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INVESTIGATING THE EFFECT OF FINANCIAL INNOVATIONS ON DEMAND FOR MONEY ON A WORLD SCALE: A SYSTEMS GMM PANEL DATA APPROACH

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Abstract

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 on a world scale. The demand for money is a very important for the conduct of monetary policy and measurement of the effectiveness of monetary policy. A systems GMM method is used to estimate the demand for money (M2) with the inclusion of financial innovations for a panel of 215 countries and territories from 2004 to 2013. The most important advantage of this systems GMM method of Blundell and Bond (1998) is its ability to minimise small sample bias with persistence in the variables and to estimate specifications with the levels and first differences specifications of the variables simultaneously. The estimated coefficient of ATM is about 0.01 percent meaning that the sensitivity of money demand to ATM is low.

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

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

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1- Introduction

Using new electronic technologies caused more than ever the expansion of e-commerce due to its 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 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 2004 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 background and methodology including a brief overview of the theoretical and econometric approach in Sections 3 and 4. Section 5 presents the results of the estimation and it ends up with summary in section 6.

2- Literature Review

In general, 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. Boeschoten (1992), Attanasio et al. (1998), Rinaldi (2001), Snellman et al. (2001), Drehmann et al. (2002), Attanasio et al. (2002), Stix (2003), Markose and Loke (2003), Duca and Van Hoose (2004), and Columba (2009) are among those study with the conclusion that technological innovation has a negative effect on currency in circulation. Examples of the studies with positive effect include: Zilberfarb (1989), Goodhart and Krueger (2001), and Attanasio et al. (2002). Finally, Boeschoten (1998), Snellman, Vesala and Humphrey (2001) and Drehmann et al. (2002) end up with mixed results.

Cross country studies on money demand have used panel data methods to analyse the long run relationship. These include Attanasio et al. (1998) who conclude that the demand for money by households that 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). Snellman et al. (2001) and Drehmann et al. (2002) come up with the result that the number of POS terminals and ATMs have significantly negative effects on money demand (based on panels of European countries). Nautz and Rondolf (2010) investigate the instability of money demand in the Euro Area while Hamdi et al. (2014) investigates the long run money demand function for the Gulf Cooperation Council countries. Hamori (2008) investigate the money demand equation but do not consider financial innovation. E. Kasekende (2016) investigate the development of financial innovation and its impact on money demand in the Sub-Saharan Africa using panel data estimation techniques for 34 countries between 1980 and 2013. The results indicate that there is a negative relationship between financial innovation and money demand. This implies that financial innovation plays a crucial role in explaining money demand in Sub-Saharan Africa and given innovations such as mobile money in the region this can have important implications for future policy design.

The only GMM application in money demand with the inclusion of financial innovation is one conducted by H. Yilmazkuday & M. Ege Yazgan (2009) who analyze the effects of credit and debit cards on the currency in circulation by using GMM estimation. They use monthly data on credit and debit cards usage of Turkey from 2002M1 to 2006M10 and find that an increase in the usage of credit and debit cards leads to a decrease in the currency demand. Another finding of their study is that the impact of the usage of the debit cards on the demand for money is greater than that of the credit cards. Also, the effect of credit cards is mostly through purchases and the effect of debit cards is mostly through withdrawals.

3- Background

In econometrics and statistics, the generalized method of moments (GMM) is a generic method for estimating parameters in statistical models. Usually it is applied in the context of semiparametric models, where the parameter of interest is finite-dimensional, whereas the full shape of the distribution function of the data may not be known, and therefore maximum likelihood estimation is not applicable. The method requires that a certain number of moment conditions were specified for the model. These moment conditions are functions of the model parameters and the data, such that their expectation is zero at the true values of the parameters. The GMM method then minimizes a certain norm of the sample averages of the moment conditions. The GMM estimators are known to be consistent, asymptotically normal, and efficient in the class of all estimators that do not use any extra information aside from that contained in the moment conditions. GMM was developed by Lars Peter Hansen in 1982 as a generalization of the method of moments, which was introduced by Karl Pearson in 1894. Hansen shared the 2013 Nobel Prize in Economics in part for this work.

