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Impact of Industrial Agglomeration on Productivity: Evidence from Iran's Food Industry

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Abstract: This paper aims to examine the effect of agglomeration on firm level productivity in Iran's food manufacturing by employing a firm level dataset during 1986–2015 among firms for four districts. The empirical results show that agglomeration in north districts are key factors in productivity growth. In this work, we apply a spatial Bayes model that uses hierarchical techniques during the three terms. The productivity clustering map is able to capture such patterns as the high productivity area that appears in the south, north districts of Iran. This paper evaluates the effect of agglomeration on firm productivity in Iran's food industries at district level. We find that regional market potential is the strong predictor of productivity; moreover, industrial agglomeration has a productivity-augmenting impact.

Keywords: Agglomeration; productivity; spatial Bayes; hierarchical; Iran

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1 Introduction

It was seen remarkable concern in analyzing the position and spatial agglomeration of economic performance in the last decade. In the greatest instances, the observational and tentative task could be followed to the primary study in spatial science and location generality (Isard, 1956). In line with Krugman (1991), problem in constructing increasing returns to measure has considered one of the basic proofs for the boundary of spatial invoices in current economic estimation. The recently scholars evaluated the economics of concentration has been developed possible by advancement in mathematical constructing and by a modified understanding of factors that impress the spatial agglomeration and economic performance: technology spillovers, increasing returns to monopolistic competition (Fujita, 1989; Fujita et al., 1999). Increasing returns to scale are necessary for describing the spatial agglomeration of economic performances. This bifurcation theorem of spatial economy demonstrates that with considering non increasing returns to measure and same concentration of sources, each person could only procreate for individual utilization and each position could be the basis of an autarky economics that commodity are generated indiscriminately on limited scale (Fujita and Thisse, 1996). Therefore, if average production costs reduce as measure of production raises at plant, manufacturing, and regional level, then it would be effective to concentrate production in specific positions. These inter-firm profits consist of better accessibility to supplementary services, access of a great labor pool with manifold proficiency, inter-industry information transfers, and the accessibility of less costly general infrastructure. The sources of these opinions could be followed as stated in the study of Marshall (1890) that determined the spatial agglomera-

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tion of economic performances could eventuate in a cumulative effect, while new income firms have a tendency to concentrate to profit with higher variety and proficiency of production procedures. Labors could further privilege from being in an agglomeration as they could anticipate higher wages and have availability to a larger selection set of employers. There are many studies on the profits to firms from moving in near vicinity to another plant in the identical industry (Selting et al., 1994). Activities in the inverse orientations are a number of dispersion forces. These contain increased costs arise from higher wages accomplish by competition among firms for expert labor, greater hires because of rising request for settlement and mercantile land, and negative spillovers like congestion. These costs counteract some or all of the profit of being established in an agglomeration. Theoretical and tentative task on regional economies and spatial economics purposes that the net profits of manufacturing agglomeration and position in condensed urban locations are inappropriately result from technology centralized and knowledge segment (Henderson et al., 2001). Because of the profits of knowledge distribution and accessibility to producer facilities are significantly greater in these segments than in low-end industry that utilizes regulated production procedure. Consequently, these technological sections could provide the high wages and hires in condensed urban areas and industry clusters. There is great number of firm-level studies on agglomeration economies (Greenstone et al., 2010). Meanwhile, these researches could not consider spatial autocorrelation, leading to relation across local natural benefits in close locations (LeSage and Pace, 2009). By comparison, prior research employ indiscrete dataset for the local scale and analyse spatial estimation since evaluating concentration impacts by Maximum Likelihood calculation (MLE), Generalized Method of Moments (GMM), also Bayesian approach (Ke, 2010; Hashiguchi and Chen, 2012). However, these assessments procedures obviate spatial correlation, they have been utilized only for the estimation on regional level productivity. The manufacturing structure studies have confirmed main efficiency variations among plants, even into closely determined industries (Olley and Pakes, 1996). These studies have scrutinized a range of sources of productivity growth such as the effect of plant size (Geroski, 1998), also plants age and process innovations across others, although the effect of transport infrastructure developments has not been evaluated instantly at the limited scale (Huergo and Jaumandreu, 2004). Higher market potential could take firms higher specialty and to utilize scale economies to a greater level. By market extension and aggregation, the spatial domain that agglomeration economies take place could further augment (Graham, 2007). By these several mechanisms, market developments could impress plant level proficiency. Iran is a specific interesting country to explore impacts of market potential on plant activity. The most relevant studies are Lall et al. (2004) and more lately Combes et al. (2010) that employ plant level dataset to consider the impact of market potential on proficiency for India, France, respectively. Transport improvements decrease the cost and increase the potential for interaction and therefore evince economic agents closer and could, moreover, increase the profits of agglomeration economies and this path derives positive productivity profits. An alternative to region defined measures that deterministically consider spatial externalities is the implication of market potential. Since then, the implication of market potential has been applied in many empirical literatures as representative for market request. Last empirical literature in this area displays that higher market potential increases factor costs and revenue (Redding and Venables, 2004). Some literatures have, furthermore, evaluated straightly the effect of market potential on firm-scale productivity. The positive elasticity of wages corresponding to market potential determined as the aggregate of concentration of other areas weighted by the reverse interval to these areas (Combes et al., 2010). They discuss that the principal profit of transport infrastructure development is that it causes more economic agents within accessible reach and hence changes the effective concentration from which agglomeration economies will be acquired. Henderson (2003) considers that technology spillover and agglomeration have significant effects on productivity for high tech firms despite that not for manufacturing firms across U.S. companies; and Braunerhjelm and Borgman (2006) estimate significant positive effects of agglomeration on productivity and progress across Swedish regions. There are great number of research of the impression of industrial variety and average organization scale on proficiency; labor enhancement, novation, and corporation commence (Glaeser et al., 2010). Thus, cross industry variety is a distinct implication than

manufacturing construction and, since multi organization firms are prevalent in any determined position, mean of organization size is just a distinctive index of industrial construction (Evans, 1986). Estimating local industrial construction density is complex due to micro scale dataset are essential to build a proper firm index. Some studies of industrial construction in specific areas are expressive though have restricted generalizability (Watts et al., 2003). At the national rather than spatial measure, tentative results indicate that an intensive industrial structure could impress firms' operation negatively, relying on the measure of concentration (Gopinath et al., 2004). The measure of structural concentration in the manufacturing sector that controls organization level productivity estimation of generally assumed origins of agglomeration economies in two sub sectors industries, depicting a significantly positive relation across a competitive construction and proficiency in knowledge intensive manufacturing however significant relation was found for a higher technology driven industry (Feser, 2002). These studies display a relation between local industrial manufacturing agglomeration and economic performance. Therefore, the consequences of the estimation of market density improvement and trend in the Iran food manufacturing could be found useful. Illustrating and demonstrating the extension of market density and its distribution among sections could make an opinion of the competitive position about agribusiness, about the feasible development of the market structure in the future and therefore, give some propositions that could be of concern to plan markets corresponding to competition and industrial plan. To consider discrepancies in activity, we have chosen a cluster estimation technique. This study have classified districts in equivalent clusters derive from the loss of uniformity minimization indicator. Our purpose was to recognize diverse classes comprising accordingly similar provinces depend on selective agricultural indicators.

