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DYNAMIC EXTERNALITIES AND REGIONAL MANUFACTURING GROWTH: EVIDENCE FROM INDIA

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Abstract:
Using Annual Survey of Industries (ASI) dataset for 11 two-digit manufacturing industries and 20 states, this paper tests the relationship between dynamic agglomeration externalities and regional manufacturing growth for India. Three types of dynamic externalities have been proposed in the literature for explaining this relationship – Marshall-Arrow-Romer (MAR) specialization externalities, Jacobs's diversity externalities, and Porter's competition externalities. This paper examines the effect of these dynamic externalities on regional manufacturing employment and total factor productivity (TFP) growth for selected Indian industries between 2001-02 and 2011-12. The panel data model results show that dynamic externalities are important in influencing employment growth but they do not seem to have an impact on the growth of manufacturing productivity. Further, the results show that specialization externalities positively affect the employment growth of capital-intensive industries whereas diversity externalities favourably affect the employment growth in labour-intensive industries. Our results suggest that the importance of dynamic externalities should not be examined by pooling all industries. The results also highlight the importance of infrastructural investments for boosting the growth of manufacturing employment and productivity.

Key words: *dynamic agglomeration externalities, regional growth, productivity, manufacturing, India*

1. Introduction

Investigation of economic growth has been at the forefront of economic research (e.g., Denison, 1962; Barro & Sala-i-Martin, 1992; Acemoglu, 2008). The economic growth literature views dynamic knowledge externalities as an engine of long-term economic and industrial growth (Romer, 1986; Lucas 1988). The growth models of Romer (1986) and Lucas (1988) argue that the presence of knowledge externalities allow for the possibility of avoiding diminishing returns. The pioneering work of Arrow (1962) also regards learning by doing as an important source of growth and focuses on the crucial role of human capital and knowledge externalities. These knowledge externalities are a form of agglomeration externalities which were first explained by Marshall (1890). These externalities arise when firms of the same or diverse industries are located closer to each other. Marshall (1890) and Krugman (1991) argue that individuals and firms locate close to each other in order to learn and gain. Such gains arise because of availability of specialized inputs and sharing of technology, labour-market pooling, and information exchanges. These externalities are likely to be observed in the manufacturing sector where firms have a tendency to agglomerate. This paper empirically examines the effect of these dynamic externalities on the growth of employment and total factor productivity of Indian industries.

Prior to the economic liberalization policies of 1991, the Indian manufacturing sector was subject to many restrictions and regulations. The industrial policies of the government were aimed at achieving balanced regional development and the decisions with regard to industrial location were taken to ensure equity (Lall & Chakravorty, 2005). Hence, the scope and possibility for the operation of agglomeration externalities was limited. However, the new industrial policy has altered this and industrial location decisions by private and foreign entrepreneurs are not based on equity but on profit considerations. Further, the transition of the Indian economy to a market-led economy in the last two decades has increased the importance of the manufacturing sector. Gao (2004) has explained that the role of such externalities on growth identified can be properly identified in a transition economy. Previous empirical studies have linked the manufacturing performance to economic reforms & import liberalization (e.g., Goldar & Kumari 2003; Deb & Ray, 2014), infrastructure (e.g., Sharma & Sehgal, 2010; Mitra, Sharma & Véganzonès-Varoudakis, 2012), and labour market regulation (Besley & Burgess, 2004; Dougherty, 2009). However, the role of dynamic agglomeration externalities in explaining the manufacturing performance has not been studied in a great detail. In addition to this, several studies consider the post-2000 period as the phase of high employment and productivity growth for the Indian manufacturing sector (e.g. Virmani & Hashim, 2011; Goldar, 2013). Therefore, it is important to examine the role of dynamic externalities in explaining this growth performance.

The remaining sections of the paper are structured in the following manner. The next section discusses the theories underlying dynamic externalities. Section 3 presents a brief summary of the literature. Section 4 explains the analytical framework and variables used in the model. Section 5 outlines the performance of manufacturing sector at the state level. Section 6 and section 7 discuss the results based on employment and TFP growth respectively. Section 8 concludes and point outs the main shortcomings of the study along with the directions for future research.

