Agglomeration economies and their effects on technical inefficiency of manufacturing firms: Evidence from Pakistan

Abid A. Burki[a] and **Mushtaq A. Khan**[b]

[a] Lahore University of Management Sciences (contact: burki@lums.edu.pk), [b] Lahore University of Management Sciences (contact: mushtaq@lums.edu.pk)

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International Growth Centre
London School of Economics and Political Science
4th Floor,
32 Lincoln's Inn Fields
Houghton Street
London WC2A 2AE
United Kingdom

For media or communications enquiries, please contact Mazida Khatun
mazida.khatun@theigc.org

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by

ABID A. BURKI
Lahore University of Management Sciences

MUSHTAQ A. KHAN
Lahore University of Management Sciences

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ABSTRACT:

This paper uses plant level data of Pakistan's manufacturing sector and investigates whether industry agglomeration has a positive or negative effect on technical inefficiency of firms. We test this hypothesis by using the translog stochastic frontier and technical inefficiency model with cross-section data from CMI for 1995-96, 2000-01 and 2005-06. We also evaluate the nature and extent of industry agglomeration. The paper shows that geographic concentration of industries was widespread, but it was declining over time. Size of population, road density, and pool of technically trained workers all helped to promote agglomeration of industries. In the beginning, firms were not valuing the importance of technological spillovers, as they were benefiting from localization economies (or intra-industry spillovers). However, this trend had reversed in more recent years, which may be attributed to the inability of firms to cope with increased regional competition. Convincing evidence shows that industry agglomeration has significantly benefited firms, indicated by a strong negative association between the agglomeration index and technical inefficiency of firms. Moreover, increased localization was beneficial for textile and leather industry, but not so for firms in food, beverage and tobacco, and chemical, rubber and plastic industries where firms were greatly benefitting from urban diversity in the districts, including information transfer, infrastructure availability, access to business services, information technology, and financial services. These results have strong policy implications.

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I. INTRODUCTION

Geographic concentration of industries is one of the most striking features of economic activity in both developed and developing countries. A vast empirical literature from developed countries suggests that firms and workers are unevenly distributed across spatial units; they agglomerate in some regions more than others [e.g., Ellison and Glaser (1997), Maurel and Sedilot (1999), Alonso-Villar et al. (2004), Bertinelli and Decrop (2005)].

Following Krugman's work, numerous theoretical models have been developed on the economics of agglomeration, but similar claims cannot be made about empirical identification of the theoretical mechanisms [Duranton and Puga (2004)]. A large empirical literature studies agglomeration economies in developed countries [e.g., Ellison and Glaeser (1997), Holmes(1999), Alecke et al. (2006), Glaeser (2008), but few such studies also discuss the nature of scale externalities in developing countries [e.g., Henderson et al. (2001)].

Given that the firms are not uniformly distributed across regions, it is important to know the consequences of industry concentration on productivity and other dimensions of firm level efficiency. Do firms benefit from industry agglomeration? Or to what extent agglomeration economies contribute to productivity of the firms? Few studies estimate average production functions to estimate firm productivity by relying on production technology which relates output (cost) to primary inputs (input prices, outputs) and a vector of economic geography variables as sources of agglomeration economies [e.g., Lall et al. (2004), Lall et al. (2005)].

These studies assume that the firms involved in production process do not face technical inefficiencies. In contrast, the vast stochastic frontier literature postulates the existence of technical inefficiencies in the production process [Aigner et al. (1977), Meeusen and van den Broeck (1977)]. Over the last more than three decades, countless empirical studies in the stochastic frontier literature have found that technical inefficiency of firms, farms and banking institutions is widespread [Caves and Barton (1990), Berger and Humphrey (1997), Bravo-Ureta et al. (2007)].[1] How sensitive technical inefficiency of firms is to agglomeration economies and other environmental production conditions have not heretofore, so far as we could determine, been investigated in any country.

The main difficulty in answering this question is to select relevant variables as sources of technical inefficiency of the firms. They may include a number of agglomeration forces such as low transportation costs, proximity to demand centers, presence of specialized labor, and natural advantage to name a few. The problem is that some of these variables as determinants of technical inefficiency are observed while others are un-observed. Since these variables may have great influence on firm performance, omitting them may produce biased results and if observed including all of them may dilute the true differential effects on firm performance. Thus, in an attempt to elicit true differential effects of the agglomeration variables on the performance of firms, we utilize two composite sources of industry agglomeration portrayed by the industry level Ellison-Glaser agglomeration index, and the regional level diversity index to measure intra-industry and inter-industry spillovers, also known as localization and urbanization economies, respectively.

[1] For a review of this literature, see among others, Forsund et al. (1980), Schmidt (1986), Bauer (1990), Lovell (1993), Greene (1993), Kumbhakar and Lovell (2000).

To implement this scheme, we use three-year (1995-96, 2000-01 and 2005-06) plant level cross-section data of the manufacturing sector of Pakistan, obtained from the Census of Manufacturing Industries (CMI). We begin by estimating the Ellison and Glaeser (1997) index of industry agglomeration to evaluate the nature, extent and sources of spatial clustering in Pakistan. We then estimate the regional level diversity index [Henderson et al. (2001) to investigate the nature of intra-industry and inter-industry spillovers and comment on its dynamic process. Next, we ask whether industry agglomeration and the diversity index have a positive or a negative effect on performance of manufacturing firms in Pakistan. We test this by using the translog stochastic production frontier and technical inefficiency effects model by applying the methods developed by Kumbhakar et al. (1991), Reifschneider and Stevenson (1991) and Battese and Coelli (1995).

The remainder of the paper is organized as follows. Section II reviews the literature on agglomeration economies. Section III discusses the nature, extent and sources of industry agglomeration. Sections IV and V describe the estimation procedures for the stochastic frontier model and data and variables. Section VI contains the estimation results, and the last section gives conclusions and policy implications of the paper.

II. REVIEW OF LITERATURE

We begin by briefly reviewing the literature on geographic concentration and spatial inequality, premised on new economic geography popularized, among others, by Krugman (1991a, 1991b).[2] In recent years, progress made in successfully modeling increasing returns to

[2] For early works, see Marshall (1890), Hotelling (1929), Florence (1948), Fuchs (1962), Henderson (1974), among others. For more recent contributions, see among others, Krugman (1991a, 1991b), Krugman and

scale has made it possible to analyze the economics of agglomeration [see, Dixit and Stiglitz (1977), Krugman (1991b), Fujita et al. (1999)]. These innovations have guided scholars to formalize some traditional concepts in the literature to explain geographic concentration of industry. They include the Marshallian concepts of the role of technological spillovers, pooling of market for skilled workers, and availability of non-tradable intermediate inputs as well as Hirshman's (1958) nonpecuniary externalities on account of forward and backward linkages and market access due to Myrdal (1957) and Arthur (1990).

In general, increasing returns to scale play an important role in explaining why economic activities are spatially concentrated. The 'folk theorem' of spatial economics [see, Fujita and Thisse (1996)] says that under non-increasing returns when high transportation costs are present, industry would locate at diversified places to minimize cost of reaching consumers. In this case, many firms would operate at small scale to produce for the available market. However, when increasing returns to scale are present, firms would benefit by locating at concentrated places where they could enhance production to cater increasing demand. Increasing returns tend to decrease per unit cost due to specialization of labor and improvements in technology leading to internal economies [Lall et al. (2004)].