2 Materials and Methods

2.1 Study area

The empirical estimation depicted below employs regional data by the Iran's annual statistical yearbook during the period 1986–2015. The data includes statistics on the magnitude of production plants in the Iran. This data consist of the position of the firm. A wider domain of data on output and inputs is accessible at the constitution level. The sample resulting from the consolidating of the statistical database comprises of Iran's food firms. This sample, from a statistical viewpoint could be noticed representation for the food firms. Information on several firm level production parameters such as value added, labors, capital, energy are employed in the estimation (Table 1). Capital is mostly evaluated by permanent inventory procedures. Moreover, this requires subsequent the sample firm over time. In this study capital is determined as the gross amount of firm and machinery. This study illustrates that defining capital as a gross share is an appropriate conjecture for capital (Doms, 1992). Labor is determined as the total number of employee worked and paid for by the firm during the accounting year. Energy is computed by the total procurement amount of fuels, electricity applied in the production procedure during the computing year. The total capital cost contains hires paid for the utilization of fixed assets in the firm and interest paid for loans. The spatial attributes enabling us to identify each firm at the region level. The firm level data have been combined with district level indexes such as density of industry in the district, and potential accessibility to urban markets. The source of statistical data are the Iran manufacturing census dataset by Iran National of Statistics. Further, this paper concentrate on food industries in Iran: districts 1, 2, 3, 4 (Fig. 1). These areas have been organized four major areas of industrial agglomeration in Iran. As the considerable increasing of industrial activities in these areas has driven the Iran economy, our sample is ideal to analyze the impact of industrial clusters on firm-level performance. Y is measured as productivity. We remove sample firms by negative value added and out of performance position. The data also provide information on plants' sales, total sum of gross wages, energy expenses plus costs on materials. This information is employed to construct the dependent variable, *TFP*. The statistical data also prepared detailed spatial information on plants' province codes which consider estimating both spatial concentration indicators (Table 1). To survey structural changes at province levels, we set out to investigate the transitions of the density of employment, the scale of the manufacturing industry, the value-added ratio, the scale of establishment, and the variety of industries, respectively. In recent years, the application of Bayesian hierarchical spatial

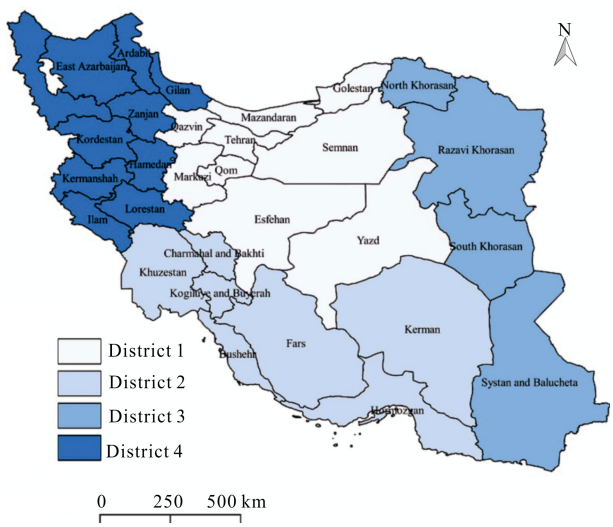

Fig. 1 The four macro districts of Iran with industrial districts

has become increasingly popular since the advances in computational techniques, such as Markov chain Monte Carlo (MCMC) procedures. Constructing regional effects that result from local referenced dataset is generally accomplished by combining the spatial dependence into the covariance structure by an autoregressive approach (Besag et al., 1991). Specifically, in this research concurrently analyzed the distribution of the manufacturing's employment within a region, the share of aggregate industry employment within an area, and the market potential of an industry in developing an agglomeration indicator. This is the specified agglomeration index in the spatial economy studies and we adopt the indicator to estimate the impact of agglomeration in this paper. This indicator depends on a comparison between the spatial concentrations of plants of a random distribution that is determined as the expected distribution in the market potential.

2.2 Measures

This study employs two well-known criteria of productivity in the studies, containing employee proficiency and total factor productivity (*TFP*). Labor productivity is a partial measurement of productivity that centralizes on estimating the productivity of labor inputs, whereas *TFP* discusses the output proficiency of applying entire inputs. To decrease the effect of variation in output prices on the estimation of productivity, the paper approves the price modified scale of labor productivity expanded by Aw and Lee (2008). This indicator is probably appropriate for estimating firm level productivity in this paper, because the state of the Iran micro database is sometimes discussed for not being enough dependable. However, as Ellison and Glaeser (1997) notice that these coefficients do not consider the effects of industrial structure and could decline to describe a precise estimate of manufacturing agglomeration. To mention the problem, Ellison and Glaeser (1997) provide the indicator of spatial concentration. The γ_k indicator (agglomeration index) obtains the following structure:

$$\gamma_k = \frac{G_k - (1 - \sum_z x_z^2)}{(1 - \sum_z x_z^2)(1 - H_k)} \tag{1}$$

where G_k is the spatial Gini parameter, while x_z is the output of manufacturing in location z, where G_K depends on the contribution of employment or output with location z in manufacturing k. $H_k = \sum_k u_k^2$ is the Herfindahl indicator of industry, by u_k indicating for the production distribution of a special plant in industries comprising of fewer and larger plants, even if regions were selected arbitrarily (Dumais et al., 2002). Supposing that there is no industrial agglomeration and every district is identical, the spatial density G_K of industry k may be proportionate to market density H_k. Ellison and Glaeser (1997) find that:

$$G_k = (1 - \sum_m X_m^2)[H_k + \gamma(1 - H_k)] \tag{2}$$

Moreover, considering the priority of accessibility to market as a main factor of the spatial concentration of economic performance, an accurate scale of availability to demand is postulated. According to Klein and Crafts (2012), this paper considers market potential that evaluates for each Iranian district k between 1986 until 2015, such as a weighted mean of output (or total value added) of entire districts j:

$$MKTPOT_{kt} = \sum_{j=1}^{M} (GDP_{jt} \cdot d_{kj}^{-1}) \tag{3}$$

By considering d_{kj} the large domain interval in kilometer across the centric of regions k and j. Basically, this index measure the capacity of demand for goods and services generated in a defined position with that position's vicinity to markets of customer. Therefore, it could be explained as the value of economic performance to that a location has accessibility to, after considering the essential transport costs to contain the space to

attain other districts. With the plant level dataset, this study demonstrates the effort to estimate Iran's manufacturing agglomeration employing the agglomeration indicator. In essence, production dataset could be applied to evaluate agglomeration index. The labor data takes priority to output data in the existing studies, as estimation applying the output data perhaps compound the effect of labor including that of capital. The agglomeration indices of Iran's food manufacturing are calculated at province level. The y_k index for all feasible compositions of manufacturing and spatial domains have augmented during the time of 1986–2015, that suggests enhancing spatial agglomeration in Iran's food manufacturing. The assumption examined in this study is that a greater level of concentration industry in an area that is, the predomination of some large plants restricts concentration economies and eventually reduces the economic operation of some firms in that industry, particularly small ones. If it is correct, a significant indication is that the density across regional manufacturing of mostly supposed profits of clusters, districts, and other forms of agglomeration is disparate, conditioned on the particular formation of the industry in the area. Also, these opinions mostly have been examined primarily in the literature and indirectly in studies of the impression of industrial diversity and average construct size on different evaluations of manufacturing performance. Purpose of this study is to apply a test of the hypothesis that estimates the implication of firm-specific model distribution more distinctly. This paper utilizes that by employing a composition of private and openly accessible dataset to evaluate the impacts of agglomeration on productivity in a defined study industry, by considering spatial different agglomeration sources.

