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The Effect of Education on Industrial Development (Evidence from Iranian Small Industries)

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Abstract

The literature show evidence that small manufacturing enterprises (SMEs) are understood as main source of technology development and employment creation. At the same time they are vulnerable to a number of restrictions such as access to finances, skilled labor and public support, while are exposed to high competition and suffer from low survival rate. This research aims to shed lights on the role that education play in the process of industrial and economic development of Iranian provinces.

This research is conducted in a number of ways. First, a comprehensive literature review is conducted to gain experience from the national and international literature to identify the state-of-art research and important theories, methods and empirical results to shape the structure of this research and identify key data requirements. Second, the status of industrial infrastructure and distribution of firms by important characteristic of education is investigated. Comparison is made at the aggregate national level. Third, based on the literature findings and analysis of the industry structure, assemble a data set at the province level that is representative with good coverage of the industry sector. Also a composite Development Infrastructure Index for provinces with available ranks in mentioned component is calculated. Based on the findings, appropriate policy recommendations to improve the conditions of SMEs infrastructure and performance will purposed.

Keywords: Small Manufacturing Enterprises, Education Component, Development Infrastructure Index**,** Iranian Provinces, Principal Components Analysis.

JEL Classification Numbers: H54, L5, L16

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1. Introduction

Small and medium-sized enterprises (SMEs)[1] make up the most important sector of a nation's economy. They provide employment opportunities for millions of individuals; their work is strongly costumer-oriented; they are a source of innovation and entrepreneurial spirit; they serve as sub-contractors for large corporations, and they create competition and are the seed for enterprises of the future (Hillary, 2000).

The world-wide contribution of SMEs to economic development is significant. In the EU, for example, 66.3% of all enterprises, measured by share of employment, are SMEs. In the case of OECD[1] member countries, the SMEs, in terms numbers, represent more than 95% of the enterprises in most countries and they hire more than half of employees in the private sector. Most OECD governments promote the entrepreneurship and consider the development of SMEs by countless policies and programs. Regarding the Asia, it is acknowledged the fact that, some of the most high performance economies of the world (Taiwan and Hong Kong), strongly count on small enterprises. About 81% of all employees in Japan are concerned in the SMEs, where an enterprise hires on average 9 employees compared to 4 in the EU. In South Africa, the number of employees in SMEs is higher, recently estimated at 60%, while this sector contributes about 40% of the total production (Salvovschi and Robu, 2011).

Small enterprises can potentially play a crucial role in enhancing entrepreneurship, creating more job opportunities relative to the capital invested, mobilizing local resources, catering for basic needs of the population and contributing to a more equitable distribution of wealth and income. Furthermore, review of the literature show evidence that SMEs are understood as a source of technology development. At the same time they are vulnerable to a number of restrictions such as access to finances, skilled labor, public supports and suffer from survival rate problems.

Governments have an important role to play in the capacity building of SMEs. First, the establishment of a level that playing field. The fundamental key to a successful SMEs development strategy is the establishment of an environment that helps SMEs to compete on a more equal basis. Governments need to re-evaluate the costs and benefits of

[1]- The abbreviation SMEs is used as small manufacturing enterprises of which most of firms are micro, small and medium manufacturing enterprises.

[1]- Organization for Economic Cooperative Development

regulations that place a disproportionate burden on SMEs, implement regulations with the flexibility needed by SMEs, and place greater emphasis on competition and procurement policies to open SMEs access to markets. Second, to target public expenditure carefully in order to use scarce public resources effectively, governments need to design a clear, coordinated strategy for SMEs development that carefully separates equity and efficiency objectives. Public expenditure should be confined to those services and target groups that are underserved by the market and for which there is a clear justification based on public goods or equity considerations. Government assistance can also play an important role in exporting success of SMEs through access to finance, infrastructure, training programs and reducing bureaucracy. Support at the regional level through investment in infrastructure that assists directly the business efficiency of SMEs is important. Policymakers also need to focus on removing barriers affecting trade. Because SMEs lack the economies of scale and the internal expertise of larger ones, therefore they need more practical external support.

