

# Relative Importance of Income, Interest and Price In The Determination of Demand for Money in India: A Time Series Analysis

Tarun Das

**Abstract:** *Relative importance of the explanatory variables in linear regression is very crucial for implementing a policy by policy makers. In India demand for money is very important in determining the effectiveness of Government policy in changing the level of income, interest rate and price. In this paper we observe from the ANOVA model that partially interest rate is the most significant variable to explain the variability of the dependent variable,  $M_1$ . But this is not the correct scenario because of the presence of multicollinearity. There is a strong multicollinearity between income and price. But while we do an average of orthopartial correlation and simple correlation, then the importance of the interest rate becomes the least. If the policy makers identify the actual reason for which it is happening and which variable is most responsible and accordingly proceed the outcome will be maximum. But in the existing literature we cannot correctly estimate the relative importance of explanatory variables in the presence of multi-collinearity – multicollinearity with or without enhancement synergism and with or without change in sign. The existing problem is not completely solved. Based on the work of Mondal (2008) this paper tries to prescribe a solution for finding the relative importance of explanatory variables in linear regression. The methodology is illustrated with the help of a time series estimation of demand for money function in India.*

**Keywords:** demand for money, regression, multicollinearity, orthopartial correlation

## 1. Introduction

The Classical Linear Regression Model (CLRM) is the most popularly used econometric model. Its use in factor analysis is common to all econometric practitioners. It is also used in the disciplines like sociology, psychology and other social sciences, medical and other bio sciences, and now in mathematics and other pure sciences. In such model, it is examined how an explained variable is linearly regressed upon a set of explanatory variables, or how the variation of an explained variable is linearly explained by a set of explanatory variables. The importance of the explanatory variables or the factors taken together in such a model is empirically judged by the proportion of variance of the explained variable to be explained by the explanatory variables and is measured by the coefficient of determination. The question of relative importance of the explanatory variables, or the question of partitioning the coefficient of determination among the explanatory variables is crucial but not yet completely resolved. Various fragmented efforts are observed in the literature from the early years of the previous century, but the problem is not yet solved as it is not properly encountered. [For example, see Hooker and Yule (1906), Tinbergen (1939), Snedecor and Cochran (1976), Lindeman et al (1980), Pedhazur (1982), Cox (1985), Kruskal (1987a, 1987b), Pratt (1987), Kruskal (1989), Kruskal and Majors (1989), Chevan and Sutherland (1991), Bring (1994), Feldman (2005), Gromping (2007), etc. Firth (1998) gives a very beautiful critical survey of the main works up to mid-nineties in this field.] The main problem of all these efforts is not to realize perfectly the theoretical framework in which the question of relative importance of the explanatory variables is raised and tried to be solved, and the implications of the tools used for that purpose.

The question of relative importance arises only in the multiple regression model where the number of explanatory

variables is more than one. The general theoretical form of the Classical Linear Multiple Regression Model is given as  $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k + U$ . It is assumed that the true theoretical relation is  $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k$  and  $U$  is the disturbance term by which the observed relation between the explained variable  $Y$  and the explanatory variables  $X_1, X_2, \dots, X_k$  is theoretically disturbed from the true theoretical relation. With the help of this model, it tries to examine how the explained variable  $Y$  is linearly explained by several explanatory variables  $X_1, X_2, \dots, X_k$ . The coefficient of  $X_j$ , denoted by  $\beta_j$ , measures the amount of change in  $Y$  for one unit change in  $X_j$ , the values of all other explanatory variables remaining constant; the coefficient is thus known as the *partial regression coefficient*. In such model it is assumed that the explanatory variables are non-stochastic and are linearly independent of the disturbance term. Thus the explanatory variables have no sampling fluctuations or they take fixed sets of values in repeated samples. Under this assumption, the sampling distributions of the estimated parameters are smoothly obtained and the process of decomposition of the explained variance into those contributed by the explanatory variables or the method of decomposition of the coefficient of determination into those due to the concerned variables is tried in the literature.