2.3 Bayesian estimation

We calculate the spatial structure for plant level dataset, and utilize a Bayesian procedure to evaluate the hierarchical spatial methods. Furthermore, the error terms are modeled to be a weighted sum of the random error at their neighbors plus some random noise, that is multivariate normal (MVN) by zero mean and diagonal variance-covariance matrix $\sigma^2 I_n$. Let Y explain the productivity. This model employ a normal distribution for every Ys, s= 1,…, K, that is contingently independent for each district, by the mean μ_s (particular for every Y_s) variance of σ^2.

$$p(Y \mid \mu, \sigma^2) = \prod_{s=1}^{K} p(Y_s \mid \mu_s, \sigma^2) \tag{4}$$

where $p(Y \mid \mu, \sigma^2) \sim N(\mu_i, \sigma^2)$

That is, provisional on the average and standard deviation, the logarithm of estimation conforms of normal distribution. The mean μ_i is a spatial procedure that would be determined by the observed data. Given that the average spatial impact is constructed with a linear structure of productivity, given that the productivity are analyzed at the food firms of four districts, the mean natural logarithm could be estimated by a nonzero steady parameter and the spatial random impacts that account for additional variability. The average of spatial effect is created from the linear structure of agglomeration effects. This model supposed that productivity belongs to the subsequent components:

$$\begin{aligned}\mu_s^{(z)} &= \mu_1^{(z)} \cdot firm[s] + \beta_2^{(z)} \cdot diversity[s] + \beta_3^{(z)} \cdot Agri[s] + \\ &\beta_4^{(z)} \cdot capital[s] + \beta_5^{(z)} \cdot energy[s] + \beta_6^{(z)} \cdot INFRA[s] + \\ &\beta_7^{(z)} \cdot labor[s] + \beta_8^{(z)} \cdot MP[s] + \beta_9^{(z)} \cdot AGE[s] + \\ &\beta_{10}^{(z)} \cdot Export[s] + \beta_{11}^{(z)} \cdot wage[s]\end{aligned} \tag{5}$$

where (z) is an indication for the structure coefficie nt on the province measure. By the way, the local random impacts are constructed as the consequence of agglomeration relative indexes. All covariates in this model were standardized to eliminate the scale impact of corresponding covariate compared to other covariates. In this point, prior distributions were de termined with the structure coefficients that are abs olute from another:

$$\begin{aligned}&p\left(\beta_0^{(m)}, \beta^{(z)}, \sigma^2, \sigma_a^2\right) = \\ &p\left(\beta_0^{m}\right) \cdot \left[\prod_{h=1}^{k} p\left(\beta_k^{z}\right)\right] \cdot p\left(\sigma^2\right) \cdot p\left(\sigma_a^2\right)\end{aligned} \tag{6}$$

This model describes normal distribution for entire regression parameters including inverse gamma for all the variance coefficients:

$$p\left(\beta_0^{(m)}\right) \sim N(0, 1 \times 10^{-100}) \tag{7}$$

$$p\left(\beta_k^z\right) \sim N(0, 1\times10^{-100}) \tag{8}$$

$$p\left(\sigma^2\right) \sim IGamma(0.001, 0.001) \tag{9}$$

This model demonstrates spatial random effects to provide the frame of the multivariate reply distribution to change in commutable paths across spatial districts and covariate components. Intrinsically, this model constructs an applied method to multivariate spatial concentration analysis. With merging across this combination density, one could catch region-characteristic conclusions. This study employs a Bayesian supposed methods and by posterior estimation extend an effective Markov chain Monte Carlo (MCMC) approach that incorporates with Gibbs and Metropolis procedures.

2.4 Model implementation

The mentioned distributions could be strait forwardly obtained and depend on common distribution groups, allowing us to compute the Gibbs sampling. Our Bayesian models were modified to the data by sampling the associated posterior distributions utilizing Markov chain Monte Carlo (MCMC) sampling, by performance with WinBUGS. By this implementation, we also operate MCMC iterations with *R* version 3.1 that was adequate to confirm the convergence form on standard assessment. The sampler produces samples from the joint posterior distribution for each parameter. In these estimations, MCMC strings were performed for a 15 000 iteration burn-in period tracked by a generation run of 30 000 samplings. Overlap of the samplers to the analogous stationary distributions was determined utilizing both visual detection of the posterior sampling record, with considering the Gelman procedure (Gelman et al., 2004). Presenting spatial dimension of sample provinces into plant level clarification generates a hierarchical framework in an evaluating equation.

3 Results

In this study, we use a Bayesian hierarchical procedure to calculate likewise a hierarchical pattern. This model estimated different processes using the deviance information criterion (DIC). Predominantly, DIC includes an extension of Akaike Information Criterion and it is defined as: $DIC = D + pd$. Where D equals with the posterior mean of the deviance and pd is the amount of efficient parameters in this procedure. *DIC* obtains both structure fit and model intricacy into consideration when evaluating models. Lower amount of *DIC* propose preferable-fitting models. The implementation of the Bayesian hierarchical linear structures could be construe by the trace plot for σ^2 for two districts shown in Fig. 2. For the σ^2, the model was performed with fifteen thousand samplings employing two sets of primary values, as shown in Figs. 3a, 3b. Table 1 displays some demonstrative statistics for three times, that is our basic estimation. Our data consists of information on firms in 180 food manufacturing industries (utilizing the 1200 SIC classification). Model analysis indicated effective and fast convergence of the strings for variance of two districts. Fig. 3 shows the trace plots of post burn-in with selective model parameters: σ^2, the agglomeration coefficient. The strings overlapped substantially, with no proof of label switching within each (strings, and so relabeling algorithm converged rapidly. We utilize the Bayesian procedure to fit the proposed model, where posterior inference about the model parameters relies on a standard Monte Carlo Markov Chain estimation, the Gibbs sampler with a Metropolis step. By Table 2, we could observe that the connection between labor productivity and industrial concentration for the food industry during three terms exhibits positive connection. However, for the food industry, as the degree of agglomeration increases, the posterior distribution of labor productivity also increases. Furthermore, in the case of the food industry, the connection between labor productivity and industrial agglomeration is clear. This is because there are many components that affect a firm's labor productivity. If we could further control other components such as firm size that influence of labor productivity, we could determine the connection between agglomeration and labor productivity. Table 2 exhibits the results for the agglomeration index for Iran's food industries at the regional level during the period 1986–2015 for Iran's region. Table 2 displays the posterior means, averaged between the 15 000 iterations, by 95% coverage percentage and the true coefficient amount utilized to obtain the dataset. The posterior calculations displayed nominal bias, and the coverage percentage were closed the nominal magnitude for all parameters. In addition, productivity was related with agglomeration and lower market potential. Higher mar-

ket potential province was related with a low increase in productivity ($\beta_{MP(high)}$ = 0.924; 95% CI =0.864, 0.985)) at district 1. The posterior means of $\beta_{MP(high)}$ are roughly 0.54–0.85 during second time, respectively. The coefficients of the market potential (β_{MP}) are also positive and significant. Furthermore, the posterior means of β_{MP} are positive (0.53) and significant. These conclusions show that agglomeration of plants in the similar industry has a significantly positive impact on food firm's proficiency.

