RAY: International Journal of Multidisciplinary Studies, E-ISSN: 2456-3064
Volume II, No. 1, April, 2017, pp. 75-90.

The Impact of Foreign Direct Investment on the Performance of Metallurgical Sector of India: An Empirical Analysis

Satabdee Banerjee
Assistant Professor,
Department of Commerce,
Netaji Nagar Day College,
Kolkata, West Bengal,
India.
banerjee_satabdi@yahoo.co.in

Structured Abstract:

Purpose: This paper aspires to identify whether Foreign Direct Investment (FDI) inflows into the Metallurgical Sector of India have any long run cointegrating relationship and / or short run causal relationship with the performance of the said sector.

Methodology: The study applies the Auto Regressive Distributed Lag (ARDL) bounds testing approach to recognize the nature of cointegrating relationship among the variables, and the Toda-Yamamoto model to Granger non-causality to comprehend the short-run dynamics among the selected variables.

Findings: It has been observed that, though there is no conclusive evidence of long run cointegration among FDI in metallurgy and the other selected variables, in the short-run there is causality running from the selected variables to FDI.

Value: Innumerous studies are being undertaken around the globe on various aspects of FDI. Whatsoever, no analysis has been attempted to identify the impact of FDI on the performance of Metallurgical sector of India, the sector being the pillar of infrastructural and industrial development of the nation. This being the first of its kind study will help in policy formulation and inspire further research.

Keywords: ARDL, FDI, Granger Non-Causality, Metallurgical Sector, Toda-Yamamoto Model.

Paper Type: Research Paper.

Introduction

The growth of the Mining & Metallurgical industry is quite critical for the growth of an economy, India being no exception. Being the supplier of inputs, this industry augments growth, productivity, employment, and strengthens all primary, secondary and tertiary sectors, to be counted as the backbone of any economy.

India has enormous mineral reserves and there is ample opportunity for growth in exports for the Indian metallurgical industry. She is a consistent net exporter of steel and copper. The rapid growth of user-industries drives the demand for metals and minerals. Some of the forward linkages of metallurgical industry are engineering goods, Foundry, Casting and Forging Devices, Minerals Exploration Equipments, Wires, Tubes and Pipes, Power and Hardware Tools, Refractories, Additives, Metal Working Devices, Safety and Rescue Equipments and innumerous more.

Metallurgical sector of India confronted enormous changes in the 90s with the onset of the liberalization and open market policies. 100 per cent Foreign Direct Investment (FDI) has been approved in this industry since 1991. Minerals like iron ore, manganese ore, chrome ore, sulphur, gold, diamond, copper, lead, zinc, molybdenum, tungsten, nickel and platinum group of minerals, which were reserved exclusively for public sector earlier, have now been thrown open for exploration by private sector. With the new norms, forms and sources of investments, the infrastructure pertaining to the industries were altered. More efficient, effective and technologically upgraded systems improved the production process and consequently the quantum of output of the industry increased along with the quality of the products. During the period 2007-2011, production has registered a Compounded Annual Growth Rate (CAGR) of 5.2 per cent (Metallurgy in India -- Ease of Doing Business, 2015). As the Indian Government comes up with the 'Make in India' campaign, aims are to make Indian metal output to become competitive with international quality standards, efficiency and manufacturing facilities. From January 2000 to June 2015, the sector has been able to draw an FDI of Rs. 413,396.77 million (US$ 8,578.45 million), i.e. 3.19 per cent of total FDI inflows in India (Department of Industrial Policy and Promotion, 2015).

Review of Literature

FDI has boomed in post-reform India. Moreover, the composition and type of FDI has changed considerably since India has liberalized. This has fuelled high expectations that FDI may serve as a catalyst to higher economic growth. The paper of Alfaro, (2003) showed that the benefits of FDI vary greatly across sectors by examining the effect of FDI on growth in the primary, manufacturing, and services sectors. An empirical analysis using cross-country data for the period 1981-1999 suggested that total FDI exerted an ambiguous effect on growth. FDIs in the primary sector, however, tend to have a negative effect on growth, while it is positive in manufacturing sector. Evidence from the service sector was, however, ambiguous.

Chakraborty & Nunnenkamp (2006) assessed the growth implications of FDI in India by subjecting industry-specific FDI and output data to Granger Causality Test (GCT) within a panel cointegration framework. It turned out that the growth effects of FDI varied widely across sectors.

The Associated Chambers of Commerce and Industry of India (2012) made an assessment of global FDI along with India's sectoral analysis. Telecommunication, Automobile, IT (Information Technology (IT) / Information Technology enabled services (ITes) sectors were given special emphasis on, whereas Pension Funds and Civil Aviation were identified as potential sectors for inflow in near future.

