Employment effect of foreign direct investment in Indian manufacturing industries

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Abstract: This paper examines the employment effects of Foreign Direct Investment (FDI) in India's manufacturing industries. It also examines whether the nature of employees mediates the employment effects of FDI in the manufacturing industries. We have employed 54 three-digit industries from the Annual Survey of Industries for the period from 2008-09 to 2015-16. Estimating an extended dynamic labour demand model through the System-Generalized Method of Moment developed by Blundell and Bond (1998), we have not observed any considerable impact of FDI on employment in the manufacturing industries. Even after controlling for the nature of employees, FDI inflow is not found to have any significant effect on domestic demand for labour in Indian manufacturing industries. The paper thus does not consider FDI as an important channel for employment generation in the manufacturing industries in India.

JEL Classification: F23; J23

Keywords: *FDI; Employment effect; Labour demand; Dynamic panel; System GMM; Manufacturing industries; India*

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1. Introduction

The policymakers, particularly in developing countries, are competing to attract foreign direct investment (FDI) by luring multinational enterprises (MNEs) with various investment incentives (i.e. fiscal and monetary incentives) and relaxation in trade regulations (Blomstrom and Kokko, 2003). An important reason, *inter alia*, for attracting FDI is the presumption that foreign firms generate employment, either directly through their own employment growth or through a spillover effect (Girma, 2005). Besides, the labour markets in developing countries are found to be highly concentrated around agriculture and informal sector, the assumption is therefore that employment generation due to FDI could shift people from agriculture or informal sector to the modern sectors (i.e. industry and services) (Lipsey, Sjoholm and Sun, 2010).

In developed countries the contribution of FDI to employment generation has been a much debated area, while in developing countries there are very few studies on the relationship between FDI inflows and employment creation. Though small in number, the studies in developing countries show a rise in employment due to the presence of foreign firms or foreign affiliates in these countries (Coniglio et al 2015; Peluffo, 2015; Karlsson et al, 2009; Waldkirch and Nunnenkamp, 2009). However, the employment effect of FDI is not distributed evenly across different types of employees in the host developing countries. Since the technologies of MNEs are highly skill-complementary in nature, they tend to influence the generation of high-skilled employees, not generation of low-skilled or un-skilled one (Peluffo, 2015). The employment effect of FDI may thus conditions upon the nature of employees in the host developing countries.

In this paper, we examine the employment effect of FDI in the local manufacturing industries in India. Since the 1991 India has been undertaking numerous internal as well as external reforms to deregulate its economy and thus to make it an investor friendly environment. These reforms have brought about substantial FDI inflows from US$ 97 million in 1990-91 to US$ 39 billion in 2017-18 (Reserve Bank of India, 2018). The FDI stock in India has increased dramatically from US$ 97 million to US$ 464 billion between 1990-91 and 2017-18; and its share in national income (GDP) has increased phenomenally to 14 percent from a meagre 0.03 percent during the this period (Reserve Bank of India, 2018).[1] It can therefore be

[1] Because of the data unavailability on FDI inflows in India, the FDI stock (inward FDI stock) is calculated from the year 1990-91 only.

expected that the dramatic increase in FDI in India may have led to generation of some employment in India. However, there is no study, to the best of our knowledge, which has dealt with understanding the relationship between FDI inflows and employment generation in Indi. This paper intends to fill this gap by examining the possibility of employment effect of FDI in Indian manufacturing industries. It also examines whether the nature of employees mediates employment effect of FDI in the local manufacturing industries in India.

The rest of the paper is organised as follows. The next section discusses the related literature on employment effect of FDI in the host countries. Section 3 presents the theoretical framework to estimate the effect of FDI on employment in host countries. The empirical methodology and required data sources are discussed in Section 4. Section 5 analyses the estimated results on employment effects of FDI in India's manufacturing industries. The final Section concludes and offers some policy suggestions.

2. Related Literature

2.1. Employment effects of FDI in host countries

There are several channels through which FDI can affect the employment situation in host countries. Firstly, in setting up affiliates or new industries in host countries and hiring workers, multinational enterprises (MNEs) can directly help employment generation in these countries (Karlsson *et al.*, 2009) Secondly, MNEs through technology spillovers can affect employment generation in host countries. MNEs own, produce, and control most of world's technologies, and they account for the bulk of global business expenditures on research and development (R&D) (UNCTAD, 2005). These technologies owing to their non-rival characteristics spill over to host countries which affect the output and thus employment generation in these countries. Thirdly, through competition effect, FDI can influence the overall demand for labour in the host countries. FDI sometimes leads to deterioration of employment in host countries when MNEs with their firm-specific advantages crowd out non-competitive domestic firms and force them to exit the market or downsize their workforce (Coniglio *et al.*, 2015).