The agglomeration economies consist of localization economies and urbanization economies. Localization economies refer to within-industry or intra-industry benefits accruing through knowledge-diffusion, buyer-supplier networks, subcontracting facilities and a pool of skilled workers. Urbanization economies arise from across-industry spillovers such as supply of other

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Venables (1995), Kim (1995), Krugman and Livas (1996), Ellison and Glaeser (1997), Fujita et al. (1999), Puga (1999), Fujita and Thisse (2002), Hanson (2005).

complementary services, e.g., financial institutions, marketing and advertising agencies, and other cheap infrastructure, etc.

The phenomenon of localized versus dispersed industries is explained by the centripetal and centrifugal forces. The centripetal forces of increasing returns lead to concentration of activities arising from internal and external economies from interaction, while the centrifugal forces lead to dispersion of activities arising from over concentration of firms in an area that increases costs of immobile factors, e.g., higher land prices and land rents, higher wages and higher commuting time for workers. Rising costs of agglomeration deter further concentration of firms in the surrounding areas and pull economic activities in the opposite direction [Fujita and Thisse (1996)]. A balance between centripetal and centrifugal forces leads to equilibrium [Kruger (1991, 1998)].

Spatial inequality outcome is determined by the balance between centripetal and centrifugal forces in a region. The theoretical models suggest that this balance would depend on model parameters [Krugman (1991b), Henderson et al. (2000), Kim (2008)]. For example, when transport costs are extremely high, the industry would be highly dispersed. With immobile labor, an initial decrease in transport cost would lead to concentration of industry. However, when transport cost is extremely low and labor is immobile, industry would tend to spread across regions because further agglomeration of industry would increase prices of immobile factors. So agglomeration of firms would be highest at intermediate levels of transport costs because the firms would like to exploit cost and demand linkages [Puga (1999)].

A number of policy implications emerge from the existing literature that helps our understanding of the spatial inequality in developed and developing countries [Kim (2008)].

Firstly, the magnitude of localization economies (within industry spillovers) is much more than urbanization economies (across industry spillovers). If policy makers want to influence spatial inequality they may use “industry-specific” policies to get desired results [Henderson et al. (2001), Kim (2008). Secondly, in general, “extractive industries” are more concentrated followed by manufacturing while services are most dispersed [Henderson (1988), Chen (1996), Henderson and Kuncoro (1996), Henderson et al. (2001)]. In manufacturing, traditional industries such as textiles are more concentrated while high-tech industries are more dispersed. However, there is no consensus on the most important source of agglomeration economies [see also, Rosenthal and Strange (2004), Overman and Venables (2005)]. Thirdly, political institutions matter in determining regional and urban spatial inequality [Kim 2008)]. Presence of strong state and local government in a country tends to promote greater spatial equality as compared with countries where federal government is relatively strong. Centralized versus decentralized governments have different political motivations due to which they prefer different set of public infrastructure that have bearing on spatial inequality. Fourthly, investments in transport and communication infrastructure seem to promote spatial equality across regions. In this regard, Rosen and Resnick (1980) indicate the link with railroad investments, and Henderson (2002) and Baum-Snow (2007) with road and highway investments. Finally, a policy meant to reduce EU spatial inequality has remained ineffective [Puga (2002)], while the Korean policy to reduce excessive agglomeration of industry around Seoul has been successful [Henderson et al. (2001)].

While the empirical evidence on spatial inequality and agglomeration economies in developed countries may have immense value, the pattern of industrial development and its impact on technical inefficiency of firms in developing countries like Pakistan is fundamentally different from the developed countries. But despite the obvious policy concerns and gaps in understanding of the industrial sector of Pakistan, there has been no systematic evidence on regional and spatial mapping of manufacturing industries in the country. Moreover, it is also unclear how agglomeration of manufacturing industries affects technical inefficiency of firms. We turn to these questions below.

III. NATURE, EXTENT AND SOURCES OF INDUSTRY AGGLOMERATION

Here our goal is to explore whether manufacturing industries in Pakistan are agglomerated, and if so, which ones. We also present evidence on what factors drive agglomeration of industries in Pakistan. We take districts as spatial units, which represent the third-level of administrative jurisdiction after provinces and administrative divisions. Because the area boundary changes for the districts are quite common, the number of administrative districts has increased from 43 in 1951 to 106 in 1998. To avoid distortions in district boundary changes overtime, we freeze district boundaries at 1981 population census when the number of administrative districts was 65. However, our sample consists of 56 districts because we treat four administrative divisions of Balochistan as districts while Islamabad and Rawalpindi are merged to form a single district.

III.1 Industry Agglomeration Index

To measure the nature and extent of geographic concentration of industries we follow the method proposed by Ellison and Glaeser (1997). The index is based on a rigorous statistical model that takes random distribution of plants across spatial units as a threshold to compare observed geographic distribution of plants. Ellison and Glaeser (1997) assume that plants make location decisions to gain from internal and external economies peculiar to a particular location. Because the industrial structure in Pakistan consists of many small, medium and large plants, proper weights are required to correct for the diverse sizes of plants and this is taken care of in the Ellison and Glaeser (EG) index. They present the following estimator to measure the agglomeration of industries

$$\theta_j = \frac{\sum_{i=1}^{M}\left(s_{ij}-x_i\right)^2-\left(1-\sum_i x_i^2\right)H_j}{\left(1-\sum_i x_i^2\right)\left(1-H_j\right)}$$

where s_{ij} is the share of industry $j's$ employment located in district i; x_i is the share of industry's overall manufacturing employment in district i; $\sum_i\left(s_{ij}-x_i\right)^2$ is an index of raw geographic concentration given by the sum of squared deviations of employment shares of the industry j known as Gini-coefficient; $H_j=\sum_k M_{kj}^2$ is a Herfindahl-style measure of the industry $j's$ plant level concentration of employment, where M_{kj} is the *k*th plant's share in industry $j's$ employment. In practice, the value of the EG index indicates the strength of agglomeration externalities in an industry. Usually a θ score of more than 0.05 indicates highly agglomerated industry; a score of between 0.05 and 0.02 suggests moderately agglomerated industry and a score of less than 0.02 shows randomly dispersed industry.

We use firm level manufacturing sector data of Pakistan from the *Census of Manufacturing Industries* (CMI) to measure industry agglomeration. The CMI provides data for 2-digit, 3-

digit, 4-digit and 5-digit classifications under the Pakistan Standard Industrial Classification (PSIC) according to geographic subdivision at the district, province and national levels. Taking data from CMI 2005-06 we measure industry agglomeration at the 3-digit level. Results of the EG index are also compared with raw geographic concentrations known as Gini index and Herfindahl index.