Wang (2009) studied the heterogeneous effects of different sector-level FDI inflows on host country's economic growth. Data from 12 Asian economies over the period of 1987 to 1997 were employed. There was strong evidence showing that FDI in manufacturing sector had a significant and positive effect whereas FDI inflows in non-manufacturing sectors of the host economies did not play a significant role in enhancing economic growth.

Objectives of the Study

Though econometric analysis of relationships among FDI and other macroeconomic variables of India, even at sectoral level, has been the focal point of both theoretical and empirical deliberations since liberalization and globalization in 90s and even earlier (Hansen & Rand, 2004; Hsiao & Hsiao, 2006; Chakraborty & Nunnenkamp, 2006, 2008; Herzer, Klasen, & Nowak-Lehmann D., 2008; Asghar, Nasreen, & Rehman, 2011; Mlachila & Takebe, 2011; Anitha, 2012; Goswami & Saikia, 2012; Ray, 2012; Singh, Chadha, & Sharma, 2012), no discussions could be found on the impact of FDI on the performance of Metallurgical Sector of India, which is of immense importance for her infrastructural development. In this context, this paper aspires to identify whether FDI inflows into the Metallurgical Sector of India have any long run cointegrating relationship and/or short run causal relationship with the performance of the said sector.

Methodology

Monthly data on FDI Equity Inflows, Production, Export and Import of Metallurgical products and BSE Metal Index, has been collected for the period of January 2007 to January 2015, i.e. for 97 months for the purpose of analysis.

Logged value of FDI inflows in the Metallurgical sector (LFDIM), logged value of S&P BSE Metal Indices (LBSEM), logged value of metallurgical produces (LPM), logged value of metallurgical produces exported (LXM) and logged value of metallurgical produces imported (LIM) have been considered to conduct the investigation.

The Auto Regressive Distributed Lag (ARDL) framework has been undertaken to study the cointegrating relationship among the variables, and the Toda-Yamamoto approach to Granger non-causality has been taken resort to understand the short-run dynamics among the selected variables.

The ARDL model has three major advantages in comparison to the Engel and Granger (1987), Johansen and Juselius (1990) and Vector Error Correction Model (VECM). Firstly, the ARDL model dealing with single cointegration, yields consistent and robust results for both the long-run and short-run relationships. Secondly, this approach is applicable irrespective of the underlying regressors being purely I(0), purely I(1), or is a mixture of both. Thirdly, ARDL test is relatively more efficient in case of small and finite sample data sizes. Moreover, all the variables of this model are assumed to be endogenous.

When the time-series are non-stationary and possibly cointegrated, Toda & Yamamoto (1995) model fits a standard VAR model in the levels of the variables and thus, minimizes the risks associated with the possibility of miss-specifying the order of integration of the series (Mavrotas & Kelly, 2001).

Discussions

When two or more time series are individually integrated in the same order i.e. I(d), where d is the order of integration, but their linear combination has a lower order of integration, then such series is understood to be cointegrated. In this paper the ARDL bounds testing approach, as popularized by Pesaran and Shin (1997, 1999) and subsequently extended by Pesaran et. al. (2001) has been applied. Here, the model is a general vector autoregressive (VAR) model of order p, in Z_t, where Z_t is a column vector composed of the five selected variables. The ARDL model used in this study is appended hereunder:

$$\Delta LY_t = \propto_0 + \sum_{i=1}^{n} \propto_{1i} \Delta LY_{t-1} + \sum_{i=0}^{n} \propto_{2i} \Delta LZ_{t-1} + \beta_1 LY_{t-1} + \beta_2 LZ_{t-1} + \mu_{1t} \quad (1)$$

Where,

Δ = the first difference operator,

LY_t = log of dependent variable,

LZ_t = log of independent variable

μ_t = the usual white noise residuals

The left-hand side of the equation signifies the dependent variable. The first part of the right hand side of the equation ($\alpha_1 - \alpha_2$) represents the short-run dynamics of the model; whereas, the parameters β_1 and β_2, on the right-hand side, correspond to the long-run relationship among the independent variables. This is actually a test of the hypothesis of no cointegration among the variables against the existence of cointegration among the variables, denoted as:

H_o: There is no long run cointegration among the variables.

H_a: There is long run cointegration among the variables.

The ARDL bounds test is based on the Wald-test (F-statistic). Two critical values are given by Pesaran et al. (2001) for the cointegration test. When the computed F-statistic is greater than the upper bound critical value, then the H_0 is rejected symptomatic of the variables being cointegrated in the long run. If the F-statistic is below the lower bound critical value, then the H_0 cannot be rejected suggesting that there is no long run cointegration among the variables. When the computed F-statistics falls between the lower and upper bound, then the results are inconclusive.