2. Review of the Literature

The level at which the enterprise is deemed small is a subject of a long debate and depends on the purpose of study. Defining the sector at the outset is important in order to outline the group of enterprises targeted. Small is relative and varies from one country to another. As a result, the World Bank accepted, in principle, the definitions used by the individual member countries (Levitsky 1989).

Often quantitative and qualitative measurements, or a combination of the two, are used. Given the lack and the low quality of data, these measurements may be a subject of considerable inaccuracy. Quantitative measures are clear and easy to apply while qualitative measures are relatively more satisfactory but difficult to use and operate (Elleithy 1994).

Ayyangari et al. (2005) based on employment provided the SME definition. **SME250** is the share of the SME sector in the total official labor force when 250 employees are taken as the cut-off for the definition of an SME. In their database there are 54 countries in the SME250 sample, 13 of which are low income countries, 24 are middle income and 17 are high income countries.

According to definition of Ministry of Industries and Mines[1] in Iran SMEs involve enterprises less than 50 employment. Statistical Centre of Iran divides enterprises into four kinds as follows: enterprises with 1-9 employees, 10-49 employees, 50-99 employees and more than 100 employees. Although there are some similarities with this definition and EU definitions, but Statistical Centre of Iran involve only less than 10 employee enterprises as SME. Central Bank of Iran defines enterprises with less than 100 employees as SMEs.

SMEs (generally those enterprises with less than 50 employees) are important to economic growth, and are especially important to creating new employment opportunities.

Harvie et al., (2010) introduce three factors for SME sector in a production network involve barriers and capabilities as follows:

1. Resource factors: skill and resources;
2. Psychological factors: attitude and perceptions;
3. External factors.

They emphasize the importance of factors bearing upon the capability and capacity of an SME, and its ability to overcome barriers arising from its small size. The first is directly related to the small size and limited resources of SMEs. These resource factors relate to access to: markets, technology, skilled labor, finance, market information, network embedded, knowledge and innovation.

According to Harvie et al. (2010), in this research we focus on the resource factors and weakness and strengthen of these factors. Also, we review firm characteristics of SMEs participation in production and manufacturing field as follows.

According to Gibrat's law growth rates of firms are independent of size. This leads to an equation suitable for estimating growth effects which expresses size this year as a linear function of size last year, where the size variables are expressed in natural logarithms.

Heshmati (2001) has rejected independence between firm size and growth of Gibrat's law using Swedish firm level panel data. He used three definitions of growth rates in terms of the number of employees, sales and assets.

Theoretical explanations that older firms have accumulated more experience that younger firms can be derived from Jovanovic (1982).

[1]- Ministry of Industries and Mines changed to Ministry of Industry, Mine and Trade in 2011.

Jovanovic postulates that, over time, firms can learn and improve their efficiency.

Also, Heshmati (2001) found a negative relationship between the age and growth of firms predicted by Jovanovic to hold in employment model, while it is positive in assets and sales growth models.

Ghosh (2009) investigated the role of ownership in shaping firm growth. More specifically, the results indicated that the extent of partial privatization is significantly and non-linearly related to firm growth, so that partial privatization beyond a defined threshold actually lowers growth. Besides, the analysis proffered evidence that there is perceptible decline in employment growth after privatization. This was apparent in simple univariate comparisons as well as in multivariate regressions.