Table 1 reveals that industry agglomeration is widespread in the Pakistani industry. The evidence shows that 35.3% industries are highly agglomerated, 38.2% are moderately agglomerated and only 26.5% are not agglomerated. The most highly concentrated industry is ship-breaking with EG index of 1.04; it also exhibits a skewed distribution of activity in only one district as indicated by a high Gini coefficient that measures the distribution of employment shares across districts. This is expected result since ship-breaking industry is located only in Gadani (Kalat division) of Balochistan. Sports and athletic goods (PSIC 392) is the second most highly agglomerated industry with the EG index value of 0.90, where high value for the Gini index (0.842) indicates that the industry is located in few districts and low value for Herfindahl index (0.077) shows that the employment is distributed across many plants. Located in Sialkot and its surrounding districts, the driving force for concentration of sports and athletic goods industry is natural advantage of specialized labor, industry spillovers and local transfer of knowledge. Other most concentrated industries represent sectors where it is critical for the industry to reach to the final consumers or the suppliers, e.g., furniture and fixtures, scientific instruments, pharmaceutical industry, wearing apparel, handicrafts and office supplies, printing and publishing, pottery and china products, paper and paper products, etc. On the other hand, the demand for least concentrated industries is diversified across many

Table 1. Agglomeration of 3-digit manufacturing industries in Pakistan, 2005-06

3-digit PSIC	Industry	Rank	No. of Plants	No. of Districts	Herfindahl index	Gini coefficient	Ellison-Glaeser index
394	Ship breaking	1	30	1	0.035	0.965	1.043
392	Sports and athletics goods	2	51	5	0.078	0.842	0.901
332	Furniture and fixtures	3	34	8	0.076	0.268	0.231
385	Scientific instruments	4	95	7	0.052	0.218	0.193
350	Pharmaceutical industry	5	213	22	0.017	0.171	0.171
322	Wearing apparel	6	236	12	0.025	0.164	0.156
393	Handicrafts and office supplies	7	43	12	0.048	0.177	0.151
342	Printing and publishing	8	43	5	0.176	0.271	0.141
361	Pottery and china products, etc.	9	97	7	0.058	0.175	0.139
341	Paper and paper products	10	131	22	0.117	0.210	0.124
325	Ginning and bailing of fibers	11	540	27	0.004	0.096	0.099
383	Electrical machinery	12	240	19	0.072	0.125	0.068
372	Non-ferrous metals	13	41	7	0.073	0.108	0.047
380	Fabricated metal, cutlery and aluminum products	14	75	15	0.058	0.092	0.044
382	Non-electrical machinery	15	206	25	0.041	0.075	0.042
354	Petroleum refining, petroleum products and coal	16	30	12	0.142	0.164	0.041
369	Other non-metallic mineral products	17	311	32	0.026	0.059	0.039
352	Other chemical products	18	150	24	0.051	0.081	0.038
356	Plastic products	19	141	20	0.017	0.048	0.035
381	Copper and brass industrial products	20	111	17	0.041	0.067	0.033
321	Made-up textiles, knitting mills, carpets and rugs	21	261	23	0.024	0.049	0.030
323	Leather and leather products	22	227	22	0.028	0.052	0.029
311	Dairy products and processed food	23	1190	55	0.010	0.033	0.026
384	Transport equipment	24	186	15	0.041	0.057	0.021
362	Glass and glass products	25	34	13	0.113	0.121	0.020
320	Spinning and weaving of cotton & wool	26	1081	44	0.006	0.023	0.019
324	Footwear manufacturing	27	35	10	0.255	0.247	0.015
331	Wood and cork products	28	15	10	0.138	0.139	0.014
351	Industrial chemicals	29	111	21	0.028	0.029	0.003
371	Iron and steel industries	30	198	18	0.463	0.426	-0.005
314	Tobacco industry	31	13	6	0.232	0.207	-0.012
313	Beverage industry	32	36	16	0.105	0.080	-0.020
355	Rubber products	33	30	10	0.198	0.161	-0.030
312	Animal feed & ice factories	34	65	20	0.104	0.067	-0.035

districts due to which they have high Gini-coefficient, e.g., iron and steel (0.426), footwear (0.247) and tobacco (0.207), but their employment is distributed across few large plants as indicated by high Herfindahl index, e.g., iron and steel (0.463), footwear (0.255), tobacco (0.232) and rubber (0.198).

We also examine whether the most agglomerated industries in 2005-06 were also so in the previous years. Due to data limitations, we conduct this analysis on the data from Punjab.[3] We select three data points over the 10-year period, i.e., 1995-96, 2000-01 and 2005-06.[4] Table 2 shows that industry rankings do not significantly diverge from the national rankings, except industry 393 and 354 mostly located in Sindh. In general, industry agglomeration levels decline overtime, except industry 381 and 383. More than 50% of the most concentrated industries experience sharp decline in first five years, which is attributed to more firms entering the industry. A fall in industry specific Gini index seems to corroborate this evidence. Likewise, moderately concentrated industries also show a consistent decline in the EG index. Where the industry concentration goes up, the magnitude of the increase is often much smaller than the decrease. An obvious exception is tobacco and non-ferrous metal industry explained by exit of some plants that makes a dramatic impact both on the Gini index and the EG index.

We also ask that what forces drive agglomeration of manufacturing industries in Pakistan. There are three types of transport costs that play an important role in “moving goods”, “moving people” and “moving ideas” or knowledge spillovers [Marshall (1920)]. Firstly, the firms like to locate near consumer demand centers and input suppliers to save shipping cost.

[3] The plant-level data of 1995-96 and 2000-01 was not available for for Sindh, KP and Balochistan provinces.
[4] CMI 1995-96 and 2000-01 had same PSIC classification, but CMI 2005-06 had a changed classification. For consistency, we regrouped CMI 2005-06 to fit into CMI 1995-96 classification.

Table 2. Geographic concentration of 3-digit industries in Punjab, 1995-96 – 2005-06

3-digit PSIC	Industry	1995-96	2000-01	2005-06
	Fifteen most concentrated industries in 1995-96			
392	Sports and athletics goods	1.047	1.069	0.913
385	Scientific instruments	0.861	0.589	0.280
362	Glass and glass products	0.504	0.307	0.191
361	Pottery and china products, etc.	0.416	0.327	0.165
371	Iron and steel industries	0.415	0.391	0.276
322	Wearing apparel	0.379	0.209	0.077
350	Pharmaceutical industry	0.355	0.351	0.339
384	Transport equipment	0.231	0.364	0.145
355	Rubber products	0.216	0.089	-0.004
380	Fabricated metal, cutlery, aluminum and products	0.213	0.109	0.173
321	Made-up textiles, knitting mills, carpets and rugs	0.189	0.215	0.038
381	Copper and brass industrial products	0.169	0.185	0.249
331	Wood and cork products	0.162	0.164	0.045
383	Electrical machinery	0.158	0.193	0.206
332	Furniture and fixtures	0.141	0.229	-0.151
	Fifteen least concentrated industries in 1995-96			
324	Footwear manufacturing	-0.113	-0.170	-0.065
312	Animal feed & ice factories	-0.106	0.00005	-0.073
372	Non-ferrous metals	-0.037	0.217	-0.003
354	Petroleum refining, petroleum products and coal	-0.031	0.054	0.192
313	Beverage industry	-0.006	-0.002	-0.029
314	Tobacco industry	0.007	0.471	0.064
351	Industrial chemicals	0.015	0.010	-0.003
311	Dairy products and processed food	0.018	0.042	0.021
356	Plastic products	0.018	0.043	0.056
382	Non-electrical machinery	0.018	0.042	0.109
393	Handicrafts and office supplies	0.021	0.044	0.078
369	Other non-metallic mineral products	0.021	0.057	0.098
352	Other chemical products	0.028	0.009	-0.026
320	Spinning and weaving of cotton & wool	0.034	0.049	0.031
323	Leather and leather products	0.095	0.050	0.029