In the analysis of cointegration, test of stationarity of the time series data is considered as a precondition. For testing the non-existence of unit-root or stationarity analysis, Augmented Dicky-Fuller (ADF) test (Dickey & Fuller, 1981), Dickey-Fuller generalized least squares (DF-GLS) test (Elliott, Rothenberg, & Stock, 1996) and Philip Perron (PP) test (Phillips & Perron, 1988) have been conducted to learn about the existence of unit roots in the data series.

The findings of Table 1 reveal that the variables were I(0) and I(1). Hence, the ARDL model is suitable for application here.

Following the earlier explanation, Table 2 identifies that there is ambiguity regarding the existence of long run cointegrating relationship between LFDIM and the other selected variables, as well as for LPM and the rest of the variables. No evidence of any long-run cointegration is there between LBSEM and the rest of the variables. LXM, as a dependent variable, has long-run cointegration with the rest of the variables at 1 per cent level of significance and LIM has long-run cointegration with the rest of the variables at 10 per cent level of significance.

Thus, only LXM and LIM qualify for further analysis in the next step, where the unrestricted error correction model (UECM) based on the assumption made by Pesaran et al. (2001) is developed. The ARDL model estimates $(p+1)^k$ number of regressions to obtain the optimal lag length for each variable, where p is the maximum number of lags to be used and k is the number of variables in the equation. When evidence of a long-run cointegrating relationship could be found among the variables, the following long run models are to be estimated:

$$LY_t = \propto_4 + \sum_{i=1}^{n} \propto_{5i} \Delta LY_{t-1} + \sum_{i=0}^{n} \propto_{6i} \Delta LZ_{t-1} + + \mu_{2t} \qquad (2)$$

When there is evidence of a long-run relationship, the error correction model (ECM), which indicates the speed of adjustment back to long run equilibrium after a short run disturbance, needs to be estimated as follows:

$$\Delta LY_t = \propto_7 + \sum_{i=1}^{n} \propto_{8i} \Delta LY_{t-1} + \sum_{i=0}^{n} \propto_{9i} \Delta LZ_{t-1} + \lambda ECM_{t-1} + \mu_{3t} \qquad (3)$$

Where, λ= the speed of adjustment parameter and

ECM = the residuals that are obtained from the estimated cointegration model.

Table 3A suggests that in case of bi-variate analysis, LXM has long-run cointegration with LBSEM (at 5 per cent level of significance), with LPM (at 1 per cent level of significance) and with LIM (at 10 per cent level of significance), but not with LFDIM. The error correction term (ect) in Table 3B being negative and significant, the model appears to be well fit and the speed of adjustment is also quite good at 68 per cent.

Similarly, Table 4A suggests that, LIM has long-run cointegration with LBSEM (at 10 per cent level of significance), with LPM (at 5 per cent level of significance) and with LXM (at 1 per cent level of significance), but not with LFDIM. The ect in Table 4B is negative and significant and the speed of adjustment is good at 40 per cent.

In the next stage, to ascertain the goodness of fit of the ARDL model, diagnostic and stability tests are conducted. The diagnostic test examines the serial correlation, heteroskedasticity and structural stability associated with the model.

Table 5, Figure 1 and Figure 2 find that the models have qualified all the requisite diagnostic tests.

Causality is simply understood to be a measure of identifying the cause and effect relationship between the dependent and the independent variables. In a non-stationary and cointegrated time-series, using a standard GCT or Wald test to test linear restrictions on the parameters of a VAR model might lead to Wald test statistic not following its usual asymptotic chi-square (χ^2) distribution under the null (Giles, 2011). The basic idea of Toda & Yamamoto approach is to artificially augment the correct VAR order, k, by the maximal order of integration, say d_{max}. Then a $(k+d_{max})^{th}$ order of VAR is estimated and the coefficients of the last lagged d_{max} vector are ignored. The following Toda-Yamamoto model has been constructed in the VAR system:

$$LY_t = \propto_{10} + \sum_{i=1}^{k} \propto_{11i} LY_{t-i} + \sum_{j=k+1}^{d_{max}} \propto_{12j} LY_{t-j} + \sum_{i=1}^{k} \beta_{3i} LZ_{t-i} + \sum_{j=k+1}^{d_{max}} \beta_{3j} LZ_{t-j} + \mu_{4t} \quad (4)$$

The hypothesis being tested in Toda and Yamamoto model, Modified-Wald (MWALD) test, is as under:

H_0: The independent variables do not granger cause the dependent variable.