The values of assessments are related to the conclusions in the last literature (Henderson, 2003). In addition, the posterior distribution of $\beta_{MP(low)}$ is 0.065 for district 4. These results generate definite proof of a positive relation across agglomeration and productivity agglomeration and productivity, respectively. The coefficients of the market potential (β_{MP}) are also positive and significant. Furthermore, the posterior means of β_{MP} are positive (0.53) and significant. These conclusions show that agglomeration of plants in the similar industry has a significantly positive impact on food firm's proficiency. The value of assessments are related to the conclusions in the last literature (Henderson, 2003). In addition, the posterior distribution of $\beta_{MP(low)}$ is 0.065 for district 4. These results generate definite proof of a positive relation across agglomeration and productivity.

Table 1 Variable definitions and basic statistics for four regions

Year/Sample size			1995 (n = 1386)				2005(n = 1640)				2015 (n = 1460)			
Variable			Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
District 1	F	Average firm size	256	16.55	2	1977	356	198.35	4	2845	300	412	10	2300
	D	Diversity	0.0257	0.016	0.005	1.34	0.0357	0.006	0.002	1.34	0.0657	0.006	0.004	1.34
	Agri	Agriculture output	15856	1643	3645	54378	16953	1054	7645	54378	21853	657	8669	54378
	K	Ln capital	6695	1634.6	126	10368	8756	9567	240	12647	8758	6457	268	16745
	E	Energy	4876	10298	2356	33867	4563	9845	2356	41867	5673	11465	2356	56487
	IN	Income	0.042	0.5813	0.012	0.645	0.048	0.7327	0.012	0.645	0.045	0.4642	0.012	0.645
	L	Ln labor	78	135	21	329	185	220	43	380	365	153	78	465
	MP	Ln market potential	0.64	0.24	0.005	1.26	0.86	0.14	0.08	1.26	1.27	0.35	0.04	1.26
	AI	Age industry	7.582	13.56	0	85	8.682	9.86	0.07	96	9.182	13.67	0.05	106
	INFRA	Infrastructure stock	367.16	586	65.4	4768	541.16	685	178.5	4768	681.16	749	205.6	4768
	EX	Export ratio	0.42	0.07	0.37	4.9	0.54	0.16	0.12	5.6	0.51	0.03	0.17	7.8
	W	Average wage	3.45	0.37	–0.58	7.45	4.82	0.29	–0.47	9.45	5.37	0.42	–0.54	12.34
District 2	F	Average firm size	224	146.78	2	1586	245	68.35	4	2264	412	298	10	2450
	D	Diversity	0.0257	0.08	0.014	1.34	0.0257	0.006	0.004	1.34	0.0257	0.006	0.008	1.34
	Agri	Agriculture output	13656	3543	2865	54378	16853	7987	5743	54378	21853	7385	7645	54378
	K	Ln capital	7845	1434.6	238	8965	9644	4756	238	10945	11739	7465	238	12355
	E	Energy	3657	8745	2356	39567	2376	9436	2356	43567	2246	14645	2356	58745
	IN	Income	0.042	0.5813	0.012	0.645	0.042	0.7327	0.012	0.645	0.042	0.4642	0.012	0.645
	L	Ln labor	57	168	88	329	124	220	65	364	287	153	128	567
	MP	Ln market potential	0.56	0.05	0.007	1.54	0.84	0.17	0.06	1.26	1.58	0.24	0.08	1.26
	AI	Age industry	10.563	8.74	0	74	11.574	9.645	0.05	84	12.289	9.38	0.03	94
	INFRA	Infrastructure stock	481.16	743	84.6	4768	567.16	743	97.6	4768	693.16	743	145.7	4768
	EX	Export ratio	0.32	0.16	0.58	5.6	0.47	0.23	0.15	5.6	0.62	0.05	0.26	5.6
	W	Average wage	2.86	0.43	–0.32	6.48	3.34	0.65	–0.41	9.56	4.67	0.26	–0.56	10.46

Continued Table

Year/sample size			1995 (n = 1386)				2005(n = 1640)				2015 (n = 1460)			
Variable			Mean	SD	Min.	Max.	Mean.	SD	Min.	Max.	Mean.	SD	Min.	Max.
District 3	F	Average firm size	140	48.95	3	1354	200	198.35	4	2246	350	298	10	1689
	D	Diversity	0.0257	0.057	0.019	1.34	0.0257	0.006	0.004	1.34	0.0257	0.006	0.006	1.34
	Agri	Agriculture output	9567	1448	3589	54378	16853	8675	6487	54378	21853	3186	7645	54378
	K	Ln capital	3892	174.6	238	15874	5783	1534.6	238	15874	7538	1534.6	238	15874
	E	Energy	2543	7537	2356	28567	2376	8965	2356	32567	2246	10866	2356	38567
	IN	Income	0.042	0.5813	0.012	0.645	0.042	0.7327	0.012	0.645	0.042	0.4642	0.012	0.645
	L	Ln labor	45	168	88	329	168	220	65	320	365	247	128	388
	MP	Ln market potential	0.58	0.15	0.67	0.98	0.68	0.34	0.05	1.26	0.86	0.18	0.06	1.26
	AI	Age industry	9.582	8.74	0	80	10.582	9.645	0.07	84	10.982	9.38	0.04	94
	INFRA	Infrastructure stock	411.16	648	45.6	4768	541.16	856	68.4	4768	681.16	954	73.6	4768
	EX	Export ratio	0.38	0.19	0.01	5.6	0.55	0.37	0.14	5.6	0.48	0.11	0.21	5.6
	W	Average wage	2.04	0.14	–0.24	4.67	2.89	0.56	–0.29	5.64	3.47	0.35	–0.31	7.37
District 4	F	Average firm size	180	67.43	3	1274	380	198.35	4	2346	460	298	10	2156
	D	Diversity	0.0257	0.156	0.001	1.34	0.0257	0.006	0.00	1.34	0.0257	0.006	0.008	1.34
	Agri	Agriculture output	13678	9574	6483	54378	16853	2645	5833	54378	21853	4534	8576	54378
	K	Ln capital	5738	194.7	238	15874	6486	1534.6	238	15874	3744	8542	238	15874
	E	Energy	2867	8954	2356	30567	2376	11454	2356	37567	2246	13984	2356	41567
	IN	Income	0.042	0.5813	0.012	0.645	0.042	0.5813	0.012	0.645	0.042	0.5813	0.012	0.645
	L	Ln labor	65	168	88	329	158	240	65	350	279	153	128	395
	MP	Ln market potential	0.48	0.54	0.46	0.94	0.78	0.67	0.18	0.98	0.95	0.68	0.35	1.17
	AI	Age industry	6.582	10.26	0	76	7.282	6.74	0	84	7.982	7.75	0	94
	INFRA	Infrastructure stock	411.16	547	57.8	4768	541.16	784	78.5	4768	681.16	984	84.6	4768
	EX	Export ratio	0.37	0.08	0.08	5.6	0.45	0.08	0.15	5.6	0.57	0.09	0.18	5.6
	W	Average wage	2.26	0.56	–0.17	4.83	2.38	0.15	–0.26	5.48	3.64	0.76	–0.32	9.37

