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Industrial Location and Spatial Inequality

Theory and Evidence from India

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Abstract

We argue that spatial inequality of industry location is a primary cause of spatial income inequality in developing nations. We focus on understanding the process of spatial industrial variation—identifying the spatial factors that have cost implications for firms, and the factors that influence the location decisions of new industrial units. The analysis has two parts. First we examine the contribution of economic geography factors to the cost structure of firms in eight industry sectors and show that local industrial diversity is the one factor with significant and substantial cost reducing effects. We then show that new private sector industrial investments in India are biased toward existing industrial and coastal districts, whereas state industrial investments (in deep decline after structural reforms) are far less biased toward such districts. We conclude that structural reforms lead to increased spatial inequality in industrialization, and therefore, income.

Keywords: income inequality, economic geography, industrial location, India
JEL classification: R11, O53

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1 Introduction

Spatial inequality refers to a condition in which different spatial or geographical units are at different levels on some variable of interest, usually (average) income. Why should different geographical units within a nation be at different income levels? This question is not answered simply. There are several overlapping reasons for the existence of intranational spatial inequality; history, natural resources, human capital, local political economy, and culture have all been identified as contributory factors. Here, we seek to understand spatial inequality in terms of industrialization and industrial location. We argue that modern economic growth is driven by productivity increases which, in turn, are driven by industrialization in the developing world. Therefore spatial units that have industrialized are more productive and have higher incomes than spatial units that have not industrialized or have industrialized less (we are not considering post-industrial, service sector-led growth, a condition that is characteristic of developed nations but quite marginal in developing nations). In other words, geographical variation in industrialization is a primary cause of geographical variation in average income in developing nations.

This is the first part of our argument, which we view as self evident and therefore will not seek to prove. Our interest is in understanding the process of spatial industrial variation, that is, in identifying the factors that determine industrial location decisions, and to show how recent policy changes have led to increasing spatial industrial inequality, and therefore, spatial income inequality. We argue, following the tradition of the cumulative causation theorists, that industrialization follows the classic 'virtuous cycle' principles. New industries locate where other industries already exist. This is done to avail of productivity advantages in existing industrial regions. However, not all industries seek such profit maximizing locations. State-owned industry location decisions include consideration of regional balance, national security, and political gains. However, the role of the state as industrial owner and industrial location regulator has been substantially curtailed under the regime of liberalization and structural reforms. Therefore, with the increasing dominance of private sector industrialization, we expect that industries will be more spatially concentrated in leading industrial regions, which will lead to higher levels of spatial inequality.

We test this theoretical framework with Indian data from the 1990s. First we test the hypothesis that economic geography factors influence productivity by examining the cost structure of eight manufacturing industry sectors.[1] In a significant departure from existing models of industry clustering, we show that only a single economic geography factor has cost-reducing effects—this is industrial diversity (which is high in metropolitan and other mixed industrial regions). Next, we show that location decisions of state-owned industry

[1] Throughout this paper the term industry specifically refers to manufacturing industry, and does not include financial or business services.

and private sector industry are, indeed, influenced by different factors, where private industrial units favor locations in existing industrial areas. We also show that the private sector is the primary source of new industrial investments. We conclude that liberalization and structural reforms have led to higher levels of spatial inequality in industrialization in India.

The material in this paper brings together two interconnected research programs. We draw on two somewhat distinct literatures, use two clearly distinct methodologies, and analyze similar but distinct datasets. Therefore, we present the arguments, the literature, the methodology, and the findings in two separate sections. Section 1 is on cost effects of manufacturing industry location, and Section 2 looks at location patterns of private and state capital, followed by a single concluding section in which we reconcile the findings of the two sections.

But, before we proceed further it is necessary to explain the meaning of spatial inequality as used in this paper. What is the appropriate scale for measuring income differences? Spatial inequalities exist at all scales—from the neighborhood, the municipality, and the district or county, through the province or state, and the nation. Which of these inequalities are most meaningful? For the purpose of this paper, we suggest that inequalities between spatial units that are also discrete policy units and for which income data are available are meaningful units. That is, there may indeed exist significant inequalities between neighborhoods, but if neighborhoods cannot create policies that affect income, or if income cannot be measured at the neighborhood level, they are not considered relevant spatial units. To the extent that municipalities can create policies that influence income generation and such income can be measured, they should be considered relevant units; however, rural areas will have to be left out of such calculations. Inequality between nations is large subject with its own literature. We are left with district and provincial inequality. The latter, also termed regional inequality, has typically been the unit of interest in inequality studies, largely because it is the smallest spatial unit for which income data are available.[2] Our ultimate interest is also in the provincial scale, which, in India, is represented by linguistically defined states. However, since location analysis is best carried out at scales smaller than Indian states (some of which are large enough to be large countries), the analysis here is undertaken at the district scale.[3]

2 Cost effects of industry location

Our empirical strategy in this section is to estimate a cost function to see how cost (thereby profits) are affected by the economic geography of the region where the firm is located. If

[2] There is a large literature on intranational regional inequality starting with the general approaches of Myrdal (1957), Hirschman (1958), Borts (1960), Williamson (1965), and Friedman (1973:41-64). More recently, Barro and Sala-i-Martin’s (1992) work on regional convergence has received attention, especially in developed nations. State-level regional inequality studies of India have been done by Chakravorty (2000) and Ghosh et al. (1998).

[3] The district is the second tier of subnational administration in India, similar to counties in the United States and municipios in Brazil.