2. Theoretical Framework

The literature identifies three theories of dynamic externalities introduced first by Glaeser, Kallal, Scheinkman, & Shleifer (1992). These are Marshall-Arrow-Romer (MAR) specialization externalities, Jacobs's diversity externalities, and Porter's competition externalities. The MAR specialization externalities are intra-industry externalities i.e. these arise when there is a localization of firms belonging to the same industry (Lall, Shalizi & Deichmann, 2004). When firms of the same industry concentrate in a region, they gain through labour-market pooling, information exchanges and easy availability of intermediate inputs (Krugman, 1991). Porter (1990) also views that specialization brings greatest advantages in information spillovers and hence promotes growth. However, the theories of MAR and Porter differ with regard to the importance of local competition in promoting growth. MAR theory argues that the existence of many firms in a region would deter growth as ideas and knowledge get imitated and the incentive to innovate is less. On the contrary, Porter emphasizes that firms would be forced to innovate due to the existence of many competitive firms in the region (Glaeser et al., 1992).

Jacobs (1969) explains the role of diversity in promoting knowledge spillovers and boosting growth. She argues that the existence of firms of different industries in a region is conducive to growth. For example, firms in the banking industry gain due to the presence of insurance, trade and other industries. Like Porter, Jacobs's diversity theory also advocates local competition as a source of knowledge spillovers and growth. Table 1 presents a summary of these three theories.

Table 1: Theories of Dynamic Agglomeration Externalities

Type of Externalities	Local Competition	Local Monopoly
Specialization	Porter	Marshall-Arrow-Romer (MAR)
Diversity	Jacobs	

Source: Based on Glaeser et al. (1992)

There is no agreement in the literature[i] regarding the impact of these externalities on the growth of manufacturing employment and productivity. Studies examining the impact of dynamic externalities on the growth of manufacturing employment and productivity have primarily focused on developed countries. Most of the existing studies have analyzed the effect of dynamic agglomeration externalities on growth of employment, thereby neglecting the impact on growth of productivity. In this context, this paper tests the three theories of dynamic externalities for the Indian manufacturing sector using data for 11 two-digit industries across the 20 states. This paper makes several important contributions to the regional economics literature. Firstly, the paper looks at the possibility that dynamic externalities may operate in a different way in labour-intensive and capital-intensive industries. Secondly, the paper examines the impact of dynamic externalities on both employment and productivity growth. Thirdly, the paper adds to the limited literature in the Indian context that has analyzed the link between regional growth and dynamic externalities.

3. Related Literature

The vast empirical literature in urban and regional economics focusing on the link between dynamic agglomeration externalities and regional growth has originated from the influential work of Glaeser et al., (1992). This study uses a dataset of six largest industries of the U.S. for 1956 and 1987. The employment growth of these six industries across 170 cities is negatively affected by specialization and favourably affected by the presence of diversity. Glaeser et al. (1992) find that diversity plays a greater role than specialization in industries across the studied cities. Their results lend support to Jacobs's ideas about knowledge spillovers taking place across industries. Another seminal study by Henderson, Kuncoro & Turner (1995) uses the data for eight manufacturing sectors of the U.S. for 1970 and 1987. Their study covers 224 metropolitan areas. They find the presence of specialization externalities in the case of mature capital goods industries and presence of both specialization and diversity externalities for hi-tech sectors. Combes (2000) applies this framework in the case of France. He finds that local specialization positively affects employment growth for industry sectors, and local employment density, firm size and local competition have an adverse effect on growth. In case of 784 local labour Italian areas, Paci and Usai (2008) find a positive effect of diversity externalities on employment growth. Thus, the empirical evidence from studies using similar methodologies and data is inconclusive.

The study by Henderson (2003) is one of the first studies to use plant-level panel data to study dynamic externalities in case of the U.S. The study uses plant level data with a five-year interval from 1972 to 1992 to estimate the production functions for machinery & high-tech sectors. The study finds evidence of strong specialization externalities in the high-tech sectors, but not in the case of the machinery subsector. The study finds weak evidence of Jacobian diversity externalities for both the sub-sectors. Other studies in the recent years have also utilized disaggregated data to study this relationship (e.g. Martin, Mayer & Mayneris, 2011; Andersson & Loof, 2011).

