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Using Blundell-Bond Estimator in Dynamic Panel Data Analysis: Case of Money Demand Function with the Inclusion of Financial Innovation

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Abstract

The banking system has experienced rapid and significant technological changes in recent years that is the subject of this paper; however, the individual effect of most of these innovations has not been estimated. 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 investigate if financial innovations has impacted the demand for money using a system (the original equation and the transformed one) GMM method. In this paper, 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 17 countries from 2006 to 2015. The results indicate that financial instruments (proxied by credit transfers, direct debits and cheques) have positive yet small impacts on the demand for real money.

Keywords: Money demand, Blundell–Bond estimation, financial innovation, dynamic panel data model

1. INTRODUCTION

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

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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.

2. 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 semi parametric 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,θ) such that

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

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:

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

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, $m(\theta_0) \approx \mathrm{E}[\mathrm{g}(Y_t, \theta)] = m(\theta)$ 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

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

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

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

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:

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

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 $\hat{W}_T$ must converge in probability to Ω^{-1}, the efficient weighting matrix (note that previously we only required that W be proportional to $\Omega^{-1}$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 behavior 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.

3. EMPIRICAL MODEL

The Keynesian money demand $M^d = (Y_t, R_t)$ is enriched with innovation (r*) so that it can be represented implicitly as $M^d = (Y_t, R_t, r^*)$ in the following linear functional form:
$M2_{it} = \beta_0 + \beta_1\, GDP_{it} + \beta_2\, IR_{it} + \beta_3\, CT_{it} + \beta_4\, DD_{it} + \beta_3\, CH_{it} + e_{it}$
The currency in circulation (broad money) is denoted by M2, real gross domestic product is denoted by GDP, R refers to the interest rate, credit transfers (a direct payment of money from one bank account to another) is denoted by CT, direct debits (an arrangement made with a bank that allows a third party to transfer money from a person's

account on agreed dates, typically in order to pay bills) is denoted by DD, cheques (an order to a bank to pay a stated sum from the drawer's account, written on a specially printed form) is denoted by CH and the error term is denoted by e_t with t spanning from 2006 to 2015. The official website of the World Bank and the Bank for International Settlements are the source of data. The measurement unit of the data (except for R) is billion US Dollars (constant 2011 dollars) and therefore, they are all in real term. 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. Income or GDP is the variable used in most of the empirical studies. Income (or GDP) per capita is not a good candidate for the scale variable mentioned above. Inflation rate is used to capture the opportunity cost of holding money. We did so by using interest rate which is definitely a more precise proxy for that purpose.

4. RESULTS

As mentioned above, Nickell (1981) states that when the time span is small, the usual fixed effects estimator is inconsistent. Regarding the fact that we have observations for only 10 years (which off course is small), fixed effects estimator is inconsistent and the random effects model is not suitable as well. Therefore, system GMM is the preferred method of estimation. This estimator is the best when T<N, no matter how small N is.

Table 1. STATA output of the Blundell-Bond estimation (Two-step results).

Variables	**Coef.**	**Std. Err.**	**z**	**P>$\|z\|$**
M2(-1)	0.6847	0.0351	19.45	0.000
GDP	-0.3167	0.0984	-3.22	0.001
GDP(-1)	0.5643	0.1253	4.50	0.000
IR	-2.5249	11.656	-0.22	0.829
CT	0.0056	0.0007	8.03	0.000
DT	0.0070	0.0035	1.98	0.048
CH	0.0104	0.0042	2.48	0.013
Cons	1.4904	43.863	0.03	0.973

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

Order	**z**	**Prob>$\|z\|$**
1	-1.179	0.2384
2	0.6911	0.4895

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

Chi2 (440)	**Prob>chi2**
4.0822	1.0000

We have instructed Stata to use the first lag of the endogenous variable (GDP) and the dependent variable (M2) as instruments. Due to the small number of countries in our sample a large number of instruments causes the Sargan test to be weak. The general guideline is that the number of instruments should be less than or equal to the number of groups. Second or deeper lags can be tried to find a good instrument, but using deeper lags reduces sample size. If the number of countries is large enough, all available lags (second and deeper lags) can be used as instruments.

