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Impact of Employment Agglomeration on Patented Innovation in U.S. Manufacturing Industries from 1986 to 2008

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ABSTRACT

This paper examines impact of employment agglomeration in fifteen U.S. manufacturing industries on their innovation activities measured by patent count. A count data model is employed in regressing patent count on employment agglomeration measures, measure of scale, and some control variables. Measures of employment agglomeration and market concentration are found to have negative impacts on innovation in U.S. manufacturing industries. Two agglomeration proxies - Gini index and Ellison-Glaeser index have a negative influence on U.S. patented innovation for the study period. This result implies that the external benefit of spatial agglomeration of similar firms has waned down. The impact of market concentration is also found to be a negative factor for innovation. This result implies that firms with larger plant size are less innovative than those with smaller plant size. Impact of 'share of workers with post graduate degrees' on innovation was found to be a positive but statistically not significant factor for innovation. The 'goods pooling' determinant displayed negative influence on innovation. These results are mostly consistent across fifteen manufacturing subsectors. Rising energy cost is found to be one of the most significant deterrents of innovation whereas, ethnic diversity is found to be a significant facilitator of it. Results of this research lend support in favor of regional economic development policies that promote coagglomeration of various interdependent and complementary industries and small scale industries, and supports ethnic diversity to spur innovation in U.S. manufacturing industries.

Key words: Agglomeration, globalization, innovation, manufacturing, patent.
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1.0 INTRODUCTION

U.S. manufacturing industries in the recent decades have demonstrated trends of growth in per worker output coupled with shrinkage in total employment. Several researchers have attributed these trends

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to automation, innovation, and off-shoring (e.g., Arthur, 2011; Harrison & McMillan, 2011; Khan & Rider, 2011; Kletzer, 2005). Globalization via forces of technological advancement and trade liberalization is putting increased pressure on U.S. industries to be innovative in order to survive and thrive. In the recent years there has been a surge in research to analyze determinants of innovation. A strand of industrial organization literature prompts us to contend that spatial agglomeration of similar firms can spur innovative activities via positive externalities of idea pooling driven knowledge spillover and synergy due to learning by doing (Marshall, 1890; Arrow, 1962; Romer, 1986). There are other bands of research work that contend that positive externality in the form of knowledge spillover occurs mainly due to co-agglomeration of diversified businesses that allows innovators to utilize complementary skills (Jacobs, 1969; Ellison and Glaeser, 1997; Glaeser, Kallal, Sheinkman, and Schleifer, 1992). Another strand of agglomeration literature contends that positive externalities are better realized when an industrial cluster is of optimal size. Some recent studies maintain that the new wave of globalization powered by forces of trade liberalization, and Information and Communications Technologies (ICTs, including the Internet) have revolutionized the idea pooling landscape by making it easier, cheaper, and faster (Khan and Rider, 2011; Cairncross 1997). According to this strand, spatial agglomeration might be losing its ground as an essential precondition of idea pooling. Strange (2009) mentions of 'great uncertainty' associated with factors that supposed to produce positive externalities in an agglomeration to foster growth in an urban area or industrial cluster and advice public policy planners to adopt caution in making spatially targeted policy interventions. Nathan and Overman (2013) contend that cluster size needs to be carefully chosen to get the most out of the policy level intervention to promote economic activity in an industrial agglomeration. However, there is a dearth of literature in examining the impact of various measures of agglomeration on U.S. manufacturing industries' innovation activities over last two decades. But this last two decades are of particular interest of researchers because during this time U.S. manufacturing industry lost significant employment and the U.S. economy has experienced new wave of globalization fostered by ICTs, and, trade liberalization spearheaded by Uruguay Round trade policy negotiations that served as the harbinger of the World Trade Organization. However, there is a dearth of research to date in investigating the impact of agglomeration and globalization on U.S. manufacturing industry's innovation activities. This paper attempts to fill that knowledge gap.

In this paper I examine impact of agglomeration and globalization on U.S. manufacturing industries' innovative activities measured by granted patent count at aggregate level, as well as, at fifteen manufacturing sub-sector levels classified by two-digit Standard Industrial Code (SIC).[2] Innovative or inventive activities that receive patient certification from U.S. Patent and Trademark Office are a subset of all innovative or inventive activities.[3] In this study, I use the patent count in manufacturing industry or subsectors thereof as the response variable and as a proxy for inventive or innovative activities. I hope the results of this empirical research would generate few insights for both academicians and economic development policy planners regarding direction of influence of few socio-economic and fiscal factors on innovative or inventive activities (measured by patent count) in U.S. manufacturing industries.

Formally, I test the following three hypotheses in this paper:
H1: Spatial concentration of similar industries will spur patented innovation activities;
H2: Innovation will be inversely related to market power, i.e., competitive industries will be more innovative than industries in a concentrated market where few large firms control relatively larger market shares;
H3: Increase in share of workers with advanced degrees in the workforce will increase innovation activities.

[2] The data is analyzed using the Standard Industrial Classification (SIC) codes. In order to maintain uniformity, the post-1997 data have been bridged from North American Industrial Classification System (NAICS) codes to SIC codes using the concordance table published by U.S. Bureau of Census.
[3] These two terms 'innovation activities' and 'invention activities' are used interchangeably in this paper.

In addition to testing these hypotheses I also attempt to examine the impact of some micro-determinants of agglomeration, and some fiscal and other control variables on innovation activities. I also seek to statistically examine whether a new wave of globalization is fostering innovation in U.S. manufacturing industries due to lowering of tariff rates and opening of internet and other ICT-related services since 1995.

Remaining sections are organized as follows: in Section 2, I provide a brief review of contemporary literature on agglomeration and innovation, in Section 3, I deal with empirical model, variables construction, and data sources, Section 4 contains discussions on regression results and in Section 5, I make some concluding remarks.

2.0 REVIEW OF LITERATURE

Schmookler and Brownlee (1962) and Schmookler (1962) analyzed data regarding determinants of economic activity and economic sources of inventive activity and found investment to be one of the main determinant of spurring industry specific inventive activities. The empirical evidence regarding the impact of agglomeration on innovation is diverse. Jaffe (1989), Jaffe and Henderson (1993), and Jaffe, Trajtenberg, and Fogarty (2000)mentioned evidence that knowledge spillovers are spatially bounded due to tacit or uncoded nature of such knowledge. Beaudry and Stefano (2003)analyze British and Italian innovation and industrial agglomeration data and reports evidence that agglomeration of firms belongs to the same industry display a negative effect on innovation activities measured by patent count. On the other hand, coagglomeration of diverse industries in a geographic region positively influenced innovations in that region. Based on the results of the empirical studies, Beaudry and Stefano (2003) contend that clustering of firms may not always be a catalyst of innovation activities. In a meta-analysis paper De Groot, Poot, & Smit (2007) compare and contrast the findings of several previously published papers regarding determinant of innovations and agglomeration and report a mixed impact of agglomeration on innovation.