Nofsinger and Wang (2011) studied the determinants of external financing in initial firm start-ups in 27 countries. They suggested that information asymmetry and moral hazard problems complicate access to start-up capital. They found that entrepreneurial experience is helpful in obtaining financing from institutional investors, and that the legal environment is important for access to external financing. The amount and diversity of sources of external financing were associated with high levels of property rights, contract enforcement, and corruption protection. Torre et al. (2010) attribute hindrances of SMEs access to finance to "opaqueness", making it difficult to ascertain if firms have the capacity to pay (by investing in viable projects), and/or the willingness to pay (due to moral hazard). This opaqueness particularly undermines credit access from institutions that engage in more impersonal or arms-length financing that requires hard, objective, and transparent information. On the other hand SME "financing gaps" are likely to be most endemic in developing and newly emerging market economies (IFC, 2010) where widespread shortage of financing occurs for all categories of SMEs and not just innovative high tech SMEs.

Firm-level productivity was hypothesized by (Shah, 2002) to improve the chance of SMEs performance. As much as 40 percent of value-added and 50 percent of employment in the SMEs were reported to be concentrated in the low productive segments and activities. Majumder (2004) showed that SMEs productivity depend more on innovation and adaptation, rather than on significant changes in capital-labor ratio. Effectiveness of labor for these enterprises depend more on training, experience, and familiarity of the workers, rather than on the range of tools that complement them. As a result, technology diffusion plays a more prominent role in their productivity rise and output growth. Lee and Kang (2007), and Rochina-Barrachina et al. (2008), considering direct measures of innovation output (such as patents, products or process innovations), find that process innovations have a positive impact on firms productivity.

Despite of that SMEs face number of barriers in their development, their small size means that they have limited resources and access to finance, lack economies of scale, have high relative costs in accessing and utilizing information technology, have skill deficiencies in the utilization of IT, have entrepreneurial, managerial, accounting and marketing skill deficiencies, lack information on market opportunities, have high transaction costs arising from gaining access to transport infrastructure and the cost of transportation, and from achieving quality accreditation, lack skills in dealing with customers both in domestic and in the export market, have limited knowledge about language and culture as well as the legal and bureaucratic issues involved in exporting, may experience a lack of business infrastructure support and in some countries may be discriminated against relative to large firms. Building capacity, improving governance, reduction transaction cost, promoting further market liberalization, addressing non-tariff barriers, increasing internet access, and facilitating trade and investment are all directly relevant to improving the capacity of small businesses to exploit export market opportunities and for their regional growth (Harvie and Lee, 2005).

3. The Data

The data used in this study were assembled from ISIPO (Iran Small Industries and Industrial Parks Organization) statistics. In this study Education component are categorized into two main dimensions: Educational courses and educational industrial tours. Data availability determines the composition of its underlying indicators. It is argued that ranking provinces based on these dimensions (a) shows position of each province with regard to industrial education and (b) pinpoints the sources of success and failure in developing industrial infrastructure. Also a composite DII for provinces with available ranks in mentioned components is calculated to show the overall position of each province.

The indicators for educational component are as follows:

- Educational courses (courses, participants, hours) / Educor1, Educor2, Educor3
- Industrial tours (tours, members, average) / Indtour1, Indtour2, Indtour3

Table 1 in the appendix shows the general statistics for the indicators used in education component based on 2013 year data. PCA methodology was used for estimation of these indicators. The sample mean and standard deviations for each indicator is reported in Table 1 too.

4. The Index Methodology

Introduction of Human Development Index (HDI) by UNDP in early 1990 followed a surge in use of non-parametric and parametric indices for measurement and comparison of countries performance in development, globalization, competition, well-being and etc. The HDI is a composite index of three indicators. Its components are to reflect three major dimensions of human development: longevity, knowledge and access to resources represented by GDP per capita, educational attainment and life expectancy (United Nations Development Programme (1995)). In recent years additional gender and poverty aspects are included. A known example of the non-parametric index is the HDI, while principal components analysis (PCA) and factor analysis (FA) are among the parametric counterparts. The indices differ mainly in respect to weighting the indicators in their aggregation. The non-parametric index assumes the weights, while the parametric approach estimates them.

