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Technological Innovation and Public Health: A Descriptive Exploratory Investigation of Relationship between Technological Innovation Indicators and Public Health Indicators in the United States from 2003 to 2007

By Preetinder Singh Gill

Eastern Michigan University Ypsilanti, Michigan

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I. Introduction

Viability of an organization or a geographical region is contingent upon its ability to stay competitive. Innovation and market competition share an inverted U relationship (Aghion et al., 2005). This means that a high amount of innovation is accompanied by reduced market competition. Thus, by being and staying highly innovative, geographical regions can establish and cement their leadership position. Schumpeter (1942) asserted that innovation is stochastically propelled by the temporal, incremental, monopolistic incentives to the innovators. It was argued that new consumer goods provide perpetual impetus for economic progress. Simply put, innovation ensures economic success.

Stewart et al. (2003) showed that US employers spend billions of dollars every year in health related expenses. Multiple studies have confirmed that better health ensures lower absenteeism and higher productivity (Wojick, 2009, Suhrcke et al., 2006 and Fuchs, 1966). Furthermore, Romer (1990) showed that increased human capital would increase growth. It could be argued that better public health ensures enhanced and enriched human capital, which in turn, ensures sustainability of an economically competitive region. The United Nations human development index presents the clearest evidence that year-over-year countries with stronger economies tend to have better public health and advanced technological accomplishments (UNDP, 2009 and WEF, 2010). Thus, it can be argued that both technological innovation and public health are critical to economic success.

II. Importance of the Research Study

Dreyfuss (2011) noted that it is challenging to measure value of knowledge and impact of knowledge generated by technological innovation. Technological assessment is widely used method for measuring the impact technological innovation. Goodman (2004) suggested that technology assessment – TA – involves appreciation of the critical role of technology in modern society and its potential for unintended, and sometimes harmful, consequences. Generally speaking, TA is a cause and effect analysis which establishes a one-dimensional relationship between a single new technology and its possible effects. Health technology assessment – HTA – is the systematic evaluation of properties, effects or other impacts of health related technologies with an objective of achieving informed policy making (Goodman, 2004). Banta (2002) compared and contrasted the development and the deployment of HTA across various nations. Perry & Thamer (1997) performed and compared HTA for the U.S. and other countries. Abelson et al. (2007) studied public involvement and accountability mechanisms in HTA. Furthermore, they distinguish specific roles for the public, and relate them to several layers of policy analysis and policy making. Researchers like Royle & Oliver (2004), Oliver et al., (2009) and Cohen et al., (2004) studied socioeconomic factors in relation to health technologies. However, the use of HTA seems to

Author : College of Technology Eastern Michigan University Ypsilanti, Michigan. E-mail : pgill1@emich.edu

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be limited to assessment of specific health related technologies and not on the complete spectrum of technological development. Furthermore, the relationship between socioeconomic factors and technological innovation was not qualified by any of these researchers.

The classical innovation diffusion theory (Rogers, 1995) asserts that relative advantage, complexity, compatibility, observability and trialability determine the success of an innovative endeavor. These measures are commonly used to assess specific attributes of a technological innovation, in relation to socioeconomic factors, to establish the possibility of its successful adoption. Although Rogers (1995) held that the construct of technological innovation is dynamic and iterative which propagates under myriad of socioeconomic forces the theory doesn't address the collective impact of technological innovation on the society. Furthermore, Gelijns and Rosenberg (1994) showed that medical technology innovation is not necessarily linear as it progresses from basic research to market application. Berwick (2003) observed that policy makers need to better understand impact of innovation since the "…processes of innovation and dissemination have their own rules, their own pace, and their own, multilayered forms of search and imagining" (p.1974). Hence, it is pertinent to study how technological innovation, at a macro level, impacts the broad socioeconomic systems including the public health.

The World Health Organization's Commission on Intellectual Property Rights, Innovation and Public Health (2006) in its report about innovation and health products asserted that research institutes and universities should maintain research priorities relevant to health concerns. Ridley (2010) reported that the WHO is promoting technological innovation as a key to improving health and well-being. However, it must be noted that the WHO's focus is limited to health care related technologies only. Türmen & Clift (2006) reported that organizations and policies outside health care sector impact technological innovation. They also maintained that without access to products of technological innovation there is no public health benefit. Nevertheless, the relationship between technological innovation and public health was not quantified.

Getz (2011) and Feller, Finnegan & Nilsson (2011) made a case for propagating open innovation to negate effects of silo-ed approach to innovation and to improve effectively of the underlying research. Wild and Langer (2008) emphasized the need to address the blank spots in the prioritization process associated implementing health related technologies. Moniruzzaman and Anderson (2008) showed that unique inverted U shaped relationship exists between injury, mortality and the economy in different countries. They stress the need to understand the relationship between innovation and health care. Hughes (2011) argued that value created by a technological innovation goes beyond the preconceived specific service specifications. Greenberg (2006) presented multiple instances where technologies not directly geared toward healthcare had substantive public health effect. Additionally, Varey (2011) argued that governments should take a holistic approach to innovation. Varey (2011) also held that policy makers can increase the efficiency of the tight budgets by investing in a boarder range of technologies beyond the ones which are exclusively linked to health care.