The results are illustrated in Table 1. The estimate of the coefficient on the expected interest rate is negative as we expected, but it is not significant. However, it is the only coefficient that is not significant. The rest of the estimated coefficients are statistically significant at 5% level. The estimate of the coefficient on lagged money demand, lagged GDP and all of the proxies for the financial innovation (CT, DT, and CH) are all positive and significant at 5% level. However, the biggest magnitude can be attributed to the lagged money demand (0.68) and lagged GDP (0.56). For example, the estimate of the coefficient on the lagged money demand says that when the money demand in the previous period increases by one unit (1 billion dollars), the current money demand increases by 0.68 unit (680 million dollars). Among the proxies for the financial innovation (CT, DT, and CH), CH (cheques) has the largest impact on the money demand with the estimated coefficient of almost 0.01. However, as can be seen from table 1, none of these proxies have large impact on the demand for money. Therefore, we can conclude that even though financial innovation in their various forms have impact on the money demand but the magnitude of these impacts are significantly less than those of lagged money demand and lagged GDP.

5. 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.

A system of two equations—the original equation and the transformed one—is created in this model which we call it system GMM. In this paper, the dynamics of the money demand with the inclusion of financial innovation (proxied by CT, DT and CH) were examined empirically by using the Arellano–Bover/Blundell–Bond estimation technique together with ordinary OLS. The aim of the analysis was to estimate the effects of financial innovation on the demand for money in the context of a dynamic panel data model. This is because, estimates provided by dynamic panel data models are more in line with theory of money demand dynamics compared to conventional fixed-effects panel data models. We prefer the Arellano–Bover/Blundell–Bond estimator for this analysis. The reasons behind this selection is as follow: It is a general estimator that is specially designed for situations with 1) a linear functional relationship; 2) a dependent variable that is dynamic and depends on its own past realizations; 3) independent variables that are not strictly exogenous. In other words, independent variables are correlated with past and possibly current realizations of the error; 4) fixed individual effects; and 5) heteroskedasticity and autocorrelation within individuals but not across them. In this paper, we estimated a conventional money demand model (as described above) with broad money (M2) as dependent variable and one lagged of dependent variable together with gross domestic product (GDP), interest rate (IRATE), credit transfers (CT), direct debits (DT) and cheques (CH), all in real terms (constant 2011 US dollar) to take into account for the effects of financial innovation as independent variables. It covers 17 countries over the period 2006-2015. GMM was selected as the preferred model among other models such as panel fixed effects.

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) Lagged money demand, lagged GDP and the proxies for financial innovation (CT, DT and CH) coefficients are all positive and significant. 3) Magnitude of the estimated coefficients of the proxies for financial innovation (CT, DT and CH) are small compared to those of lagged money demand and lagged GDP meaning that financial innovation does not have huge impact on money demand. 4) Among these proxies for financial innovation (CT, DT and CH), cheques (CH) has the biggest impact on the demand for money and, 5) Lagged money demand is the most important determinant of the current money demand followed by lagged GDP. We used the first lag of the endogenous variable (GDP) and the dependent variable (M2) as instruments. As for the estimated coefficient for cheque, 1 unit (1 billion dollars) increase in the value of transactions for cheque will lead to 0.01 unit (10 million dollars) increase in money demand. The coefficient of the interest rate is negative yet insignificant. In table 4, cross 1 to cross 17 denotes countries as follow respectively: Australia, Brazil, China, Hong Kong, India, Japan, South Korea, Mexico, Russia, Saudi Arabia, Singapore, South Africa, Sweden, Switzerland, Turkey, United Kingdom and United States.

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