Secondly, agglomeration of industries also offers economies on account of labor market pooling, which also allow labor to optimally allocate time to maximize productivity. Finally, agglomeration allows firms to gain from free flow of ideas or technology spillovers. For instance, finance industry is often concentrated in urban centers where density speeds up the flow of new ideas [Ellison and Glaeser (1999)].[5] Natural advantage is another key factor motivating firms to locate in regions where the considerations of Marshall's agglomeration forces may otherwise be weak or non-existent. However, these models cannot be translated easily into variables that may be employed in empirical specifications to find out the determinants of agglomeration. Our objective here is to investigate the role of Marshall's agglomeration forces in determining geographic concentration of industries.

We analyze factors that help explain the causes of agglomeration by using an empirical specification that allows us to relate the Ellison-Glaser index of industry concentration to industry characteristics and agglomeration forces. The empirical specification used is

$$\theta = \rho + \beta A + \kappa + \lambda + \varepsilon \tag{1}$$

where θ depicts the EG industry agglomeration index, A is a vector of industry characteristics that explain agglomeration, κ and λ are year and industry fixed-effects where the industry effects refer to 2-digit industries in each 3-digit industry, and ε is a random error term.

Market access is determined by the ease of connectivity with the market centers in spatial vicinity of the firm, which in turn depends on the availability of good road infrastructure, firm's distance from the market, size of the market and the availability of quality transport

[5] Similarly, Arzaghi and Henderson (2008) draw our attention to the benefits of networking to marketing firms in Manhattan.

networks. Absence of all or some of these factors limits the extent of the market for a firm because it would be unable to connect to a wider market area.

Spatial inequality in road infrastructure constrains market efficiency by creating factor scarcities that prevent the spatial units to use comparative advantage to specialize in production. Recent literature also suggests that improvements in roads at the regional level can significantly contribute to the pursuit of socially inclusive growth [Khandker et al. (2009), Jacoby and Minten (2009)]. We take district level data on road density from the Punjab Highway Department and the Provincial Development Statistics to proxy for market access and transportation cost.[6] We also take district population as an indicator of market access.

We construct education and skill endowment variables as indicators of labor pooling in each district. We apply a multivariate statistical weighting approach known as the method of principal components [see, Greene (1997)] to select the principal components that account for the largest variance.[7] To construct district level formal and technical education variables we employ external information and take corresponding data of 29 district level formal education and skill–specific indicators from Pakistan's *Labor Force Survey* 1995-96, 2000-01 and 2005-06. After varimax rotation, we retain four principal components using Kaiser eigenvalue criterion that account for 82.2% variation in the total variance. However, 73.5% of the variance was explained by the first two factors. Therefore, we select factor 1 (F1) and factor 2 (F2) where factor 1 accounts for 51% variance and is characterized by high factor loadings on

[6] The road density is based on national highway roads, farm to market roads and district government roads. However, they do not cover the road network maintained by cantonment boards and defense housing authorities located in big cities. We assume that omission of data on cantonment and DHA roads would not directly affect firm location in other districts.

[7] Only small number of principal components from large number of variables is chosen that contribute highly in explaining the variance. Components associated with smallest eigen values are discarded because they are least informative. We adopt Kaiser-Gutman Rule whereby only principal components associated with eigen values greater than one are retained.

formal education (e.g., primary, secondary, intermediate, under-graduate and graduate degrees, and professional degrees), while factor 2 has high factor loadings on technical skills (e.g., vocational training, technician, garment making, leather works, polishing and soldering, interior decoration and carpentry, etc.).

Due to data limitations, we conduct this analysis on pooled data of Punjab's manufacturing sector obtained from CMI for three five year intervals 1995-96, 2000-01 and 2005-06.[8] As before, we use the 1981 district boundaries to identify spatial units and focus on 3-digit industries to measure industry concentration. Table 3 shows descriptive statistics on agglomeration and sources of agglomeration variables. The industry agglomeration index (the EG index) is worked out by taking the product of each industry's agglomeration index, θ , and

Table 3. Descriptive statistics for agglomeration regressions

Variable	Mean	Std. Dev.	Min	Max
Ellison and Glaeser index (θ)	0.0179	0.076	-0.098	1.068
Road density	0.3420	0.146	0.044	0.697
Population (millions)	3.5329	1.632	0.852	7.419
Principal component formal education index (F1)	0.5459	1.284	-0.725	4.575
Principal component technical education index (F2)	0.4313	2.129	-0.815	10.381
Year 2000-01 (yes=1, no=0)	0.3125	0.463	0	1
Year 2005-06 (yes=1, no=0)	0.3637	0.481	0	1
Food, beverage and tobacco (yes=1, no=0)	0.1714	0.377	0	1
Textile and leather (yes=1, no=0)	0.2513	0.434	0	1
Wood and wood products (yes=1, no=0)	0.0389	0.193	0	1
Paper and paper products (yes=1, no=0)	0.0422	0.201	0	1
Chemical, rubber and plastic (yes=1, no=0)	0.1690	0.375	0	1
Mineral products (yes=1, no=0)	0.0745	0.262	0	1
Basic metal (yes=1, no=0)	0.0355	0.185	0	1
Metal products (yes=1, no=0)	0.1868	0.390	0	1
Other industry and handicrafts (yes=1, no=0)	0.0300	0.170	0	1
N	899	--	--	--

[8] The CMI 1996-97 and 2000-01 were conducted on the basis of same PSIC, but the classification was changed for CMI 2005-06. To produce consistent and comparable estimates, we regrouped CMI 2005-06 data according to CMI 1995-96 classification.

the industry's share of manufacturing in each district, i.e., $\theta \times s$. The data indicates that spatial inequality in road density, population and principal component formal education and technical education index has been large, as indicated by high standard deviations. But caution is warranted as correlation coefficient between road density, population and principal component formal education (F1) is very high, which is expected to create robustness issues in the full regression models.

The model in Eq.(1) is estimated by using pooled data consisting of 899 observations. Table 4 presents four models where in column (1) we present the full model, in column (2) we include only population variable, in column (3) we include only road density variable, and in column (4) we include the two principal component variables, F1 and F2. All models include a complete set of year and 2-digit industry fixed effects. Overall, the empirical estimates are quite robust. Total variation explained by these models is about 9%.