Since Marshall (1890), three types of agglomeration externalities are well known. One is Marshall-Arrow-Romer type externality (abbreviated as 'M-A-R externalities'). This type of externality mainly arises from spatial concentration of firms belonged to a common industry. Another type is 'Jacob externality that emanates mainly from the co-agglomeration of firms from different industries, thus providing opportunities for inter-industry collaboration and knowledge-sharing. The main source of Jacob externalities is inter-industry collaboration, which allows firms to tap into economic knowledge from different sources. This sharing of knowledge among different kinds of industries is more relevant for product innovations. A third type of externalities is known as 'urbanization externality' referring to external effects of agglomeration derived from density of agglomeration or 'city size'.

Gini Index and Ellison-Glaeser Index (EGI) are two frequently cited measures of agglomeration (Ellison and Glaeser, 1997; Rosenthal and Strange, 2001). Herfindahl Index is a measure of distribution of industrial concentration. The EGI is constructed using the Gini index and the Herfindahl index.

Marshall (1890) mentioned of three micro-determinants of spatial agglomeration: labor pooling, goods pooling, and idea pooling. Goods Pooling (GP) provides the cost savings opportunity to agglomerated "input-heavy" firms when they rent out expensive and indivisible capital inputs and facilities to other firms. For example: when firm A's idle crane and forklifts are 'rented' by firm B located nearby, both the firms benefit. Labor Pooling (LP) is a cost saving source for agglomerated firms due to efficient matching of the demand and supply sides of the labor market. For example, when educational institutions become steady source of supply of graduates possessing skills and knowledge sought after by the area businesses, the search costs for those local firms arguably decreases, and thus LP provides a cost saving opportunity. Idea Pooling (IP) saves cost for agglomerated firms by fostering employees' sharing of knowledge about industrial best practices and R&D activities within and between firms. For example, when firms spatially agglomerate, their employees have greater opportunities due to geographic proximity to share knowledge and ideas critical for innovation activities. Agglomerated firms can arguably reduce their cost of innovation, and, thus can raise productivity, market share and profitability through idea pooling. Tambe and Hitt (2014)reported empirical study results implying that when companies hired IT workers from their competitors innovation productivity augmented for incumbent firms due to positive externalities of knowledge spillover (idea pooling).

In this paper, I analyze the impact of agglomeration on innovation measured by number of patents granted for U.S. manufacturing industries between 1986 and 2008. Researchers in a number of studies (e.g., Glaeser, Kallal, Sheinkman, and Schleifer, 1992; Henderson, Kuncoro, and Turner, 1995; Greunz, 2004) find evidence of M-A-R externalities due to agglomeration of firms and employment. Kerr and Kominers (2010) cite mention of Silicon Valley being a well-known example of the cluster that arguably is benefitting from technology spillovers and labor pooling. Several papers mention of IP as the main factor that fosters innovative activities (e.g., Ellison and Glaeser, 1997; Rosenthal and Strange, 2001&2004). Some other literature (e.g., Audretsch and Feldman, 1996; Duranton and Puga, 2000; Glaeser et al., 1992) report evidence of 'Jacob externality' which is derived from idea pooling options created by co-agglomeration of diverse groups of complementary firms. After analyzing 16 manufacturing industries' patent data gathered from 153 European regions Greunz (2004) find evidence of positive externalities of both M-A-R and Jacob externalities.

In this paper I use two different measures of agglomeration to test its influence on patented innovation in U.S. manufacturing industries. Following section contains discussions of the empirical model, variables, and data.

3.0 DATA AND METHODOLOGY

The dependent variable is a count variable that assumes non-negative integer values. The U.S. patents analyzed in this paper are granted by the U.S. Patent and Trademark Office. Because the dependent variable is count variable, ordinary least squares (OLS) will not be an appropriate technique for data analysis (Greunz, 2004; Pradhan, 2013). For this kind of variables recommended alternative statistical techniques are Poisson and Negative Binomial (NB) models (Hausman, Hall, and Griliches, 1984; Cameron and Trivedi, 1998). However, a major limitation of Poisson model relies on equidispersion, i.e., $E(y_I \mid x_i) = \lambda_i = \exp(\alpha + x'_i \beta)$ where x_i is a vector of covariates. The econometrics literature including STATA documentations maintain that NB and its alternatives such as zero-inflated Poisson (ZIP) model and zero inflated NB (ZINB) model are suitable for over dispersed count variables with excessive zeros (Drukker, 2007).

The baseline regression model I employ is as follows:

$$\begin{aligned}(Patcount)_{ist} &= B_0 + B_1(Gini)_{ist} + B_2(postgradem p)_{ist} + B_3(\text{cost}mat2valship)_{ist} \\ &+ B_4(state\min wage)_{ist} + B_5(CIT)_{ist} + B_6(PIT)_{ist} + B_7(energy\text{cost})_{ist} + B_8(ADR)_{ist} \\ &+ B_9(ethnodiversity)_{ist} + B_{10}(Inv-to-ship)_{ist} + B_{11}(T95)_{ist} + \varepsilon_{ist}\end{aligned}$$

Then I also analyze a variant model with following specification:

$$\begin{aligned}(Patcount)_{ist} &= B_0 + B_1(EGI)_{ist} + B_2(HHI)_{ist} + B_3(postgradem p)_{ist} + B_4(\text{cost}mat2valship)_{ist} \\ &+ B_5(state\min wage)_{ist} + B_6(CIT)_{ist} + B_7(PIT)_{ist} + B_8(energy\text{cost})_{ist} + B_9(ADR)_{ist} \\ &+ B_{10}(ethnodiversity)_{ist} + B_{11}(Inv-to-ship)_{ist} + B_{12}(T95)_{ist} + \varepsilon_{ist}\end{aligned}$$