Majority of the studies following Glaeser et al. framework use employment growth as an outcome variable. An important contribution of Dekle (2002) is to argue against the use of employment growth regressions for explaining productivity growth. He advocates using direct measures of productivity growth such as TFP growth to explain industrial productivity growth. Studying the role of dynamic externalites using data for 48 Japanese prefectures in 1975 and 1995, he finds that dynamic externalities do not remain significant when TFP growth is used as an dependent variable. Cingano & Schivardi (2004) also argue against the use of employment growth regressions to explain the growth of productivity. In case of Italian local labour systems from 1986 to 1998, they find that TFP growth is favourably affected by specialization externalities. They find that employment growth regressions yield opposite results i.e. in favour of Jacobian diversity externalities. In recent years, the research on dynamic agglomeration externalities has shifted to the use of direct productivity measures. (e.g., Henderson, 2003; Marrocu, Paci & Usai, 2013; Martin et al., 2011).

The choice of geographical and industrial unit of analysis is another important issue when anlaysing dynamic agglomeration externalities (Beaudry & Schiffauerova, 2009; Matlaba, Holmes & McCann, 2012). This paper uses 'state' as a geographical unit of analysis. The externalities could be properly measured at more disaggregated levels but due to data constraints, the present study restricts the analysis to 'state' level. There are many empirical studies that have studied dynamic externalities at the state/provincial level (e.g., Batisse, 2002; Gao, 2004; Matlaba et al., 2012). This paper takes a 'two-digit industry' of the manufacturing sector as an industrial unit of analysis.

Studies linking the dynamic externalities and regional growth are limited in the Indian context. Ghani, Kerr & Tiwari (2013) use plant-level data for the years 1989 and 2010 to measure specialization and diversity of Indian districts and link them with employment and productivity growth of the plants. They find an increase in diversity and a decline of specialization of Indian districts. Further, they find that both specialization and diversity of the districts give a boost to productivity growth of manufacturing plants. On the other hand, they find that employment growth is favourably influenced by specialization of districts. Cleary, there is an insufficient literature linking dynamic agglomeration externalities with regional growth. Further, the existing studies have focused more on static externalities (e.g., Lall et al., 2004; Mitra, 1999, 2000). The exisitng studies do not account for the possibility of differential impact of dynamic externalities in labour-intensive and capital-intensive industries. The next section explains the methodology and variables used in this paper.

4. Analytical Framework and Data

Based on previous studies, we use employment growth to represent the growth of an industry in a region (e.g., Glaeser et al., 1992; Combes, 2000; Paci & Usai, 2008) and TFP growth as a measure of the growth of industrial productivity (e.g., Dekle, 2002; Cingano & Schivardi, 2004; Marrocu et al., 2013). Following Glaeser et al. (1992) and Dekle (2002), the employment growth regressions take the following form:

$$\begin{aligned} Employment\ Growth_{is,2001-2011} &= \beta_0 + \beta_1 Specialization_{is} + \beta_2 Diversity_{is} + \beta_3 Competition_{is} \\ &+ \beta_4\ Level\ of\ Employment_{is} + \beta_5\ Level\ of\ Wages_{is} + \beta_6 X_s + \alpha_i + u_{is} \end{aligned}$$

Where employment $growth_{is}$ is the growth of employment of industry 'i' in state 's' during the period 2001-02 to 2011-12 and specialization, diversity and competition are measures of MAR, Jacobs, and Porter externalities respectively. The model includes industry dummies to control for heterogeneity among industries. The vector X includes the state-specific control variables viz. human capital and per capita credit given to industry in a state (as a proxy of policy support by the state governments). Following the literature, the explanatory variables are log-transformed and are measured at the initial time period to deal with endogeneity (e.g. Glaeser et al., 1992; Batisse, 2002; Marrocu et al, 2013). The initial employment and initial wages in a 'state-industry' in 2001-02 are included as control variables following Glaeser et al. (1992) and Henderson et al. (1995). The empirical model based on TFP growth takes the following form (Dekle, 2002; Marrocu et al., 2013):

$$TFPG_{is,2001-2011} = \beta_0 + \beta_1 Specialization_{is} + \beta_2 Diversity_{is} + \beta_3 Competition_{is} + \beta_4 \, Level\ of\ TFP_{is} + \beta_5 X_s + \alpha_i + u_{is}$$

Where $TFPG_{is}$ is the growth rate of TFP of industry 'i' in state's' during the period 2001-02 to 2011-12. We include the initial level of TFP to control for mean-reversion following previous studies (e.g., Dekle 2002; Cingano & Schivardi, 2004; Marrocu et al., 2013).