Table 4. OLS specifications for agglomeration regressions

Variable	Full model	Model 2	Model 3	Model 4
	(1)	(2)	(3)	(4)
Road density	0.0365*	--	0.0549**	--
	(1.79)		(2.14)	
Population (millions)	0.0046	0.0047**	--	--
	(0.93)	(2.06)		
Principal component formal education index (F1)	-0.0029	--	--	0.0044
	(-0.44)			(1.40)
Principal component technical education index (F2)	0.00050	--	--	0.0014*
	(0.37)			(1.70)
Year 2000-01 (yes=1, no=0)	-0.0008	-0.0016	-0.0036	-0.0001
	(-0.31)	(-0.62)	(-1.33)	(-0.05)
Year 2005-06 (yes=1, no=0)	-0.0129**	-0.0117**	-0.0174**	-0.0107**
	(-2.75)	(-2.86)	(-2.81)	(-2.07)
Industry fixed effects included	Yes	Yes	Yes	Yes
Constant	-0.0179	-0.0075	-0.0080	0.0045
	(-1.19)	(-0.94)	(-1.06)	(1.29)
R^2	0.093	0.0904	0.0896	0.0877
N	899	899	899	899

Note: All the models are estimated by the OLS. Numbers in parenthesis are *t*-values obtained from robust standard errors corrected for clustering at the district level. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

We note a declining dynamic concentration levels in 3-digit industries in Punjab. In the first five year period (i.e., 1995-96 to 2000-01), the agglomeration of manufacturing industries shows no change as implied by a statistically insignificant coefficient on dummy variable for 2000-01. However, in the second five year period, industry agglomeration significantly declines as revealed by a statistically significant coefficient on year 2005-06. Due to high correlations between explanatory variables, the coefficients of population, F1 and F2 are statistically insignificant in the full model, while the coefficient on road density is marginally significant. Our estimates in model 2 imply that the size of district population increases agglomeration; in model 3 road density variable indicates that increased road density promotes more agglomeration. The estimates using F1 and F2 in model 4 are also positive, but statistically significant only for the technical education index at the 10% level. The results suggest that formal education is not a constraint for industry concentration in Punjab but increase in technical education index does lead to a significant increase in concentration levels.

III.2 Localization vs. Urbanization Externalities

Localization and urbanization externalities are related to local scale externalities that arise from local information spillovers linked to input and output markets and local technological developments. If firms in a district learn from local firms in their own industry, this is called localization externalities; if firms learn from all firms in the district, it is termed as urbanization economies [Henderson et al. (2001)]. While several urban areas dominate in

Pakistan, the relative strength of "localization economies" versus "urbanization economies" is not known.

We follow Henderson et al. (2001) to measure the scale of local externalities by a diversity index written as $g_i^s = \sum_{n=1}^{N}\left[\left(E_{in}/E_i\right) - \left(E_n/E\right)\right]^2$ where i and n index district and industry, respectively, g_i^s is the index of localization and urbanization economies in ith district, E_n is for employment in industry n, E is for total national manufacturing employment, and E_i is for employment in ith district and E_{in} is for employment in ith district in nth industry. A lower value of g_i^s (minimum value is zero) indicates that the city is non-specialized (high diversity) while a higher value (approaching two) indicates complete specialization. In other words, as g_i^s goes up specialization increases and the diversity falls. Henderson et al. (2001) find a negative relationship between g_i^s and productivity in Korea.

As before, we use CMI data of Punjab for 1995-96, 2000-01 and 2005-06 and calculate g_i^s index of 3-digit industries for 29 districts of Punjab. Table 5 shows that localization economies are much stronger than urbanization economies as the diversity index has higher values for most of the districts with a mean of 0.253 in 1995-96. The evidence suggests that there is a greater role for within-industry externalities whereas inter-industry learning appears to be weak.

The on-going dynamic process further reveals that the raw diversity index, g_i^s, falls overtime, indicating that inter-industry spillovers were encouraging the diversity of local industries at an increasing rate. For example, while in the first five years the index moderately falls (3.6%), in

Table 5. Localization versus urbanization externalities in Punjab, 1995-95 to 2005-06

	g_i^s, 1995-96	g_i^s, 2000-01	g_i^s, 2005-06
Sheikhupura	0.0169	0.0539	0.0312
Khushab	0.0407	0.0385	0.0623
Khanewal	0.0493	0.0448	0.1891
Multan	0.0529	0.0452	0.0811
D.G. Khan	0.0625	0.2092	0.0843
Attock	0.0806	0.0735	0.0937
Faisalabad	0.0892	0.076	0.0489
Jhang	0.0919	0.1259	0.2931
T.T. Singh	0.1013	0.2746	0.2907
Gujranwala	0.1196	0.1620	0.0373
Chakwal	0.1381	0.1149	0.1386
Bahawalpur	0.1504	0.2804	0.4388
Kasur	0.1612	0.1286	0.1142
Muzaffargarh	0.1718	0.1975	0.0427
Lahore	0.1724	0.2279	0.1372
Sargodha	0.1967	0.1762	0.2775
Rawalpindi	0.2057	0.0249	0.0280
R.Y. Khan	0.2256	0.2566	0.4002
Sialkot	0.2574	0.5092	0.3548
Gujrat	0.2963	0.3342	0.2082
Mianwali	0.3126	0.4481	0.4431
Vehari	0.3465	0.1553	0.1695
Jhelum	0.3471	0.2824	0.1634
Bahawalnagar	0.3955	0.4615	0.2429
Sahiwal	0.4233	0.0532	0.2364
Okara	0.4896	0.4567	0.2252
Layyah	0.6518	0.7641	0.7094
Bhakkar	0.7365	0.1244	0.1238
Rajanpur	0.9589	0.9778	0.3583
Mean	0.253	0.244	0.208

the second five year period the index falls more drastically (15%), indicating increase in the forces of diversity that may be leading to increased productivity.

By pooling data of 3-digit industries in three surveys, we regress the $g_i^s(t)$ index on district population along with controls for survey years. Our results reported below (standard errors in parentheses) clearly indicate that district population is negatively correlated with the index

$$\begin{aligned} g_i^s(t) = \underset{(0.128)}{1.09} - \underset{(0.0086)}{0.061} \ln(Dist_{pop}) + \underset{(0.0113)}{0.004} Year_{00-01} - \underset{(0.0109)}{0.021} Year_{05-06} \\ \mathrm{N} = 901;\ R^2 = 0.062. \end{aligned}$$

of specialization. The time dummy for the second five year period is statistically significant, which confirms earlier results that the index declines in 2005-06 as compared with 1995-96.

IV. ESTIMATION PROCEDURES FOR THE STOCHASTIC FRONTIER MODEL

The frontier literature in the econometric practice assumes that the boundary of the production function is defined by "best practice" firms representing the maximum potential output for a given set of inputs. Firms operating on the production frontier are regarded as technically efficient and those away from the frontier are termed as technically inefficient. It has been observed that deviations from the frontier or technical inefficiency are widespread in many sectors including manufacturing sector.