Finally, FDI inflows can affect employment in host countries when foreign affiliates establish linkages (backward or forward linkages) with domestic firms in these countries. For example, when foreign firms purchase locally produced goods, demand addressed to upstream industries could increase which leads to potential job creation in host countries (Jude and Silaghi, 2016).It is also plausible that foreign firms introduces new or better quality inputs to be used in the production of upstream domestic firms, making them more competitive and helping them expand production and employment in host countries (Karlsson *et al*., 2009).

However, employment effect of FDI is not spontaneous to occur. It may condition upon some factors such as characteristics of FDI and characteristics of the host country. The heterogeneous nature of FDI such as share of foreign ownership in foreign affiliates, trade-orientation of foreign firms, nationality of foreign firms, production technologies chosen by foreign firms, and so on can mediate or moderate the employment effect of FDI in host countries. Secondly, the characteristics of host country such as skill-level of employees can mediate the employment effect of FDI in host countries. The foreign firms tend to use relatively advanced technologies, requiring skilled workers or less workers to produce in host countries which may bring about a reduction on demand for labour in these countries.

2.2. Empirical evidence on employment effects of FDI

Empirical studies have not yet reached at any consensus on contribution of FDI to employment generation in host countries. In the studies of developed economies, we have seen somewhat mixed results with respect to the effect of FDI on employment, as revealed from the following studies. In the study of Central and Eastern European countries (CEEC), Jude and Silaghi (2015) have discovered a phenomenon of creative destruction due to FDI. They find that the introduction of labour saving technologies by foreign firms have led to an initial negative effect on employment, while the progressive vertical integration of FDI into the domestic economy eventually brought about a positive long run effect. Prior to the study of Jude and Silaghi, Onaran (2008) in a study of 8 CEEC found an overall insignificant effect of FDI on employment. While considering manufacturing industries within these countries, she concluded that FDI had significant positive effect on employment only in Lithuania and in some medium and low skill sectors in Slovakia. In the cross-country studies, Hijzen et al (2013) also found that FDI is associated with a fall in employment in Germany and the UK, though this effect is not found to be significant. At the other end of the spectrum, Dinga and Mnich (2010) employing data from Czech National Bank underscore that FDI brings about improvement in the local labour market by increasing the employment rate and reducing the level of unemployment. In the study of Swedish manufacturing data, Bandick and Karpaty (2011) also confirmed the positive employment effect of FDI and they found the employment effect of FDI is stronger for skilled employees. Similarly, using matched employer-employee data, Almeida (2007) revealed an increase in employment following foreign acquisition in Portugal.

In developing economies, there are scarce researches analyzing effect of FDI on employment. Nevertheless, most of the studies confirm the positive effect of FDI on employment in host developing countries. Coniglio *et al.* (2015) have analysed the relationship between foreign ownership and employment at firm level for 19 Sub-Saharan African countries, and their results suggests that foreign-owned firms generate more jobs compared to domestic firms, even though the employment generated is less-skill intensive in nature. In the study of Uruguay, Peluffo (2015) found that FDI has positive and significant effect on employment, but she asserts that FDI is found to be associated with an increased demand for skilled labour compared to unskilled one. Similarly, Karlsson *et al* (2009), using firm-level information on Chinese manufacturing sector during 1998-2004, unraveled a positive effect of FDI on employment in Chinese manufacturing sector and they attribute this effect to the high survival rate of foreign-owned firms. And, in the study of Mexico, Waldkirch and Nunnenkamp (2009) noticed that FDI is found to have increased employment in both skilled and unskilled workforce, though the employment effect of FDI is stronger in export-oriented industries.

In the study of a less developed country, Indonesia, Lipsey *et al* (2010) explored positive relationship between foreign ownership and employment. On the basis of data of a large number of plants between 1975 and 2005, the authors underscored that foreign-owned manufacturing plants in Indonesia grew more rapidly in employment than plants that were domestically owned.

It is followed from the above discussion that studies from developing and less-developed countries are affirmative about the effect of FDI on employment whereas the studies from developed countries are inconclusive about the effect of FDI on employment in host countries. In addition, as clear from the discussion, the employment effect of FDI is found to be more or less conditional on the nature of employees (i.e. the skill-level of employees) in host countries.