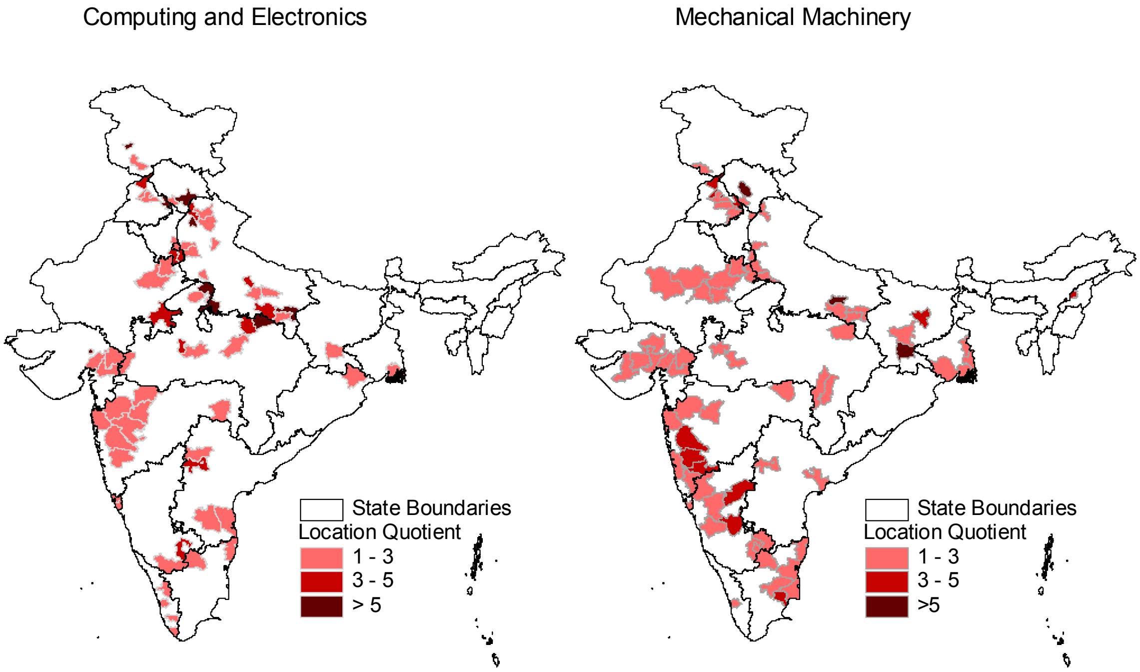
specific factors related to the local economic geography have cost reducing impacts, then firms are likely to choose regions with disproportionately higher levels of these factors. The analytic framework to examine location of manufacturing industry primarily draws on recent findings from the 'new economic geography' (NEG) literature. Here, Krugman (1991) and Fujita et al. (1999) analytically model increasing returns, which stem from technological and pecuniary externalities. In models of technological externalities, interfirm information spillovers provide the incentives for agglomeration. Assuming that each firm produces different information, the benefits of interaction increases with the number of firms. This provides incentives for the entrepreneur to locate the firm in close proximity to other firms, leading to agglomeration.

In addition, there are pecuniary benefits from sharing specialized input factors, utilizing scale economies in the production of shared inputs, collaboration to share information, and from the presence of interrelated industries. Transport costs are also important. According to Krugman (1991) agglomeration occurs at intermediate transport costs when the spatial mobility of labor is low (Fujita and Thisse 1996). Transport costs can be reduced by locating in areas with good access to input and output markets which also have high quality infrastructure linking firms to urban market centers. In summary, insights from NEG and regional science models suggest that own and interrelated industry concentrations, availability of reliable infrastructure to reduce transport costs and enhance market access, regional amenities and economic diversity are important for reducing costs, thereby influencing location and agglomeration of industry.

To provide visual evidence on the degree to which industry locations are clustered over the national space, we include district level maps of location quotients (LQ) for four industry sectors in Figure 1. The LQ is simple measure of regional concentration used in regional science. It calculates the ratio of the share of a given variable to the share of population. Here, LQ = 1 indicates that the region's share of a particular sector is equal to its share of all industry. If LQ = 3 it indicates that the region's share of that sector is three times its share of all industry. Our goal is to analyze the cost implications of these location decisions.

Before moving on to describing the economic geography variables and specifying the econometric specification, it is useful to think why these sources of externalities may matter in the estimation of costs over and beyond the benefits that are capitalized in the price of input factors. After all, if a region has relatively better endowments, the benefits should be reflected in lower prices of intermediate inputs, and may also bid up the prices of labor and capital as the more people and firms migrate to that region. If the extent of agglomeration economies are purely market based, it is possible that net benefits are capitalized. However, non pecuniary externalities of information and knowledge sharing do not lend themselves to direct capitalization. Further, market failures including coordination failure reduce the extent to which the economic geography variables are

Figure 1: Spatial distribution of employment



Data Source: Sampling Frame, Annual Survey of Industries, CSO, 1998-99

capitalized in input prices. Finally, the extent to which these costs and benefits are capitalized into input prices is an empirical question, and one that we will examine in the following sections.

2.1 Economic geography variables

We now identify and define the specific economic geography variables that are expected to influence industry location by generating competitive cost effects.

Market access

In principle, improved access to consumer markets (including interindustry buyers and suppliers) will increase the demand for a firm's products, thereby providing the incentive to increase scale and invest in cost reducing technologies. Access to markets is determined by the distance from and the size and density of market centers in the vicinity of the firm. There is no prior reason why the extent of the market should be limited on a firm’s spatial vicinity (i.e. its own district), as long as there are adequate transport networks to connect its products to a greater market area, which could be the province, the nation or rest of the world. To model this type of potential interaction through a transport network, we draw on the classic gravity model, which is commonly used in the analysis of trade between regions and countries (Evenett and Keller 2002). Following Hansen (1959), we calculate access from the following definition:

$$I_i^{ne} = \sum_j S_j \cdot e^{\left(-d_{ij}^b / 2a^2\right)}$$

where I_i^{ne} is the potential accessibility indicator for location i based on the negative exponential distance decay function, S_j is a size indicator at destination j (for example, population, purchasing power or employment), d_{ij} is a measure of distance (or more generally, *friction*) between origin i and destination j, and b describes how increasing distance reduces the expected level of interaction, and the parameter a is the distance to the point of inflection of the negative exponential function. We use the market access (MA) indicator developed by Lall et al. (2004a), who use population as the measure of size in S_j and network distance as the basis of the inverse weighting parameter. Their accessibility index describes market access using information on the Indian road network system and the location and population of urban centers.[4]

In addition to market access, we develop indicators of local spatial externalities, which include own and Interindustry linkages. The main distinction in modeling these externalities and the treatment of market access is that we limit the spatial extent of the potential externality to the firm's own district. We follow this approach as much of the literature on technological and pecuniary externalities suggests that localization economies are limited to firms that are located in close proximity (close being defined as census tracts in USA literature). Thus, given the already large size of Indian districts, we do not consider the impact of firms located in neighboring districts. Our aggregation scheme does introduce a problem as we tend to underestimate parameters for localization economies as the 'true' interaction often occurs as spatial scales below the district (for example, neighborhoods).[5] We develop the following indicators of local spatial externalities.

Own industry concentration

The co-location of firms in the same industry (localization economies) generate externalities that enhance productivity of all firms in that industry (Henderson 1988; Henderson 2000; Ciccone and Hall 1996). Of the several ways of measuring localization economies we use own industry employment in the district to measure localization economies. Own industry employment is calculated from employment statistics provided in the 1998-99 sampling frame of the ASI, which provides employment data on the universe of industrial establishments in India.

