the variables in the model.

The results can be divided into 4 groups. 1) long run without financial innovations, 2) long run with financial innovations, 3) short run without financial innovations, and 4) short run with financial innovations.

The specifications for the model in case of low income countries (as shown in table 5), seem appropriate and in line with the money demand theory. Long run without financial innovations indicate that the variables are statistically significant. However, interest rate (IR) does not bear the expected sign suggesting it does not have a significant impact on money demand.

These results suggest that financial innovation plays a crucial role in determining money demand in both the long run and the short run. Financial innovation (except for ATM in the short run) is significant at 5 percent level in both the long run and the short run. A percentage point increase in ATM and CBB leads to 11.0 and 28.1 percent increase in money demand in the long run. Similarly, the short run results depict a positive relationship between financial innovation (CBB) and money demand of 10.9 percent.

In short, the results indicate that ATM and bank concentration (denoted by ATM & CBB, respectively) affect money demand positively in the long run and insignificant and positively in the short run. Income captured by the real GDP has a positive impact on money demand in both the short run and long run (according to table 5).

Although the signs and levels of significance are similar between the models without financial innovation for GDP, the coefficients appear to be slightly lower for that with financial innovation in both long run and short run. For example, the income coefficients appear to be lower with financial innovation as a one percent increase in GDP leads to a 0.92 percent and 0.77 percent increase in money demand in the long run and short run, respectively while those without financial innovation are 0.93 and 1.29 percent, respectively. Similarly, comparing long run and short run estimates, indicates that GDP coefficient in the long run is lower than that of short run without financial innovation (0.93 vs 1.29) while it is vice versa in the presence of financial innovation meaning that GDP coefficient in the long run is higher than that of short run with financial innovation (0.92 vs 0.77)

The models indicate that the error correction term is negative and significant at a 5 percent level with financial innovation. This confirms that there is cointegration and money demand (excluding financial innovation) appears to be stable for low income countries. The models (without financial innovation) indicate that 14.9 percent of the disequilibrium is eliminated in the short run period. In other words, the speed of adjustment would take approximately 6 years and 8 months to return to equilibrium.

We can draw similar conclusions for the rest of the tables. Results for lower middle income countries indicate that only bank concentration (CBB) in the long run is significant. It has a negative impact on money demand. Results for higher middle income countries show that ATM and CBB are both significant in the long run while having a positive relationship with the demand for money (Table 7). For high income countries, however, again it is only CBB that is significant in the long run with the negative impact on money demand.

According to table 1 in appendix, it is easy to show that the GDP estimate is highest for high income countries in the long run both with and without financial innovation. In the short run, however, the GDP estimate is highest for low income countries. We did this comparison for ATM and CBB coefficient in Table 2 (appendix). ATM coefficient is significant and positive for low income countries and upper middle income countries in the long run. The magnitude of the estimated coefficient in the latter is higher (0.22 compared to 0.11). In the short run though, none of ATM coefficient is significant.

Regarding CBB coefficient, the story is different. Estimated coefficient of bank concentration (CBB), are all significant in the long run. However, it is positive for low income countries and upper middle income countries while it is negative for the other two (lower middle income countries and high income countries). CBB is most influential in low income countries with the magnitude of 0.28. It is significant only in low income countries and lower middle income countries in the short run. They are positive while it is higher in lower middle income countries than the other. Overall, ATM and bank concentration behave differently depending on which income group the countries belong to and whether it is short run or long run.

Conclusions

Knowing the relationship between financial innovation and money demand is essential in the implementation of monetary policy. Despite the fact that this relationship has been widely researched, no study have ever focused on the differences with regard to income per capita, and those that have are generally country case studies. This paper has investigated the relationship between financial innovation and money demand in 4 different income groups each consisting 25, 38, 43 and 33 countries between 2004 and 2015, using panel data estimation technique (PMG).