Kruskal (1987a) proposes the method of averaging over orderings for obtaining the relative importance of different variables. He suggests to average 'accounted for proportions of variance over orderings – that is, to average squared partial correlations' [Kruskal (1987b)]. A variation of this is to average actual reductions of remaining variance rather than proportions – that is to average so-called semi-partial correlation coefficients. This is also discussed but

discarded by Kruskal (1987a). This variation is also proposed earlier by Lindeman et al (1980, pp. 120-127) on the ground that this leads to perfect decomposition of the coefficient of determination. However, Kruskal (1987a) argues, 'it is misleading to look at actual variance accounted for because variable in order can at best only take care of what variance is left over from the first variable's work'.

Chevan and Sutherland (1991) demonstrate a method based on a theorem of hierarchies taken from mathematics to decompose  $R^2$  through incremental partitioning. A validation test by them demonstrates that the algorithm is sensitive to the relationships in the data rather than the *proportion of variability accounted for by the statistical model* used. The method gives identical result with that proposed by Lindeman et al (1980) which is based on some simple logic though it is discarded by Kruskal (1987a) based on some statistical logic. Feldman (2005) proposes a method based on a theorem of cooperative game – to arrive at the proportional value of the game – to decompose  $R^2$  through incremental proportional partitioning. Thus, he suggests some modifications over 'Hierarchical Partitioning' of Chevan and Sutherland (1991). Feldman (2005) also addresses to some admissibility criteria for measures of relative importance and finds that his proposed method satisfies them. Gromping (2007) compares the performances of the LMG method [proposed by Lindeman, Merenda and Gold (1980) and supported by Chevan and Sutherland (1991)] and the PMVD method [*Proportional Marginal Variance Decomposition* method proposed by Feldman (2005)] and finds that the second one is better than the first one. Thus, the mathematical logic inherent in the 'hierarchical partitioning' or the game theoretic logic inherent in the 'Proportional Marginal Variance Decomposition' seems to surpass the statistical logic of 'proportion of variability accounted for' by the explanatory variables.

In this paper we have tried to develop a model in Indian context on demand for money ( $M_1$ ) to illustrate the relative importance of explanatory variables. From the existing literature demand for money is seen to be influenced by income, price and rate of interest as suggested by Keynes (1936), Baumol (1952). Here we try to estimate which variable among these three, that is, income, price and rate of interest will be more significant for explaining the variability of demand for money.

## 2. Hypotheses

The following are the hypotheses to be tested in our study.

1. Transaction and precautionary demand for money ( $M_1$ ) being more relevant than speculative demand in a developing country like India, GDP and WPI are more significant than interest rate.
2. Partial correlation, as used in the existing literature, plays unimportant role in determining the true importance of

the explanatory variables. It is able to explain the marginal importance of the variables only.

3. True partial importance can be explained only by orthopartial correlation.
4. True importance of the variables can be described only by an average of orthopartial and simple correlation.

## 3. Data Base

In this model, we have taken narrow money ( $M_1$ ) as demand for money, Gross Domestic Product (GDP) as income, average commercial bank deposit rate for above 5 years time deposit as Interest Rate and Wholesale Price Index (WPI) as price in Indian context for simplicity. We cover the time period from 1970-71 to 2001-02. The relevant data on  $M_1$ , GDP at factor cost (1993-94 prices), Interest Rate and WPI are obtained from *Monetary Statistics and Handbook of Statistics on Indian Economy, RBI*.

## 4. Empirical Methodology and Benchmark Results

We aim to investigate the impact of GDP, Rate of Interest and WPI on  $M_1$  (Demand for Money) in Indian context. At first we consider ordinary least squares (OLS) specifications and try to estimate partial correlation, that is, relative importance of the explanatory variables.

Thus, our empirical specification is as follows

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon_i$$

Where, Y is the  $M_1$ ,  $X_1$  is GDP,  $X_2$  is Interest Rate and  $X_3$  is Wholesale Price Index.

### Granger Causality Test

As we use a time series model, firstly we check Granger Causality Test. From Granger Causality Test between  $M_1$  and GDP, GDP does not Granger cause  $M_1$ , which is statistically significant at 5% level ('P' value is 0.04680). Between  $M_1$  and Interest Rate, Interest Rate does not Granger cause  $M_1$ , which is statistically significant at 10% level (0.07535). And between  $M_1$  and WPI, WPI does not Granger cause  $M_1$ , which is also statistically significant at 5% level (0.03141) (Table-1). From this test, we see that there is one way relationship.