It is important to note that notwithstanding substantial FDI inflows there is hardly any study examining the effect of FDI on employment in India. The present study therefore makes an endeavour to examine the employment effect of FDI in India.

3. Theoretical framework

We use the dynamic labour demand framework to estimate the effect of FDI on employment in India's manufacturing industries.[2]The labour demand function can be derived from the following Cobb-Douglas production function for industry *i* at time *t*:

$$Y_{it} = A^{\gamma} K_{it}^{\alpha} N_{it}^{\beta} \qquad (1)$$

where *Y*=real output; *K*= capital stock; *N*= unit of labour utilised; and α and β represent the factor share coefficients and γallows for factors changing the efficiency of the production process (Milner and Wright, 1998; Greenaway et al., 1999). The profit maximising firm will employ labour and capital at such levels that the marginal revenue productivity of labour is equal to the wage (*w*) and the marginal revenue productivity of capital is equal to the cost of capital (*r*). Solving this system simultaneously for optimal capital and substituting the optimal value of capital in equation (1) yields the following:

$$Y_{it} = A^{\gamma} \left(\frac{\alpha}{\beta} N \frac{w_{it}}{r_t}\right)^{\alpha} N_{it}^{\beta} \ (2)$$

Note that wages are assumed to vary both over time and across industries, whereas the cost of capital (*r*) only varies over time. Taking logarithm on both sides of equation (2) and rearranging the terms, we obtain the labour demand of industry *i*at time *t:*

$$lnN_{it} = \emptyset_0 + \emptyset_1 lnY_{it} + \emptyset_2 ln\frac{w_{it}}{r_t} (3)$$

where:

$$\emptyset_0 = -(\gamma lnA + \alpha ln\alpha - \alpha \ln\beta)/(\alpha + \beta)$$
$$\emptyset_1 = 1/(\alpha + \beta)\, \emptyset_2 = -\alpha/(\alpha + \beta).$$

Considering the role of FDI, it is documented that FDI can influence the technical efficiency parameter *A* (Borensztein*et al*., 1998). We can therefore assume that the technical efficiency of production increases over time and its evolution can be influenced by technological transfer through FDI. Greenaway et al. (1999) argued in favour of trade induced technological change and modelled the technical efficiency factor in accordance. Similar to Greenaway et al. (1999) and focusing on FDI induced technological change, we model technical efficiency as a function of FDI (this was done by Jude *et al.* (2016) and Waldkirch*et al.* (2009)).

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[2] See Nickell (1986); Hamermesh (1993); and Bresson et al. (1996), for dynamic labour demand functions.

$A_{it} = e^{\delta_0 T_i} FDI_{it}^{\delta_1}$ (4)

where T is the time trend and δ_0,δ_1>*0.*

Taking logarithm ofA_{it}replacing it in Equation (3), we obtain the following:

$$lnN_{it} = \theta + \emptyset_1 lnY_{it} + \emptyset_2 ln\frac{w_{it}}{r_t} + \emptyset_3 lnFDI_{it} + \emptyset_4 T \qquad (5)$$

where $\theta = -(\alpha \ln\alpha - \alpha ln\beta)/(\alpha + \beta)$; $\emptyset_3 = \mu\delta_1$; $\emptyset_4 = \mu\delta_0$; $\mu = -\gamma/(\alpha + \beta)$.

Following Milner and Wright (1998) and Onaran (2008), we also assume the cost of capital to vary only over time and it can be addressed in the empirical estimation by including a time dummies, thereby capturing the variation over time. We can thus transform the Eq. (5) as follows:

$$lnN_{i,t} = \theta + \emptyset_1 lnY_{i,t} + \emptyset_2 lnw_{i,t} + \emptyset_3 lnFDI_{i,t} + \emptyset_4 T \qquad (6)$$

Further, "if there are costs associated with employment adjustment then the level of employment may deviate from its steady state as adjustment to equilibrium takes place" (Greenaway et al., 1999, p. 492). In order to take this into account, a lagged employment is introduced as an additional determinant of current employment.[3] Furthermore, as argued by Greenaway et al. (1999) that merely specifying dynamics in terms of lags of the dependent variable implicitly imposes a common evolution for employment following a change in an explanatory variable; and this restriction can be relaxed by introducing a distributed lag structure for the independent variables. We adopt this approach because we are agnostic about the source of the dynamics in the employment equation. We can thus have the dynamic labour demand model as follows:

$$lnN_{i,t} = \theta + \emptyset_0 lnN_{i,t-1} + \emptyset_{11} lnY_{i,t} + \emptyset_{12} lnY_{i,t-1} + \emptyset_{21} lnw_{i,t} + \emptyset_{22} lnw_{i,t-1} + \emptyset_{31} lnFDI_{i,t} + \emptyset_{32} lnFDI_{i,t-1} + \lambda_t + v_i + e_{i,t} \qquad (7)$$

where λ_t is the time-specific effect; v_i is the individual specific effect (the so-called, unobserved heterogeneity); ande_{it} is the random error term, $e_{i,t} \sim N(0, \sigma_e^2)$, $\sigma_e^2 > 0$.