H_1: The independent variables granger causes the dependent variable.

To implement the Toda-Yamamoto approach to Granger non-causality, initially the lag length (k) of the VAR model was determined by finding out the minimum value as per the Akaike Information Criterion (AIC). The lag length criterion according to all AIC, Final Prediction Error (FPE) and Hannan-Quinn (HQ) Information Criterion selected the 16th lag. But as the model could not qualify the stability test and it restricted the further increase of lags, finally lag 15 was considered after it qualified the diagnostic tests. Thereafter the maximum order of integration (d_{max}) for the variables was selected.

Table 6 reports the χ^2-test statistic along with the estimated p-values. The results for the multivariate and bi-variate Granger non-causality tests establish that, according to the MWALD test, there is causality running from LBSEM, LPM, LXM and LIM taken together, to LFDIM. As the p-value is 0.00 per cent, it is evident that the probability of seeing a value for the test statistic of 243.0797 or larger, if the hypothesis is true, is negligible. Hence, the null hypothesis cannot be accepted, meaning that, the independent variables together causes LFDIM. This implies that, in the short-run FDI equity inflows in the metallurgical sector of India is impacted by the performance of the said sector, as measured by the stock index movements, production, exports and imports. When considered individually, there is uni-directional causality running from LBSEM, LXM and LIM to LFDIM. Similarly, the multivariate Granger non-causality gives evidence of LBSEM being caused by the other variables. But to one's amazement, individually, only LIM causes LBSEM. Neither LFDIM, nor LPM, nor LXM can cause LBSEM. For LPM as a dependent variable also, there is strong evidence of the existence of a multivariate causal relationship. But in isolation, only LFDIM and LIM can cause LPM. LXM is caused by all LFDIM, LBSEM, LPM and LIM, both, when considered together as well as in isolation. Only LIM, or imports of metallurgical sector, is not caused by any of the variables, even in bi-variate study. The findings corroborate that, there is existence of bi-directional causality only between LFDIM and LXM. So FDI in metallurgical sector of India has strong causal relation with the sector's exports signifying that, FDI promotes exports and exports propel FDI inflows into the said sector.

Conclusion

In a nutshell, it can be concluded that, though in the short-run there is evidence of causality running from LBSEM, LPM, LXM and LIM taken together, to LFDIM, there is no conclusive evidence of long run cointegration among LFDIM and the other selected variables of India. Hence, this result is not in sync with the findings of Alfaro (2003) and Wang (2009) where a positive impact of FDI has been observed on the manufacturing sector, (though they do not specifically comment on the metalurgical sector). More convincing results might be obtained if more observations could be included for the study. LFDIM has neither long run, nor short run relationship with LBSEM, i.e. the stock market performance of Indian

Metallurgical sector. A quite strong relationship can be observed between LFDIM and LXM, both in the long run as well as in the short run. This signifies that, FDI in the metallurgical sector of India has a positive impact on export promotion of the sector, but only when the other factors like production, stock market performance and imports are also encouraging. Finally, though LIM has a long run cointegration with the rest of the selected variables, in the short run, none of the variables can cause LIM. There is only uni-directional causality running from LIM to the rest of the variables. Hence, in the short run, the performance of the metallurgical sector of India is influenced by imports.

Recommendations

The Metallurgical sector of India is growing with the innovative techniques helping the product market to enlarge. It has recorded a strong 19.8 per cent expansion in 2011 at US$ 141.9 billion to touch US$ 305.5 billion by 2015. Big acquisitions are taking place in the expectation of synergic effects. However, the journey of the impressive growth of the Indian metal sector is not free from obstacles leading from economic slowdowns, price and demand fluctuations in the global market, crude oil prices, land acquisition issues, environmental concerns etc. (IL&FS Environment, 2010). FDI, though believed to be a strong propeller of growth, is not uniform across all the sectors of every nation till perpetuity. Its impact even varies depending on the nature and form of FDI, the technology absorption capacity of the particular sector and human capital. Hence, it is of utmost importance to make sector specific study to decide the depth and spread of FDI in Indian context, especially for Metallurgical sector so as to make it a facilitator of industrial development, and not an impediment towards it.

References

Alfaro, L. (2003). *Foreign Direct Investment and Growth: Does the Sector Matter?* Retrieved July 25, 2015, from www.people.hbs.edu/: http://www.people.hbs.edu/lalfaro/fdisectorial.pdf

Anitha, R. (2012). Foreign Direct Investment and Economic Growth in India. *International Journal of Marketing, Financial Services & Management Research , 1* (8), 108-125.