### Unit Root Test

Now we check unit root test. To gauge the appropriateness of the ARDL cointegration analysis, two unit root tests, viz. ADF test and PP test were conducted for the sample periods. From both these tests,  $M_1$ , GDP and WPI are indicated to be a stationary series of I (2) by both the tests at 1% level of significance. But interest rate is to be stationary series of I(1) by both the tests at 1% level of significance (Table-2). The overall picture that emerges is that the three variables considered are not necessarily integrated of the same order.

**Table 1**

Series	Null Hypothesis	"F"- Statistics		"P"-Value	
$M_1$ AND GDP	GDP DOES NOT GRANGER CAUSE $M_1$ $M_1$ DOES NOT GRANGER CAUSE GDP	3.47**	0.57	0.04680	0.57206
$M_1$ AND INT	INT DOES NOT GRANGER CAUSE $M_1$ $M_1$ DOES NOT GRANGER CAUSE INT	2.87*	2.33	0.07535	0.11737
$M_1$ AND WPI	WPI DOES NOT GRANGER CAUSE $M_1$ $M_1$ DOES NOT	3.99**	2.41	0.03141	0.11001

	GRANGER CAUSE WPI		
--	-------------------	--	--

Note: \* and \*\* denote rejection of the null hypothesis at 10% and 5% levels respectively.

**Table 2**

Variable(X)	ADF			PP		
	X	$\Delta X$	$\Delta^2 X$	X	$\Delta X$	$\Delta^2 X$
	t-value	t-value	t-value	t-value	t-value	t-value
$M_1$	4.10	0.12	-6.47**	11.89	0.25	-10.85**
GDP	4.44	-1.50	-6.29**	8.93	-2.26	-11.46**
Interest rate	-2.61	-4.58**	-6.34**	-2.05	-3.82**	-7.65**
WPI	1.97	-1.87	-5.46**	3.62	-2.70	-8.62**

Note: \* and \*\* denote statistical significance at 5% and 1% levels, respectively.

### Linear Regression Analysis (OLS)

Now we regress Y on  $X_1$ ,  $X_2$  and  $X_3$ . From this regression we get that  $R^2$  is 0.9797, which is statistically significant. Here the coefficient of interest rate is highly significant at 1% level, the coefficient of WPI is significant at 5% level but the coefficient of GDP is statistically insignificant. GDP and WPI are directly related to  $M_1$  and Interest Rate is inversely related to  $M_1$ . If we want to know the partial correlation or relative importance of the variable ( $t^2/t^2 + \text{degree of freedom}$ ) as in the existing literature then we see that interest rate is the most significant variable which

explains about 51% of the variability of Y. WPI is the second significant variable which explains about 14% of the variability of Y. And the role of GDP is negligible (Table-3). But there is a strong multicollinearity between GDP and WPI while Variance Influencing Factor (VIF) about 137 and 144 respectively. Consequently what we have achieved is erroneous because of the presence of multicollinearity. In the presence of multicollinearity, we cannot correctly estimate the explanatory power of explanatory variables.

**Table 3**

Variable	Coefficient	Standard Error	'T' Stat	'P' Value	Partial Correlation
INTERCEPT	36485.01	42183.01	0.8649	0.394432	
GDP	0.159916	0.130494	1.22546	0.230611	0.050904
Interest rate	-14809.5	2709.513	-5.46574**	7.78E-06	0.516193
WPI	729.4424	343.2885	2.124867*	0.042559	0.138861

Note: \* and \*\* denote statistical significance at 5% and 1% levels respectively.

### 5. Relative Importance of Explanatory Variables

While we are interested to know the partial significance of the explanatory variables we observe the significance of the partial regression coefficient. The partial regression coefficient can be interpreted in two ways.

- 1) The coefficient can be interpreted as the amount of change in that part of Y which is not influenced by other explanatory variables with one unit change in that part of  $X_j$  which is not explained by other explanatory variables.
- 2) It can also be interpreted as the amount of change in Y for one unit change in that part of  $X_j$  which is not explained by other explanatory variables.