Suppose the available data consists of T observations $\{Y_t\}$ t = 1,...,T, where each observation Y_t is an n-dimensional multivariate random variable. We assume that the data come from a certain statistical model, defined up to an unknown parameter $\theta \in \Theta$. The goal of the estimation problem is to find the "true" value of this parameter, θ_0, or at least a reasonably close estimate. A general assumption of GMM is that the data Y_t be generated by a weakly stationary ergodic stochastic process. (The case of independent and identically distributed (iid) variables Y_t is a special case of this condition). In order to apply GMM, we need to have "moment conditions", i.e. we need to know a vector-valued function $g(Y,\theta)$ such that

$$m(\theta_0) \equiv E[g(Y_t, \theta_0)] = 0$$

where E denotes expectation, and Y_t is a generic observation. Moreover, the function $m(\theta)$ must differ from zero for $\theta \neq \theta_0$, or otherwise the parameter θ will not be point-identified. The basic idea behind GMM is to replace the theoretical expected value E[·] with its empirical analog sample average:

$$\hat{m}(\theta) \equiv \frac{1}{T} \sum_{t=1}^{T} g(Y_t, \theta)$$

and then to minimize the norm of this expression with respect to θ. The minimizing value of θ is our estimate for θ_0. By the law of large numbers, $m(\theta_0) \approx E[g(Y_t, \theta)] = m(\theta)$ for large values of T, and thus we expect that $\hat{m}(\theta_0) \approx m(\theta_0) = 0$. The generalized method of moments looks for a number $\hat{\theta}$ which would make $\hat{m}(\hat{\theta})$ as close to zero as possible. Mathematically, this is equivalent to minimizing a certain norm of $\hat{m}(\theta)$ (norm of m, denoted as $\|m\|$, measures the distance between m and zero). The properties of the resulting estimator will depend on the particular choice of the norm function, and therefore the theory of GMM considers an entire family of norms, defined as

$$\|\hat{m}(\theta)\|_W^2 = \hat{m}(\theta)^T W \hat{m}(\theta)$$

where W is a positive-definite weighting matrix, and m^T denotes transposition. In practice, the weighting matrix W is computed based on the available data set, which will be denoted as $\widehat{W}$. Thus, the GMM estimator can be written as

$$\hat{\theta} = argmin_{\theta \in \Theta} = \left(\frac{1}{T} \sum_{t=1}^{T} g(Y_t, \theta)\right)^T \widehat{W} \left(\frac{1}{T} \sum_{t=1}^{T} g(Y_t, \theta)\right)$$

Under suitable conditions this estimator is consistent, asymptotically normal, and with right choice of weighting matrix $\widehat{W}$ also asymptotically efficient.

Sargan–Hansen J-test

When the number of moment conditions is greater than the dimension of the parameter vector θ, the model is said to be over-identified. Over-identification allows us to check whether the model's moment conditions match the data well or not. Conceptually we can check whether $\hat{m}(\hat{\theta})$ is sufficiently close to zero to suggest that the model fits the data well. The GMM method has then replaced the problem of solving the equation $\hat{m}(\theta) = 0$, which chooses θ to match the restrictions exactly, by a minimization calculation. The minimization can always be conducted even when no θ_0 exists such that $m(\theta_0) = 0$. This is what J-test does. The J-test is also called a test for over-identifying restrictions. Formally we consider two hypotheses:

H_0 : $m(\theta_0)$ = 0 (the null hypothesis that the model is "valid"), and

H_1 : $m(\theta_0) \neq 0$ (the alternative hypothesis that model is "invalid"; the data does not come close to meeting the restrictions)