Asghar, D. N., Nasreen, D. S., & Rehman, D. H. (2011). Relationship between FDI and Economic Growth in Selected Asian Countries: A Panel Data Analysis. *Review of Economics & Finance* , 84-96.

Chakraborty, C., & Nunnenkamp, P. (2008). Economic Reforms, FDI, and Economic Growth in India: A Sector Level Analysis. *World Development , 36* (7), 1192-1212.

Chakraborty, C., & Nunnenkamp, P. (2006). *Economic Reforms, Foreign Direct Investment and its Economic Effects in India.* The Kiel Institute for the World Economy.

Department of Industrial Policy and Promotion. (2015). *Consolidated FDI Policy.* Department of Industrial Policy and Promotion.

Department of Industrial Policy and Promotion. (2014, September). *Make in India*. Retrieved June 22, 2015, from Make in India: http://www.makeinindia.com

Dickey, D. A., & Fuller, D. A. (1981). The Likelihood Ratio Statistics For Autoregressive Time Series With a Unit Root. *Econometrica , 49* (4), 1057-1072.

Elliott, G., Rothenberg, T. J., & Stock, J. H. (1996). Efficient Tests for an Autoregressive Unit Root. *Econometrica , 64* (4), 813-836.

Giles, D. (2011, April 29). *Testing for Granger Causality*. (D. Giles, Editor) Retrieved December 15, 2016, from Econometrics Beat: Dave Giles' Blog: https://davegiles.blogspot.in/2011/04/testing-for-granger-causality.html#comment-form

Goswami, C., & Saikia, K. K. (2012). FDI and its relation with exports in India, status and prospect in north east region. *Procedia - Social and Behavioral Sciences* , 123-132.

Hansen, H., & Rand, J. (2004). *On the Causal Links between FDI and Growth in Developing Countries.* Copenhagen: Institute of Economics, University of Copenhagen.

Herzer, D., Klasen, S., & Nowak-Lehmann D., F. (2008). In search of FDI-led growth in developing countries: The Way Forward. *Economic Modelling* , 793-810.

Hsiao, F. S., & Hsiao, M.-C. W. (2006). FDI, exports, and GDP in East and Southeast Asia—Panel data versus time-series causality analyses. *Journal of Asian Economics* , 1082-1106.

IL&FS Environment. (August 2010). *Technical EIA Guidance Manual for Metallurgical Industry.* Hyderabad: The Ministry of Environment & Forests, Government of India.

Mavrotas, G., & Kelly, R. (2001). Old Wine in New Bottles: Testing Causality between Savings & Growth. *The Manc hester School Supplement* , 97-105.

Metallurgy in India -- Ease of Doing Business. (2015). Retrieved January 11, 2017, from Maier Vidorno: http://www.maiervidorno.com/metallurgy-india-ease-business/

Mining & Metallurgy Industry in India, An Untapped market with strong growth potential. (2015, July-September). Retrieved January 11, 2017, from Maier Vidorno:

http://www.maiervidorno.com/mining-metallurgy-industry-india-untapped-market-strong-growth-potential/

Mlachila, M., & Takebe, M. (2011). *FDI from BRICs to LICs: Emerging Growth Driver?* International Monetary Fund.

National Council of Applied Economic Research. (2009). *FDI in India and its Growth Linkages.* Department of Industrial Policy and Promotion.

Pesaran, M. H., & Shin, Y. (1997). An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics , 16* (3), 289-326.

Pesaran, M. H., Shin, Y., & Smith, R. J. (1999, February). Bounds Testing Approaches to the Analysis of Long Run Relationships. *Discussion Paper Series Number 46* . Edinburgh School of Economics.

Phillips, P., & Perron, P. (1988). Testing for a Unit Root in Time Series Regression. *Biometrika , 75*, 335-346.

Ray, S. (2012). Impact of Foreign Direct Investment on Economic Growth in India: A Co integration Analysis. *Advances in Information Technology and Management , 2* (1), 187-201.

Singh, D. J., Chadha, S., & Sharma, A. (2012). Role of Foreign Direct Investment in India: An Analytical Study. *International Journal of Engineering and Science , 1* (5), 34-42.

The Associated Chambers of Commerce and Industry of India. (2012). *India's Experience with FDI: Role of a Game Changer.* New Delhi: ASSOCHAM India.

Toda, H., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics , 66* (1-2), 225-250.

Wang, M. (2009). Manufacturing FDI and Economic Growth: Evidence from Asian Economies. *Applied Economics , 41* (8), 1-24.