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4 The urban centers database used in Lall et al. (2004a) includes latitude and longitude coordinates and 1991 population for 3,752 cities with a total population of about 217 million. The digital transport network dataset includes an estimated 400,000km of roads categorized into four classes by quality. The weighting parameter used in the accessibility computation is an estimate of travel time. As the exact geographic location of each firm is not publicly available, the authors summarize the accessibility for each district by averaging the individual values for all points that fall into the district.

5 This however is the best available option as we cannot identify firms under the level of the distict.

Interindustry linkages

In addition to *intra*industry externality effects, we also include a measure to evaluate the importance of *inter*industry linkages in explaining firm level profitability, and thereby location decisions. In particular, we are interesting in finding out if proximity to suppliers reduces the cost of inputs, in addition to providing non pecuniary benefits of information/technology sharing.[6] There are several approaches that can be used to define and measure supplier access—input-output linkage-based, labor skill-based, and technology flow-based. The most common approach is to use the national level input-output account as a template for identifying strengths and weaknesses in regional buyer–supplier linkages (Feser and Bergman 2000). Commonly, backward linkages are measured as technical coefficients from a national industry by industry transactions table. Technical coefficients are defined as column industry purchases from the row industry divided by the sum of all column industry sales and relate the dollar value of intermediate purchases from the upstream sector required to produce a dollar of the column industry's output. Thus, the technical coefficient measures the degree of the column industry's dependence on other industries for inputs to production. Following the methodology adopted in Lall et al. (2004b), we measure the firm's dependence on backward linkages as the sum of its industry's backward linkages with all other relevant sectors. For each column industry, backward linkages with each row industry are defined as the technical coefficient weighted by the region's location quotient for the row industry. A matrix of regionally weighted backward linkages is defined as:

$$\underset{(r \times j)}{\Lambda} = \underset{(r \times i)}{L}\,\underset{(i \times j)}{\Omega}$$

where L is a region by industry matrix of location quotients for selling sectors and Ω[7] is a national direct requirements matrix of technical coefficients with purchasing industries as columns and supplying sectors as rows. Each column vector of Λ is a composite measure of the j^{th} industry's backward linkages for regions *r*. Therefore, a firm in region *r* and industry *j* has a measure of backward linkages Λ_{rj}.

Economic diversity

In addition to buyer–supplier linkages, there are other sources of interindustry externalities. Prominent among these is the classic Chinitz-Jacobs' diversity. The diversity measure provides a summary measure of urbanization economies, which accrue across industry sectors and provide benefits to all firms in the agglomeration. Chinitz (1961) and Jacobs

6 In this analysis, we limit the analysis to buyer/supplier access, and do not include explicit measures of forward linkages (i.e., final demand). This is because the market access measure captures much of the forward linkages (sales to other firms and final consumers).

7 For Ω, we use a 1996 matrix of national technical coefficients from the Input Output Transactions Table 1993-94, Ministry of Statistics and Programme Implementation. Each element of L is a standard location quotient calculated as the sum of employment in region *r* and industry *i*.

(1969) proposed that important knowledge transfers primarily occur across industries and the diversity of local industry mix is important for these externality benefits. Here, we use the well known Herfindahl measure to examine the degree of economic diversity in each district. The Herfindahl index of a region r (H_r) is the sum of squares of employment shares of all industries in region r:[8]

$$H_r = \sum_i \left(\frac{E_{ir}}{E_r}\right)^2$$

2.2 Econometric specification

In this subsection, we present the econometric specification to test the effects of economic geography factors in explaining the location of economic activity. Our basic premise is that firms will locate in a particular location if profits exceed some critical level demanded by entrepreneurs. We estimate a cost function with a mix of micro-level factory data and economic geography variables which may influence the cost structure of a production unit. A traditional cost function for a firm i is (subscript i is dropped for simplicity):

$$C = f(Y, w) \tag{1}$$

where C is the total cost of production for firm i, Y is its total output, w is an n-dimensional vector of input prices. However, the economic geography—or the characteristics of the region where the firm is located—is also an important factor affecting the firm's cost structure. We modify the basic cost function to include the influence of location-based externalities:

$$C_r = f(Y, w_r, A_r) \tag{2}$$

where C_r is the total cost of a firm i in region r, w_r is an input price vector for the firm in district r, and A is a m-dimensional vector of location externalities (i.e., economic geography variables such as access to markets, buyer supplier networks, own industry concentration) at location r.

The model has four conventional inputs: capital, labor, energy, and materials. Therefore, the total cost is the sum of the costs for all four inputs. With respect to agglomeration economies, it is assumed that there are four sources of agglomeration economies at the district level such that $A=\{A_1, A_2, A_3, A_4\}$, where A_1 is the market access measure, A_2 is the concentration of own industry employment, A_3 is the strength of buyer–supplier linkages, and A_4 is the relative diversity in the region.

8. For more intuitive interpretation of the measure, for the diversity index in our model, H_r is subtracted from unity. Therefore, DV_r=1-H_r. A higher value of DV_r signifies that the regional economy is relatively more diversified.

Shephard's Lemma produces the optimal cost-minimizing factor demand function for input j corresponding to input prices as follows:

$$X_{j,r} = \frac{\partial C_r}{\partial w_{j,r}}(Y, w_r, A_r),\ j = 1,2,3,4,....,n \tag{3}$$

where $X_{j,r}$ is the factor demand for j^{th} input of a firm in district r. It is clear that the firm's factor demand is determined by its output, factor prices, and location externalities. Therefore, production equilibrium is defined by a series of equations derived from equation (2) and (3). The empirical implementation of above model is based on a translog functional form, which is a second-order approximation of any general cost function. Since there are four conventional inputs and four location externalities (agglomeration) variables, a translog cost function can be written as:

$$\ln C = \alpha_0 + \alpha_y \ln Y + \sum_j \alpha_j \ln w_j + \sum_l \alpha_l \ln A_l + 1/2\beta_{yy}(\ln Y)^2 + 1/2\sum_j \sum_k \beta_{jk} \ln w_j \ln w_k +$$
$$\sum_j \beta_{jy} \ln Y \ln w_j + 1/2\sum_l \sum_q \gamma_{lq} \ln A_l A_q + \sum\sum \gamma_{jl} \ln w_j A_l + \sum_l \gamma_{ly} \ln Y \ln A_l$$

$$(j\neq k; l\neq q; j,k=1,2,3,4\ ; l,q=1,2,3,4) \tag{4}$$

The final model estimated includes two additional dummy variables that identify locational characteristics that may not be captured by agglomeration variables. Locations are categorized as rural, non-metro urban (D_1), and metro urban (D_2), and rural location is used as a reference category. In addition, we use a dummy variable to test if there are differences between public and private sector firms, and age to examine if profitability varies by firm age.