[3] This lagged structure in the labour demand function is justified because there are different adjustment costs when employing aggregated measures of employment across different skill categories (Nickell, 1986). And it is necessary if serially correlated technological shocks are present (Greenaway *et al*., 1999).

4. Methodology and data

4.1. Empirical methodology

Equation (7) contains a lagged dependent variable as an explanatory variable which poses a challenge to estimation because the equation also contains the unobserved time-variant and time-invariant effects. Time-variant effects can be captured through inclusion of time dummies, however the common estimators—within-group or differenced estimators—are not found to be appropriate if the model is dynamic in nature. Further, most of explanatory variables are likely to be jointly endogenous with the dependent variable; thus, the biases resulting from simultaneous or reverse causations need to be corrected while estimating the regression equation.

Generalised Method of Moment (GMM) estimators—difference-GMM and system-GMM—are mostly resorted to estimate the dynamic panel data models, like Equation (7). The difference-GMM estimator was developed by Arellano and Bond (1991) to control for the unobserved time-invariant effects and joint-endogeneity in dynamic panel model. This estimator first differences the regression equation to remove the time-invariant unobserved effects, then, it uses the previous observations of explanatory variables and lagged dependent variables as instruments (known as internal instruments) to correct the likely endogeneity of the differenced lagged dependent variable $(lnN_{i,t-1} - lnN_{i,t-2})$ with the differenced error term $(e_{i,t} - e_{i,t-1})$. This method of estimating dynamic panel regression is superior to fixed effect estimation. Nevertheless, the differenced-GMM estimator is found to have been associated with the following shortcomings. It assumes that the error terms are not serially correlated, so if the errors are auto-correlated then it fails to give efficient estimate of coefficients. Blundell and Bond (1998) assert that the explanatory variables are persistent over time, the lagged value of these variables are weak instruments for the differenced regression equation and the weak instruments influence the asymptotic and small-sample performance of the difference-GMM estimator toward inefficient and biased estimates, respectively.

The potential bias and imprecision akin to the difference-GMM estimator are however efficiently taken care by system-GMM estimator, developed by Arellano and Bover (1995) and Blundell and Bond (1998). The system-GMM estimator combines the equation in level and equation in differences into a system; and employs previous observations of the regressors as instruments for equation in differences and the lagged differences of the regressors as instruments for equation in levels. However, the validity of this estimator is conditional upon the fact that instruments are exogenous—i.e. they are not correlated with the error terms. Sargan and Hansen-J tests are therefore designed to detect the violation of this condition.[4]Again, the validity of the estimator relies on another condition, i.e. the errors of regression equation are not serially correlated. In this regard, Arellano-Bondauto-correlation (AR) test is designed to check the autocorrelation in the model.[5]

GMM estimators in general and system-GMM estimator in particular are appropriate in dealing with endogeneity bias and joint-endogeneity of explanatory variables with the dependent variables and thereby providing unbiased and more efficient estimate of the true parameters of the model. These estimator is suggested when we have small number of time period and large number of group (as is the case the present study). In addition, the GMM-estimator has two additional advantages which are as follows: (i) it does not require any distributional assumptions, such as normality which is subject to diagnostic testing; and (ii) it allows for heteroscedasticity of unknown form, which can be allowed for by estimating robust parameters (Petreski, 2009).

4.2. Data description

Our sample consists of a balanced panel, covering 54 industries (at three-digit level of National Industrial Classification (NIC) 2008) over a period of maximum 9 years (2008-09 to 2015-16).We have not extended our period of analysis prior to 2008-09 because of data constraint. Our data sources are Annual Survey of Industries (ASI) and FDI Newsletter. The former is provided by the Central Statistical Office, Ministry of Statistics and Programme Implementation, India and the latter is provided by the department of industrial policy and promotion, Ministry of Commerce and Industry, India.