Table 2 Posterior means and 95% credible intervals for the proposed model

Year		1986–1995			1996–2005			2006–2015		
Variables		Mean	SD	95%CI	Mean	SD	95%CI	Mean	SD	95%CI
District 1										
Log FC										
Average firm size	β_{F1}	0.0105	(0.026)	[0.009, 0.012]	0.0305	(0.010)	[0.025, 0.036]	0.0575	(0.024)	[0.047, 0.068]
Diversity	β_{D1}	0.4625	(0.003)	[0.456, 0.469]	0.482	(0.008)	[0.478, 0.486]	0.47	(0.010)	[0.461, 0.479]
Agriculture production	β_{Agri1}	0.065	(0.037)	[0.052, 0.078]	0.088	(0.017)	[0.067, 0. 109]	0.107	(0.026)	[0.086, 0.128]
Ln capital	β_{K1}	0.1205	(0.008)	[0.105,0.136]	0.147	(0.025)	[0.128, 0.166]	0.1475	(0.019)	[0.137, 0.158]
Energy	β_{E1}	0.030	(0.010)	[0.027, 0.033]	0.084	(0.005)	[0.074, 0.095]	0.0366	(0.035)	[0.066, 0.073]
Income	β_{IN}	0.006	(0.036)	[0.005, 0.007]	0.010	(0.028)	[0.008, 0.012]	0.0075	(0.018)	[0.006, 0.009]
Ln labor	β_{L1}	0.274	(0.046)	[0.264, 0.285]	0.341	(0.034)	[0.324, 0.358]	0.3275	(0.012)	[0.307, 0.348]
Ln MP(high)	β_{MP1}	0.687	(0.028)	[0.646, 0.728]	0.859	(0.017)	[0.735, 0.984]	0.924	(0.027)	[0.864, 0.985]
Ln MP(low)	β_{MP1}	0.029	(0.025)	[0.021, 0.037]	0.060	(0.017)	[0.052, 0.068]	0.054	(0.027)	[0.043, 0.065]
Age industry	β_{Age1}	0.017	(0.062)	[0.014, 0.021]	0.025	(0.009)	[0.019, 0.032]	0.031	(0.104)	[0.027, 0.035]
INFRA	β_{Infra1}	0.060	(0.005)	[0.046, 0.075]	0.074	(0.113)	[0.064, 0.084]	0.088	(0.046)	[0.078, 0.098]

Continued Table

Year		1986–1995			1996–2005			2006–2015		
Variables		Mean	SD	95%CI	Mean	SD	95%CI	Mean	SD	95%CI
Export ratio	β_{Ex1}	0.057	(0.017)	[0.047, 0.068]	0.104	(0.047)	[0.093, 0.115]	0.0615	(0.008)	[0.048, 0.075]
Average wage	β_{w1}	0.0065	(0.004)	[0.004, 0.009]	0.009	(0.029)	[0.007, 0.012]	0.017	(0.016)	[0.015, 0.019]
σ_μ^2		55.8			41.6			9.54		
DIC		3288			3345			3345		
District 2										
Log FC										
Average firm size	β_{F2}	0.0225	(0.016)	[0.019, 0.026]	0.0395	(0.240)	[0.031, 0.048]	0.0655	(0.017)	[0.056, 0.075]
Diversity	β_{D2}	0.3900	(0.018)	[0.386, 0.394]	0.4240	(0.025)	[0.416, 0.432]	0.3425	(0.045)	[0.338, 0.347]
Agriculture production	β_{Agri2}	0.0815	(0.023)	[0.065, 0.098]	0.1155	(0.008)	[0.107, 0.124]	0.0735	(0.106)	[0.063, 0.084]
Ln capital	β_{K2}	0.1060	(0.105)	[0.095,0.117]	0.1725	(0.003)	[0.147, 0.198]	0.1215	(0.024)	[0.104, 0.139]
Energy	β_{E2}	0.0450	(0.012)	[0.036, 0.054]	0.0200	(0.014)	[0.031, 0.049]	0.0465	(0.097)	[0.041, 0.052]
Income	β_{IN}	0.0065	(0.036)	[0.005, 0.008]	0.0055	(0.028)	[0.002, 0.009]	0.0080	(0.015)	[0.006, 0.010]
Ln labor	β_{L2}	0.3765	(0.003)	[0.355, 0.398]	0.2595	(0.026)	[0.245, 0.274]	0.3060	(0.085)	[0.285, 0.327]
Ln MP(high)	β_{MP2}	0.5880	(0.027)	[0.512, 0.664]	0.7950	(0.009)	[0.652, 0.938]	0.8080	(0.033)	[0.743, 0.847]
Ln MP(low)	β_{MP2}	0.0340	(0.022)	[0.027, 0.041]	0.0575	(0.004)	[0.042, 0.073]	0.0500	(0.006)	[0.043, 0.058]
Age industry	β_{Age2}	0.2220	(0.016)	[0.206, 0.238]	0.1510	(0.003)	[0.128, 0.175]	0.1000	(0.027)	[0.084, 0.117]
INFRA	β_{Infra2}	0.0650	(0.019)	[0.054, 0.076]	0.0620	(0.008)	[0.042, 0.082]	0.0765	(0.003)	[0.068, 0.085]
Export ratio	β_{Ex2}	0.0100	(0.01)	[0.006,0.014]	0.0200	(0.048)	[0.012, 0.028]	0.0235	(0.095)	[0.021, 0.026]
Average wage	β_{w2}	0.0080	(0.014)	[0.007, 0.009]	0.0130	(0.058)	[0.011, 0.015]	0.0145	(0.005)	[0.012, 0.017]
σ_μ^2		51.6000			47.5000			10.87		
DIC		3256			3236			3224		
District 3										
Log FC										
Average firm size	β_{F3}	0.011	(0.022)	[0.009, 0.013]	0.0165	(0.016)	[0.008, 0.025]	0.022	(0.037)	[0.012, 0.032]
diversity	β_{D3}	0.0215	(0.035)	[0.016, 0.027]	0.0355	(0.028)	[0.027, 0.044]	0.0445	(0.026)	[0.036, 0.053]
Agriculture production	β_{Agri3}	0.0535	(0.106)	[0.042, 0.065]	0.087	(0.008)	[0.078, 0.096]	0.0675	(0.010)	[0.051, 0.084]
Ln capital	β_{K3}	0.095	(0.025)	[0.086, 0.104]	0.130	(0.024)	[0.114, 0.147]	0.1100	(0.015)	[0.094, 0.126]
Energy	β_{E3}	0.020	(0.015)	[0.012, 0.028]	0.025	(0.036)	[0.018, 0.033]	0.032	(0.004)	[0.026, 0.039]
Income	β_{IN}	0.005	(0.005)	[0.004, 0.007]	0.010	(0.007)	[0.008, 0.012]	0.007	(0.028)	[0.005, 0.009]
Ln labor	β_{L3}	0.293	(0.014)	[0.268, 0.318]	0.247	(0.056)	[0.218, 0.276]	0.306	(0.035)	[0.285, 0.327]
Ln MP(high)	β_{MP3}	0.431	(0.006)	[0.364, 0.516]	0.541	(0.008)	[0.414, 0.668]	0.658	(0.006)	[0.554, 0.763]
Ln MP(low)	β_{MP3}	0.025	(0.006)	[0.017, 0.034]	0.035	(0.008)	[0.026, 0.045]	0.047	(0.006)	[0.038, 0.056]
Age industry	β_{Age3}	0.036	(0.018)	[0.035, 0.037]	0.025	(0.015)	[0.022, 0.028]	0.035	(0.014)	[0.034, 0.039]
INFRA	β_{Infra3}	0.039	(0.105)	[0.031, 0.047]	0.044	(0.046)	[0.038, 0.051]	0.049	(0.006)	[0.041, 0.058]
Export ratio	β_{Ex3}	0.010	(0.006)	[0.006,0.014]	0.020	(0.048)	[0.012, 0.028]	0.023	(0.017)	[0.021, 0.026]
Average wage	β_{w3}	0.017	(0.005)	[0.015, 0.019]	0.015	(0.002)	[0.013, 0.018]	0.010	(0.036)	[0.008, 0.013]
σ_μ^2		52.7			45.4			9.430		
DIC		3337			3468			3456		
District 4										
Log FC										
Average firm size	β_{F4}	0.027	(0.010)	[0.019, 0.035]	–0.057	(0.136)	[–0.028,- 0.086]	–0.096	(0.024)	[–0.065, –0.127]
diversity	β_{D4}	0.461	(0.028)	[0.454, 0.468]	0.549	(0.002)	[0.548, 0.550]	0.439	(0.028)	[0.437, 0.442]