The impact of the economic geography factors on the cost structure (or profitability) of the firm can be evaluated by deriving the elasticity of costs with respect to the economic geography variables. From equation (4) the cost elasticities are:

$$\frac{\partial C}{\partial A_l} = \alpha_l + \sum_j \gamma_{jl} \ln w_j + \sum_q \gamma_{lq} \ln A_q + \gamma_{ly} \ln Y \tag{5}$$

and, the elasticities of input demands with respect to agglomeration factors A_l is:

$$\frac{\partial \ln v_j}{\partial \ln A_l} = \frac{\partial C}{\partial A_l} + \frac{\gamma_{jl}}{A_l} \tag{6}$$

2.3 Data sources

We use plant-level data for 1998-99 from the Annual Survey of Industries (ASI) conducted by the Central Statistical Office of the Government of India. The 'factory' or plant is the unit of observation in the survey and data are based on returns provided by factories. Data on various firm-level production parameters such as output, sales, value added, labor cost, employees, capital, materials and energy are used in the analysis (see Table 1 for details). In summary, factory-level output is defined as the ex-factory value of products manufactured during the accounting year for sale. Capital is defined as the gross value of plant and machinery. It includes not only the book value of installed plant and machinery, but also the approximate value of rented-in plant and machinery. Labor is defined as the total number of employee man days worked and paid for by the factory during the accounting year.

Table 1: Characteristics of firms in the study sectors

Location	Industry	Firms	Employment	Wages/ Employee	Output/ Employee	Value Added/ Employee
nationwide	all industries	23201	4,605	60	277	127
	food processing	4168	671	47	253	147
	textiles	3409	1,111	44	140	76
	leather	468	79	41	211	135
	paper products & printing	1043	129	70	314	204
	chemicals	2811	474	83	376	79
	metals	2331	410	77	261	114
	mechanical machinery	1300	237	78	189	95
	electrical/electronics	1267	251	101	344	65
	other industries	6404	1,243	54	385	195
non urban		8343	1,494	50	301	126
non metro urban		9446	1,972	58	235	125
metropolitan areas		5412	1,139	74	320	133

Note: Data for employment, wages/employee, output/employee and value added/employee are in thousands.

Source: ASI 1998-99.

The factory or plant level data from the Indian ASI allows us to compute input costs. With respect to input costs and input prices, capital cost is defined as the sum of rent paid for land, building, plant, and machinery, repair and maintenance cost for fixed capital, and interest on capital. Labor cost is calculated as the total wage paid for employees. Energy cost is the sum of electricity (both generated and purchased), petrol, diesel, oil, and coal consumed. The value of self-generated electricity is calculated from the average price that a firm pays to purchase electricity. Material cost is the total aggregate purchase value for domestic and foreign intermediate inputs. We define the price of capital as the ratio of total rent to the net fixed capital. The price of labor is calculated by dividing total wage by the number of employees. Energy and material prices are defined as weighted expenditure per unit output. Output value is weighted by factor cost shares.

2.4 Analysis results

Summary results for the estimated cost functions of the economic geography variables, as defined in Equation (5), are reported in Table 3. To make allowances for the heterogeneity in firm size, and test if in fact there are differences in production costs and the impact of economic geography across firms of different sizes, we classify firms into three categories: small, medium, and large. Small firms are defined as those with less than 50 employees, medium sized are between 50-99 employees and large firms have 100 or more employees. The number of firms by size category are reported in Table 2.[9]

Table 2: Number of establishments

Industry	Small (0-49)	Medium (50-99)	Large (100+)	Total
Food and beverages	1,808	708	1,484	4,000
Textiles	1,289	406	1,613	3,308
Leather	227	73	144	444
Printing and publishing	657	151	212	1,020
Chemicals	1,544	350	870	2,764
Metals	1,372	296	615	2,283
Mechanical machinery	799	160	316	1,275
Electrical/electronics	709	168	375	1,252
Total	8,405	2,312	5,629	16,346

Source: See text.

There are four sets of location/economic geography variables in the analysis: (a) access to markets (Access); (b) own industry concentration (Emp); (c) buyer supplier or input–output linkages (IO link); (d) local economic diversity (Diversity). The results for each industry sector are provided in four parts. The first column has industry-wide cost elasticities. These are followed by estimates for small, medium, and large firms respectively. As we can see, sorting by firm size shows that there is significant variation in the extent to which firms of different sizes benefit from location based characteristics. In general, there is considerable heterogeneity in the impact of location characteristics on costs incurred at the firm level. This heterogeneity applies to the overall effects across industries, and includes differences across firms of different sizes and by sources of agglomeration economies.

9. There are some cells in Table 3 with no values. We do not report the estimated parameters in these cases as the number of observations (see Table 2) are too few to allow any meaningful interpretation of the results, especially when the model estimates around 50 parameters. As a rule of thumb, we do not report results for estimations with less than 200 observations (firms).

Table 3. Cost elasticities of economic geography variables

	Access				Emp				IO Link				Diversity			
	overall	small (0-49)	medium (50-99)	large (100+)	overall	small (0-49)	medium (50-99)	large (100+)	overall	small (0-49)	medium (50-99)	large (100+)	overall	small (0-49)	medium (50-99)	large (100+)
Food and beverages	-0.002	-0.001	-0.001	0.000	0.016	0.000	0.002	0.011	0.006	-0.001	-0.002	0.024	-0.075	0.000	-0.012	-0.067
Textiles	0.004	0.023	0.008	-0.022	0.016	0.004	-0.033	-0.001	-0.002	-0.005	0.037	0.011	-0.102	-0.121	-0.210	-0.005
Leather	0.072	-0.017			0.025	0.005			-0.014	0.010			-0.023	-0.172		
Printing and publishing	0.022	0.005		0.032	0.000	0.012		0.034	-0.009	-0.005		-0.092	-0.062	-0.248		0.0516
Chemicals	-0.016	-0.024	-0.056	-0.044	0.021	0.021	0.059	0.049	0.000	0.003	-0.041	-0.012	-0.076	-0.457	0.042	0.250
Metals	-0.017	-0.008	0.163	-0.012	0.003	0.004	0.137	-0.036	-0.012	0.000	-0.177	0.033	0.003	-0.163	0.603	0.039
Mechanical machinery	-0.047	-0.016		0.091	0.000	0.006		-0.018	-0.001	0.000		-0.026	-0.007	-0.042		0.167
Electrical/electronics	0.008	-0.009		0.035	0.019	0.038		0.035	-0.004	0.004		0.378	-0.162	-0.835		-2.355

Note: Coefficients in bold are significant at 1%, coefficients underlined are significant at 5%.