Total employees, workers, and supervisory and managerial staff are collected from the ASI database. Here, workers are considered as blue collar employees and supervisory and

[4]The Sargan test has null hypothesis—the instruments as a group are exogenous. Thus, the higher p-value of Sargan statistic is generally preferred, because it rejects the null hypothesis and ensures the validity of system-GMM estimator. However, in robust estimation, we are generally report Hansen-J statistic instead of Sargan; and both Sargan and Hansen-J statistic have the same null hypothesis.

[5] AR test has a null hypothesis of "no autocorrelation", and it is applied to the difference residuals. The test for AR (1) process in first differences usually rejects the null hypothesis, but this is expected since $\Delta e_{i,t} = e_{i,t} - e_{i,t-1}$ and $\Delta e_{i,t-1} = e_{i,t-1} - e_{i,t-2}$ both have $e_{i,t-1}$. The test for AR (2) in first differences is more important because it will detect autocorrelation in levels. If we fail to reject the null gives support to the model and ensures the validity of system-GMM estimator.

managerial staffs are as white collar employees.[6]Total wages and salaries, and wages and salaries for blue and white collar employees, obtained from the ASI database, are deflated by the Consumer Price Index for industrial workers (base year 2004-05) from the Labour Bureau of India. Since we need average wage (wage) for our analysis, it is obtained by dividing total wages and salaries by total employees. Similarly, wage for blue and white collar employees are obtained by dividing wages and salaries of blue and white collar employees by blue and white collar employees, respectively. Here, the gross value added, obtained from the ASI database, is a proxy measure for output and it is deflated by two-digit industrial wholesale price indices (base year 2004-05) obtained from the Office of the Economic Advisory, Ministry of Commerce and Industry, India.FDI is the FDI inflows at two-digit industry level, taken from the FDI Newsletter. The nominal value of FDI is deflated by GDP deflator (base year 2004-05) to reach at real FDI value.

Table 1: Description of variables employed.

Total employment	Natural logarithm of the total employees
White collar employment	Natural logarithm of supervisory and managerial staffs
Blue collar employment	Natural logarithm of the workers
Output	Natural logarithm of gross value added
Wage	Natural logarithm of average wages
White collar wage	Natural logarithm of average wage of supervisory and managerial staff
Blue collar wage	Natural logarithm of average wage of the workers
FDI	Natural logarithm of FDI

Our panel data has 432 observations on 54 three-digit industries during 2008-09 through 2015-16. These three-digit industries are belonging to the 18 two-digit industries, viz., food products (10), textiles (13), leather and leather related products (15), wood and wood products (16), paper and paper products (17), printing (18), coke and petroleum products (19), chemicals (20), pharmaceuticals (21), rubber products (22), other non-metallic mineral products (23), basic metals (24), computer & electronics (26), electrical equipments (27), machinery and equipments (28), motor vehicles, trailer and semi-trailers (29), other transport equipments (30), and other manufacturing (32).

[6]Workers, the blue collar workers include all persons employed directly or indirectly in any manufacturing process or in cleaning any part of machinery or premises used for manufacturing process or in any kind of work connected with manufacturing process or the subject of manufacturing process. And, the persons engaged in repair and maintenance of production of fixed asset for factory's own use or persons employed for generation of electricity, etc. are also blue collar workers.

Table 1 offers a description of the variables used, while Table 2 reports the summary statistics of the dependent and independent variables used in the estimation. FDI inflows in India's manufacturing industries, as portrayed in Figure 1, shows that FDI inflows has increased to Rs. 2691 from Rs. 1081 billion between 2008-09 and 2015-16, but it is fluctuating throughout. Figure 2 depicts total employment in manufacturing industries which shows a very flat increase from 8.87 million to 11 million during 2008-09 to 2015-16, registering around 2 million jobs in organised manufacturing industries in India.

Table 2:Summary statistics of the dependent and explanatory variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
Total employment	432	11.25	1.65	3.64	14.04
Blue collar employment	432	10.96	1.67	3.04	13.89
White collar employment	432	9.03	1.63	1.61	11.87
Wage	432	11.56	0.48	10.25	13.54
Blue collar wage	432	11.09	0.39	10.14	13.33
White collar wage	432	12.73	0.54	9.77	15.85
Output	432	24.37	1.84	16.24	27.68
FDI	432	23.16	1.53	17.70	26.05

Note: All the variables are in natural logarithm forms.