III. Problem Statement and Objective of the Study

The relationship between technological indicators and innovation indicators has not been adequately studied. In order to address this gap, the study explored the relationship between technological innovation indicators & public health indicators for the four U.S. Census regions over a period of five years. This in turn involved descriptive and inferential data analyses with regards to selected technological innovation indicators and public health indicators to address specific research questions. The research questions are listed in the following section.

Benefits of this study include: 1) better understanding of the relationship between technological innovation and public health, 2) creation of a knowledge base to provide opportunities for informed decision making by policy makers and 3) comparing public health and technological innovation in the four U.S. Census regions and over five years.

IV. Research Questions

1) Is there a statistically significant difference between median values of technological innovation indicators or median values of public health indicators for the four U.S. Census regions?

2a) What relationship, if any, exists between technological innovation indicators and public health indicators in the Midwest U.S. Census region?

2b) What relationship, if any, exists between technological innovation indicators and public health indicators in the Northeast U.S. Census region?

2c) What relationship, if any, exists between technological innovation indicators and public health indicators in the South U.S. Census region?

2d) What relationship, if any, exists between technological innovation indicators and public health indicators in the West U.S. Census regions?

V. Hypothesis

The hypotheses associated with this study were tested at a significance level with p value $\leq$ 0.05. The hypotheses tested were:

1) There is no statistically significant difference between median values of technological innovation indicators or median values of public health indicators associated with the four U.S. Census regions.

2a) There is no statistically significant relationship between any technological innovation indicator and any public health indicator in the Midwest U.S. Census region.

2b) There is no statistically significant relationship between any technological innovation indicator and any public health indicator in the Northeast U.S. Census region.

2c) There is no statistically significant relationship between any technological innovation indicator and any public health indicator in the South U.S. Census region.

2d) There is no statistically significant relationship between any technological innovation indicator and any public health indicator in the West U.S. Census region.

VI. Delimitations/Limitations

Delimitation: Data from the District of Columbia and other U.S. territories were not included in the study.

Delimitation: The smallest geographical unit included in the study was a single U.S. Census region (U.S. Census Bureau, 2000)

Delimitation: Chatterjee and Sorenesen (1998) provided evidence for the application of the Pareto principle in regression analyses. Accordingly, it can be argued that a relatively small number of indicators can represent a given construct. Hutton (2000) Cummings (2004), Mackay (2007) and Mizell (2009) also underscore that a small number of indicators can help in effectively describing a construct.

Delimitation: The public health indicators, for this study, were selected from the 26 leading health indicators tracked by the U.S. Department of Health and Human Services (2012).

Delimitation: The technological innovation indicators, for this study, were selected from list of innovation indicators tracked by Organization for Economic Co-operation (2012) and studied by Reffitt & Sorenson (2007) for Michigan Department of Labor & Economic Growth.

Delimitation: Six technological innovation indicators and five public health indicators were selected by the author in consensus with the research adviser.

Delimitation: Effectiveness of individual technological innovations and significance specific health issues were not evaluated.

Delimitation: The study did not quantify the resources, time, effort and knowledge needed to generate technological innovation or alleviate public health problems.

Limitation: The data were collected from publicly available sources commissioned by governmental agencies and/or organizations.

Limitation: 2003-2007 is the only contagious period for which data are available for the selected technological innovation indicators and public health indicators. Availability of data influenced selection of the indicators.

Limitation: The data collected for the study were limited to the fifty U.S. states.

Limitation: Constructs of technological innovation and public health are defined in terms of the respective indicators. Hence, formative models were used for structural equation modeling (Henseler, Ringle, & Sinkovics, 2009).

VII. Definition of Terms

Government Agency: An administrative unit of government authorized by law or regulation to perform a specific function (Princeton University, 2012) and Rutgers University, 2003).

Pareto Principle: The concept that most of a given set of results are due to a small number of causal factors e.g., 80 percent of the results can be explained by 20 percent of the causes (Food and Agriculture Organization of United Nations, 2010).

Indicator Score: Indicator score signifies desirability. In case of technological innovation indicators higher absolute value signifies better indicator score. In case of public health indicators lower absolute value signifies better indicator score. Poor indicator score signifies undesirable level of an indicator. Best indicator score signifies desirable level of an indicator. Fair indicator score signifies a value between poor and best indicator scores.

Power Law: A power law is a special kind of mathematical relationship between two quantities. When the number or frequency of an object or event varies as a power of some attribute of that object, the number or frequency is said to follow a power law. A power law could be expressed as $f(x) = \alpha * x^{\beta} + \varepsilon$ where α is a constant, β is the scaling factor and ε is the error term (Katz, 2006). Power laws are scale invariant. In other words, if x is scaled by a constant, γ, then f(x) would be scaled by a constant γ^{β}.

Public Health Indicator: A public health indicator is "…a variable with characteristics of quality, quantity and time used to measure, directly or indirectly …" an aspect of public health (Gruskin & Ferguson, 2009, p. 714)

- Health status indicator is the percent of people reporting that their general health is fair or poor in the annual behavioral risk factor surveillance survey conducted by the U.S. Centers for Disease Control and Prevention.