Source: See text.

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Let us begin by looking at the impact of access to markets. Market access measures effective demand for a firm's products and inputs and the ease through which they can reach buyers and suppliers. Therefore, good market access is likely to reduce the cost of intermediate inputs as well as increase demand for the firm's products. The entrepreneur will have incentives to increase scale of production and invest in cost reducing technologies (Lall et al. 2004). At the industry-wide level, the results show that market access does not have a significant net cost reducing impact in most industry sectors. The estimated cost elasticities are negative and statistically significant for two industry sectors—metals and mechanical machinery—the elasticity values are insignificant for other sectors. For example, in mechanical machinery, the coefficient of –0.047 means that a 10 percent improvement in market access will be associated with an approximately 0.5 percent reduction in overall costs at the firm level. There is a counter intuitive result for the leather industry, where the cost elasticity is positive and significant. For small firms, the estimated elasticities are generally negative, indicating benefits from improved market access. However, the estimates are statistically significant at the 5 percent level for only two industry sectors—chemicals and metals. We also find a positive and significant estimate for the textiles industry, suggesting that there are costs associated with higher market access. Most of the estimates for medium and large industries are not statistically significant.

Next we look at results for own industry concentration, which is measured as the sum of employment in the particular industry in the region. The industry-wide estimates suggest that there are no net benefits of being located in own industry concentrations. All the estimated elasticities are positive, which suggests that costs increase if firms locate in regions with high concentrations of the same industry. These coefficients are statistically significant at the 1 percent level for four sectors and significant at 5 percent for one industry sector. We find that even when disaggregated by firm size, own industry concentration systematically provides no net benefits; on the contrary, in some instances, own industry concentration increases costs at the firm level.

The elasticities for input–output linkages (IO link) show that for most industry sectors, proximity to buyers and suppliers potentially reduces costs at the firm level. While the estimated elasticities are negative for six sectors, it is only statistically significant at the 5 percent level for the metals industry. The coefficient of –0.01 means that a 10 percent increase in the strength of buyer–supplier linkages is associated with firm-level cost reductions of 0.1 percent. That is, doubling the strength of buyer–supplier linkages is associated with a 1 percent reduction in firm level production costs. When we look at the elasticities for small firms, we find that the estimates are insignificant for most cases. For medium size firms, the elasticity is negative and significant for the metals sector. The coefficient of –0.17 means that a doubling of IO linkages is associated with a 17 percent reduction in firm-level costs. This effect is considerably stronger than the other estimates, where the cost elasticities rarely exceed 5 percent. For large firms, we find that costs increase for food and beverages and for electrical/electronics, when firms are located in regions with relatively higher buyer–supplier linkages. In fact, the coefficient of 0.38 for electrical/electronics means that doubling of IO links increases costs by 38 percent.

The estimates for local economic diversity indicate that there are considerable cost reducing benefits from being located in a diverse region. The industry-wide estimates are negative for all sectors, and significant at the 1 percent level for the Food and Beverages and Textiles sectors. The coefficient of -0.10 for Textiles means that doubling of the region's economic diversity will reduce firm-level costs by 10 percent. The results are even stronger for small firms. The estimated elasticities are negative for all industry sectors, and statistically significant for five sectors. The magnitude of these effects is really striking. For example, the estimated cost elasticity for electrical/electronics is 83 percent and for chemicals it is 46 percent. These estimates clearly indicate that there are very significant benefits of being located in a diverse economic region. For medium and larger firms however, the results do not show similar benefits of location in diverse economic regions. The cost reducing effects of being located in a diverse region are greater for small firms as they can rely on location-based externalities to a larger extent than medium and big firms. The benefits come from better opportunities for subcontracting, access to a general pool of skilled labor, and access to business services, such as banking, advertising, and legal services. In addition to these pecuniary externalities, there are potential technological externalities from knowledge transfer across industries. Larger firms being more vertically integrated and with higher fixed costs are not likely to benefit from these externalities.[10]

In general, we find that the regional economic geography has a reasonable degree of impact on the cost structure of firms. The sources and the magnitudes of these impacts vary considerably across industry sectors. The only major source of benefits that are likely to influence location choice at the margin is the location's economic diversity. This is further likely to be the case for small firms. The magnitude of the other effects are so small (elasticity values less than 5 percent), that they are unlikely to influence firm location choices.

3 Location patterns of private and state capital

This section contains an empirical test of the hypothesis that the location logic of state capital is different from that of private capital. Much of this material is summarized from Chakravorty (2003). Private capital seeks profit maximizing or efficient locations. As shown above, these are the already leading, diverse industrial regions that have the necessary infrastructure and economies of agglomeration (which, we show, are not necessarily cost-reducing). The location decisions of state capital, on the other hand, are not as oriented towards the leading industrial regions because, besides efficiency, these decisions are based on equity and security considerations.

10. While the estimated elasticity for large electrical/electronics firms is 235 percent, it is likely that this result is a statistical artifact, and driven by some outliers.

We will not revisit the literature on industrial location theory that is summarized well in Fujita et al. (1999). The basic assumption in this literature is that all capital is private capital, and all location decisions are made by profit maximizing private firms. The fact that the state is a significant owner of firms and industries is not considered. There are three major reasons why this is an omission of some consequence. First, state decisions on industry location are not necessarily or usually profit maximizing.[11] Second, in all developing nations industrialization has been state-led, so that the state, to some degree, still owns the 'commanding heights' of the industrial sector. Third, state industrial location decisions have considerable influence on the location decisions of private firms (mainly through the provision of shared infrastructure and localization economies).

Let us, like others before us, presume that market considerations are the only ones that need to be factored into the industrial location decision. There are two broad approaches to identifying the factors that influence firm location: One is survey-based; it asks decision-makers what location factors are important to them. The second is a modeling approach used to identify the revealed preferences based on site/region characteristics. A large number of factors, with some overlap, have been identified using these two approaches. In general, the most important firm location criteria are: market access, infrastructure availability, agglomeration economies, state regulations (such as environmental and pollution standards, incentives in lagging regions or for emerging technologies), and the general level of political support (see Hanushek and Song 1978; Webber 1984; McCann 1998). The survey-based approaches reveal that there is a substantial random element in the choice of location: personal reasons, chance, and opportunity, are given as explanations almost half the time (see Mueller and Morgan 1962; Calzonetti and Walker 1991).