Continued Table

Year		1986–1995			1996–2005			2006–2015		
Variables		Mean	SD	95%CI	Mean	SD	95%CI	Mean	SD	95%CI
Agriculture production	β_{Agri4}	0.037	(0.005)	[0.033, 0.042]	0.059	(0.008)	[0.042, 0.076]	0.053	(0.033)	[0.038, 0.069]
Ln capital	β_{K4}	0.111	(0.036)	[0.096, 0.127]	0.128	(0.054)	[0.118, 0.139]	0.144	(0.105)	[0.125, 0.164]
Energy	β_{E4}	0.013	(0.015)	[0.010, 0.017]	0.031	(0.036)	[0.026, 0.036]	0.020	(0.004)	[0.018, 0.022]
Income	β_{IN}	0.005	(0.005)	[0.004, 0.007]	0.010	(0.007)	[0.008, 0.012]	0.007	(0.028)	[0.005, 0.009]
Ln labor	β_{L4}	0.293	(0.014)	[0.268, 0.318]	0.256	(0.016)	[0.238, 0.275]	0.305	(0.005)	[0.284, 0.327]
Ln MP(high)	β_{MP4}	0.544	(0.035)	[0.464, 0.625]	0.604	(0.042)	[0.564, 0.645]	0.632	(0.014)	[0.583, 0.682]
Ln MP(low)	β_{MP4}	0.041	(0.035)	[0.034, 0.048]	0.065	(0.042)	[0.052, 0.078]	0.057	(0.014)	[0.046, 0.068]
Age industry	β_{Age4}	0.015	(0.027)	[0.012, 0.019]	0.020	(0.003)	[0.016, 0.025]	0.025	(0.006)	[0.021, 0.030]
INFRA	β_{Infra4}	0.036	(0.014)	[0.025, 0.048]	0.052	(0.047)	[0.048, 0.057]	0.052	(0.023)	[0.042, 0.063]
Export ratio	β_{Ex4}	0.053	(0.005)	[0.045, 0.062]	0.030	(0.003)	[0.025, 0.036]	0.023	(0.038)	[0.017, 0.029]
Average wage	β_{w4}	0.007	(0.008)	[0.006, 0.008]	0.013	(0.014)	[0.012, 0.014]	0.009	(0.045)	[0.006, 0.013]
σ_{μ}^2		53.6			42.5			10.8		
DIC		3456			3478			3567		

Notes: Descriptions: 95% CI depicts 95 percent credible interval of the posterior distribution for each coefficient district 1, district 2, district 3, district 4. Estimation consisted of fitting the regional Best-fit model to the each region's observed data separately; model used a hierarchical structure in which at least some parameters were shared across regions, and fitting was done simultaneously across all 4 regions; version of the hierarchical structure sharing parameters across 4 regions of Iran; all parameters shared. DIC is a goodness-of-fit measure for Bayesian models and is computed as the sum of the effective number of parameters (pd) and the expectation of deviance (D); Log FC explains firm concentration that used to agglomeration concentration index

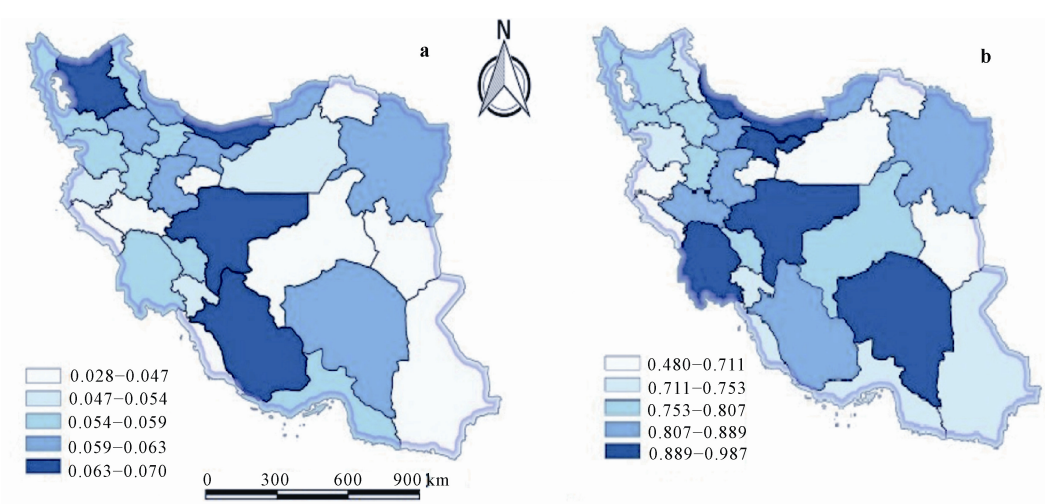

Fig. 2 Predicted joint probabilities by defined group: a) lowest joint probability, agglomeration–low market potential; b) highest joint probability, agglomeration-high market potential