TFP growth is calculated using the growth accounting technique. This methodology originated from the studies by Solow (1957), and Jorgenson & Griliches (1967). This paper uses the following Translog index of TFP growth (based on Goldar, 2004; 2013). Here, β and (1-β) are the income shares of capital and labour respectively. The LHS of the above equation gives us the estimates of TFP growth. The measures of output (Y), labour (L) and capital stock (K) shown in the above equation are summarized in table 2.

$$\Delta \ln TFP(t) = \Delta \ln Y(t) - [\frac{(1-\beta)(t)+(1-\beta)(t-1)}{2}\Delta \ln L(t)] - [\frac{\beta(t)+\beta(t-1)}{2}\Delta \ln K(t)]$$

Table 2: TFP growth: Measurement of Output, Labour Input and Capital Input

Variables	**Measurement**
Measure of Output	Gross value added (Single Deflation method)
Measure of Labour Input	Total number of persons engaged
Measure of Capital Input	Net fixed capital stock (Perpetual Inventory Method) $K_T = K_0 + \sum_{t=1}^{T} I_t$

Source: Author's compilation

The measures of dynamic externalities are constructed following the previous studies (e.g., Glaeser et al., 1992; Combes, 2000; Dekle, 2002). The MAR specialization externalities are measured with the help of a **location quotient**. It is the most widely and well-known measure of MAR externalities (Beaudry & Schiffauerova, 2009). It is given by:

Specialization, $L.Q._{is} = \dfrac{\dfrac{E_{is}}{\sum E_{is}}}{\dfrac{E_{in}}{\sum E_{in}}}$

Where E_{is} represents employment in industry, 'i in state 's' and E_{in} shows employment in industry 'i' in the nation. We expect a positive coefficient of this measure of externalities.

The Jacobs's diversity externalities are measured by using a **modified Herfindahl index** as in previous studies (e.g. Cingano & Schivardi, 2004; Gao, 2004; Marrocu et al., 2013). It measures the sum of squared employment shares of all sectors in state's' except for the sector for which diversity is calculated. Therefore, higher values of this index indicate lesser diversity. We expect a negative coefficient if Jacobs's diversity externalities are important and favorable. The index is given by:

Diversity, $HHI_{is} = \sum_{k \neq i} d_{ks}^2$

Where d_{is} = employment share of industry 'i' in state's'.

Porter's competition externalities are captured by calculating an **index of competition**. It is calculated as the ratio of number of firms per employee in a particular state-industry to this number at the all-India level (Glaeser et al., 1992; Dekle, 2002; Gao, 2004). It is given by:

Competition $Index_{is} = \dfrac{\dfrac{N_{is}}{E_{is}}}{\dfrac{N_i}{E_i}}$

Where N_{is} is the number of firms in industry 'i' in state's'. N_i is the number of firms in the industry 'i' at the national level. E_{is} represents the employment in industry 'i' in state's', and E_i is the employment in industry 'i' at the national level. We expect a positive coefficient on this measure of externalities.

Table 3: Summary of Variables Used

Main Dependent Variables	Measured by:	Data Sources
TFP growth (dependent variable)	Translog Index of TFP (Growth Accounting technique)	ASI
Employment Growth	CAGR of employment in industry i in state s	ASI

Main Independent Variables		
Specialization (MAR externalities)	Ln (Location Quotient)	ASI
Diversity (Jacobs externalities)	Ln(Modified Herfindahl Index)	ASI
Competition (Porter externalities)	Ln(Index of Competition)	ASI
Human Capital	Ln(HDI)	India Human Development Report
Per capita credit given to industry	Ln(Per capita credit given to industry)	CMIE Prowess
Infrastructure at the state level	Ln(Infrastructure Index)	Ghosh & De (2004)

Source: Author's compilation

Data

The data for two-digit industries across the 20 states is drawn from Annual Survey of Industries (ASI) for the period 2001-02 to 2011-12. In 2011-12, the share of these 20 states in total manufacturing employment and value-added stood at above 95 percent. Not all the 20 states have the existence of all two-digit manufacturing industries. Therefore, only the 11 two-digit industries present in all the 20 states are included in the analysis.[ii] The current prices data is converted to constant prices by using the appropriate deflators which have been taken from the 'Office of Economic Adviser', Department of Industrial Policy and Promotion. The dataset is a panel of industries across states, and Hausman-test[iii] is used to select between fixed and random effects specification. Table 3 summarizes the measurement of important variables as well as the data sources used for these variables.