The general stochastic frontier specification was introduced by Aigner et al. (1977) and Meeusen and Van den Broeck (1977), which postulates the existence of technical inefficiency in the production process. To illustrate, let the production technology be represented by

$$Y_{it} = f(X_{it}, \beta)\, e^{v_{it} - u_{it}} \tag{2}$$

where Y_{it} is the value-added output of the *i*th firm in *t*th time, $X_{it}\ (i = 1,...,n)$ is a $1 \times k$ vector of factor inputs, β is a $k \times 1$ vector of unknown parameters to be estimated, and $f(X_{it}; \beta)$ is the frontier production function. As usual in frontier literature, the stochastic composite error term is decomposed into v_{it} and u_{it} where v_{it} is the stochastic (white noise) error term that captures the random effects of measurement errors in output, external shocks and events outside a firm's control. Both v_{it} and u_{it} are taken to be independently and identically distributed (iid) with variance σ_v^2 and σ_u^2. Moreover, v_{it} is independently distributed of u_{it}.

We adopt the approach outlined by Kumbhakar et al. (1991), Reifschneider and Stevenson (1991) and Battese and Coelli (1995) and relate technical inefficiency of firms to a set of explanatory variables given by

$$u_{it} = Z_{it}\delta + w_{it} \tag{3}$$

where Z_{it} are factors that may influence the technical inefficiency of firms, δ represents a vector of unknown firm and time-specific parameters to be estimated, and w_{it} is distributed as $N(0, \sigma_w^2)$ obtained by truncation from below where the point of truncation occurs at $-Z_i\delta$, or $w_i \geq -Z_i\delta$.

To test the effects of agglomeration economies on technical inefficiency of firms, we estimate the translog production function model under the assumption that firms regard output as endogenous and adjust production when input prices change.[9] Our estimated model takes the following form

$$\ln Y_{it} = \beta_0 + \sum_{k=1}^{2}\alpha_k \ln X_{it} + \frac{1}{2}\sum_{k=1}^{2}\sum_{l=1}^{2}\gamma_{kl} \ln X_{it} \ln X_{jt} + \theta_t t + \frac{1}{2}\theta_{tt} t^2 + \sum_{k=1}^{2}\lambda_k \ln X_{it}\, t + v_{it} - u_{it} \tag{4}$$

where $\gamma_{kl} = \gamma_{lk}$, Y is value-added output, X is a vector of inputs consisting of labor and capital and t refers to the time trend variable for the year of observation for each firm.

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[9] On this, see also Lall et al. (2004)

Since our objective is to explore the effects of agglomeration economies on technical inefficiency of firms, the inefficiency model specification is defined by a linear function of explanatory variables consisting of agglomeration effects, firm-specific effects and industry effects written as:

$$u_{it} = \delta_0 + \delta_1 AI_{jt} + \delta_2 DI_{dt} + \sum_{r=3}^{6} \delta_r SIZE_{it} + \sum_{r=7}^{11} \delta_r IND_c + w_{it} \tag{5}$$

where dependent variable, u, is measured in units of inefficiency ranging over the $(0, \infty)$ interval so that a score of zero indicates full efficiency and scores of more than zero indicate inefficiency, and hence coefficients with positive sign indicate increase in inefficiency, and vice versa. As previously discussed, AI is agglomeration index measured by Ellison-Glaeser index that varies at 3-digit PSIC over time, DI is the diversity index also discussed previously, which measures the scale of localization externalities (intra-industry spillovers) and urbanization externalities (inter-industry spillovers) that vary at the district level over time; $SIZE$ is a vector of firm size dummy variables that vary across firms over time including small-firm, medium-firm, large-firm and very large firm where very small firm is an excluded category; IND is a vector of dummy variables that control for industry fixed effects at 2-digit PSIC; t specifies time-varying inefficiency effects, and w_{it} is a random variable distributed $N(0, \sigma_w^2)$.

We also incorporate in the Eq.(5) an interaction between diversity index, *DI*, and industry dummy to allow the dynamics of technical inefficiency to vary for localization and urbanization economies by 2-digit industries.

$$u_{it} = \delta_0 + \delta_1 AI_{jt} + \delta_2 DI_{dt} \times IND_c + \sum_{r=3}^{6} \delta_r SIZE_{it} + \sum_{r=7}^{11} \delta_r IND_c + w_{it} \qquad (6)$$

Equation (6) indicates that technical inefficiency effects are linearly related to industry agglomeration that varies at 3-digit PSIC, the interaction of diversity index (that varies across districts) with 2-digit industries, firm size dummy variables, industry fixed effects and an intercept term.

V. THE DATA AND VARIABLES

We use plant level data from three latest rounds of Census of Manufacturing Industries (CMI) for 1995-96, 2000-01 and 2005-06, conducted by the Federal Bureau of Statistics of the Government of Pakistan. The plant level data consists of 10325 observations that come from 2342 observations from 1995-96 and 2344 observations from 2000-01 rounds for Punjab, and 5639 observations from 2005-06 rounds for Punjab, Sindh, KP and Balochistan.[10] The census data is based on an obligatory return filled by the factories under Section 9 & 10 of General Statistics Act, 1975 and Section 5 and 6 of Industrial Statistics Act, 1942. We use data on firm level production attributes such as value added output, labor and capital.

Our measure of value added output is defined as the value of output less the value of material, energy and industrial services, viz., value of materials and supplies for production (including cost of all fuel and purchased electricity); and cost of industrial services received (mainly payments for contract and commission work and repair and maintenance work).

[10] CMI data of Sindh, KP and Balochistan for 1995-96 and 2000-01 is not available.

Labor is measured by the man days employed and paid for by each firm during the accounting year. It includes all part time and full time production and non-production workers who work in the establishment and receive remuneration in cash or in-kind. Those termed as working proprietors, unpaid family workers and home workers are excluded in this definition.

Ideally, capital should be measured by the perpetual inventory method that requires firm level data over time. However, tracking of the firms in CMI data over time is not possible because same identification codes are not used across census. Following, Lall et al. (2004), we define capital by the gross value of plant and machinery, which includes value of buildings, plant and machinery, land and major improvements to land, transport equipment, furniture and fixtures, and other assets of each firm. All the nominal values were duly adjusted for inflation. Descriptive statistics are presented in Table 6 for the relevant variables (value added output, labor, capital, time trend, Ellison-Glaeser agglomeration index, diversity index, industry, firm size).

VI. ESTIMATION RESULTS

The maximum likelihood parameter estimates of the translog production function and the inefficiency effects model defined in Eqs. (4) – (6) are estimated simultaneously through a coded three step maximum likelihood estimation procedure using the computer program FRONTIER 4.1 [Coelli (1996)] and reported in Table 7 (asymptotic *t*-statistics in parenthesis).[11] Two different cases are reported: model 1 reports the inefficiency related δ

[11] These estimates are unbiased, except the intercept term.