1. Tables & Graphs

Table 1

Unit Root Tests

			LFDIM	LBSEM	LPM	LXM	LIM
At levels	ADF	Intercept	-3.142785 [0] (0.0266)**	-2.567609 [1] (0.1031)	-0.836910 [1] (0.8039)	-4.382759 [0] (0.0006)*	-3.273786 [1] (0.0187)**
		Intercept + Trend	-1.668048 [0] (0.7582)	-2.696818 [1] (0.2403)	-4.626437 [1] (0.0016)*	-5.792131 [0] (0.0000)*	-5.412691 [0] (0.0001)*
	DF-GLS @	Intercept	0.159603 [4]	-2.320032 [1]**	0.792111 [1]	-4.145240 [0]*	-1.789889 [1]***
		Intercept + Trend	-1.471217 [4]	-2.453242 [1]**	-4.635869 [1]*	-5.622603 [0]*	-5.066605 [0]*
	PP	Intercept	-2.956131 [6] (0.0426)**	-2.668845 [6] (0.0830)***	-1.268264 [2] (0.6419)	-4.179230 [2] (0.0012)*	-4.594592 [2] (0.0003)*
		Intercept + Trend	-1.737029 [6] (0.7275)	-2.741396 [6] (0.2227)	-10.31890 [6] (0.0000)*	-5.724428 [1] (0.0000)*	-5.378181 [2] (0.0001)*
At first differences	ADF	Intercept	-8.828675 [0] (0.0000)*	-8.182190 [0] (0.0000)*	-23.07663 [0] (0.0001)*	-13.87664 [0] (0.0001)*	-14.80728 [0] (0.0001)*
		Intercept + Trend	-9.439210 [0] (0.0000)*	-8.172582 [0] (0.0000)*	-22.95518 [0] (0.0000)*	-13.80654 [0] (0.0000)*	-14.73141 [0] (0.0000)*
	DF-GLS @	Intercept	-8.511410 [0]*	-7.084736 [0]*	-0.084354 [11]	-13.43065 [0]*	-12.04202 [0]*
		Intercept + Trend	-8.902577 [0]*	-7.800842 [0]*	-1.698607 [11]	-13.77946 [0]*	-13.81913 [0]*
	PP	Intercept	-9.158827 [7] (0.0000)*	-8.361633 [5] (0.0000)*	-52.83391 [25] (0.0001)*	-32.80111 [49] (0.0001)*	-30.75913 [42] (0.0001)*
		Intercept + Trend	-9.470081 [6] (0.0000)*	-8.348868 [5] (0.0000)*	-52.55965 [25] (0.0001)*	-32.64609 [49] (0.0001)*	-30.54820 [42] (0.0001)*

Figures in [ ] represent Lag Lengths based on SIC in case of ADF Test and Bandwidth based on Newey-West in case of PP Test, *,** and *** indicate the statistical significance level of one per cent, five per cent and ten per cent respectively; Figures ( ) represent MacKinnon (1996) one sided *p* values.

@ Critical Values [MacKinnon (1996)] of Elliott-Rothenberg-Stock DF- GLS Test are shown as under:

	Intercept			Intercept + Trend		
	1 per cent	5 per cent	10 per cent	1 per cent	5 per cent	10 per cent
At levels	-2.589020	-1.944175	-1.614554	-3.591400	-3.039600	-2.749000
At First Difference	-2.588292	-1.944072	-1.614616	-3.580000	-3.030000	-2.740000

Table 2

Results from ARDL Bounds Test

Dependent Variable	AIC Lags	*F* Statistics	Decision
F_{LFDIM} (LFDIM| LBSEM, LPM, LXM, LIM)	4	2.933687	Inconclusive at 5% level of significance
F_{LBSEM} (LBSEM| LFDIM, LPM, LXM, LIM)	4	1.479566	Not cointegrated
F_{LPM} (LPM| LFDIM, LBSEM, LXM, LIM)	4	3.072261	Inconclusive at 5% level of significance
F_{LXM} (LXM| LFDIM, LBSEM, LPM, LIM)	4	7.082302	Cointegrated at 1% level of significance
F_{LIM} (LIM| LFDIM, LBSEM, LPM, LXM)	4	3.674467	Cointegrated at 10% level of significance
	Lower Bound	***Upper Bound***	
1 per cent level of significance	3.74	5.06	
5 per cent level of significance	2.86	4.01	
10 per cent level of significance	2.45	3.52	