Table 1A contains a brief description of each variable used in the above model. The dependent variable is patent count which has been arranged in Standard Industrial Classification (SIC) system using SIC-NAICS (North American Industrial Classification) concordance table published by the U.S. Census Bureau. The patent data was collected from the U.S. Patent and Trademark Office database. In the regression model, the subscripts 'i' implies SIC 3-digit industrial sectors where i = 1,2,3,…., 44 refers to manufacturing subsectors for which I have collected patent data, the subscript 's' indicates 48 continental States (i.e., all U.S. States excluding Alaska and Hawaii), and subscript 't' represents years between 1986 and 2008 (i.e., t= 1986, 1987, 1988, …., 2008). Gini and EGI stand for two widely used agglomeration measures (Ellison and Glaeser, 1997; Rosenthal and Strange, 2001). Ellison and Glaeser's Gini index (EGG_i) is another well-known measure of employment agglomeration by industry and is constructed as follows: $EGG_i \equiv \sum_{m=1}^{M}(X_m - S_{im})^2$, where 0 < EGG_i< 1.0, and employment agglomeration in industry 'i' is increasing in EGG_i. Following Rosenthal and Strange (2001), X_i is location (county) i's share of total (state-level) employment, and S_i is the location's (county's) share of employment in a particular industry relative to total employment in that industry in the greater jurisdiction (State). The problem with this approach in the measuring agglomeration is that the value of EGG_i> 0 does not necessarily signify that industry i is agglomerated because of external economies of scale. For example, suppose an industry is made up of a small number of large plants and that this where 0 < EGGi < 1.0, and employment agglomeration in industry i is increasing in EGG_i (i.e., higher the EGG_i higher the agglomeration of employment in the geographic space). The problem with this approach is that the value of EGG_i> 0 does not necessarily mean that the incumbent industry i is agglomerated because of external economies of scale. For example, suppose an industry is made up of a small number of large plants and that this industrial structure is the result of internal economies of scale. In this case, EGG_i takes on a large value, but this is because of internal economies of scale and not external economies of scale, namely the micro-determinants of agglomeration.[4] To overcome this issue, Ellison and Glaeser (1997) propose the following measure: $EGI_{ist} \equiv \frac{EGG_{ist} - \left(1 - \sum_c X_{ct}^2\right)H_{ist}}{\left(1 - \sum_c X_{ct}^2\right)(1 - H_{ist})}$ where X_{ct} is the manufacturing share in county 'c' in year 't' and state 's', and the summation is over all the counties in states. The Herfindahl index is given by $H_{ist} \equiv \sum_{k=1}^{K} Z_{istk}^2$ for the K plants of industry i in state s and year t. Finally, Z_{iskt} represents the employment share of the *k*th plant of industry i in state s and year t.[5]

In the case of a perfectly competitive industry with a large number of small plants, H_{is} approaches zero, and EGI_{is} approaches EGG_{is} / (1-$\sum X_{is}^2$) .[6] In this case, EGI measures spatial concentration and, unlike the Gini coefficient (EGG_{is}), is independent of agglomeration due to internal economies of scale. According to this measure, EGI_{is} takes on a value of zero when industry i is not concentrated in some region(s) but is spread evenly, as would result from a random location process. EGI_{is} takes on a positive value when industry 'i' is concentrated in some region(s). In short, we use EGI because this measure of industrial agglomeration controls for industry-specific agglomeration due to internal economies of scale and thus allows us to measure the impact of agglomeration on patented innovation. I constructed the Herfindahl index variable as a measure of plant size. The data for Gini indices and EGI indices were created using historical U.S. County Business pattern data published by the U.S. Bureau of Census.

There is a set of control variables used in this analysis. Now I briefly discuss the variable construction and data sources. The 'postgrademp' variable is constructed as the ratio of employees with graduate

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[4] As an example, Ellison and Glaeser (1997) referred to the situation of the U.S. vacuum cleaner industry (SIC code 3635). Roughly 75 percent of the total employment in this sector is contained in one of the four largest plants, but this concentration is driven by the inherent organization of the industry and not necessarily the agglomeration forces. The EGI was developed 'to facilitate comparisons across industries, across countries or over time. When plants' location decisions are made as in the model, differences in the size of the industry, the size and distribution of plants, or the fineness of the geographic data that are available should not affect the index'(Ellison and Glaeser, 1997, p. 890).

[5] Rosenthal and Strange (2001), Bertinelli and Decrop (2005), and many other researchers have used the Ellison Glaeser Index (EGI) as a measure of agglomeration. The Herfindahl index is calculated for the plant size distribution of each industry in a particular year in a particular state using the county business pattern data.

[6] We calculate the Herfindahl index using the median employment for different plant-size levels for each industry and year covered in this study.

degrees (masters and above) to all employees. The data for this variable was collected from the Current Population Survey March supplement data files. 'The variable 'Cost of materials to the value of shipment' measures input heaviness of an industry. These costs include material input costs excluding payroll costs. I constructed this variable using the Survey data of Manufacturers (ASM) –Geographic Area Series reports published by Bureau of Census. The variable 'inventory to shipment' measures perishability of manufactured products. Industries with highly perishable goods tend to have low inventories to avoid expenditure on specialized storage facilities.[7] These two variables also are created using ASM historical data. The variables 'state minimum wage', 'maximum State Corporate income tax rate' and 'maximum State Income tax rate' are straightforward and these data were obtained from the annual editions of 'The Book of States' published by the Council of State Governments. The variable 'energy cost to value of shipment' was created by dividing cost of electricity and gasoline with a total value of the shipment in the industry. This variable was created using data from the 'Annual Survey of Manufacturers-Geographic Area Series' data published by the U.S. Bureau of Census. The 'Average import duty rate' (ADR) variable was created using the data from U.S. International Trade Commission (www.usitc.gov) database. The variable 'ethnic diversity' was created as follows:

$$\left(\frac{sum of\ percent share of\ all\ minority ethnic groups}{Percent share of\ majority ethnic groups}\right)_{ist}.$$

To be more specific, let's review an example. Assume the ethnic (or diasporic) composition of population of State X is as follows: group A = 40 percent, group B = 35 percent, group C = 25 percent. Also assume, State Y's ethnic (or diasporic) composition of the population is as follows: group A = 50 percent, group B = 30 percent and ethnic group C = 20 percent. Given the demographic composition stated above, the ethnic diversity index of State X will be equal to (60/40) = 1.5 and ethnic diversity index of country Y will be equal to (50/50) = 1. Here we will conclude that State X has more ethnic (or diasporic) diversity than State Y. The 'T95' is a time dummy variable set equal to '1' for the years in the sample after 1995 and zero otherwise. I contend that the new wave of globalization since the mid-1990s changed the economic landscape via dual forces viz. technological advancement and trade liberalization. In 1995 internet became available for the first time for members of the general public for commercial and personal usage. Also, the same year was marked by the official inception of World Trade Organization upon successful completion of the Uruguay Round. I contend there was a structural break in the economic landscape since 1995 due to the dual forces of technological advancement and trade liberalization that fostered a new wave of globalization.

TABLE 1A: Variable description and summary statistics

Variable name	Variable description	Mean (Standard deviation)
Patcount	Patent count	72.387 (153.764)
Emp	Employment in various manufacturing subsectors	2336.041 (9,833.742)
Est	No. of manufacturing establishments	104.256 (311.764)
EGI	Ellison-Glaeser agglomeration indices	0.159 (0.307)
HI	Herfindahl indices of agglomeration measure	0.457 (0.261)
Gini	Gini indices of agglomeration measure	0.342 (0.326)
Postgrad	Ratio of employees with graduate degree to all employees	0.046 (0.044)
Costmat2valship	Ratio of cost of materials to value of shipment	0.492 (0.037)
Inv- to- ship	Ratio of inventory to value of shipment	.124 (0.222)

[7] Following Rosenthal and Strange (2001) fresh fruits, milk, and dairy products, even print copies of daily newspapers and any other time sensitive, climate sensitive manufacturing goods will fall in this category.