The term partial regression coefficient actually fits to the second interpretation though we are used to fit it to the first in econometric literature. The coefficient of  $X_j$  interpreted in the first way can better be named as *marginal regression coefficient*. [See Mondal (2008) for details.]

If we are interested in the significance of the *marginal regression coefficient* (or in the *marginal significance* of the regression coefficient) we have to consider the regression of residue of Y on residue of all  $X_j$ , and if we are interested in the significance of the *partial regression coefficient* (or in the *partial significance* of the regression coefficient) we have to consider the regression of Y on residue of all  $X_j$ . The correlation obtained in the first regression is known in the existing literature as the *partial correlation*, though it is

not correctly partial. The correct partial correlation can be obtained only in the second regression and thus, Mondal (2008) names it the *orthopartial correlation* (ortho meaning correct).

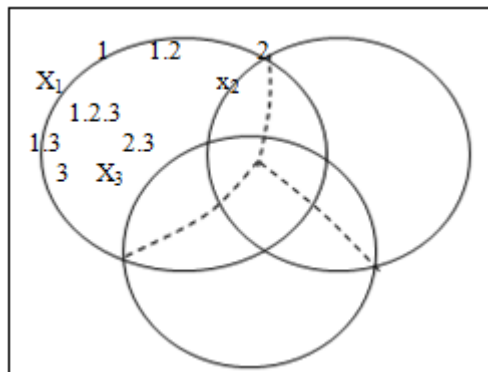
The squared orthopartial correlation of  $X_j$  with Y is effectively the incremental correlation due to  $X_j$  (which is logically, but not mathematically, explained also as the semi-partial correlation by Cohen and Cohen (1980) and others) when it is entered after all other explanatory variables. Thus, in a model with two explanatory variables, this squared *orthopartial correlation* implies the relative importance of the concerned variable on the one extreme, and the squared simple correlation implies the same on the other extreme. Hence, the principle of averaging of the squared simple correlation and the incremental correlation (which is actually squared orthopartial correlation) becomes statistically relevant.

In our model we observe, the coefficient of determination, i.e.,  $R^2 = 0.9797$ . The squared simple correlations of  $M_1$  (Y) with GDP( $X_1$ ), Interest Rate( $X_2$ ) and WPI( $X_3$ ) are respectively  $r_1^2 = 0.9579$ ,  $r_2^2 = 0.1161$  and  $r_3^2 = 0.9462$ . As  $r_1^2 + r_2^2 + r_3^2 = 2.0202 > R^2 = 0.9797$  the explanation of the variance of Y provided by  $X_1$ ,  $X_2$  and  $X_3$  are overlapping or the variables  $X_1$ ,  $X_2$  and  $X_3$  are partially linearly related as shown in the Venn diagram (Diagram-1). This overlapping portion is due to the presence of multicollinearity. The rectangular box represents variance of Y

The orthopartial correlation of  $X_1$ ,  $X_2$  and  $X_3$  are 0.0010, 0.0215 and 0.0032 respectively (i.e., regression of  $Y$  with the residue of  $X_1$  on  $X_2$  and  $X_3$ ,  $X_2$  on  $X_1$  and  $X_3$  and  $X_3$  on  $X_1$  and  $X_2$  respectively). The overlapping area out of 0.9797 value of  $R^2$  is either due to  $X_1$  only, or due to  $X_2$  only, or due to  $X_3$  only, or due partially to  $X_1$ , partially to  $X_2$  and partially to  $X_3$ .

The importance of  $X_1$ , measured by its explanatory power, lies in between 0.0010 (the squared orthopartial correlation of  $X_1$ ), and 0.9579 (the squared simple correlation of  $X_1$ ). Therefore, the average importance of  $X_1$  is an average of 0.0010 and 0.9579 and that of  $X_2$  is an average of 0.0215 and 0.1161 and that of  $X_3$  is an average of 0.0032 and 0.9462.

The overlapping portion between  $X_1$  and  $X_2$  (denoted by the area 1.2), which is shown in the Venn diagram (Diagram-1) is obtained from the regression of  $Y$  with the residue of  $X_1$  on  $X_3$  which is subtracted from the orthopartial correlation of  $X_1$  or from the regression of  $Y$  with the residue of  $X_2$  on  $X_3$  which is subtracted from the orthopartial correlation of  $X_2$ , and its value is estimated to be 0.0109.