This analysis follows the revealed preference modeling approach. We consider the following categories of factors:

(1) **Capital**, which refers to the quantity and productivity of the existing capital investments, and the availability of industrial capital from lenders.
(2) **Labor**, which refers the size of the industrial and total labor pool in the region, and the productivity of industrial labor. The size of the industrial labor pool is a measure of urbanization economies.
(3) **Infrastructure** includes elements of physical and social infrastructure. Physical infrastructure elements such as roads and transportation hubs (ports, airports) are widely considered to be key determinants of plant location. Indicators of social

[11] Other approaches to location analysis recognize the 'different locational considerations' of state capital, especially the following ones. First, the need to include and provide for the 'poor and the geographically peripheral'. Second, the absence of competition in what are often (loss-making) monopolies. Third, the need to seek popular support, and the use of state investment as a method of doing so; Fourth, the use of industrial location as the principal tool in regional development policy. Fifth, one must consider the location of security-oriented or defense-related industry, which is obviously not dictated by market factors. See Harrington and Wharf (1995), Markusen et al. (1991), Chapman and Walker (1991).

infrastructure such as health and education standards provide an understanding of quality of life conditions, and may be considered to be worker amenities, which may be critical for some industries.

(4) **Regulation** broadly refers to the system of incentives (such as tax breaks) and disincentives (such as environmental standards) which have to be factored into the location decision. This kind of highly localized or disaggregated information is difficult to get at the national level. This is especially true of India, where the key to decision-making may not be the localized incentive system but a sense of political support for private sector-led industrialization in the region. Regimes that are ideologically opposed to liberalization are unlikely to provide the conditions that welcome new private investments, or may be perceived to be unfriendly to capital.

(5) **Geography** includes spatial characteristics such as coastal or metropolitan location. Coastal locations provide access to the external world and physical amenities desired by high-level managers. Metropolitan locations provide large local markets, urbanization economies, and, often, localization economies.

3.1 Data and summary conditions

Earlier we have shown why it is necessary to conduct location analysis using small spatial units. We have also discussed the ASI database. Here the ASI for 1993-94 provides data for the pre-reform or initial conditions.[12] The second or post-reform database was created from the published records of the private sector firms, the Center for Monitoring the Indian Economy (CMIE). It is widely acknowledged that the best economic data in India are being generated by the CMIE (especially since there is no state agency tracking post-reform projects). The database used here is a collation of new project information published quarterly by the CMIE for the period 1992-98. The 1991 data were ignored, as they were unlikely to be an accurate list of 'new' investments; after all, the reforms had only been announced in July 1991. This database, with about 4,650 records or projects (covering the entire period), containing only those projects that have been completed or are under implementation, and those that are not being funded solely by local government, forms the basis of all the post-reform calculations.

The new or post-reform investments, as identified from the CMIE data, total just over seven trillion Indian rupees (not including the direct investments made by state/local governments, which have been ignored throughout this analysis).[13] Exactly 50 percent of

12. Since the 1993-94 data cover every unit that was in operation in 1993, whenever built, and since the period 1991-93 (the first two reform years) is too short for any substantial industrial unit to be approved and go into production, this is the most realistic measure of Indian industry for the pre-reform period.

13. These figures also do not include investments in Jammu and Kashmir nor any of the far northeastern states (Arunachal Pradesh, Manipur, Meghalay, Mizoram, Nagaland, or Tripura). The total of these investments comprise less than 0.2 percent of nationwide investment, is almost entirely by the central and state governments, and is probably of dubious reliability. These data can be ignored without much loss of information or rigor.

Table 4: Distribution of industrial investment by type of ownership

	Fixed Capital				
	1973-74	1985-86	1989-90	1994-95	1992-98
Public	60.1	61.6	55.0	43.3	30.7
Joint	5.6	10.2	7.5	9.5	12.0
Private	34.3	28.2	37.5	47.2	57.3

Source: Annual Survey of Industries (different years), and CMIE for 1998 (authors' calculations).

this investment is by the domestic private sector, 7.3 percent is FDI, 30.7 percent is by the central government, and 12 percent is in the joint sector (or private–public partnerships). For the purposes of the analysis here, the domestic private sector and FDI are added together to comprise the private sector. The joint sector data, which belongs in neither of our exclusive categories, have also been omitted from the analysis.

Table 5: Summary investment statistics by location

	Private Sector	Central Government
Number of districts with investment	294	164
Average investment in receiving districts	13.55	11.40
All India per-district investment	9.84	4.61
Metropolitan Districts		
number of districts with investment	17	14
average investment per receiving district	40.14	25.14
share of total sectoral investment (%)	17.13	18.82
Non-Metropolitan districts		
number of districts with investment	277	150
average investment per receiving district	11.92	10.12
share of total sectoral investment (%)	82.87	81.18
Coastal Districts		
number of districts with investment	48	32
average investment per receiving district	40.82	22.00
share of total sectoral investment (%)	49.18	37.65
Inland Districts		
number of districts with investment	246	132
average investment per receiving district	8.23	8.84
share of total sectoral investment (%)	50.82	62.35

Source: Data sources are discussed in the text.

Note. The investment averages are in billion rupees (in June 2003, US$1=INR48).

Table 4 shows the extent to which the relative shares of the public and private sectors have evolved since the early 1970s. The decline of the public sector since the beginning of the Rajiv Gandhi reforms in 1985-86 is evident. The new investment data (1992-98) suggests that this decline has accelerated. This is a fundamental condition of liberalization and structural reform, and underlines our assertion that the state's role in industry ownership and location is now much diminished. Table 5 provides some indications on the spatial distribution of the post-reform investments. The data show that private sector investments have a wider spatial coverage and a much stronger coastal bias (almost half the total private investments are in the coastal districts). The metropolitan data are unclear; certainly the intensity of investments in these districts is far higher than the non-metropolitan averages for both private and state sectors, but there appears to be some dispersal away from metropolitan districts.

3.2 The model and methodological notes

Following the earlier discussions, a general model of new investment location determination can be written formally as:

$$I_{new} = f\{K, L, I, R, S\} \quad (7)$$

Where K, L, I, R, and S represent sets of explanatory Capital, Labor, Infrastructure, Regulation, and Spatial/Geographical variables respectively. I_{new} is the log transformation of the raw investment amount where the investment amount depends on the sector being modeled. That is, I_{new} is I_{newP} when only private sector investments are considered, and is I_{newG} when only central government investments are considered. The *Capital* set K has three variables:[14]

1. ASI-LOG is the log of total pre-reform investment (fixed capital).
2. INDUSTRIAL CREDIT is per capita lending to local industry by financial institutions.
3. CAPITAL_PROD is a measure of the productivity of capital at the district level, and is calculated as the value added per unit of fixed capital for existing industry (calculated from the ASI data).