Minwage	State minimum wage	5.455 (0.864)
CIT	Maximum State corporate income tax rate	6.694 (0.852)
PIT	Maximum State personal income tax rate	5.849 (2.452)
Energy2vos	Ratio of energy cost to value of shipment	0.023 (0.006)
ADR	Average import duty rate	4.950 (1.381)
Ethno-diversity	Ethnic diversity	0.248 (0.184)
T95	Time dummy variable for globalization	0.656 (0.475)

Source: Author's own calculation

Table 1B: Number of US patents by inventors' locations

	pre-1996	1996	2000	2004	2008	2012	Year-to-date total	Percent change '96-'12
Alabama	2,176	183	209	171	132	169	5,251	-7.65
Alaska	461	52	42	37	21	40	1,162	-23.08
Arizona	5,842	413	526	425	405	487	13,463	17.92
Arkansas	1,233	103	102	80	75	93	2,779	-9.71
California	57,219	4,437	5,215	4,306	3,883	4,799	134,661	8.16
Colorado	5,805	538	540	418	337	528	13,512	-1.86
Connecticut	5,771	362	438	298	244	305	11,847	-15.75
Delaware	654	72	53	63	25	47	1,531	-34.72
Florida	16,084	1,447	1,725	1,452	1,294	1,713	41,500	18.38
Georgia	4,529	426	522	359	360	564	12,219	32.39
Hawaii	914	70	76	52	58	68	1,994	-2.86
Idaho	1,450	112	173	122	96	108	3,616	-3.57
Illinois	13,902	973	1,110	767	607	675	28,124	-30.63
Indiana	4,535	310	430	282	197	294	9,624	-5.16
Iowa	2,565	128	173	128	105	126	5,001	-1.56
Kansas	2,385	150	201	145	101	113	4,844	-24.67
Kentucky	1,807	124	133	114	109	127	3,918	2.42
Louisiana	3,797	283	381	229	183	256	8,123	-9.54
Maine	910	69	82	50	33	44	1,864	-36.23
Maryland	6,077	429	482	351	274	397	12,908	-7.46
Massachusetts	8,573	660	833	561	499	712	19,946	7.88
Michigan	12,807	845	974	717	616	665	25,594	-21.30
Minnesota	6,323	428	592	468	338	426	14,311	-0.47
Mississippi	1,087	92	107	77	41	73	2,428	-20.65
Missouri	4,297	313	403	239	230	245	9,529	-21.73
Montana	1,258	108	105	54	55	55	2,482	-49.07
Nebraska	1,670	86	113	80	86	142	3,247	65.12
Nevada	1,856	172	307	200	166	228	5,600	32.56
New Hampshire	1,483	164	150	123	68	121	3,621	-26.22
New Jersey	11,611	836	943	740	557	728	24,737	-12.92
New Mexico	1,568	122	135	105	86	119	3,450	-2.46
New York	23,677	1,628	1,773	1,349	1,107	1,359	48,019	-16.52
North Carolina	4,773	428	547	451	280	385	12,153	-10.05
North Dakota	659	49	57	33	31	25	1,312	-48.98
Ohio	10,822	669	814	667	550	587	22,334	-12.26
Oklahoma	4,074	228	225	152	123	180	7,037	-21.05
Oregon	4,682	352	366	332	467	318	10,842	-9.66
Pennsylvania	11,489	890	1,011	708	515	678	24,640	-23.82
Rhode Island	1,172	95	82	63	72	72	2,454	-24.21
South Carolina	2,365	217	246	195	158	210	5,748	-3.23
South Dakota	510	27	50	38	26	82	1,200	203.70
Tennessee	3,301	274	327	257	210	328	7,932	19.71
Texas	16,570	1,370	1,608	1,144	1,010	1,338	38,290	-2.34
Utah	2,893	245	286	237	366	357	7,956	45.71
Vermont	670	82	63	43	18	28	1,515	-65.85

Virginia	5,218	389	496	354	321	427	12,205	9.77
Washington	6,462	485	553	457	457	535	15,110	10.31
West Virginia	803	54	56	51	35	50	1,645	-7.41
Wisconsin	4,740	380	501	378	314	364	11,127	-4.21
Wyoming	579	34	48	33	25	40	1,186	17.65
All States	297,143	22,453	26,456	20,194	17,406	21,908	667,532	-2.43

Source: Author's calculations using U.S. Patent and Trademark Office database.

Table 1A presents the variable description and summary statistics. Table 1B presents the number of total granted patents by inventors' home State for the pre-1996 years and from 1996 through 2002 at four years interval (i.e., 1996, 2000, 2004, 2008, and 2012). Based on growth rates in granted patent count over last 16 years (from 1996 to 2012) ten most innovative States are South Dakota (203.7 percent), Nebraska (65.12 percent), Utah (45.71 percent), Nevada(32.56 percent), Georgia (32.39 percent), Tennessee (19.71 percent), Florida (18.38 percent), Arizona (17.92 percent), Wyoming (17.65 percent), and Washington (10.31 percent). Ten least innovative States during the period are Vermont (-65.85 percent), Montana (-49.07 percent), North Dakota (-48.98 percent), Maine (-36.23 percent), Delaware (-34.72 percent), Illinois (-30.63 percent), New Hampshire (-26.22 percent), Kansas (-24.67 percent), Rhode Island (-24.21 percent), and Pennsylvania (-23.82 percent).