Table 3A

Estimated Long Run coefficients using the ARDL approach

Dependent Variable	Regressor	Coefficient	Standard Error	T-Ratio	Probability
LXM ARDL (1, 0, 0, 0, 1) selected based on AIC	LFDIM	-0.136828	0.103302	-1.324547	0.1885
	LBSEM	0.228248	0.114166	1.999262**	0.0485
	LPM	2.488459	0.502862	4.948587*	0.0000
	LIM	-0.298185	0.154247	-1.933161***	0.0562
	C	-14.560878	3.621286	-4.020913*	0.0001

Table 3B

Error Correction representation for the selected ARDL model

<table>
<tr><th>Dependent Variable</th><th>Regressor</th><th>Coefficient</th><th>Standard Error</th><th>T-Ratio</th><th>Probability</th></tr>
<tr><td rowspan="14">LXM
ARDL
(1, 0, 0, 0, 1)
selected
based on AIC</td><td>D(LFDIM)</td><td>-0.093642</td><td>0.070584</td><td>-1.326665</td><td>0.1878</td></tr>
<tr><td>D(LBSEM)</td><td>0.156208</td><td>0.080232</td><td>1.946962***</td><td>0.0545</td></tr>
<tr><td>D(LPRODM)</td><td>1.703049</td><td>0.397734</td><td>4.281884*</td><td>0.0000</td></tr>
<tr><td>D(LIM)</td><td>-0.393000</td><td>0.113822</td><td>-3.452772*</td><td>0.0008</td></tr>
<tr><td>ect(-1)</td><td>-0.684379</td><td>0.092673</td><td>-7.384844*</td><td>0.0000</td></tr>
<tr><td colspan="5">ect = LXM - (-0.1368*LFDIM + 0.2282*LBSEM + 2.4885*LPM - 0.2982*LIM - 4.5609)</td></tr>
<tr><td>R-squared</td><td>0.612290</td><td colspan="2">Mean dependent var</td><td>6.462611</td></tr>
<tr><td>Adjusted R-squared</td><td>0.587543</td><td colspan="2">S.D. dependent var</td><td>0.370087</td></tr>
<tr><td>S.E. of regression</td><td>0.237680</td><td colspan="2">Akaike info criterion</td><td>0.031008</td></tr>
<tr><td>Sum squared resid</td><td>5.310242</td><td colspan="2">Schwarz criterion</td><td>0.212254</td></tr>
<tr><td>Log likelihood</td><td>5.434105</td><td colspan="2">Hannan-Quinn criter.</td><td>0.104381</td></tr>
<tr><td>F-statistic</td><td>24.74157</td><td colspan="2">Durbin-Watson stat</td><td>1.997690</td></tr>
<tr><td>Prob(F-statistic)</td><td>0.000000</td><td colspan="3"></td></tr>
</table>

*, ** and *** indicate the statistical significance level of one per cent, five per cent and ten per cent respectively

Table 4A

Estimated Long Run coefficients using the ARDL approach

<table>
<tr><th>Dependent Variable</th><th>Regressor</th><th>Coefficient</th><th>Standard Error</th><th>T-Ratio</th><th>Probability</th></tr>
<tr><td rowspan="5">LIM
ARDL
(2, 0, 2, 0, 0)
selected based on AIC</td><td>LFDIM</td><td>-0.066587</td><td>0.153010</td><td>-0.435180</td><td>0.6645</td></tr>
<tr><td>LBSEM</td><td>0.293154</td><td>0.171913</td><td>1.705242***</td><td>0.0916</td></tr>
<tr><td>LPM</td><td>2.341237</td><td>0.918464</td><td>2.549079**</td><td>0.0125</td></tr>
<tr><td>LXM</td><td>-0.714322</td><td>0.224937</td><td>-3.175647*</td><td>0.0020</td></tr>
<tr><td>C</td><td>-11.935806</td><td>6.303351</td><td>-1.893565***</td><td>0.0615</td></tr>
</table>

Table 4B

Error Correction representation for the selected ARDL model

Dependent Variable	Regressor	Coefficient	Standard Error	T-Ratio	Probability
LIM ARDL (2, 0, 2, 0, 0) selected based on AIC	D(LIM(-1))	-0.186230	0.093195	-1.998281**	0.0487
	D(LFDIM)	-0.026679	0.060050	-0.444274	0.6579
	D(LBSEM)	-0.163419	0.168835	-0.967916	0.3357
	D(LBSEM(-1))	0.340689	0.168891	2.017220**	0.0466
	D(LPM)	0.938040	0.333849	2.809773*	0.0061
	D(LXM)	-0.286200	0.076046	-3.763527*	0.0003
	ect(-1)	-0.400660	0.089918	-4.455815*	0.0000
	ect = LIM - (-0.0666*LFDIM + 0.2932*LBSEM + 2.3412*LPM-0.7143*LXM - 11.9358)				
	R-squared	0.354597	Mean dependent var		0.006654
	Adjusted R-squared	0.297858	S.D. dependent var		0.246352
	S.E. of regression	0.206428	Akaike info criterion		-0.232042
	Sum squared resid	3.877735	Schwarz criterion		0.002423
	Log likelihood	20.60210	Hannan-Quinn criter.		-0.137150
	F-statistic	6.249636	Durbin-Watson stat		1.908584
	Prob(F-statistic)	0.000002			