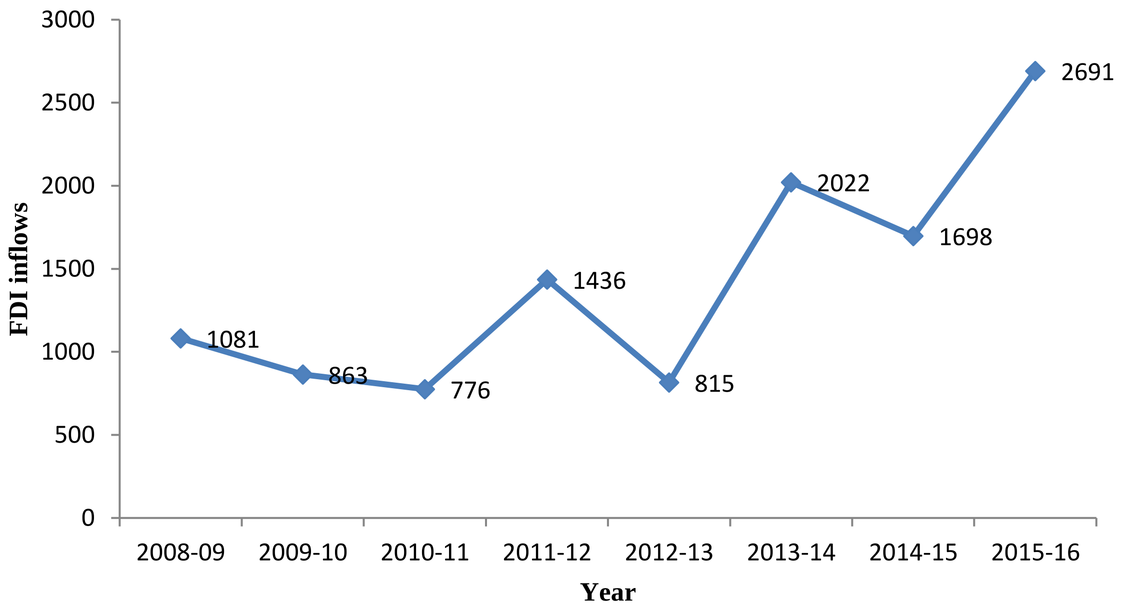

Figure 1: FDI inflows in manufacturing industries (value in Rs billion)

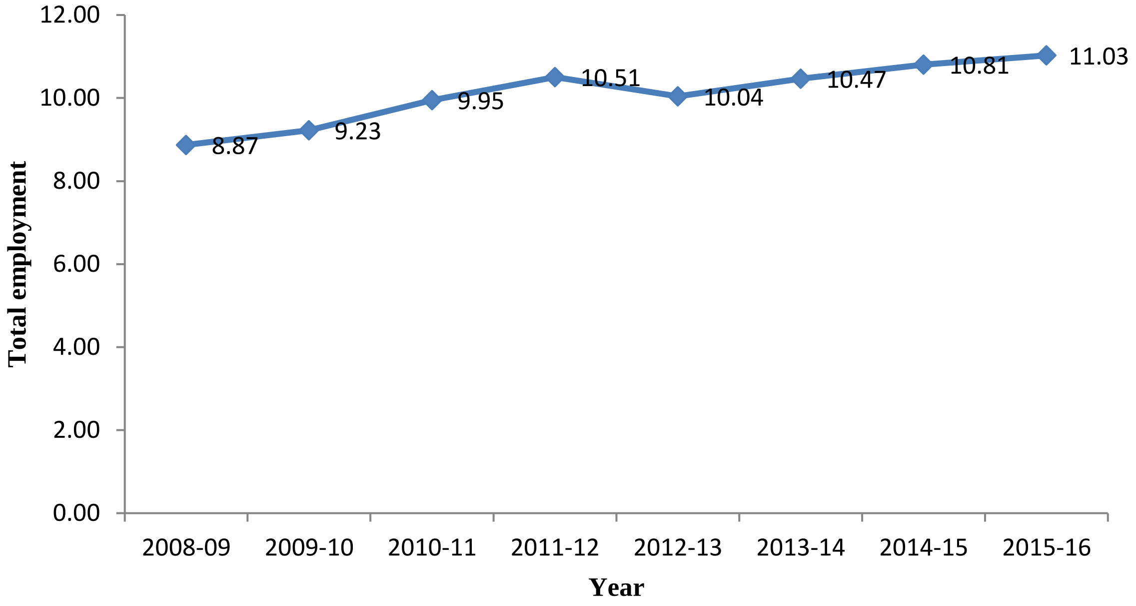

Figure 2: Total Employment in manufacturing industries (value in million)