Table 02: U.S. Granted patent count by types from 1986-2012

Year of Grant	Utility Patent Grants, U.S. Origin	Utility Patents as percent of total patent grants U.S. origin	Total design & plant patent US origin	Design and plant patents as percent of total patent grants U.S. origin	Total patent grants U.S. origin
1986	38,126	90%	4,148	10%	42,274
1987	43,520	92%	3,854	8%	47,374
1988	40,497	91%	4,167	9%	44,664
1989	50,185	92%	4,157	8%	54,342
1990	47,391	90%	5,120	10%	52,511
1991	51,177	89%	6,439	11%	57,616
1992	52,253	88%	6,814	12%	59,067
1993	53,231	87%	8,227	13%	61,458
1994	56,066	87%	8,679	13%	64,745
1995	55,739	86%	9,146	14%	64,885
1996	61,104	88%	8,263	12%	69,367
1997	61,708	89%	7,771	11%	69,479
1998	80,289	88%	11,071	12%	91,360
1999	83,906	89%	10,782	11%	94,688
2000	85,068	88%	11,720	12%	96,788
2001	87,600	88%	11,744	12%	99,344
2002	86,971	89%	10,748	11%	97,719
2003	87,893	89%	11,223	11%	99,116
2004	84,270	89%	10,005	11%	94,275
2005	74,637	91%	7,376	9%	82,013
2006	89,823	88%	12,308	12%	102,131
2007	79,526	85%	13,752	15%	93,278
2008	77,502	84%	15,110	16%	92,612
2009	82,382	86%	13,582	14%	95,964
2010	107,791	88%	14,380	12%	122,171
2011	108,622	89%	12,757	11%	121,379
2012	121,026	91%	11,832	9%	132,858

Source: U.S. Patent and Trademark Office database

Table 2 shows the classification of granted patents of U.S. origin into utility patents, design patents, and plant patents. The table shows that between 1986 and 2012 share of utility patents are on an average about 90 percent of the total patents and the rest (approximately 10 percent) are design patents and plant patents. Table 3 shows patent counts by nine census divisions and their percent shares of nationwide patent counts for the years 1996, 2000, 2004, 2008, and 2012. According to 2012 data, out of nine divisions, top three innovative divisions are Pacific (26 percent), South Atlantic (17 percent), and Middle Atlantic (13 percent).

Table 3: Patented innovation count by nine U.S. Census division from 1996-2012

Year	East North Central	East South Central	Mid-Atlantic	Mountain	New England	Pacific	South Atlantic	West North Central	West South Central
1996	3,177	673	3,354	1,744	1,432	5,396	3,462	1,181	1,984
	(14%)	(3%)	(15%)	(8%)	(6%)	(24%)	(15%)	5%	(9%)
2000	3,829	776	3,727	2,120	1,648	6,252	4,127	1,589	2,316
	(15%)	(3%)	(14%)	(8%)	(6%)	(24%)	(16%)	6%	(9%)
2004	2,811	619	2,797	1,594	1,138	5,184	3,276	1,131	1,605
	(14%)	(3%)	(14%)	(8%)	(6%)	(26%)	(16%)	6%	(8%)
2008	2,284	492	2,179	1,536	934	4,886	2,747	917	1,391
	(13%)	(3%)	(13%)	(9%)	(5%)	(28%)	(16%)	5%	(8%)
2012	2,585	697	2,765	1,922	1,282	5,760	3,793	1,159	1,867
	(12%)	(3%)	(13%)	(9%)	(6%)	(26%)	(17%)	5%	(9%)

Percent share of the Census division's patent is given in the parenthesis. New England Census Division includes: Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont; Middle Atlantic Census Division includes: New Jersey, New York, Pennsylvania; East North Central Census Division includes: Indiana, Illinois, Michigan, Ohio, Wisconsin; West North Central Census Division includes following States: Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota; South Atlantic Census Division includes: Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia; East South Central Census Division includes: Alabama, Kentucky, Mississippi, Tennessee; West South Central Census Division includes: Arkansas, Louisiana, Oklahoma, Texas; Mountain Census Division includes: Arizona, Colorado, Idaho, New Mexico, Montana, Utah, Nevada, Wyoming; and Pacific Census Division includes Alaska, California, Hawaii, Oregon, and Washington.

Source: Author's calculations using U.S. Patent and Trademark Office database.

Table 4 lists top ten innovative manufacturing industries at SIC 3-digit level for the years 1986 and 2008.

Table 4: Top ten innovative sic 3-digit manufacturing industries.

1986			2008		
sic	Industry	Patent count	sic	Industry	Patent count
353	Construction and Related Machinery	7,786	369	Misc. Electrical Equipment & Supplies	10,519
365	Household Audio & Video Equipment	5,523	367	Electronic Components and Accessories	9,683
369	Misc. Electrical Equipment & Supplies	4,253	365	Household Audio & Video Equipment	8,566
344	Fabricated Structural Metal Products	3,947	366	Communications Equipment	8,388
367	Electronic Components and Accessories	2,459	353	Construction and Related Machinery	7,691
391	Jewelry, Silverware and Plated Ware	2,456	384	Medical Instruments & Supplies	4,226
371	Motor Vehicles and Equipment	1,669	391	Jewelry, Silverware and Plated Ware	3,732
289	Misc. Chemical Products	1,495	344	Fabricated Structural Metal Products	3,303
366	Communications Equipment	1,247	345	Screw Machine Products, Bolts, etc.	3,303
382	Measuring and Controlling Devices	1,202	371	Motor Vehicles and Equipment	2,874

Source: Author's calculation using USPTO data.

For 1986, these ten most innovative industries were construction and related machinery (SIC 353), household audio and video equipment (SIC 365), misc. electrical equipment & supplies (SIC 369), fabricated structural metalproducts (SIC 344), electronic components and accessories (SIC 367), Jewelry, silverware and plated ware (SIC 391), motor vehicles and equipment (SIC371), misc. chemical products (SIC 289), communications' equipment (SIC366), measuring and Controlling Devices (SIC 382). For 2008, top ten innovative manufacturing industries were: Misc. Electrical Equipment & Supplies (SIC 369), Electronic Components and Accessories (SIC367), Household Audio & Video Equipment (SIC365), Communications Equipment (SIC366), Construction and Related Machinery (SIC353), Medical Instruments & Supplies (SIC384), Jewelry, Silverware and Plated Ware (SIC391), Fabricated Structural Metal Products (SIC 344), Screw Machine Products, Bolts, etc. (SIC345), and Motor Vehicles and Equipment (SIC 371).

4.0 REGRESSION RESULT

Table 5 presents the estimated coefficients of the nationwide regressions of manufacturing industries. Because the dependent variable is patent count, I use negative binomial model and zero inflated negative binomial models employing two employment agglomeration measures as regressors: Gini indices and Ellison-Glaeser Indices (EGI).