5. Regional Performance of Manufacturing Sector in India

Table 4 shows the extent of regional disparities in manufacturing value added and employment in India during 2001-02 to 2011-12. The declining share in manufacturing employment and value added is observed for relatively less-industrialized states like West Bengal, U.P., Kerala, Jharkhand, and Delhi. All these states have a labour-intensive manufacturing process as their share in manufacturing employment exceeds their share in value added. The literature has established that new industries tend to locate where there is an existence of industries (Lall & Chakravorty, 2005). This implies that these less industrialized states of India are at a serious disadvantage which may cause slower economic growth of these regions. Nine out of twenty states have experienced a decline in their share in total manufacturing employment during this period. The decline in the share of value added is observed for seven states.

The highest share in manufacturing value added and employment is observed for the industrialized states like Maharashtra, Gujarat, Tamil Nadu and Andhra

Pradesh. Together, these four states account for about 43 percent of total gross value added and about 50 percent of total manufacturing employment in 2001-02. The largest gainer in employment and value-added share is observed for Uttarakhand. For example, during 2001-02 to 2011-12, its share in value added increased from 0.48 percent to 3.51 percent. Its employment share also increased from 0.54 percent to 2.61 percent during the same period. The change in share of employment and value added also moves in opposite directions for some states like Andhra Pradesh, Assam, Chhattisgarh, Maharashtra, and Punjab. The next section presents the results based on employment growth as the dependent variable for 11 two-digit industries over the period 2001-02 to 2011-12.

6. Employment Results

The dynamic externalities coefficients are estimated by pooling all the eleven industries as done in the previous studies. On the basis of Hausman test, the random effects model is used for estimation. The modified Wald test shows the presence of heteroscedasticity which is corrected by using White (robust) standard errors. Table 5 presents the descriptive statistics for the important variables used in the model.

Table 4: States Share in Manufacturing Value Added and Employment, 2001-02 and 2011-12

States	Share in VA (2001-02)	Share in VA (2011-12)	Change in VA share	Share in Employment (2001-02)	Share in Employment (2011-02)	Change in employment share
A.P.	5.94	6.99	1.05	11.39	9.91	-1.48
Assam	0.55	0.83	0.28	1.46	1.38	-0.08
Bihar	0.36	0.45	0.09	0.81	0.93	0.12
Chhattisgarh	1.63	1.49	-0.14	1.23	1.35	0.12
Delhi	1.12	0.59	-0.53	1.50	0.81	-0.69
Gujarat	11.48	11.61	0.13	9.14	10.32	1.18
Haryana	3.87	3.87	0	3.79	4.45	0.66
H.P.	0.75	2.26	1.51	0.48	1.24	0.76
Jharkhand	2.06	1.97	-0.09	2.07	1.71	-0.36
Karnataka	5.44	11.94	6.5	6.30	6.72	0.42
Kerala	1.87	1.09	-0.78	4.02	2.91	-1.11
Maharashtra	16.84	18.57	1.73	14.84	12.84	-2
M.P.	3.12	2.26	-0.86	2.53	2.31	-0.22
Orissa	1.31	2.50	1.19	1.52	2.16	0.64
Punjab	3.00	3.88	0.88	4.56	4.51	-0.05
Rajasthan	2.88	4.32	1.44	3.01	3.56	0.55
T.N.	8.39	9.73	1.34	14.25	14.57	0.32
Uttarakhand	0.48	3.51	3.03	0.54	2.61	2.07
U.P.	5.93	4.68	-1.25	6.65	6.45	-0.2
W.B.	3.61	2.62	-0.99	7.04	4.90	-2.14

Source: Author's Calculations using ASI data

Table 5: Descriptive Statistics

State-Industry Variables	Mean	Std. deviation	Observations
Employment Growth	0.0661	0.0893	220
TFP average annual growth	0.0497	0.0671	220
Specialization Index (L.Q.)	1.0676	1.1524	220
Diversity Index (Modified HHI)	0.1420	0.1100	220
Competition Index	1.3577	1.1868	220
Human Development Index (HDI)	0.4265	0.4265	20
Infrastructure Index	4.1110	1.9180	20
Per Capita Credit to Industry	0.0032	0.0049	20