Under hypothesis H_0, the following so-called J-statistic is asymptotically *chi-squared* with *k–l* degrees of freedom. Define *J* to be:

$$J \equiv T.\left(\frac{1}{T}\sum_{t=1}^{T} g(Y_t,\hat{\theta})\right)^T \widehat{W}\left(\frac{1}{T}\sum_{t=1}^{T} g(Y_t,\hat{\theta})\right) \xrightarrow{d} \chi^2_{k-l} \quad \text{under } H_0$$

where $\hat{\theta}$ is the GMM estimator of the parameter θ_0, k is the number of moment conditions (dimension of vector *g*), and *l* is the number of estimated parameters (dimension of vector *θ*). Matrix $\widehat{W}_T$ must converge in probability to Ω^{-1}, the efficient weighting matrix (note that previously we only required that *W* be proportional to Ω^{-1} for estimator to be efficient; however in order to conduct the J-test *W* must be exactly equal to Ω^{-1}, not simply proportional). Under the alternative hypothesis H_1, the J-statistic is asymptotically unbounded:

$J^P \rightarrow$ under H_1

To conduct the test we compute the value of *J* from the data. It is a nonnegative number. We compare it with (for example) the 0.95 quantile of the χ^2_{k-l} distribution:

H_0 is rejected at 95% confidence level if $J > \chi^2_{k-l,0.95}$

H_1 cannot be rejected at 95% confidence level if $J < \chi^2_{k-l,0.95}$

Arellano-Bover/Blundell-Bond estimator

Nickell (1981) states that when the time span is small, the usual fixed effects estimator is inconsistent. We face the same problem if we want to apply the ordinary least squares (OLS) estimator based on first differences. Anderson and Hsiao (1981) proposed the instrumental variable (IV) estimator and generalized method of moments (GMM) estimator to avoid this problem. Blundell and Bond (1998) noticed that these estimators are not still free of problems. The problem is when the dynamic panel autoregressive coefficient (ρ) approaches one (ρ=1), the instrument will be weak. In this situation, when T is small, the estimators are asymptotically random, and when T is large the unweighted GMM estimator may be inconsistent meaning that the behaviour of the estimator depends on T. To address this issue, Arellano and Bover (1995) and Blundel and Bond (1998) proposed a system GMM procedure that uses moment conditions based on the level equations together with the usual Arellano and Bond type orthogonality conditions that yields consistent estimators for all ρ values.

4- Methodology

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

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

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 Y_t 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. The Keynesian money demand $M^d = (Y_t, R_t)$ is enriched with innovation (r*) so that it can be represented implicitly as $M^d = (Y_t, R_t, r^*)$.

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):

$$\text{Log } M2_{it} = \beta_0 + \beta_1 \text{Log } GDP_{it} + \beta_2 R_{it} + \beta_3 \text{Log } (ATM_{it}) + e_{it}$$

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.

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. ARDL is desired due to the small number of time-series observations but it faces the challenge of identifying long-run elasticities explicitly. On the other hand, ECM estimation takes 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.

5- Results

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.

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)	Prob>chi2
110.2809	0.3430

Also, according to Arellano-Bond Serial Correlation Test (with probability of 0.00 for first order and 0.09 for second order) and Sargan test of overidentifying restrictions (with probability of 0.34), the estimated model passed both authocorrolation and Sargan tests. Therefore, the instruments for differenced equation (that is the second lag of money demand) and instruments for level equation (that is the first 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 we 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 over-identifying restrictions as well while having significant and meaningful coefficients.

6- Summary

A panel dataset is a given sample of individuals over time. In other words, it is multiple observations on each individual in the sample. There are two different kinds of panel data models that includes fixed effects models and random effects models. These models form a wide range of linear models. Dynamic panel data models are a special case of panel data models. A dynamic panel data model that includes the lagged dependent variable adds to the complexity of these models by introducing endogeneity bias of estimates. To address this issue, several approaches have been developed. In this paper, we use the Arellano-Bover/Blundell-Bond Generalized method of moments (GMM) estimator to estimate the panel models. This estimator is an extension of the Arellano-Bond model. Arellano-Bond models use past values and different transformations of past values of the potentially problematic independent variable as instruments together with other instrumental variables. The Arellano–Bover/Blundell–Bond estimator is an extension of the Arellano–Bond estimator in the sense that it makes an additional assumption that first differences of instrument variables are uncorrelated with the fixed effects. In this way, more instruments can be introduced in the model which in turn leads to a significantly higher efficiency.

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).

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