Table 5: Regression of patented innovations

	Variant model with Gini indices		Variant model with EGI	
Variables	Negative Binomial	ZI Negative Binomial (year fixed effects)	Negative Binomial	ZI Negative Binomial (year fixed effects)
Gini index	-1.196***	-1.240***	-	-
	(0.025)	(0.025)	-	-
Ellison-Glaeser Index	-	-	-0.352***	-0.374***
	-	-	(0.013)	(0.013)
Herfindahl index	-	-	-2.137***	-2.137***
	-	-	(0.029)	(0.029)
Share of employees with Master degree and above	0.252	0.191	0.110	0.043
	(0.159)	(0.158)	(0.154)	(0.152)
Ration of cost of materials to value of	-1.055***	-1.108***	-0.786***	-0.816***
	(0.197)	(0.197)	(0.194)	(0.193)
State minimum wage	0.030***	0.030***	0.027***	0.028***
	(0.008)	(0.008)	(0.008)	(0.008)
Max. State corporate income tax rate	0.120***	0.116***	0.105***	0.103***
	(0.010)	(0.010)	(0.009)	(0.009)
Maximum state income tax	-0.002	-0.002	0.010***	0.011***
	(0.004)	(0.004)	(0.004)	(0.004)
Energy cost	-4.177***	-4.064***	-3.584***	-3.438***
	(0.534)	(0.539)	(0.592)	(0.597)
Import Duty Rate	-0.236***	-0.236***	-0.237***	-0.240***
	(0.011)	(0.011)	(0.001)	(0.011)
Ethnic diversity	2.550***	2.531***	2.303***	2.296***
	(0.053)	(0.053)	(0.050)	(0.050)
Inventory to shipment	-0.280	-0.122	-0.503***	-0.341
	(0.397)	(0.396)	(0.380)	(0.379)
T95	0.414***	0.533***	0.328***	-0.441***
	(0.016)	(0.033)	(0.015)	(0.032)

Constant	4.690***	4.583***	5.097***	4.955***
	(0.159)	(0.162)	(0.156)	(0.158)
Observations	25,505	25,505	25,505	25,505
Log likelihood ratio	-132,577.96	-13,2416.3	-131,314.73	-131,178.7
LR Chi squared	7,059.23	7,382.53	9585.70	9,857.67
Probability>Chi squared	0.000	0.000	0.000	0.000

Notes: We report statistical significance of the estimated coefficients at the conventional 10 percent (*), 5 percent (**), and 1 percent (***) levels. Standard errors are given in parentheses. Zero inflated (ZI) models also have a year fixed effects.

Column 2 and 3 present the regression results of negative binomial (NB) specification and zero inflated negative binomial (ZINB) specification using EGI as one of the regressors. Columns 4 and 5 contain regression results with EGI as one of the regressors in the NB and ZINB specifications respectively. The ZINB models also control for year fixed effects. The estimated coefficients of Gini and EGI variables turned out to be negative and statistically significant at 1 percent level. The estimated coefficients of Herfindahl indices are also negative and statistically significant at 1 percent level implying that manufacturing industries with higher market concentration (where market share is dominated by relatively fewer large firms) are less innovative than more competitive industries. This result is aligned with some empirical work. For example, Sharma (2007) studies data from 57 countries and finds that small firms are producing more innovations per unit of R&D spending than large firms. Schumpeter (1934, 1942, 1947, 1951) contended that small firms were more innovative (although he later also contended that under certain assumptions, larger corporations could be more innovative). A 2013 report listing world's top fifty most innovative companies was dominated by small companies.[8] The estimated coefficients for high skilled labor (labor with master degrees and above) are positive for all but one models (with the exception of zero inflated negative binomial regression with EGI). However, contrary to expectation, this variable was not found to be statistically significant across the baseline model and variant models in Table 5.

The estimated coefficients of variable 'cost of materials to the value of shipment' (a proxy for GP) are negative and statistically significant at 1 percent level across EGI and Gini regressions with NB and ZINB specifications. These results may imply that input-heavy industries are less innovative. Examples of some industries with higher ratio of cost of materials to value of shipment are broadwoven fabric mills (sic 221), cotton paperboard mills (SIC 263), screw machine products, bolts (SIC 345), metal services (SIC347) etc. The estimated coefficient of state minimum wage is positive and statistically significant at 1 percent level across baseline and variant specifications though none is statistically significant.

The influence of state level corporate income tax is positive and statistically significant at 1 percent level across the baseline model and variant model specifications. The influence of state level personal income tax (PIT) is mixed; in the baseline model with Gini indices as regressors, I found impact of PIT on innovation to be negative, although this result was not statistically significant. However, impact of PIT on innovation is positive and statistically significant at 1 percent level.

The estimated coefficients of variable energy cost to value of the shipment are negative and statistically significant across the baseline models and variant models. The results imply that lower energy cost is the preferred location attribute used by the innovative firms to make location decisions. The estimated coefficients of the import duty rate are a negative determinant of innovation. This result is intuitive because lower import duty rate would expose U.S. manufacturers to face global competition and thus would provide an incentive for local producers to be more innovative.

The variable 'ethnic diversity' is positive and statistically significant which implies that the states with higher ethnic diversity are more innovative. This result is intuitive. Hunt, J. and Gauthier-Loiselle

[8]http://www.fastcompany.com/section/most-innovative-companies-2013

(2008),Kerr (2008a, 2008b, 2009)along with many other researchers report positive influence of ethnic diversity in U.S. patenting. Nathan (2012) finds positive influence of ethnic minority groups on British innovative activities measured by patent counts. The estimated coefficients of inventory to shipment variable are negative and statistically significant. This variable measures perishability of the product. A product with higher inventory to shipment ratio may imply that the product is not much susceptible to decay or expiration and, hence, its inventory can be stored without requiring expensive climate controlled warehousing and transportation services. The results suggest that more perishable the product is less innovative the associated industry will be.

The variable T95 is the globalization variable that takes on a value of 1 if year>= 1995 and zero (0) otherwise. I contend that a new wave of globalization fueled by advances in Information and Communications Technologies including the Internet and trade liberalization due to the intervention by World Trade Organization emerged following the conclusion of the Uruguay round. The estimated coefficient of this variable is positive and significant conform the hypothesis that the new wave of globalization increased innovation activities. Now we discuss some sectoral regression results as they are presented in Table 6A through Table 6C. In these tables, I present EGI regression results (NB) for fifteen SIC 2 digit level industries.

Table 6A: Negative binomial regression of patented innovation in fifteen manufacturing sub-sectors