There are three *Labor* variables:

1. LOGPOP is the log of district population.
2. LABOR_MANUF is the percentage of workers employed in non-household manufacturing industry.
3. LABOR_PROD is a measure of the productivity of labor and is calculated as the value added per unit of factory labor (calculated from the ASI data).

14. The data definitions and sources, unless mentioned otherwise, are as follows. **Literacy:** from the 1991 population census, reported in 'Profiles of Districts', defined as the percentage of the population that is literate. **Infant Mortality:** from Rajan and Mohanchandran (1998), defined as the number of deaths per 1,000 live births at age 5, estimated from the 1991 population census. **Manufacturing Labor**: from the 1991 population census, reported in 'Profiles of Districts', defined as the percentage of workers employed in non-household manufacturing industries. **Industrial Credit**: reported in 'Profiles of Districts', defined as the per capita bank credit to industries derived from the information on scheduled commercial bank branches, deposits and credits on the last Friday of March 1993. 'Profiles of Districts' is a CMIE publication in 1993 from Bombay.

There are three *Infrastructure* variables:

1. INFRA is a measure of physical infrastructure, and is calculated as a function of proximity to national highways, airports and ports. The values of INFRA range from 0 to 3, where 3 represents a situation where the given district has at least one national highway passing through it (weight 1), has at least one airport within 100 kilometers (weight 1), and has at least one port within 100 kilometers (weight 1). INFRA is expected to be positively related to I_{new}, especially I_{newP}.
2. LITERACY, is the percentage of the adult population that is literate.
3. INFNT_MORT is the mortality rate at age five years per 1000 live births.

The only *Regulation* variable is:

1. SOCIALIST, which is a dummy variable that takes a value of 1 for every district in West Bengal and Kerala, the two consistently communist-ruled states in the country. Districts in Tripura (another socialist state) were not used in the analysis, and we chose not to assign districts in Bihar as socialist. Bihar has what may be called a populist caste-based government, and giving it the distinction of socialism, for better or worse, may be inappropriate. The other problem with including Bihar in this category is that every other state that has had left-of-center governments in the early 1990s (such as Karnataka and Orissa) would also have to be similarly characterized. As far as this variable is meant to represent political will, which may be resistance to liberalization, or its counterpart, enthusiasm for reforms, Bihar should be so categorized. But, understanding the lack of investment in Bihar is an important goal, and we preferred not to cloud the issue by introducing the socialist element.

The *Spatial* set S has three elements:

1. COASTAL, a dummy variable that takes a value of 1 for all coastal districts (57 districts were classified coastal, i.e., situated on either the Bay of Bengal or the Gulf of Arabia).
2. METROPOLITAN, a dummy variable that takes a value of 1 for all metropolitan districts i.e., the core city district and the surrounding suburban districts (26 districts were classified metropolitan).
3. SPATIAL LAG: SPATIAL LAG is a term that corrects for spatial autocorrelation and also has geographical meaning.[15] It is a measure of spatial clustering, and the parameter estimates for this term will indicate the degree to which new investments cluster together; i.e., the extent to which I_{newP} is likely to locate in the proximity of other I_{newP}.

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15. The existence of spatial autocorrelation or spatial dependence poses serious problems in regression modeling, much like serial autocorrelation does (see Anselin 1995). One of the ways of dealing with this problem is to add a 'spatial lag' term on the right-hand side, where the lag value for a given parcel is some summary of the dependent variable in proximate parcels. The argument for using the spatial lag correction for a given district is that its investment is not independently caused by the regressors, but is dependent on the regional investment situation. Therefore, the spatial lag term corrects for spatial autocorrelation in spatial regression models, and at the same time is a measure of clustering.

Table 6. Determinants of probability of receiving investment

Variable	Private sector	Central government
ASI-LOG	0.170 ***	0.177 *
	(11.01)	(6.22)
IND_CREDIT	$4*10^{-4}$	$4*10^{-4}$
	(0.46)	(1.91)
CAPITAL_PROD	-0.405	0.224
	(1.89)	(0.65)
LOGPOP	0.663 ***	0.947 ***
	(7.70)	(14.47)
LABOR_MANUF	0.093 *	0.059 *
	(2.77)	(3.04)
LABOR_PROD	0.003 **	$9*10^{-4}$
	(5.86)	(2.21)
INFRA	0.353 **	0.093
	(4.52)	(0.50)
LITERACY	-0.003	-0.007
	(0.06)	(0.38)
INFNT_MORT	-0.002	$-3*10^{-4}$
	(0.16)	(0.01)
SOCIALIST	-1.189 *	0.181
	(3.67)	(0.12)
COASTAL	-0.733	-0.366
	(1.57)	(0.845)
METROPOLITAN	4.109	-0.215
	(0.11)	(0.07)
SPATIAL_LAG	0.429 ***	0.076
	(22.98)	(0.55)
Constant	-7.957 ***	-11.225 ***
	(13.68)	(29.89)
Chi-square	172.32	117.40
Correctly predicted non-zero districts	91.50%	59.15%

Notes: Total number of districts = 405. Number of districts with non-zero private sector investment = 292. Number of districts with non-zero central government investment = 164. Figures in parenthesis are Wald statistics. ***Significant at 1%. **Significant at 5%. *Significant at 10%.

Source: Authors' calculations.

A major problem in undertaking Ordinary Least Squares (OLS) regressions with this data is that the assumption of normality of the dependent variable is seriously violated. There are large numbers of districts with no investment (the private sector has 292 districts with investment, 113 without investment; the central government sector has 164 districts with investment, 241 without investment). These are not missing data, but are real measured absence of industrial investment. Hence, we cannot use OLS models on the full dataset. But using only the non-zero data would not allow analysis of the absence of investment.

Therefore we use two sets of models: a linear model set for the non-zero cases; and a logistic model set where the dependent variable is binary—i.e., it takes a value of 1 when there is some non-zero investment (call this ‘success’), and 0 when there is no investment (call this situation ‘failure’).

3.3 Model findings

The private sector logistic model (see Table 6) has far greater explanatory power than the model for the central government. The Chi-square value is higher, as is the percentage of correctly predicted non-zero new investment districts. The two most important determinants of success or failure for private investment, that is, whether or not a district receives any new private sector investment, are the quantity of investment in the pre-reform era (ASI-LOG), and the quantity of new private investment in the neighboring districts in the post-reform era (Spatial Lag). On the other hand, the Spatial Lag term is not significant for central government investment, implying that there are no clustering effects in this case. Similarly the ASI-LOG variable has the expected but less significant effect in the central government model.