Note: Based on 220 state-industry observations used in the study

Table 6: State-Industry Employment Growth: 2001-02 to 2011-12

VARIABLES	(1) Emp growth	(2) Emp growth	(3) Emp growth	(4) Emp growth
Employment level	-0.0467***	-0.0569***	-0.0428***	-0.0583***
	(0.0123)	(0.0147)	(0.0108)	(0.0135)
Wage level	0.0232***	0.0286***	0.0252***	0.0328***
	(0.00605)	(0.00734)	(0.00602)	(0.00753)
Human Capital	0.00473	0.00695	-0.00190	-0.00264
	(0.0227)	(0.0217)	(0.0226)	(0.0230)
Infrastructure	0.0317***	0.0301***	0.0312***	0.0224***
	(0.00810)	(0.00798)	(0.00793)	(0.00645)
Per capita Credit to	0.0163	0.0127	0.0158	0.0132
	(0.0111)	(0.00991)	(0.0105)	(0.00878)
Specialization	0.00326			0.0150
	(0.00934)			(0.0113)
Diversity		-0.0215*		-0.0225**
		(0.0111)		(0.0112)
Competition			0.0265***	0.0385***
			(0.00685)	(0.00705)
Constant	0.374***	0.356***	0.314***	0.342***
	(0.119)	(0.108)	(0.102)	(0.0963)
Observations (N)	220	220	220	220
Number of industries	11	11	11	11
R^2	0.19	0.21	0.22	0.25

Note: 1. p-values are reported in parentheses
*** p<0.01, ** p<0.05, * p<0.1
2. All regressions include industry dummies
3. The dependent variable is employment growth (in decimal form)

Columns (1) to (3) of table 6 show the effect of externalities on regional employment growth separately whereas column (4) considers all the measures of externalities together. Column (1) shows that MAR specialization externalities do not have any impact on employment growth. This implies that concentration of firms belonging to the same industry has no effect on the growth of manufacturing employment. The inclusion of other variables does not alter the conclusion about MAR specialization externalities as shown in column (4). Column (2) shows that Jacobs's diversity externalities have a negative and statistically significant coefficient. This implies that manufacturing employment growth is positively influenced by Jacobs's diversity externalities and an industry facing a more diversified environment is likely to grow faster in that region. Column (3) shows that the competition externalities have a favourable effect on manufacturing employment growth. This holds true when all the externalities are considered simultaneously in column (4). Therefore, our results are in favour Jacobs's diversity and Porter's competition externalities, but do not show the importance of MAR specialization externalities in influencing the growth of manufacturing employment in India.

Table 7: State-Industry Employment Growth: 2001-02 to 2011-12
Labour-Intensive and Capital-Intensive Industries

VARIABLES	(1) L-intensive Emp growth	(2) K-intensive Emp growth
Employment level	-0.0418***	-0.110***
	(0.00896)	(0.0242)
Wages level	0.0247***	0.0544***
	(0.00665)	(0.0119)
Human Capital	-0.000646	-0.0156
	(0.0324)	(0.0639)
Infrastructure	0.0213*	0.0338**
	(0.0117)	(0.0131)
Per Capita Credit to Industry	0.00493	0.0454**
	(0.0104)	(0.0185)
Specialization	0.000181	0.0725***
	(0.00921)	(0.0219)
Diversity	-0.0168*	-0.0247
	(0.00993)	(0.0197)
Competition	0.0345***	0.0654**
	(0.0113)	(0.0303)
Constant	0.214***	0.838***
	(0.0789)	(0.221)

Observations (N)	160	60
Number of industries	8	3
R^2	0.26	0.42

Note: 1. p-values are reported in parentheses
*** p<0.01, ** p<0.05, * p<0.1
2. All regressions include industry dummies
3. The dependent variable is employment growth (in decimal form)

The coefficient of 'level of employment' variable is negative and significant. This variable is a measure of base effect which means that states with a higher employment level in an industry observed slower employment growth. The 'level of wages' has a positive and significant coefficient implying that initial wages are positively associated with employment growth. The importance of a well-functioning infrastructure is clear from its positive and significant impact on employment growth. Therefore, investment in infrastructure should be raised in order to increase the growth of manufacturing employment. Human capital and credit given to industry does not significantly affect employment growth of an industry in a state.