Variable	Food (SIC20)	Textile (SIC22)	Apparel (SIC23)	Lumber (SIC24)	Paper (SIC26)
Ellison-Glaeser Index	-0.568***	-0.043	-0.468***	-0.776***	1.115***
	(0.199)	(0.416)	(0.142)	(0.187)	(0.338)
Herfindahl index	-3.162***	-1.418***	-3.945***	-2.026***	-0.983***
	(0.369)	(0.233)	(0.416)	(0.609)	(0.237)
Share of employees with	-0.653	0.001	-0.659	0.001	0.001
graduate degree	(0.814)	0.001	(0.664)	0.001	0.001
Cost of materials to value of shipment	-0.875	10.475	-0.517	-76.426***	-16.133
	(1.404)	(13.281)	(0.720)	(11.570)	(11.734)
State minimum wage	-0.123**	0.177	-0.073**	-0.127	-0.133
	(0.048)	(0.113)	(0.032)	(0.077)	(0.090)
Maximum State corporate	0.053	0.329**	0.144***	0.076	0.551***
income tax rate	(0.065)	(0.133)	(0.038)	(0.091)	(0.128)
Maximum State income tax rates	0.016	-0.066**	0.010	-0.009	-0.086***
	(0.022)	(0.031)	(0.015)	(0.024)	(0.032)
Energy cost	3.991	-61.700***	-15.512***	-3.172	-12.433
	(6.946)	(10.460)	(4.976)	(9.152)	(9.324)
Import Duty Rate	-0.075*	-15.294***	0.023	-4.422*	-21.384***
	(0.041)	(2.636)	(0.028)	(2.366)	(2.384)
Ethnic diversity	-0.260	1.410***	1.265***	1.337***	2.199***
	(0.309)	(0.376)	(0.236)	(0.285)	(0.313)
Inventory to shipment	-2.979	32.556***	-1.580	-2.915	17.746**
	(2.257)	(9.100)	(1.581)	(5.946)	(7.034)
T95	0.877***	0.221**	0.557***	0.542***	-0.137
	(0.111)	(0.099)	(0.071)	(0.092)	(0.086)
Constant	3.073***	67.149***	2.773***	60.672***	109.765***
	(1.055)	(11.079)	(0.623)	(10.300)	(10.488)
Observations	665	295	668	465	507
Log likelihood ratio	-1,779.439	-1,040.654	-2,376.630	-1007.592	-1624.647
LR Chi -squared	307.939	229.385	480.70	310.726	306.604
Prob > Chi-squared	0.000	0.000	0.000	0.000	0.000

Notes: We report statistical significance of the estimated coefficients at the conventional 10 percent (*), 5 percent (**), and 1 percent (***) levels. Standard errors are given in parentheses.

Table 6A presents NB-EGI regression results for Food (SIC 20), Textile (SIC 22), Apparel (SIC 23), Lumber (SIC 24), and Paper (SIC 26). For Food industry, estimated coefficient for agglomeration measure (EGI) variable turned out to be negative and significant at c1 percent level. The impact of market concentration or plant size (measured by Herfindahl index) on innovation turned out to be negative and significant. Also, estimated coefficient of high skilled labor (share of employees with post graduate degrees) is negative and not significant.

In textile industry, estimated coefficients for EGI turned out to be negative and significant and the coefficient for establishment count turned out to be positive yet not significant. The scale economy influences innovation adversely. The influence of high skilled labor is positive on patent count; however, it is not significant. The estimated coefficients for the agglomeration variables, scale economy variable and high skilled labor variable for apparel industry (SIC 23) and lumber industry (SIC 24) are similar but slightly differ in significance and magnitude. The impact of market concentration or plant size is negative on innovative activities for both the industries. However, the influence of workers with post graduate degree has a negative influence on patent count for apparel industry but a positive influence for the lumber industry.

The influence of EGI is positive and significant on innovation in the paper industry. The influence of plant size is negative and significant. The impact of highly skilled labor is positive for innovation activities in this industry but it is not statistically significant.

Table 6B: Negative binomial regression of patented innovation in fifteen manufacturing sub-sectors

Variables	Chemical (SIC28)	Rubber (SIC30)	Stone, Clay (SIC32)	Primary metal (SIC33)	Fabr. Metal (SIC34)
Ellison-Glaeser Index	-0.174	-	-0.189*	-0.259	-0.146***
	(0.126)	(0.071)	(0.112)	(0.193)	(0.028)
Herfindahl index	-2.464***	-	-1.420***	-1.478***	-0.882***
	(0.204)	(0.203)	(0.203)	(0.167)	(0.072)
Share of employees with Master degree and above	-0.278	0.381	0.463	0.452	0.184
	(0.681)	(0.432)	(0.541)	(0.459)	(0.225)
Ration of cost of materials to value of shipment	2.078***	0.070	-0.226	-0.918	-0.111
	(0.724)	(0.493)	(0.904)	(0.655)	(0.316)
State minimum wage	-0.010	-0.048**	-0.077*	0.064**	-0.005
	(0.031)	(0.024)	(0.041)	(0.029)	(0.014)
Maximum State corporate income tax rate	0.148***	0.134***	0.101*	0.139***	0.076***
	(0.040)	(0.033)	(0.055)	(0.038)	(0.017)
Maximum State income tax	-0.061***	0.034***	0.061***	-0.022	-0.011
	(0.014)	(0.012)	(0.020)	(0.013)	(0.007)
Energy cost	-4.270	-6.027	-0.561	1.001	-6.836***
	(3.647)	(4.002)	(4.138)	(1.995)	(2.071)
Import Duty Rate	0.381***	0.615***	0.040	-0.011	0.009
	(0.091)	(0.100)	(0.024)	(0.082)	(0.036)
Ethnic diversity	1.681***	1.395***	1.388***	0.454**	1.861***
	(0.201)	(0.163)	(0.282)	(0.192)	(0.094)
Inventory to shipment	0.664	-3.247***	0.769	-0.531	-1.197**
	(1.659)	(1.124)	(1.470)	(1.396)	(0.566)
T95	0.873***	0.060	0.738***	0.222***	0.233***
	(0.059)	(0.051)	(0.092)	(0.062)	(0.028)

Constant	-0.507	1.084	2.218***	1.008	3.816***
	(0.719)	(0.688)	(0.739)	(0.662)	(0.287)
Observations	1,322	1,264	577	1,284	3,582
Log likelihood ratio	-5873.565	-	-2304.747	3439.741	-19244.97
LR Chi squared	1085.066	935.85	257.683	689.697	2271.940
Prob > chi-squared	0.000	0.000	0.000	0.000	0.000

Notes We report statistical significance of the estimated coefficients at the conventional 10 percent (*), 5 percent (**), and 1 percent (***) levels.

Table 6B presents NB regression results for chemical (SIC 28), rubber (sic 30), stone and clay (SIC 32), primary metal (SIC 33), and fabricated metal (SIC 34) industry. The estimated coefficients for EGI is negative across five industries but statistically significant only for rubber, stone clay and fabricated metal industries. The coefficients for Herfindahl index are negative and statistically significant for all these five industries. The impact of high skilled labor is positive on innovation activities in four out of these five industries (except for chemical industry), however, none of these coefficients are statistically significant.