*, ** and *** indicate the statistical significance level of one per cent, five per cent and ten per cent respectively

Table 5

Diagnostic Tests on Selected ARDL Models

Dependent Variable	Tests	Test statistic	Probability (lags)	Decision
F_{LXM} (LXM| LFDIM, LBSEM, LPM, LIM)	Serial Correlation LM Test	0.025531	0.9873 (2)	No Serial Correlation
	Breusch-Pagan-Godfrey Heteroskedasticity Test	8.198658	0.2239 (6)	Homoskedastic
	CUSUM test			Stable
F_{LIM} (LIM| LFDIM, LBSEM, LPM, LXM)	Serial Correlation LM Test	0.878246	0.6446 (2)	No Serial Correlation
	Breusch-Pagan-Godfrey Heteroskedasticity Test	7.022956	0.5342 (8)	Homoskedastic
	CUSUM test			Stable

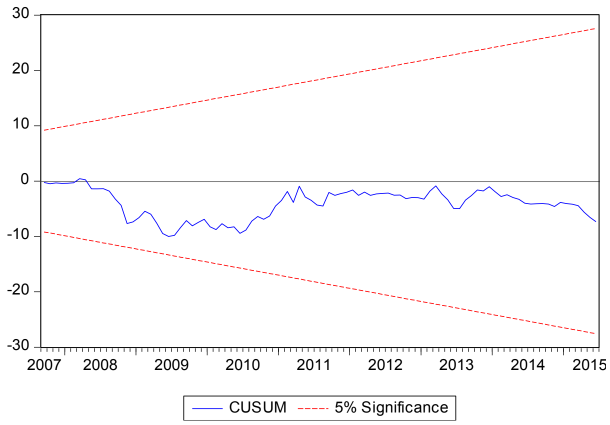

Figure 1: Plot of CUSUM for coefficient stability for ECM model of LXM

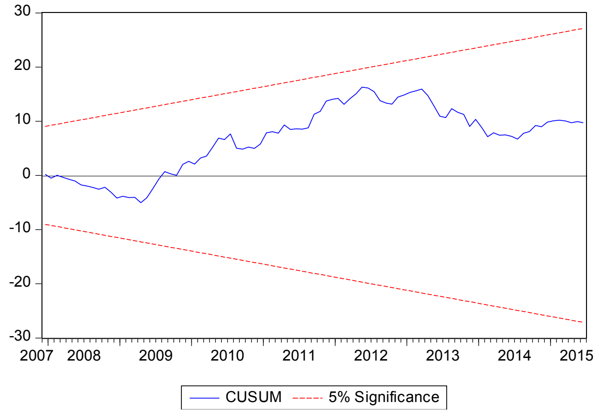

Figure 2: Plot of CUSUM for coefficient stability for ECM model of LIM

Table 6

Toda-Yamamoto Granger Non-Causality Test

Dependent Variable	χ^2 Statistics (p-value)					All Variables	Direction of Causality
	LFDIM	LBSEM	LPM	LXM	LIM		
LFDIM	-	29.69615 (0.0131)**	18.79046 (0.2234)	53.37849 (0.0000)*	51.34351 (0.0000)*	243.0797 (0.0000)*	LBSEM, LXM, LIM → LFDIM
LBSEM	17.08048 (0.3141)	-	19.61096 (0.1874)	20.61769 (0.1495)	25.54154 (0.0431)**	83.48954 (0.0242)**	LIM → LBSEM
LPM	31.68266 (0.0071)*	22.25571 (0.1013)	-	16.36224 (0.3584)	23.85454 (0.0676)***	123.4966 (0.0000)*	LFDIM, LIM → LPM
LXM	25.59102 (0.0425)**	29.97602 (0.0120)**	29.21600 (0.0151)**	-	23.12722 (0.0815)***	160.4934 (0.0000)*	LFDIM, LBSEM, LPM, LIM → LXM
LIM	8.745934 (0.8904)	13.32189 (0.5775)	7.343366 (0.9474)	17.79466 (0.2736)	-	65.45019 (0.2933)	-

*, ** and *** indicate the statistical significance level of one per cent, five per cent and ten per cent respectively