PCA is a statistical technique that linearly transforms an original set of variables into a substantially smaller set of uncorrelated variables that represents most of the information in the original set of variables. Its goal is to reduce the dimensionality of the original data set. A small set of uncorrelated variables (factors or components) is much easier to understand and use in further analysis than a large set of correlated variables. The idea was originally conceived by Pearson (1901) and later independently developed by Hotelling (1933). The advantage in reducing the dimensions is ranking the units of comparison in a unique way avoiding contradictions in units' performance ranking.

PCA is sometimes used prior to some factor analytic procedures to determine the dimensionality of the common factor space. It can also be used to select a subset of variables from a larger set of variables. That is, rather than substituting the principal components for the original variables we can select a set of variables that have high correlations with the principal components. PCA is also used in regression analysis to address multicollinearity problems (i.e., imprecise regression parameter estimates due to highly correlated explanatory variables). The technique is also useful in displaying multivariate data graphically so that, for example, outlying or atypical observations can be detected. This is based on the facts that the principal components represent the variation in the original variables and there are considerably fewer graphical displays of the principal components to visually examine relative to the original variables. Lim and Nguyen (2013) compared the weighting schemes in traditional, principal component and dynamic factor approaches to summarizing information from a number of component variables. They determined that, the traditional way has been to select a set of variables and then to sum them into one overall index using weights that are inversely related to the variations in the components. Moreover, they founded that, recent approaches, such as the dynamic principal component and the dynamic factor approaches, use more sophisticated statistical and econometric techniques to extract the index. They proposed a simple way to recast the dynamic factor index into a weighted average form. Due to availability of only cross-sectional data, such more advanced dynamic factor approaches are not used here.

Also, in several studies, common factor analysis (CFA) and PCA were used in either the computation of an index or to reduce several variables into fewer dimensions. While some researchers prefer the CFA approach, a majority prefer the PCA method. For instance using several indications of economic integration and international interaction, Andersen and Herbertsson (2003) used a multivariate factor analysis technique to compute an openness index based on trade for 23 OECD countries using several indications of economic integration and international integration. Archibugi and Coco (2004) presented an index (ArCo) of technological capabilities for a large number of countries. They reported data on three technological infrastructures such as internet, telephony and electricity. Analyzing the relationship between economic factors, such as income inequality and poverty, Heshmati (2006) used PCA to addressing the measurement of two indices of globalization and their impacts on poverty rate and income inequality reductions. Heshmati and Oh (2006) compared two indices: the Lisbon Development Strategy Index and another index calculated by the PCA method. They found that despite differences in ranking countries between those two indices, the United States surpassed almost all EU-member states. Also, Heshmati et al. (2008) estimated two forms of parametric index using PCA. The first model used a pool of all indicators without classification of the indicators by type of well-being, while the second model estimated first the sub-components separately and then used the share of variance explained by each principal component to compute the weighted average of each component and their aggregation into an index of overall child well-being in high income countries. The method has the advantage that it utilizes all information about well-being embedded in the indicators. Archibugi et al. (2009) based on Technology Index (Tech) introduced by World Economic Forum attempted to rank countries position on the ground of economic and technological indicators. Tech includes three principal categories of technology: Innovative capability, Technology transfer and Diffusion of new information and communications technologies.

As mentioned above, the PCA is preferred by majority of researchers than the CFA. The CFA can be used to separate variance into two uncorrelated components. Therefore for those computing indices that relay on the common similarity over components, the PCA method might be better alternative than the CFA technique.

For the non-parametric index, the index is based on normalization of individual indicators and subsequent aggregation using an ad hoc weighting system as follows:

$$INDEX_i = \sum_{j=1}^{J} \omega_j \left(\sum_{m=1}^{M} \omega_m \left(\frac{X_{jmi} \quad X_{jm}^{\min}}{X_{jm}^{\max} \quad X_{jm}^{\min}} \right) \right) \quad (1)$$

Where i indicate province; m and j are within and between major component variables; ω_m are the weights attached to each contributing X-variable within a component; ω_j are weights attached to each of the main component; and *min* and *max* are minimum and maximum values of respective indicators across provinces. This index serves as a benchmark and it is similar to the commonly used HDI index.