Table 6C: Regression of patented innovation: Manufacturing sub-sectors

Variables	Ind. Machine (SIC35)	Electronic equip. (SIC36)	Transport equip (SIC37)	Instrument (SIC38)	Misc. mfg. (SIC39)
Ellison-Glaeser Index	-0.455***	-0.202***	-0.398***	-0.123***	-0.077*
	(0.039)	(0.060)	(0.051)	(0.031)	(0.043)
Herfindahl index	-3.495***	-2.482***	-0.685***	-2.883***	-1.900***
	(0.091)	(0.105)	(0.075)	(0.123)	(0.057)
Share of employees with Master degree and above	0.431	-0.133	-0.794*	0.437	0.475
	(0.318)	(0.354)	(0.430)	(0.902)	(0.296)
Ration of cost of materials to value of shipment	-0.408	1.935***	-2.597***	-0.470	-0.771*
	(0.373)	(0.646)	(0.490)	(0.567)	(0.398)
State minimum wage	-0.012	0.011	0.116***	-0.041*	-0.075***
	(0.015)	(0.027)	(0.020)	(0.023)	(0.014)
Maximum State corporate income tax rate	0.043***	0.208***	0.067***	0.118***	-0.034**
	(0.016)	(0.027)	(0.023)	(0.029)	(0.016)
Maximum State Income tax	-0.028***	-0.075***	0.095***	-0.011	0.010
	(0.007)	(0.012)	(0.009)	(0.012)	(0.006)
Energy cost	-5.776***	-13.321***	-1.306	-10.986***	-8.648***
	(1.888)	(4.012)	(1.578)	(2.719)	(2.088)
Import Duty Rate	-0.085***	-1.263***	-0.045**	-0.268**	-0.140***
	(0.018)	(0.095)	(0.020)	(0.117)	(0.029)
Ethnic diversity	1.504***	2.124***	1.217***	1.930***	2.605***
	(0.090)	(0.165)	(0.132)	(0.149)	(0.086)
Inventory to shipment	0.464	0.169	-4.347***	0.316	-0.031
	(0.723)	(1.316)	(0.931)	(1.305)	(0.796)
T95	0.348***	0.844***	0.355***	0.212***	0.278***
	(0.029)	(0.048)	(0.037)	(0.046)	(0.027)
Constant	5.920***	8.883***	4.289***	5.124***	5.978***
	(0.269)	(0.680)	(0.383)	(0.695)	(0.338)
Observations	2,667	2,613	3,715	1,968	3,913
Log likelihood ratio	15,699.653	14270.724	18757.756	-9037.06	-
LR Chi squared	2,508.376	1695.754	1273.960	1636.851	2817.231

Prob > Chi-squared	0.000	0.000	0.000	0.000	0.000

Notes: We report statistical significance of the estimated coefficients at the conventional 10 percent (*), 5 percent (**), and 1 percent (***) levels.

Table 6C summarizes NB regression result highlights for industrial machinery (SIC 35), electronica and electronic equipment (SIC 36), transportation equipment (SIC 37), instruments (SIC 38), and miscellaneous manufacturing (SIC 39). The influence of EGI variable is found to be negative and significant on innovation activities for all these five industries. The coefficients for Herfindahl index are negative and statistically significant for all these five industries. The impact of high skilled labor is positive on innovation activities in three of these five industries. These three industries are industrial machinery, instrument, and miscellaneous manufacturing. High skilled workers seem to have a negative impact on innovation activities in electronic equipment industry and transportation equipment industry. Out of these two negative coefficients, one representing 'transportation equipment' is statistically significant at 10 percent level.

In summary, I find statistical evidence in support of one hypothesis out of three. Hypothesis 1 was not supported by the regression results as coefficients for Gini and EGI are found to be negative and statistically significant factor for innovation. I find evidence in favor of the second hypothesis. Manufacturing industries where market shares are concentrated in the hands of few larger plants are found to be less innovative as the estimated coefficients for Herfindahl index was negative and significant at conventional levels. The hypothesis 3 was not supported by the results as the estimated coefficient for the variable “ratio of workers with post graduate degrees to all workers” was positive in few instances and negative in the rest of the specifications and none but one was statistically significant. This result may call for use of a better proxy than ‘share of workers with a postgraduate degree’ to capture some statistically significant influence of ‘highly specialized knowledge workers’ on patented innovation activities.

A review of the magnitude, direction, and statistical significance levels of estimated coefficients of some control variables would surely draw particular attention to energy cost and ethnic diversity as regressors. Energy cost seems to be one of the most influential deterrents of patented innovation. On the contrary, ethnic diversity seems to serve as a significant positive factor for innovation. Per Table 5 results, 1 percent increase in energy cost will decrease patented innovation by 4.17 percent, but 1 percent increase in ethnic diversity will increase patented innovation by 2.6 percent.

Per Table 5 and Table 6 results estimated coefficient of globalization variable “T95” is found to be positive and statistically significant determinant of innovation across all specifications (except for paper SIC26). Also, the variable ‘import duty rate’ found to be negative and statistically significant for the specifications for entire manufacturing industry and for nine out of fifteen SIC 2-digit level manufacturing sub-industries.

5.0 CONCLUSION AND POLICY IMPLICATIONS

The intuition that an agglomeration may be a source of negative externalities beyond certain “optimal cluster size” usually attributes that to counterproductive impacts of traffic congestion, pollution etc. associated with sprawling spatial concentration of firms. From the regression results for EGI and Gini measures of agglomeration, it can be said that clustering in itself was not found to be a booster of innovation; rather, it played a negative influence on innovation activities. In addition to the optimal size argument, it is rational to also contend that impact of agglomeration on innovation will be different depending on the types of industries and their varied market structures with degrees of competitiveness.

Impact of plant size distribution on innovation was found to be negative and statistically significant for both manufacturing industry level regression and for individual regressions of fifteen SIC 2-digit level sub-industries. This result may imply that competitive manufacturing industries are more innovative than industries with market share concentrated in few larger firms. Whether an agglomeration will spur innovation by generating positive externalities via idea pooling may depend on many factors including size optimality of agglomeration, life cycle of incumbent industry, advances in information and communications technologies, enforcement of intellectual property rights, and intensity of global competition. Current study hints that forces of trade liberalization and advances in ICTs might have made long distance idea pooling easier, and, thus might have waned the positive impact of traditional, spatially bound idea pooling on innovation.

Finally, due to the fact that energy cost stood out to be one the high impact negative factors for innovation, and ethnic diversity stood out to be one of the high impact positive factors of patented innovation, further empirical research aimed at exploring these relationships over a longer time horizon may produce additional insights for both academicians and economic development policy planners. One academic take away of this study is that the agglomeration of similar firms in a geographical space is not always a guaranteed booster of innovation. This take away should inspire future researchers to devise creative models to examine if coagglomeartion of complementary firms is a more reliable factor of invention-spurring positive externalities. From policy planners' perspectives there are perhaps three insights regarding boosting of inventive activities in U.S. manufacturing industries. One, focus on coagglomeration of various interdependent and complementary industries (instead of solely focusing on agglomeration of similar manufacturing firms) may result in more inventive activities (more patents). Two, nurturing of small-scale industries may increase competitiveness in the industry which in turn, may increases inventive activities. Third, adoption of policies that promotes ethnic diversity may spur inventive activities.

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