5. Empirical results

This section presents the estimated effect of FDI on employment in Indian manufacturing industries during 2008-09 through 2015-16. We have estimated three sets of regression to see the employment effect of FDI in Indian manufacturing industries. In the first set, we have estimated the effect of FDI on total employment in India's manufacturing sector. In the second and the third set, we have examined how FDI inflows affect the white and blue collar employment, respectively. In each set of regression, first we estimate the dynamic labour demand equation without FDI; then we include FDI to see its impact on employment in generation in local manufacturing industries. All these regressions are estimated by two-step system-GMM estimator. The results of them are presented in Table 3 through Table 5, which are as follows:

Table 3 presents the estimation of two models—one without FDI and other with FDI. Each of these models includes a lagged depended variable along with the level and lagged explanatory variables. In both models presented in Table 3, the Hansen J test and Arellano and Bond auto-correlation test are statistically insignificant which indicates the correct specification of models. To note that the coefficients of lagged dependent variable in both the models are strongly significant and quantitatively important, indicating the path dependency of employment.

In model (1), the coefficient on current average wage is negative and strongly significant at 0.1 percent level of significance, indicating the wage growth has negative effect on total employment; whereas the lagged average wage does not have any apparent effect on employment which is evident from its insignificant coefficient. The current output has positive effect on employment generation which is evident from its highly significant coefficient. The lagged output is though found to have a negative effect on current employment, i.e. the growth in previous year output leads to reduction in demand for labour in the current year. The reduction in employment due to previous year output is however lesser than the acceleration in employment because of present year output.

Table 3: Estimation of dynamic labour demand in manufacturing industries, dependent variable: total employment and time period: 2008-09 to 2015-16

Independent variables	(1)	(2)
$\text{Dependent variable}_{t-1}$	0.558^{***}(0.112)	0.558^{***}(0.128)
Wage	-0.945^{***}(0.133)	-0.903^{***}(0.132)
Wage_{t-1}	0.331(0.206)	0.336 (0.218)
Output	0.623^{***}(0.068)	0.612^{***}(0.074)
Output_{t-1}	-0.174^{*}(0.076)	-0.172^{*}(0.084)
FDI		-0.0304 (0.046)
FDI_{t-1}		-0.0117 (0.034)
Year dummies	Yes	Yes
Observations	378	378
No. of Industries	54	54
Instruments	43	43
Hansen $p-$value	0.506	0.605
AR2 $p-$value	0.406	0.501

Notes: $^{*}p< 0.05$, $^{**}p< 0.01$, $^{***}p< 0.001$. Values in parentheses are robust standard errors.All the variables are in logarithm form. The system-GMM estimations of dynamic labour demand are undertaken by STATA software (xtabond2).

The specification (2) of Table 3 includes FDI to see the effect of FDI on employment generation. Here, the effects of output and wages on employment are almost same as we have found in model (1). However, both the estimated coefficient on the current FDI as well as on the lagged FDI is negative but not statistically significant at the conventional level of significance. This indicates FDI inflow does not have any significant impact on employment generation in the local manufacturing industries. This result is surprising because most studies on developing countries find a positive contribution of FDI to employment generation in the host developing countries. The following could be provided to explain the absence of significance impact of FDI on employment. In India, as observed by Malik (2015), among others, the presence of foreign firms has not brought about any significant spillover benefit to domestic firms in the same industry. It is theorised, the employment effects of FDI take place via spillover effects, the absence of spillover effect of FDI can therefore be attributed to the insignificant effects of FDI on employment in India's manufacturing industries.

However, the contribution of FDI towards employment generation in host countries is conditional on some mediating factors such as nature of employees. So, in order to take into account how the nature of employees affect the employment effect of FDI, we have run two more sets of regressions—one estimating effect of FDI on white collar employment and the other estimating employment effects of FDI on blue collar employment—which are presented in Table 4 and 5, respectively.

Table 4: Estimation of dynamic labour demand in manufacturing industries, dependent variable: white collar employment and time period: 2008-09 to 2015-16

Independent variables	(1)	(2)
$\text{Dependent variable}_{t-1}$	$0.534^{***}(0.098)$	$0.486^{***}(0.114)$
White collar wage	$-0.528^{*}(0.201)$	$-0.477^{**}(0.169)$
$\text{White collar wage}_{t-1}$	0.182(0.193)	0.153(0.166)
Output	$0.509^{***}(0.067)$	$0.535^{***}(0.086)$
Output_{t-1}	-0.0458(0.102)	-0.037(0.112)
FDI		-0.042(0.052)
FDI_{t-1}		-0.060(0.058)
Year dummies	Yes	Yes
Observations	378	378
No. of Industries	54	54
Instruments	43	43
Hansen $p-\text{value}$	0.708	0.531
AR2 $p-\text{value}$	0.535	0.659

Notes: $^{*}p< 0.05$, $^{**}p< 0.01$, $^{***}p< 0.001$. Values in parentheses are robust standard errors. All the variables are in logarithm form. The system-GMM estimations of dynamic labour demand are undertaken by STATA software (xtabond2).