Financial innovation is found to be an important variable in determining money demand in the long run and partly in the short run and to have a positive effect on the demand for money in both the long run (except for bank concentration in lower middle income countries and high income countries) and the short run. The traditional determinants for money demand conclude the opportunity cost of holding money (proxied by the interest rate) and income (proxied by GDP). GDP were found to be positively related to money demand as expected. However, IR (interest rate) is positive and insignificant in most cases. Introducing the interest rate into the model did not suggest it plays a major role in determining money demand particularly in the short run. Comparing the models with and without financial innovation, showed differing coefficients estimates for income in either of the four income groups. This suggests that not including financial innovation, may have led to biased estimates. There was some evidence of stability, with all of the error correction terms negative and significant, though the speed of adjustment varied across the different income groups.

These results suggest that excluding financial innovations may lead to the misspecification of money demand function and biased estimates which can be noted by monetary authorities in implementing monetary policy. A stable and well specified demand function is of great importance for decision making processes.

However, as we noted above, financial innovation (ATM & bank concentration) behave differently in different income groups meaning that the effect of these innovations on money demand is different in the countries with high income per capita than that of say countries with low per capita income.

There are of course limitations to the analysis undertaken in this study. We ignored the differences in the countries within a particular income group and also we did not take into account for the effects of other financial instruments such as mobile money which requires further work to be done using country case studies.

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Appendix

Table 1: Name of low income countries (L), lower middle income countries (LM), higher middle income countries (UM) and high income countries (H) used in the estimations

L	LM	UM	H
Afghanistan	Armenia	Angola	Antigua and Barbuda
Burundi	Bolivia	Albania	Australia
Benin	Bhutan	Argentina	Bahamas, The
Burkina Faso	Cote d'Ivoire	Azerbaijan	Barbados
Bangladesh	Cameroon	Bulgaria	Brunei Darussalam
Congo, Dem. Rep.	Congo, Rep.	Bosnia and Herzegovina	Canada
Comoros	Djibouti	Belarus	Switzerland
Cabo Verde	Egypt, Arab Rep.	Belize	Chile
Ethiopia	Micronesia, Fed. Sts.	Brazil	Czech Republic
Kenya	Georgia	Botswana	Estonia
Liberia	Guatemala	China	Equatorial Guinea
Madagascar	Guyana	Colombia	Croatia
Mali	Honduras	Costa Rica	Iceland
Myanmar	Indonesia	Dominica	Israel
Mozambique	India	Dominican Republic	Japan
Malawi	Kyrgyz Republic	Algeria	St. Kitts and Nevis
Niger	Lao PDR	Fiji	Korea, Rep.
Nepal	Sri Lanka	Gabon	Kuwait
Rwanda	Lesotho	Grenada	Lithuania
Sierra Leone	Morocco	Hungary	Latvia
Chad	Moldova	Iran, Islamic Rep.	Macao SAR, China
Togo	Mongolia	Iraq	Norway
Tajikistan	Mauritania	Jamaica	New Zealand
Tanzania	Nigeria	Jordan	Poland
Uganda	Nicaragua	Kazakhstan	Qatar
	Philippines	Lebanon	Russian Federation
	Papua New Guinea	Libya	Singapore
	Paraguay	St. Lucia	Slovak Republic
	Senegal	Maldives	Sweden
	Solomon Islands	Mexico	Trinidad and Tobago
	Sao Tome and Principe	Macedonia, FYR	Uruguay
	Swaziland	Mauritius	United States
	Timor-Leste	Malaysia	United Kingdom
	Ukraine	Namibia	
	Vietnam	Panama	
	Vanuatu	Peru	
	Yemen, Rep.	Romania	
	Zambia	Serbia	
		Suriname	
		Seychelles	
		Thailand	
		St. Vincent and the Grenadines	
		Venezuela, RB	
		South Africa	

Table 2: Comparison of GDP estimates for low income countries (L), lower middle income countries (LM), higher middle income countries (UM) and high income countries (H)