For our study, use of sub-indices and a composite of Development Infrastructure Index (DII) could help provinces to evaluate their status of industrial infrastructure. Also, it will benefit from information on the isolated effects of education component on industrial and economic development.

The credit indicators are separately calculated using the non-parametric PCA approach and aggregated to form the composite DII index. The PCA compute the same aggregate index parametrically, However, PCA does not allow decomposition of the overall index into its underlying components, unless they are estimated individually, but an aggregation is not possible without assuming some weights:

Development Infrastructure Index (DII) = $\sum_{i=1}^{2} Indice_{ic}$ (2)

Where $Indice_{ic}$ is the rank of the province c via indicators i.

The non-parametric and parametric indices are computed/estimated using SAS[1] software. To maintain the rationality and objectivity of PCA technique, some tests and criteria are usually conducted to determine the percentage of each variable as denoted by each factor. Eigenvalue is the most common measurement technique used in this dimension reduction approach. Only principal components with an eigenvalue larger than 1.0 are considered. Eigenvectors signs indicates their effects and a coefficient of greater than ±0.30 are considered as contributor indicators to the principal components.

5. Empirical Results

The index numbers were computed based on only the 2013 year data. The previous year of 2012 data contained too many missing units. Another reason for excluding 2012 is that most of the indicators were given in their cumulative forms. Table 1 shows the general statistics for the variables or indicators used in both two sub-indexes based on 2013 year data. PCA methodology was used for estimation of these sub-indexes. The sample mean and standard deviations for each indicator is reported in Table 1.

Generally, for a given data matrix not all sample points, we had data missing. Assume that m individuals have complete records that are arranged as the first m rows of $\mathbf{Y}$, and $(n - m)$ individuals have missing data points in the last $(n - m)$ rows. If an observation is missing, it can be estimated using a regression equation computed from the complete portion of the sample. Without loss of generality, assume that the ith individual has a missing observation on the jth variable. The dependent variable in this case is $\boldsymbol{Y}_j$ and we have the estimate

[1]-Statistical Analysis System (software)

$$\hat{y}_{ij} = \hat{\beta}_0 + \sum_{k=1}^{j-1} \hat{\beta}_k y_{ik} + \sum_{k=j+1}^{p} \hat{\beta}_k y_{ik} \qquad (3)$$

Since the method does not utilize all of the sample information when estimating regression equations, a more general approach is to use the entire data matrix when estimating the regression equation.

It should be noted that the summary statistics includes the units missing values imputation. The minor number of imputations has very limited impacts and only on few indicators summary statistics.

Correlation coefficients among indicators are reported in Table 2. Such as mentioned in previous section, when PCA is used, high correlations among variables within a component of the index is considered a valid measure because unlike traditional regression analysis, the method is not subject to multicollinearity or autocorrelation problems. For education component correlations between education courses and education industrial tours was high (0.82).

It is worth to mention that this component is formed for the non-parametric index where the researchers determine the index components and their composition and weights. In the PCA approach the outcome is determined by the indicators actual relationship.

Also correlation coefficient among the education component and DII are presented in Table 3. Table 3 reports correlation matrix, which signal correlation coefficient are positive. The value is high, however, indicating that the education component taken into account highlight high (0.794) aspect of the overall index Development Infrastructure Index (DII).

Any PC with eigenvalue less than 1 contains less information than one of the original variables and so is not worth retaining. If the data set contains groups of variables having large within-group correlations, but small between group correlations, then there is one PC associated with each group whose eigenvalue is >1, whereas any other PCs associated with the group have eigenvalues <1. Thus, the rule will generally retain one, and only one, PC associated with each indicator such group of variables, which seems to be a reasonable course of action for data of this type.