Table 7 presents the results for the eight labour-intensive and three capital-intensive industries. We do not find any effect of MAR specialization externalities on employment growth of labour-intensive industries. However, we find diversity and competition externalities seem to exert a positive effect on employment growth of labour-intensive industries. Thus, the labour-intensive industries gain from knowledge spillovers and experience growth from concentrating in a diversified environment. On the other hand, capital-intensive industries benefit from locating in a specialized and competitive environment. We do not find Jacobs's diversity externalities to be important for capital-intensive industries.

The results for capital-intensive industries are strikingly different from those of labour-intensive industries. The reason for this difference could be the fact the capital-intensive industries have a relatively high level of technological intensity than labour-intensive industries. Several empirical studies have reported the prevalence of MAR specialization externalities in high-tech sectors (e.g., Van der Panne, 2004). In these capital-intensive high-tech industries, the possibility of learning and sharing knowledge is higher between firms of the same industry. Therefore, a specialized environment exerts a positive influence on the employment growth of capital-intensive industries.

7. TFP Results

Table 8 presents the results based on TFP growth for all the eleven industries. In column (1) to (3), none of the externalities variables appear significant. When these externalities are considered simultaneously in column (4), they remain insignificant. Therefore, we find that dynamic agglomeration externalities are not important in influencing the industrial productivity growth. The separate regressions for labour-intensive and capital-intensive industries also exhibit insignificant results.

These results support the findings by Dekle (2002) who measures productivity growth by TFP growth for Japanese manufacturing industries at the prefectural level. He also concludes that dynamic externalities do not have any effect on the growth of industrial productivity but are important in influencing the growth of industrial employment. Our findings also support the conclusion of earlier studies that do not favour the use of employment growth to explain productivity growth (e.g., Dekle, 2002; Cingano & Schivardi, 2004).

One of the reasons for this insignificant impact on industrial productivity could be the fact that when TFP growth is used as an outcome variable, all the three components of agglomeration externalities become linear components of TFP growth, which could lead to specification problems. On the other hand, such problems do not arise when we use employment growth as the dependent variable. Further, there are serious measurement issues that arise in the measurement of TFP growth at a disaggregated level. The lack of reliable data on capital stock[iv], fluctuating value added series (with negative values for some state-industry pairs), and other measurement issues cast doubt on the accurate measurement of TFP growth at a disaggregated level. Therefore, it is important to interpret our findings based on TFP growth regressions with great caution. In contrast, the results based on employment growth regressions are less likely to be prone to such specification and measurement errors. It is precisely due to this reason that most of the empirical studies have used employment growth for making inferences about industrial growth.

Table 8: State-Industry TFP Growth: 2001-02 to 2011-12: All Industries

VARIABLES	(1) TFPG	(2) TFPG	(3) TFPG	(4) TFPG
TFP level	-0.0146* (0.00769)	-0.0140* (0.00716)	-0.0148** (0.00754)	-0.0143** (0.00702)
Human Capital	-0.0116 (0.0241)	-0.0122 (0.0249)	-0.0171 (0.0227)	-0.0185 (0.0229)
Infrastructure	0.0165*** (0.00636)	0.0165*** (0.00528)	0.0156*** (0.00579)	0.0160*** (0.00583)
Per Capita Credit	0.00517 (0.00824)	0.00872 (0.00992)	0.00596 (0.00781)	0.00950 (0.00930)
Specialization	-0.00420 (0.00595)			0.00347 (0.00860)
Diversity		0.00929 (0.00702)		0.00861 (0.00719)
Competition			0.0114** (0.00515)	0.0127 (0.00966)
Constant	0.0346	0.0796	0.0362	0.0779

	(0.0309)	(0.0515)	(0.0302)	(0.0505)
Observations	220	220	220	220
Number of industries	11	11	11	11
R^2	0.05	0.06	0.06	0.07

Note: 1. p-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1
2. All regressions include industry dummies
3. The dependent variable is TFP growth (in decimal form)

8. Conclusion

The paper finds that dynamic externalities seem to have a favourable effect on the growth of manufacturing employment but these do not seem important in influencing the growth of manufacturing productivity. However, as mentioned earlier, the results based on TFP growth should be interpreted cautiously due to the serious measurement and data challenges involved in measuring productivity growth at a disaggregated level. The results highlight that importance of dynamic externalities should not be examined by pooling all industries. The dynamic externalities may have a differential impact according to the nature of an industry. Specifically, we find that labour intensive industries benefit from diversity externalities whereas capital-intensive industries gain more from specialization. Competition externalities have a benign effect on employment growth in both types of industries. These findings imply that the policies of specialization and diversification should be formulated according to the nature of an industry.