Table 6. Descriptive statistics for the stochastic frontier and technical inefficiency model

	Mean	Std. Dev	Min	Max
Frontier production function:				
Value added output (*Y*), Rs. million	109.88	760.75	0.05	44871.38
Labor (*L*)	148	435	1	14296
Capital (*K*), Rs. million	122.36	647.11	0.008	24950.32
Time (*t*)	8	4	1	11
Inefficiency effects model:				
Ellison-Glaeser agglomeration index	0.102	0.157	-0.17	1.07
Diversity index (localization vs. urbanization economies)	0.094	0.137	0.01	0.88
Diversity index × food, beverage and tobacco (yes=1, no=0)	0.029	0.112	0	0.88
Diversity index × textile and leather (yes=1, no=0)	0.034	0.077	0	0.88
Diversity index × chemical, rubber and plastics (yes=1, no=0)	0.005	0.023	0	0.43
Diversity index × mineral products (yes=1, no=0)	0.006	0.054	0	0.88
Diversity index × basic metal and metal products (yes=1, no=0)	0.013	0.042	0	0.67
Diversity index × wood, wood products, paper products, printing and handicrafts (yes=1, no=0)	0.007	0.042	0	0.51
Very small firms (yes=1, no=0)	0.073	0.260	0	1
Small firm (yes=1, no=0)	0.073	0.260	0	1
Medium firm (yes=1, no=0)	0.606	0.489	0	1
Large firm (yes=1, no=0)	0.146	0.353	0	1
Very large firm (yes=1, no=0)	0.098	0.297	0	1
Food, beverage and tobacco	0.181	0.385	0	1
Textile and leather	0.401	0.490	0	1
Chemical, rubber and plastic	0.102	0.302	0	1
Mineral products	0.052	0.223	0	1
Basic metal and metal products	0.202	0.402	0	1
Wood, wood products, paper products, printing and handicrafts	0.0616	0.240	0	1
Time	8	4	1	11
Full sample	10325	--	--	

coefficients in Eq.(5), while model 2 reports the inefficiency coefficients in Eq.(6). For hypothesis testing we generally take model 1.

Hypothesis testing regarding functional forms and the model specifications is conducted by using the one-sided generalized likelihood ratio test statistics[12] that has approximately a χ^2 distribution, except cases where the null hypothesis involves the restrictions where γ is equal to 0 [see, Coelli (1995)]. In all such cases, the asymptotic distribution of the likelihood ratio test for the null hypothesis is a mixture of χ^2 distribution where the appropriate critical values are drawn from Kodde and Palm (1986). The null hypothesis that the correct functional form for the production structure of our sample of firms is Cobb-Douglas is tested and rejected at the 1% level of statistical significance in favor of the translog production function given in Eq.(4).[13] Moreover, the hypothesis of Hicks-neutral technical change is also tested and rejected at the 1% level on the basis of χ^2 distribution in favor of non-neutral technological change.[14]

The parameters $\sigma^2 = (\sigma_v^2 + \sigma_u^2)$ and $\gamma = (\sigma_u^2 / \sigma^2)$ are linked with the variances of the random variables, v_{it} and u_{it}. If the estimated γ-parameter is found to be zero then σ_u^2 is also zero, which indicates that the inefficiency effects are not stochastic and the model is adequately

[12] The generalized likelihood ratio test is defined by $LR = -2\{\ln[LH_0 / LH_1]\} = -2\{\ln[L(H_0)] - \ln[L(H_1)]\}$, where $L(H_0)$ and $L(H_1)$ is value of the likelihood function under the null hypothesis and alternative hypothesis, respectively [Coelli et al. (1998)]. Under the null hypothesis the test statistic has approximately χ^2 distribution with parameters equal to the difference between the parameters involved in the null and alternative hypothesis.

[13] The value of the generalized likelihood ratio test statistics was 454.8 against the critical value of 16.81 for the χ_6^2 distribution.

[14] The likelihood ratio test statistics was 392.7 against the critical value of 9.21 for the χ_2^2 distribution.

Table 7. ML estimates of stochastic frontier and technical inefficiency effects model

Variables	(1)	(2)
Frontier production function (dependent variable is $\ln Y$ *)*		
Constant	8.450***	8.694***
	(17.32)	(17.66)
$\ln L$	1.074***	1.086***
	(9.72)	(9.91)
$\ln K$	0.215***	0.172**
	(2.77)	(2.20)
$\ln L^2$	-0.139***	-0.140***
	(-6.92)	(-6.91)
$\ln K^2$	0.002	0.005
	(0.32)	(0.78)
$\ln L \times \ln K$	0.017*	0.017*
	(1.74)	(1.71)
t	-0.326***	-0.251***
	(-7.41)	(-6.32)
t^2	0.039***	0.033***
	(8.52)	(9.83)
$\ln L \times t$	0.019***	0.023***
	(5.07)	(6.12)
$\ln K \times t$	0.005***	0.003
	(2.74)	(1.51)
Inefficiency effects model (dependent variable is u_{it} *)*		
Constant	-1.624***	-0.943***
	(-3.35)	(-2.68)
Ellison-Glaeser agglomeration index	-1.312***	-1.088***
	(-8.83)	(-6.41)
Diversity index (Localization/urbanization economies)	0.565***	--
	(5.17)	
Diversity index × food, beverage and tobacco (yes=1, no=0)	--	1.667***
		(11.65)
Diversity index × textile and leather (yes=1, no=0)	--	-1.142***
		(-5.18)
Diversity index × chemical, rubber and plastics (yes=1, no=0)	--	1.982***
		(2.64)
Diversity index × mineral products (yes=1, no=0)	--	-0.002
		(-0.009)
Diversity index × basic metal and metal products (yes=1, no=0)	--	-0.317
		(-0.734)
Diversity index × wood, wood products, paper products, printing and handicrafts (yes=1, no=0)	--	-0.437
		(-0.696)
Time	0.506***	0.442***
	(9.09)	(11.21)
Small firm (yes=1, no=0)	-1.468***	-1.515***
	(-6.38)	(-7.07)
Medium firm (yes=1, no=0)	-0.861***	-0.940***
	(-6.32)	(-7.17)
Large firm (yes=1, no=0)	-0.876***	-0.930***
	(-7.87)	(-8.58)
Very large firm (yes=1, no=0)	-0.424***	-0.434***
	(-4.96)	(-5.14)
Industry fixed-effects included	Yes	Yes
$\sigma^2 = \sigma_u^2 + \sigma_v^2$	1.272***	1.229***
	(50.86)	(50.97)
γ	0.481***	0.477***
	(23.62)	(22.48)
Log-likelihood	-14787.154	-14706.149
Mean technical efficiency (%)	58.94	57.85
Sample size	10325	10325

represented by a traditional mean response function [Battese and Coelli (1993)]. This hypothesis is also rejected on our data: the estimate of the γ-parameter is significantly greater than zero $(\gamma = 0.481, t = 23.62)$, which is indicative of the fact that the frontier production function model is a significant improvement over the standard OLS model. We also test the null hypothesis that technical inefficiency effects are absent from the model (i.e., $\gamma = \delta_0 = ... = \delta_U = 0$), which is strongly rejected at the 1% level of statistical significance.[15]

VI.1 Production Frontier Results

There is little difference in the estimated coefficients for the production function in models 1 and 2. The parameter estimates under the specification in model 1 reveal that the value added output is statistically significantly correlated with labor and capital where labor is the most important determinant. The results indicate that the estimated production function is well behaved, indicating that it is monotonic and concave. Our test for monotonicity condition is satisfied at all data points. The curvature condition holds as weak concavity condition is satisfied: both f_{LL} and f_{KK} are statistically non-positive and f_{LK} is statistically positive. The time trend parameters of the production function at the point of approximation (mean of the data points) indicate that the production function is shifting outwards.[16]

[15] The likelihood ratio test statistics was 631.1 against the critical value of 25.55 at $\alpha = 0.01$ for the χ^2_{12} distribution obtained from Kodde and Palm (1986).