Another criterion for choosing PCs is to select a cumulative percentage of total variation which one desires that the selected PCs contribute. It is defined by "percentage of variation" accounted for the first *m* PCs. PCs are chosen to have the largest possible variance, and the variance of the *k*th PC is l_k. Furthermore, $\sum_{k=1}^{p} l_k$ is the sum of the variances of the PCs. The obvious definition of "percentage of variation" accounted for by the first *m* PCs" is therefore

$$t_m = \frac{100}{p} \sum_{k=1}^{m} l_k \qquad (4)$$

in the case of a correlation matrix.

Choosing a cut-off t^* somewhere between 70% and 90% and retaining *m* PCs, where *m* is the smallest integer for which $t_m > t^*$, preserves in the first *m* PCs most of the information. Such as obvious in Table 4, for our case, according to eigenvalue criteria and cumulative percentage of total variation, the first six PCs retain.

Principal components and their aggregate index in the province level have shown in the Table 6. According to above mentioned criterions provinces ranked based on prin1. The main result of calculations is reported in Table 6.

6. Conclusion

This research conducted a comprehensive literature review to gain experience from the national and international literature to identify the state-of-art research and important theories, methods and empirical results to shape the structure of this research.

Moreover, to devise a policy conducive to boosting the formation of province and hence contributing to overall industrial development, there is a need to study the impacts of SMEs on the regional development. Policies cannot be effective without understanding the socio-economic effects of these enterprises on the development. Therefore this research provided an original focus on SMEs and their influences in the context of industrial development in Iranian provinces and suggested suitable policy measures to enhance development infrastructures.

By taking into account correlations of the mentioned component with DII, the provinces that want to adopt prioritize their development plans based on above criterions can customize them to their needs.

In discussing about SMEs at the global level, concepts like startups, performance, survival, growth, finances, skilled labor, publics support, and competition are frequently investigated. According to the World Bank report, that investigated the economic situation of countries at the global level, the Iranian economy is in the transition phase from production to enhanced productivity. Under such circumstance, it seems abnormal that, there is not data for measurement and evaluation of the above mentioned concepts. Especially, in SMEs sector, due to changing regulations in an uncertain manner and uncertain time intervals, complexity of accessibility

to data is reduplicated. In addition, the reliable information about sales, profits, costs, value-added and technology level was not accessible. The above reasons justifies the main problem is in the industrial infrastructure.
As mentioned, the proposed recommendations are for development of infrastructure. For the mid-term development program the following recommendations according to findings from review of the literature are made. The fundamental key to a successful SMEs development strategy is the establishment of an environment that helps SMEs to compete on a more equal basis. Governments need to re-evaluate the costs and benefits of regulations that place a disproportionate burden on SMEs, implement regulations with the flexibility needed by SMEs, and place greater emphasis on competition and procurement policies to open SMEs access to markets. To target public expenditure carefully in order to use scarce public resources more effectively, governments need to design a clear and well-coordinated strategy for SMEs development that carefully separates equity and efficiency objectives. Public expenditure should be confined to those services and target groups that are underserved by the market and for which there is a clear justification based on public goods or equity considerations. Policymakers also need to focus on removing barriers affecting trade relations. Because SMEs lack the economies of scale and the internal expertise of larger ones, therefore they need more practical external support.

Regarding above barriers and potentials, (Harvie and Lee, 2005) according to Ottawa meeting of APEC in September 1997 (APEC, 1998) introduce five key areas of importance to the capacity building of SMEs. These key issues are: access to markets, technology, human resources, financing and information. These capacity building areas are equally important to promote industrial development and performance in regional and national level.