The set of Labor variables (population size, size of manufacturing labor force, and labor productivity) are all significant for the private sector model, indicating that labor considerations play a significant role in the private sector location decision. In the central government model, labor is a less important consideration—the district population size is significant, as is, to a lesser extent, the size of the manufacturing labor force, but labor productivity is of no consequence. The role of infrastructure is as expected. The literacy and infant mortality levels have little bearing on whether a district receives private sector or central government investment. The availability of physical infrastructure, on the other hand, plays a weak positive role in attracting private sector investment, but has no bearing on locating central government investment. Finally, private investment tends to avoid socialist states, but central government investments appear to be indifferent to local political orientation.

The OLS regression model (see Table 7) for the private sector is strong and robust; for the central government it is weak, with little explanatory power. The two most revealing trends of the logistic models are further confirmed here: First, the two most significant predictors of the quantity of new private investment are ASI-LOG and Spatial Lag, whereas in the central government model, ASI-LOG is not significant; however, the Spatial Lag variable is significant (unlike in the logistic model), suggesting that though the odds of getting new central government investment are no better in clusters, when such investments do take place, the quantity of investment is spatially correlated. In other words, the quantity of existing investment in a given district *i* or the quantity of new private investment in the neighbors of district *i*, are the most important predictors of the quantity of new private sector investment in that district. Second, Labor characteristics are significant in predicting the quantity of new private sector investments, but not for central government investments.

In fact, population size and manufacturing labor force size have the counter-intuitive sign (though not statistically significant) in the central government model.

Table 7. Determinants of quantity of investment

Variable	Private sector (n = 292)	Central government (n = 164)
ASI-LOG	0.161 ***	0.077
	(3.33)	(0.89)
IND_CREDIT	$2*10^{-6}$	$3*10^{-4}$ *
	(0.02)	(1.91)
CAPITAL_PROD	0.059	0.109
	(0.19)	(0.32)
LOGPOP	1.453	-0.335
	(0.81)	(1.11)
LABOR_MANUF	0.063 ***	0.001 *
	(2.63)	(1.70)
LABOR_PROD	0.001 **	-0.042
	(2.35)	(1.21)
LITERACY	-0.0005	-0.113
	(0.06)	(0.67)
INFNT_MORT	0.006 **	-0.007
	(2.35)	(0.45)
INFRA	0.162	$9*10^{-5}$
	(1.52)	(0.02)
SOCIALIST	-0.826 *	-0.583
	(1.93)	(1.04)
COASTAL	0.965 ***	0.540
	(3.18)	(1.21)
METROPOLITAN	0.609	0.532
	(1.23)	(0.77)
SPATIAL_LAG	0.225 ***	0.337 ***
	(3.51)	(2.63)
Constant	-0.276	6.408 **
	(0.19)	(2.48)
F (significance)	11.13 (.00)	2.30 (.00)
R-square (adjusted)	0.310	0.094

Note: This is an OLS regression model. The dependent variable is LOG of (private sector or central government) investment. ***Significant at 1% (two-tailed). **Significant at 5% (two-tailed). *Significant at 10% (two-tailed).

Source: Authors' calculations.

The infrastructure variables generally have the least explanatory power in both OLS models. In the central government model, none of the infrastructure variables are significant. Unexpectedly, infant mortality is seen to be weakly but positively related to new private sector investment. It is possible that this is an artifact of the coexistence of high infant mortality levels and richness of natural resource availability. Finally, the coastal variable is strongly significant in the private sector model. This is expected from the data reported in Table 5.

3.4 Discussion

This analysis was based on the argument that private sector investment location decisions are based on profit-maximizing or efficiency-related factors, whereas the central government investment location decisions would be less influenced by them. We also argued that in seeking efficient locations, private sector investments would tend to favor existing industrial clusters and metropolitan centers with access to the coast, and avoid regions with inhospitable local governments. The results provide definite support for both propositions. Location decisions of the private sector are indeed guided by efficiency-related factors to a far greater extent than such decisions by the central government. In addition, private sector investments are seen to favor existing industrial clusters (providing support for the idea that the already leading industrial regions would benefit most), and coastal districts, and are seen to be averse to communist or socialist states. There is less support for the argument that such investments also favor metropolitan regions. On the other hand, central government investments appear not to be guided by any clear geographical consideration. These findings are consistent in both modeling frameworks: success/failure, and the quantity of new investment—in other words, in determining whether or not a district gets new investment, and in determining the quantity of new investment.

It is clear that for the private sector the most significant factors are the size of investment from the pre-reform period in the same district, and the size of new post-reform investment in the neighboring districts. The first factor suggests continuity, or evidence of a historical process of investment location. The second factor suggests that new investments are clustered. In the central government models there is very weak evidence of some continuity (none as far as the quantity of new investment is concerned); and somewhat stronger evidence of clustering (though not nearly as strong as for the private sector).[16]

4. Conclusion

Our main finding from the first part of the analysis is that industrial diversity (that is, the local presence of a mix of industries) provides significant cost savings for individual firms. Empirical evidence from Indian firms shows that this cost saving is the most significant

16. Note that these models are unable to identify all the factors that influence industrial location decisions. There is a random element in the distribution (remember that personal preference or chance is the most common factor in the location decision). Also there are non-random local factors—such as local- or state-level policy changes (tax incentives, the location of export processing and/or free trade zones, etc.), and some intangibles like culture, entrepreneurship, and initiative—that have not been modeled here.

factor for firms of all sizes and in all sectors of manufacturing industry. Other spatial factors that, in theory, have some productivity enhancing effects (such as market access, own industry clustering) are found to have little or no influence on profitability. At the national level, this raises questions on the validity of developing 'specialized clusters' in remote areas, as instruments to promote regional development in lagging or backward regions. Such approaches have been implemented with limited success historically, but have seen a resurgence with the 'Porter style' competitive advantage analysis. On the other hand, policies that encourage the creation and growth of mixed industrial districts are likely to be more successful than single industry concentrations.

The second part of the analysis confirms our expectations that private industry seeks profit-maximizing locations whereas state industry is far less oriented toward such locations. The emerging spatial pattern of industrialization is led by investments by the private sector which is demonstrably averse to lagging and inland regions, just as the central government is becoming a weaker player. If the state will not or cannot be any more involved (for the foreseeable future the state can only be less involved in industrial ownership), and the private sector cannot be induced to lagging regions till some local political–economic problems are resolved, and these local problems may not be resolved without investment and growth, how can industrial development reach the lagging regions, and, without spatially balanced industrial growth, how can spatial income inequalities be mitigated?

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