**Diagram 1**

In the same way we obtain the overlapping portion between  $X_1$  and  $X_3$  (denoted by the area 1.3) and between  $X_2$  and  $X_3$  (denoted by the area 2.3) and the values are 0.8592 and -0.0030 respectively.

The overlapping area is decomposed by Proportional marginal variance decomposition (PMVD) method. This method was proposed by Feldman (2005), and Gromping (2007) supported the method. And this method was modified by Mondal (2008).

By PMVD method we decompose the area 1.2 and get the shares of  $X_1$  and  $X_2$  which are 0.0005 and 0.0103 respectively. And by this method we also decompose the overlapping portion i.e., 1.3 and 2.3 and get the share of  $X_1$  and  $X_3$  as 0.2144 and 0.6447 respectively, and the shares of  $X_2$  and  $X_3$  are -0.0026 and -0.0003 respectively.

The overlapping portion of the three explanatory variables (denoted by the area 1.2.3) are obtained from the squared simple correlation of  $X_1$  which is subtracted from the area 1.2 and 1.3 or from the squared simple correlation of  $X_2$  which is subtracted from the area 1.2 and 2.3 or from the squared simple correlation of  $X_3$  which is subtracted from the area 1.2 and 1.3, and its value is 0.0867. By PMVD we decompose the area 1.2.3 and we get the shares of  $X_1$ ,  $X_2$  and  $X_3$  as 0.0210, .0028 and 0.0629.

The relative importance of GDP ( $X_1$ ) is the sum of orthopartial correlation of  $X_1$  (0.0010), the share of  $X_1$  in 1.2 and 1.3 (0.0005 and 0.2144) and the share of  $X_1$  in 1.2.3 (0.0210) as 0.2369.

The relative importance of Interest Rate ( $X_2$ ) is the sum of orthopartial correlation of  $X_2$  (0.0215), the share of  $X_2$  in 1.2 and 2.3 (0.0103 and -0.0026) and the share of  $X_2$  in 1.2.3 (0.0028) as 0.0322.

The relative importance of WPI ( $X_3$ ) is the sum of orthopartial correlation of  $X_3$  (0.0032), the share of  $X_3$  in 1.3 and 2.3 (0.6447 and -0.0003) and the share of  $X_3$  in 1.2.3 (0.0629) as 0.7105 (as shown in table-4). Orthopartial correlations are equal to simple correlations, in sign as well as in value, in the absence of any linear relation among  $X_1$ ,  $X_2$  and  $X_3$ . They, in the presence of multicollinearity, are normally less in value than simple correlations as is illustrated in the example above. Or, normally, the sum of the squared simple correlations of the three variables is greater than the coefficient of determination. But as Hamilton (1987, 1988) indicates and as Shieh (2001) explains there may be situations of multicollinearity where the sum of the squared simple correlations of the two variables is less than the coefficient of determination or the squared simple correlations are less than squared orthopartial correlations. This situation is known as enhancement-synergism (For further explanation see Mondal (2008)). In our model there is no enhancement-synergism.

**Table 4**

			1.3	1+1.3			1.2+1.2.3		REL IMP
	1	$X_3$	0.8592	0.8603	(+ve)	$X_2$	0.0976	1+1.2+1.3+1.2.3	
$X_1$	0.0011		1.2	1+1.2			1.3+1.2.3	0.9579	0.237
	(+ve)	$X_2$	0.0109	0.0119	(+ve)	$X_3$	0.9460	(+ve)	
			2.3	2+2.3			1.2+1.2.3		
	2	$X_3$	-0.003	0.0186	(-ve)	$X_1$	0.0976	2+2.3+1.2+1.2.3	0.032
$X_2$	0.0216		1.2	2+1.2			2.3+1.2.3	0.1162	
	(-ve)	$X_1$	0.0109	0.0325	(-ve)	$X_3$	0.0837	(+ve)	
			3.2	3+3.2			1.3+1.2.3		
	3	$X_2$	-0.003	0.0003	(-ve)	$X_1$	0.9460	3+3.1+3.2+1.2.3	
$X_3$	0.0033		3.1	3+1.3			3.2+1.2.3	0.9462	0.710
	(+ve)	$X_1$	0.8592	0.8625	(+ve)	$X_2$	0.0837	(+ve)	