One of the important and interested research works after investigating the education of education on industrial development is clustering among SMEs. In addition, due to paying much more attention by government and private sector to this topic, it is expected to have related data in detailed forms in the near future. It is suggested to investigate and find potentials and failures of clustering among SMEs in the national and provincial level

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APPENDIX

Table1. Education component index and its underlying indicators

Variable	Minimum	Maximum	Mean	Std Dev
Education courses 1	56.00	1242.00	314.55	274.03
Education courses 2	1425.00	40169.00	8948.29	8634.92
Education courses 3	21523.00	588054.00	198606.87	16354.53
Industrial tours 1	11.00	232.00	59.35	51.77
Industrial tours 2	227.00	5870.00	1400.48	1240.55
Industrial tours 3	13.00	40.00	24.42	5.25

Table 2. Pearson correlation matrix of education components (n=31)

	1	2	3	4	5	6	7	8	
Education component: Education courses	1.00								
Industrial tours	0.82	1.00							

Table 3. Correlation matrix of DII sub-index

	Education	DII
Education	1.000	
DII	0.794	1.000

Table 4. Eigenvalues of correlation matrix, n=31

Principal Component	Eigenvalue	Difference	Proportion	Cumulative
1	10.9472502	7.8728901	0.4760	0.4760
2	3.0743601	1.3720595	0.1337	0.6096
3	1.7023006	0.1858589	0.0740	0.6836
4	1.5164417	0.1858993	0.0659	0.7496
5	1.3305425	0.1703744	0.0578	0.8074
6	1.1601681	0.2428082	0.0504	0.8579

Table 5. Eigenvectors by sub-index, n=31

	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6
Education component: Education courses	0.2503	0.0136	-0.2526	0.0998	-0.1651	-0.0114
Industrial tours	0.2394	-0.0192	-0.2377	-0.3116	-0.1863	0.0044

Table 6. Mean value of DII and rank number

Province	Education		DII		PC	
	Rank	Mean	Rank	Mean	Rank	Prin1
Esfahan	3	0.648	1	3.293	1	2.899
Razavi Khorasan	1	0.890	2	3.222	2	1.903
Khouzestan	6	0.292	3	2.975	5	1.243
East Azarbayejan	12	0.190	4	2.865	6	1.002
Fars	2	0.743	5	2.562	3	1.777
Tehran	5	0.315	6	2.033	4	1.434
Mazandaran	24	0.049	7	1.806	22	-0.606
Semnan	10	0.233	8	1.496	10	0.110
Markazi	4	0.319	9	1.460	7	0.555
West Azarbayejan	8	0.265	10	1.448	11	0.015
Yazd	13	0.183	11	1.447	8	0.205
Kerman	15	0.169	12	0.321	9	0.187
Gilan	18	0.096	13	1.284	13	-0.223
Golestan	16	0.159	14	1.272	16	-0.338
Kermanshah	19	0.117	15	1.184	20	-0.534
Hamedan	7	0.279	16	1.121	12	-0.108
Qazvin	9	0.261	17	1.062	17	-0.366
Sistan and Balouchestan	18	0.122	18	1.023	14	-0.308
Kurdistan	20	0.087	19	0.994	23	-0.627
Zanjan	14	0.170	20	0.944	19	-0.453
North Khorasan	22	0.063	21	0.893	30	-1.108
Qom	11	0.205	22	0.887	18	-0.414
Boushehr	26	0.031	23	0.886	25	-0.829
Ardebil	21	0.075	24	0.807	21	-0.546
Charmahal and Bakhtyari	17	0.125	25	0.758	15	-0.317
Alborz	23	0.061	26	0.735	24	-0.648
Lorestan	30	0.002	27	0.708	29	-1.059
South Khorasan	29	0.008	28	0.661	27	-0.985
Ilam	28	0.014	29	0.400	31	-1.111
Hormozgan	27	0.023	30	0.360	26	-0.930
Kohgilouyeh and Bouyerahmad	25	0.040	31	0.270	28	-1.301
Mean		0.201		1.361		0.000
Std Dev		0.211		0.828		1.000