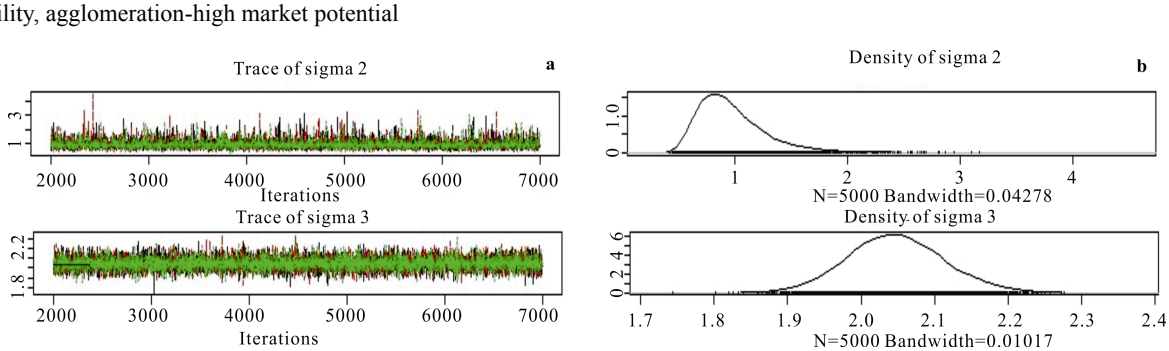

Fig. 3 (a) Post burn-in MCMC trace plots; (b) densities of the posterior samples from the 2 parameter from the proposed model σ^2, variance parameter for the district 2 and district 3

4 Discussion

We predict that β_{INFRA} would be positive due to industrial concentration could decrease the expenditures of acquiring inputs, subsequent of former studies (Rosenthal and Strange, 2001; Ellison et al., 2010), we estimate the indicator of input distribution from the magnitude of common inputs separated with gross production. β_{MP} have a positive effect if the capacity to catch positive agglomeration impacts is serious. This model predicts that β_{INFRA} could have a positive effect since industrial concentration could decrease the expenditures of obtaining materials, denominated input distribution impacts (Duranton and Puga, 2004). Therefore, plants greatly rely on intermediate inputs are more probably to catch such positive agglomeration impacts. This model supposed that old firms are more presumably than new plants to encompass business compete in the market. If these benefits via business experiments are significantly great to obtain from agglomeration effect, the coefficient β_{AGE} would be positive. However, some scholars explained a negative effect of plant age on proficiency in Germany (Bernard and Jensen, 2004). Interestingly, the relation between agglomeration indicator and firm size have significantly negative coefficient was found at district 4 during second time. The posterior mean of β_{MP} for considering districts, representing that agglomeration impact positively associate with market potential. This result indicates that food firms established in provinces with higher market potential have a tendency to have higher productivity. The posterior probabilities of β_{INFRA} are 7% for district 1, 6% for district 2, and 3% for district 3. There is positive correlation between agglomeration significantly great effect by district 1 (0.687), but the coefficient market potential was 0.43 for district 3 during 1986–1995 (Figs. 2a, b). The north region of the state presents high agglomeration. We do not find strong proof for the connection between agglomeration effects and income. Leahy et al. (2010) analyzed the spatial concentration of formations at the Australian industries and found that the coefficient for the agglomeration index has a considerable positive effect by a one percent statistical level. Fig. 4 shows the division of regions based on our regional clustering. Depend on the outcomes of ward's procedure, this model divided Iran provinces into four homogeneous groups. The first class of provinces is represented by cluster one. Cluster 1 contained the fourteen provinces these provinces were mainly located on the north and south province. Mazandaran province, Tehran province, Esfahan province, Fars province, Khorasan Razavi province showed the higher productivity among provinces at cluster 1, and cluster 2 consisted of 6 provinces. The cluster 3 includes the most remotely located western provinces. These provinces used to be isolated from other areas of the country and behave differently in comparison to other regions. the cluster 4 contained the four provinces in this cluster were geographically separated, cluster 4 consists of South Khorasan province, Syastan and Baluchestan province, North Khorasan province, Ghom province. These results indicated their higher productivity during the period of the 2008. Fig. 4 represents the pattern of hierarchical clusters of Iran provinces generated through this method. In some studies, researches determined hierarchical clusters for European positions both employing Neoclassical structures (Postiglione et al., 2010; Postiglione et al., 2013). Therefore, considering to the geographical expression of hierarchical clusters (Table 3), this method could only distinguish some uniformity in the Iran province's productivity classified pattern at districts 1 and 2 (Figs. 4a, 4b). Furthermore, we can observe that cluster 1, identified by the highest value of agglomeration, are mainly consist of provinces of district 1 and district 2. In addition, it is interesting to distinct the special pattern of the regions: the map results two different demeanor, displaying a disparate path of productivity growth for districts. The clusters are not consistently composed by neighbor provinces, and this principle is related with model's presumption. For instance, note that the region containing Mazandaran province is placed in the similar cluster of Kerman province. In other words, our result explains that district1 and district 2 define the same demeanor in terms of productivity growth. The capital investment has a significantly positive effect on productivity. The share of wage worker is shown to relate a significantly positive coefficient after controlling for other parameters, indicating that firms with a higher intensity of employees' advantage connected with higher relation productivity. Hence, the evaluated coefficients on district defined variables, income, infrastructure, firm age, and investments have

positive significant effect in all estimations. This estimate indicates that food manufacturing placed in provinces including higher income, adequate infrastructure, great market potential tend to have higher productivity.