[16] The estimated measure of technological change at the point of approximation was obtained by taking the derivative of $\ln Y$ with respect to t and evaluated at the mean of the data points.

VI.2 Technical Inefficiency Effects of Industry Concentration

A central question of this study is how industry agglomeration index and diversity index explain the variation in estimated technical inefficiency of firms. Table 7 presents the maximum likelihood parameter estimates for the two models specified in Eq.(5) and Eq.(6). The estimates provide measures of technical efficiency for each firm in our data set. We note that technical efficiency is relatively low, with a mean value of 59% in model 1. The mean value for efficiency does not vary greatly in model 2, however. These results indicate that these firms operate much below their full production potential. Results imply that, on average, these firms could save about 41% of the currently used inputs by being fully technically efficient. Because the dependent variable is technical inefficiency, a negative (positive) sign on estimated coefficients indicates decrease (increase) in technical inefficiency, or increase (decrease) in efficiency.

In our framework, increase in the value of the agglomeration index depicts the strength of agglomeration externalities in an industry. The null hypothesis is that the agglomeration index is not related to the technical inefficiency of firms. In the alternative hypothesis, a positive relationship implies that concentration makes firms more inefficient (less efficient), on the contrary, a negative relationship indicates that concentration decreases (increases) technical inefficiency (efficiency). The negative sign on the coefficient for agglomeration index $(\delta = 1.312,\, t = -8.83)$ suggests that technical inefficiency of the firms was decreasing with increase in the value of the index. The differential impact of industry concentration is clearly observable as the firms coming from more agglomerated 3-digit industries were facing more favorable exogenous operating conditions, presumably due to presence of economies.

We also include in our analysis a diversity index variable, which accounts for the possibility that technical inefficiency of firms may vary due to a combination of localization (intra-industry spillover) and urbanization (inter-industry spillover) effects. Increase in the value of the diversity index refers to increase in localization or specialization (decrease in diversity) while a decrease in the value refers to urbanization or increase in diversity. Extensive empirical literature supports the positive effects of localization economies on the participating firms [e.g., Henderson (1988), Ciccone and Hall (1995), Henderson et al. (2001)]. However, increased regional competition between firms to acquire basic inputs may raise costs, and the firms using basic production technologies and un-skilled or semi-skilled workers may be unable to cope with the rising costs, and hence such firms may be unable to benefit enough from localization externalities [Lall et al. (2004)].

The evidence presented in Section III indicates that the diversity index was indeed falling with the passage of time. It appears that technological spillovers and inter-industry learning was gaining more significance for the reasons stated above, and further localization was being discouraged. Thus the impact of localization economies on technical inefficiency of firms may not always be negative. The growing importance of the technological spillovers (inter-industry effects) may be represented by a positive sign while the importance of localization economies (intra-industry effects) may be reflected by a negative sign on the diversity index. The estimates in model 1 show that the diversity index has indeed a statistically positive association with the technical inefficiency of firms in our data set $(\delta = 0.565,\ t = 5.17)$, which reveals that, all else being equal, decreased specialization (increase in diversity) was decreasing technical inefficiency of the firms. However, the impact of the diversity index on technical inefficiency of firms may not be uniform across industries.

To further investigate the effects of the diversity index across industries, we include the interaction of the diversity index with six industry dummies. The results in model 2 indicate that increased diversity produces mixed effects across industries. The benefits of intra-industry spillovers are positive in four industries as indicated by the negative sign, but they are statistically significant for only textile and leather industry. In other words, intra-industry learning economies still play a dominant role; firms learn from other firms in the same district. By contrast, increase in the diversity index increases technical inefficiency of firms in food, beverage and tobacco; and chemical rubber and plastics industries. These firms greatly benefit from the diversity of the population in their respective regions. For these firms, benefits mainly accrue from inter-industry learning from all firms in the district, which include transfer of information, availability of infrastructure, access to specialized business services, information technology and financial services.

The other results show that technical inefficiency is inversely proportional to the size of the firm. Small firms achieve the lowest technical inefficiency, followed by medium and large firms, and then very large firms. The positive and significant estimate for the time trend variable $(\delta = 0.509, t = 9.09)$ suggests that technical inefficiency of the firms continues to increase throughout the ten-year period. The declining mean technical efficiency over the three five-year intervals from 79% in 1995-96, 52% in 2000-01 and 49% in 2005-06 tends to confirm the worsening performance of the manufacturing sector as a whole. The deterioration in technical inefficiency of the firms may be attributed to a policy of tariff rationalization leading to drastic cut in average tariff rates between 1995 and 2004. For example, Schuler (2004) notes that the weighted average tariff levels in Pakistan were gradually reduced from 46.1% in 1995 to 41.4% in 1998, 19.6% in 2001 and 13.8% in 2004 where the most drastic tariff cuts occurred between 1998 and 2004, which may have affected relative technical inefficiency of the firms in the most protected sectors.

VII. CONCLUSIONS AND POLICY IMPLICATIONS

In this paper, we investigate the agglomeration of manufacturing industries and its consequences on technical inefficiency of manufacturing firms in Pakistan. Using plant level cross-section data obtained from CMI for 1995-96, 2000-01 and 2005-06, we examine the nature and extent of industry agglomeration by using the Ellison-Glaeser agglomeration index and identify factors that cause agglomeration of industries. Moreover, we also measure the extent of local scale externalities by using the Henderson diversity index.

On the whole, the findings of this paper are that geographic concentration of manufacturing industries is widespread in Pakistan, but it was declining over time. We find that the size of district level population, increase in district road density, and increase in district level pool of technically trained workers all helped in promoting agglomeration of manufacturing industries. The determinants of industry agglomeration explain the causes of dense economic activity across spatial units, and the difficulties faced by policy makers in attracting manufacturing activities in remote districts.

As in some developed countries, localization economies were much more important in Pakistan than urbanization economies, indicating that the firms did not adequately value the importance of technological spillovers and inter-industry learning. However, a reversal in this pattern was observed in more recent surveys, which may be due to the inability of firms to cope with increased regional competition.

Our results show a significant impact of the agglomeration index in decreasing technical inefficiency of the firms. The null hypothesis that industry agglomeration index was not related to technical inefficiency was strongly rejected. In other words, firms from agglomerated industries faced more favorable exogenous operating conditions.

In general, any further increase in localization was counterproductive for the firms in our data set; however, this effect was not uniform across all industries. We find that localization economies were still beneficial in textile and leather industry where firms were learning from other firms in the same district. By contrast, firms in food, beverage and tobacco; and chemical, rubber and plastic industries were greatly benefitting from population diversity in districts, as they were benefitting from inter-industry learning economies, especially due to transfer of information, availability of infrastructure, access to specialized business services, information technology, and financial services, etc. Finally, technical inefficiency of firms was found to be inversely proportional to the size of the firm in our sample.

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