From Table-4 we show the results of the regression by path analysis from orthopartial correlation to simple regression. Here we see that the orthopartial correlation of  $X_1$ , that means variable  $X_1$  explain that part of  $Y$  which is not explained by  $X_2$  and  $X_3$ .  $X_2$  and  $X_3$  explain the dependent variable  $Y$  to the extent of 0.9787. So  $X_1$  explains 0.0011 (area 1) out of 0.0213 (total explanatory power=1). But there exists some overlapping portion among the three explanatory variables. Now we show that the overlapping portion between  $X_1$  and  $X_3$ , i.e., 1.3 (0.8592). If we consider that the area 1.3 is fully explained by the  $X_1$  then we add the area 1+1.3 (0.8603). Therefore we see that the value of area 1+1.3 (0.8603) is greater than the area 1 (0.0011). This is due to the presence of multicollinearity without enhancement synergism. Similarly, the overlapping portion between  $X_1$  and  $X_2$ , i.e., area 1.2 (0.0109) is fully explained by  $X_1$  then the area is 1+1.2 (0.0119), the value being greater than area 1. This is due to the presence of multicollinearity without enhancement synergism. Now we consider the overlapping portion among the three explanatory variables, i.e., area 1.2.3 and add these overlapping portions with area 1 to get the total explanatory power of  $X_1$  which is equal to the simple regression of  $Y$  on  $X_1$ , i.e., 0.9579. Therefore the range of variable  $X_1$  is 0.0011 to 0.9579 to explain the dependent variable  $Y$  where the minimum value is 0.0011 and maximum value is 0.9579 and the average importance of this variable occurs between these two values, and the average importance is 23.7%. But the marginal correlation of the explanatory variable  $X_1$  is 5.09%. We know that  $X_2$  and  $X_3$  jointly explain 0.9787. Thus marginally  $X_1$  explains 5.09% out of 0.0213 which is actually wrong. Although the average importance is in this range (minimum and maximum value) yet this is wrong. In this case we observe that marginally the importance of variable  $X_1$  is less where Orthopartially variable  $X_1$  is a significant variable.

Similarly we observe from Table-4 that orthopartial correlation of  $X_2$  is 0.0216. If we add the overlapping portions with area 2(2+1.2+2.3+1.2.3), we get the total explanatory power, i.e., 0.1162 which is equal to the simple regression. There exists the problem of multicollinearity without enhancement synergism when we add the area-2.3 with area-2. Therefore the average importance of the variable is 3.22%. But the marginal correlation of  $X_2$  is 51.61%. We know that  $X_1$  and  $X_3$  jointly explain  $Y$  to the extent of 0.9582. So  $X_2$  explains 0.5161 out of 0.0418, which is wrong. Also we observe that marginal correlation exceeds the simple correlation. In this case marginally the importance of variable  $X_2$  is the most significant variable where Orthopartially variable  $X_2$  is least significant.

Again we observe from Table-4 that orthopartial correlation of  $X_3$  is 0.0013. If we add the overlapping portions with area 3(3+1.3+2.3+1.2.3), we get the total explanatory power 0.9462 which is equal to the simple regression. There exists the problem of multicollinearity without enhancement synergism when we add the area 3 and 2.3. Therefore the average importance of the variable is 71.05%. But the marginal correlation of  $X_3$  is 13.88%. We know that  $X_1$  and  $X_2$  jointly explain  $Y$  to the extent of 0.9765. So marginally  $X_2$  explains 0.1388 out of 0.0235 which is wrong. In this case also we see that marginally the variable  $X_3$  is less

important where Orthopartially variable  $X_3$  is the most significant variable.

## 6. Conclusion

From the existing ANOVA model, partially (marginally) interest rate is the most significant variable (it explains 51% of the variability of demand for money). WPI is the second significant variable which explains 13.88% of the variability of  $M_1$ . GDP is less significant variable which explains 5% of the variability of  $M_1$ . Speculative demand for money has a very crucial role in the Indian economy.