Table 4 documents the effect of FDI on white collar employment in the local manufacturing industries. In specification (2) of Table 4, the current output is found to have a highly significant effect on white collar employment, and the current white collar wage rate has negative effect of white collar employment; whereas both the lagged output and white collar wage rate do not seem to have any significant influence on white collar employment. And, importantly, as obvious from the coefficients on level FDI, the increase in FDI inflows in current period does crowd out white collar employment, but this is not found to be statistically significant. Similarly, the lagged FDI inflow is not found to have any apparent effect on white collar employment in manufacturing industries. This finding however goes against the proposition that FDI is skill-biased in nature because it is assumed to complements skilled labour or white collar employment.

Table 5: Estimation of dynamic labour demand in manufacturing industries, dependent variable: blue collar employment and time period: 2008-09 to 2015-16

Independent variables	(1)	(2)
Dependent variable$_{t-1}$	0.633***(0.148)	0.587*** (0.138)
Blue collar wage	-0.586** (0.212)	-0.575* (0.219)
Blue collar wage$_{t-1}$	-0.032 (0.127)	0.021 (0.119)
Output	0.712*** (0.065)	0.717*** (0.066)
Output$_{t-1}$	-0.336** (0.115)	-0.309* (0.119)
FDI		-0.057 (0.045)
FDI$_{t-1}$		-0.030 (0.046)
Year dummies	Yes	Yes
Observations	378	378
No. of Industries	54	54
Instruments	43	43
Hansen $p-$value	0.168	0.313
AR2 $p-$value	0.375	0.437

Notes:$^{*}p< 0.05$, $^{**}p< 0.01$, $^{***}p< 0.001$. Values in parentheses are robust standard errors.All the variables are in logarithm form. The system-GMM estimations of dynamic labour demand are undertaken by STATA software (xtabond2).

The specification (2) of Table 5 is also not registered any effect of FDI on blue collar employment which is not significantly different from zero. It is observed that the current and lagged FDI inflows though lead to reduction in blue collar employment, but these effects are not statistically significant at the conventional level of significance. It can be said that through the technological superiority of FDI crowds out the non-competitive firms and thereby bringing down the growth of white as well as blue collar employment; these reduction in employment is however considered to be insignificant.

It is thus followed from the above discussion that the nature of employees is not found to be mediating the employment effect of FDI in India's manufacturing industries during the period under consideration.

6. Conclusion

There is a strong presupposition favouring a positive effect of FDI on employment generation in host developing countries. Nevertheless, there is hardly any effort made by the academia or policy makers to evaluate the employment effect of FDI in India. This paper therefore contributes to the understanding of employment effect of FDI in India's manufacturing industries during 2008-09 to 2015-16. We have employed a simple theoretical model of labour demand, wherein FDI is presumed to improve the efficiency of labour usage. The dynamic panel model has been estimated by system-GMM, developed by Blundell and Bond (1998).

The analysis shows that the current output and current wageare the main determinants of employment dynamics in Indian manufacturing industries as they are statistically significant and quantitatively important for all sets of regressions. It is seen that increase in output will lead to increase in employment generation in India which reputes the argument of job-less growth in Indian economy. Increase in wage is however found to have brought down the demand for labour by domestic firms in India's manufacturing industries; and this finding goes in line with theoretical argument.

Our analysis has however not found any significant effect of FDI on employment in manufacturing industries between 2008-09 and 2015-16. Even after controlling for the nature of employees in terms of their skill-level, we have not witnessed any apparent effect of FDI on employment in manufacturing industries. These findings indicate that FDI is not found to have contributed to the employment generation in India; and it may be because of the following reasons: foreign firms are high-skill-bias in nature and the presence of skill-gap between foreign firms and domestic firms with respect to employees are in fact not contributing to any employment in India. This paper thus suggests that FDI inflows cannot be considered for employment generation in the manufacturing sector in India.

The present paper has however examined the effect of FDI on employment in the same industry, not across industries. Hence, the effect of FDI on employment via backward or forward linkages should be studied to evaluate the vertical employment effect of FDI in India's manufacturing industries.

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