The evidence in favour of dynamic agglomeration externalities in influencing employment and industrial growth has important policy implications for the 'Make in India' program of the government. The results also highlight the importance of infrastructural investments for boosting the growth of manufacturing employment and productivity. Availability of an efficient road network, telecommunication facilities, power, water and other infrastructural support would accelerate the manufacturing growth in the country.

There are certain limitations of this study which point towards the directions for future research in this area. Firstly, the present study is limited to the registered manufacturing sector of India. However, the service sector is growing rapidly in the Indian economy and contributes about 55 percent to the GDP. Therefore, these agglomeration externalities may also be important for the firms operating within the services sector. The future research can look at the impact of these dynamic agglomeration externalities in the services sector. Secondly, the study examines the effect of dynamic externalities on manufacturing growth using 'state' as a geographical unit. Due to data constraints, the analysis could not be conducted at disaggregated geographical levels. The measurement of dynamic agglomeration externalities is highly sensitive to geographical unit of analysis. If the disaggregated geographical level data becomes available, then the future research could study the impact of these externalities on employment and productivity growth. Thirdly, the study does not solve the endogeneity problems completely. Use of firm-level data and controlling for state-specific effects by using better proxies could provide more valuable insights.

End-notes:

[1] Beaudry & Schiffauerova (2009) in their detailed review attempt to explain the reasons for the unsettled empirical debate between Marshallian and Jacobian externalities.

[1] Following the terminology of Glaeser et al. (1992), the unit of analysis in this paper is a 'two-digit industry in a state' (or state-industry). In the selected 20 states, 13 two-digit industries are present. However, we include only 11 as it was not possible to construct a comparable time-series for the remaining two industries due to changes in national industrial classification which took place in 2008.

[1] Hausman (1978) proposed a test to choose between random effects and fixed effects model. This test is based on the null hypothesis that random effects is the appropriate model. It checks whether the random effects and the regressors are orthogonal (Greene, 2008).

[1] We have attempted to estimate capital stock using the perpetual inventory method. However, the adjustments and approximations involved in this process do not provide an idea estimate of net capital stock.

9. References

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Appendix A.1
Selected Two-digit Industries according to NIC, 2004

Industry NIC (2004)	Industry Description
15	Food Products and Beverages
17	Textiles
20	Wood and Products of Wood
21	Paper and Paper Products
22	Publishing, Printing
24	Chemicals and Products
25	Rubber and Plastic Products
26	Other Non-Metallic Mineral Products
27	Basic Metals
28	Fabricated Metal products, except machinery and equipment
29	Machinery and Equipment n.e.c.
31	Electrical Machinery and Apparatus
36	Furniture; Manufacturing N.E.C.

Source: Annual Survey of Industries, Central Statistics Office

A.2: Selected Indian States

Name of States (20)	Andhra Pradesh, Assam, Bihar, Chhattisgarh, Delhi, Gujarat, Haryana, Himachal Pradesh, Jharkhand, Karnataka, Kerala, Maharashtra, Madhya Pradesh, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttarakhand, Uttar Pradesh, West Bengal

A.3: Measurement of Capital Input: The Perpetual Inventory Method

There is an agreement in the literature that book value is a flawed and unreliable measure of capital stock (Goldar, 1986; Hulten, 1991). The present study uses the perpetual inventory method (PIM) which is one of the most widely used method to estimate capital stock. This method takes net fixed capital stock (NFKS) at constant prices as the measure of capital input. Following Goldar (2004; 2013) and Trivedi (2004), we take K_0 as the benchmark capital stock; I_t as net fixed capital formation (NFKF) in year t at base year prices. Therefore, the standard PIM equation to estimate capital stock in year T, K_T, is given by:

$$K_T = K_0 + \sum_{t=1}^{T} I_t$$

The net fixed capital stock estimate for the registered manufacturing sector for India is obtained from 'National Accounts Statistics' (NAS). First, we make benchmark estimates of capital stock in the two-digit industries at the all-India level and then arrive at state-level benchmark estimates of capital stock in these two-digit industries.