In respect of the relative importance, Orthopartially Interest Rate in our present worked out model is the most significant variable which explains 2.16% of the variability of  $M_1$ . But when we add the total share of interest rate, it explains only 3.22% of the variability of  $M_1$  and becomes the least significant variable. After the summation of total share of WPI, it is the most significant variable which explains 71% of the variability of  $M_1$ . Accordingly GDP is the second significant variable which explains 23.70% of the variability of  $M_1$ . The role of Speculative demand for money is negligible in India. Rather the role of transaction and precautionary demand for money has greater importance in India.

## References

- [1] Bring, Johan. (1994), "How to Standardise Regression Coefficients", *The American Statistician*, 48(3) Aug, pp. 209-213.
- [2] Baumol, W. (1952), "The Transaction Demand for Cash. An Inventory Theoretic Approach", *Quarterly Journal of Economics*, 66(4), 545-56.
- [3] Chevan Albert and Michael Sutherland (1991), "Hierarchical Partitioning", *The American Statistician*, 45 (2), pp. 90-96.
- [4] Cox, L. A. (1985), "A New Measure of Attributable Risk for Public Health Applications", *Management Science*, 31, pp. 800-813.
- [5] Cox, D. R. and Wermuth, N. (1996), *Multivariate Dependencies*, Chapman and Hall, London.
- [6] Feldman, B. (2005), "Relative Importance and Value", Unpublished manuscript (Version 1.1, March 19), Online at <http://www.prismanalytics.com/docs/RelativeImportance050319.pdf>.
- [7] Firth, David (1998), "Relative importance of explanatory variables", Presented in the Conference on Statistical Issues in the Social Sciences, Stockholm, Oct, Online at <http://www.nuff.ox.ac.uk/sociology/alcd/relimp.pdf>.
- [8] Gromping, Ulrike (2007), "Estimators of Relative Importance in Linear Regression Based on Variance Decomposition", *The American Statistician*, 61 (2) May, pp 139-147.
- [9] Hooker and Yule (1906), "Note on estimating the relative influence of two variables upon a third", *Journal of the Royal Statistical Society*, 69, pp. 197-200.

- [10] Kruskal, W. (1987a), "Relative Importance by Averaging over Ordering", *The American Statistician*, 41 (1), pp. 6-10.
- [11] Kruskal, W. (1987b), "Correction to 'Relative Importance and Value'", *The American Statistician*, 41 (4), p. 341.
- [12] Kruskal, W. and R. Majors (1989), Concepts of Relative Importance in Recent Scientific Literature", *The American Statistician*, 43 (1), pp. 2-6.
- [13] Kruskal, W. H. (1989), "Hooker and Yule on relative importance: A statistical detective story", *International Statistical Review*, 57, pp. 83-88.
- [14] Keynes, M. K. (1936), "The General Theory of Employment, Interest and Money", *Macmillan Cambridge University Press, for Royal Economic Society in 1936*.
- [15] Lindeman, R. H., P. F. Merenda and R. Z. Gold (1980), Introduction to Bivariate and Multivariate Analysis, Glenview, IL, Scott, Foresman.
- [16] Mondal, D. (2008), "On the Test of Significance of Linear Multiple Regression Coefficients", *Communications in Statistics - Simulation and Computation* 37(4):713-730.
- [17] Pedhazur (1982), Multiple Regression in Behavioural Research, 2nd ed., New York: Holt, Rinehart & Winston.
- [18] Pratt, J. W. (1987), "Dividing the Indivisible: Using Simple Symmetry to Partition Variance Explained" in Proceedings of Second Tampere Conference in Statistics, eds., T. Pukkila and S. Puntanen, University of Tampere, Finland, pp. 245-260.
- [19] Snedecor, G. W. and Cochran, W. G. (1976), Statistical Methods (6th Edn.), Iowa State University Press, Ames.
- [20] Tinbergen, J. (1939), Business Cycles in the United States of America, 1919-1932, League of Nations.
- [21]<sup>1</sup> I am indebted to Professor Debasish Mondal, Department of Economics with Rural Development, Vidyasagar University (West Bengal, India) for his guidance in the preparation of this paper.