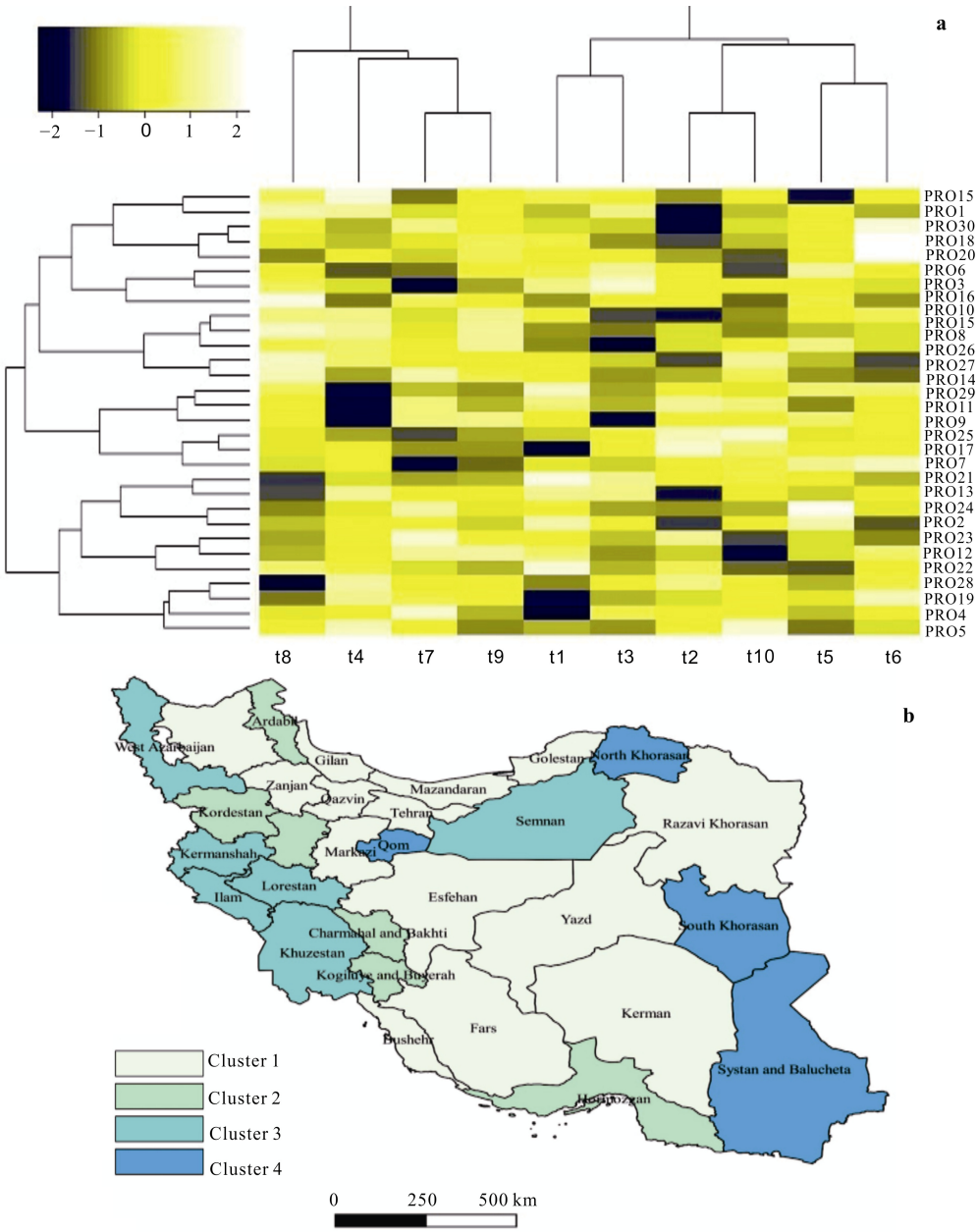

Fig. 4 The division of regions based on regional clustering (a). The number of events aggregated within 30 spatio-temporal dimensions. Legend PRO (1–30) has been considered for productivity of 30 provinces of Iran (b)

Table 3 Summary census of the component 'Productivity' (steady 1995–2015 million Rial)

Classification	Mean	Median	SD	Min.	Max.
Cluster 1	26538.69	24310.12	8644.26	10546.84	49564.83
Cluster 2	18671.24	16678.45	5468.31	7713.92	32124.33
Cluster 3	11577.64	94662.21	4769.49	6932.11	30742.58
Cluster 4	7881.36	55973.38	2563.28	1546.87	26541.28

5 Conclusions

This study evaluates the concentration effects in the 30 provinces of Iran applying manufacturing firm level data for 1986 to 2015. Afterwards, in this paper, we estimated the correlation between industrial concentration and plant level productivity in Iran's food industry. Many of spatial economic viewpoints have employed the implication of agglomeration to illustrate the establishment of industrial concentration and anticipated a positive effect of spatial agglomeration on productivity carried on by positive externalities. However, existing tentative studies using indiscrete dataset of developed provinces have also analyzed result of agglomeration economies by manufacturing industries. This study has investigated the linkage between industrial concentration and economic performance in Iran, considering particularly displaying the rating of spatial concentration of food industry and estimates the role of industrial concentration as channels of plant level efficiency. In this study, we analyze the effects of industrial concentration on firm's productivity. Whenever, plenty of urban economic viewpoints have forecasted a positive influence of spatial agglomeration on productivity accomplish by positive spillovers. By using spatial Bayes dataset of Iran's food firms during the time 1986-2015, this paper illustrated and argued the spatial concentration of the food industry. This could be imputed to the strategy that food firms to establish firms in the locations, with a concern to providing the high local plus export markets. Estimates generated from several specifications proved the prevalent discovery that industrial agglomeration has a significantly positive effect on plant labor productivity, approving the operation of the New Economic Geography viewpoint to grow and transitional state like Iran's economy. Interestingly, the productivity-augmenting impact accomplish by industrial agglomeration was determined to be more robust for small plants. This could be imputed to the positive externalities of industrial agglomeration that could mainly decrease the dealing costs of labor and intermediate inputs for small firms so that they profit much more from the gains of industrial agglomeration as they promulgate their productivity. The firms with higher market potential in more clustered areas could generate more exterior economic profits of agglomeration than `savings from lower transportation fees, and so forth. Then, the administration could construct an industrial zone for small firms to facilitate them to improve their productivity and advancement. This is an area where more research could be conducted in the future. This is one of the studies to utilize a share of firm level to estimate the share of agglomeration economies to productivity. The econometric estimates demonstrate that the individual parameter estimates for agglomeration economies are factor augmenting. On the other hand, the basic effects of agglomeration economies change greatly across districts. We find that market access and industrial agglomeration provide net benefits in industry sectors. High levels of industrial activity in district 1 and district 2 observed at least two reasons for this. There is the great incongruence in the spatial concentration of firms associate with capital of Iran. Excluding of high density links connecting large urban areas and the centers, connectivity of other urban areas is sporadic. By this view, a feasible case for modifying proficiency in industry position would be to improve the accessibility and quality of local transport infrastructure linking smaller urban areas to the rest of the network. Whenever investments in inter-regional infrastructure and legal reform are essential status for increasing productivity, they are distinctly not efficient. Lall and Rodrigo (2001) found that in Indian industry the existence of significant firm level technical productivity decrease degree from 50% to 60% of the most practice volumes. It is clear that there has been propensity against industrial concentration between the south and north areas in the food industries. The contemporary and definite plan for food plants to advance productivity is to facilitate them to enhance technological capacity. This study explains a multivariate cluster estimation of food manufacturing sector implement in Iran provinces in the period of 2005 to 2015, and identifies significant differences further the dynamics of transition. In the subsequent stage, the differences between classes were confirmed. To distinguish indexes that were of a significantly different level in one class evaluated with another, the Kruskal-Wallis rank test method was utilized. The Kruskal-Wallis rank test demonstrated the presence of statistically significant variations across classes at a level of significance of 0.05 for a number of analyzed components, containing agricultural production, concentration index, market potential, productivity in the first analyzed period of 2005 to 2015. We employ a spatial Bayes model with calculating different scales

of clustering applying plant level data for 1986 and 2015, in this study displayed that Iran's industrialization has been followed by higher spatial density, enhancing area proficiency, and more collaboration among plants in industries and within districts. The increased spatial density is similar to the industrial manufacturing enhancing in the food sector way in other countries.

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