- Insurance indicator is the percent of people reporting that they have any kind of health care coverage in the annual behavioral risk factor surveillance survey conducted by the U.S. Centers for Disease Control and Prevention.
- Obesity and overweight rate indicator is the percent of people reporting that their weight classification by body mass index is overweight or obese in the annual behavioral risk factor surveillance survey conducted by the U.S. Centers for Disease Control and Prevention.
- Preterm birth rate indicator is the ratio of the births before 36 weeks of gestation to the total number of births as reported on U.S. Centers for Disease Control and Prevention's Natality public-use data on CDC WONDER Online Database.
- Suicide rate indicator is the ratio of suicide deaths per capita of population as reported by on U.S. Centers for Disease Control and Prevention's National Center for Injury Prevention and Control.
- Tobacco use indicator: is the percent of people reporting that they are current smokers in the annual behavioral risk factor surveillance survey conducted by the U.S. Centers for Disease Control and Prevention.

U.S. Census Region: A grouping of 50 federated states into four groups by the U.S. Census Bureau (2000)

- Midwest region consists of Indiana, Illinois, Michigan, Ohio, Wisconsin, Iowa, Nebraska, Kansas, North Dakota, Minnesota, South Dakota and, Missouri
- Northeast region consists of Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont, New Jersey, New York and, Pennsylvania
- South region consists of Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia, Alabama, Kentucky , Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma and, Texas
- West region consists of Arizona, Colorado, Idaho, New Mexico, Montana, Utah, Nevada, Wyoming, Alaska, California, Hawaii, Oregon, Washington

Sub-linear Relation: A sub-linear relationship is quantified by $\beta < 1$ in the power law equation. Negative sub-linear relation signifies $-1 < \beta < 0$.

Super-linear Relation: A super-linear relationship is quantified by $\beta > 1$ in the power law equation.

Technological Innovation Indicator: A technological innovation indicator is "…a variable with characteristics of quality, quantity and time used to measure, directly or indirectly …" an aspect of technological innovation (Gruskin & Ferguson, 2009, p. 714)

- Articles per 1000 capita indicator is the number of articles per 1000 people in a state - reported by U.S. National Science Foundation's National Center for Science and Engineering Statistics.
- Patents per 1000 capita indicator is the number of patents per 1000 people in a state – reported by U.S. Patents and Trademarks Office.
- Percentage of workforce in scientist and engineer occupation indicator is the number of workers who work as scientists and engineers expressed as a percentage of the total work force in a state - reported by U.S. National Science Foundation's National Center for Science and Engineering Statistics.
- Value of R&D performed as percent of GDP indicator is the volume research and development investment expressed as a percentage of the state GDP - reported by U.S. National Science Foundation's National Center for Science and Engineering Statistics.
- Venture capital per \$1000 of GDP indicator is the volume of venture capital investment in a state per \$1000 of the state GDP - as reported by U.S. National Science Foundation's National Center for Science and Engineering Statistics.

VIII. Assumptions

It was assumed that the data collected by the governmental agencies is an accurate representation of the underlying population. It was assumed that no bias exists in the process of data collection and reporting on the behalf of the governmental agencies. It was assumed that the governmental agencies ensured safety, confidentiality and anonymity of human subjects when publishing the data. Nevertheless, the data obtained from the governmental agencies was free of any and all type of personal identification information. Furthermore, the indicators and associated PLS SEM formative models selected by the author were assumed to be substantively representative of the technological innovation and public health, albeit to varying extents. It was assumed that algorithms and outputs from Statgraphics Centurion XV® version 15.2.14 and SmartPLS 2.0 M3 provide an accurate descriptive analysis of the data.

IX. Methodology

The research study commenced with identifying governmental sources of the technological innovation and public health indicators. The author and the research adviser selected a set of 5 technological innovation indicators and a set of 6 public health indicators. Kruskal-Wallis median comparison tests were performed to assess whether there were significant differences between indicator scores from the four U.S. Census regions.

The study then followed a correlational and inferential design. The correlational portion of the study involved forming single variable power law regression equations. The technological innovation indicators served as the independent variables. The public health indicators served as the dependent variables. As a result of this exercise 30 power law regression equations were generated for each U.S. Census region. The scaling factors were examined to establish if the independent and dependent variables fit sub-linear or super-linear relationships. The α coefficients were calculated to ascertain slopes of the power law regression equations. The inferential portion of the study involved performing the formative structural equation modeling to study causal relations between innovation inputs, innovation outputs and health outcomes.

X. Population and Sample

All fifty U.S. states formed the population for this study. Data categories included: 1) census of the population for suicide, preterm births, articles, patents, workforce, R&D and, venture capital investment indicators and 2) sampling of the population for health status, insurance, obesity and tobacco use indicators.

XI. Data Collection

Data collection involved downloading indicator data from various governmental agencies. The governmental agencies were short-listed by the author based on their mandated objectives with regards to technological innovation, intellectual property and, public health. Data sources for various indicators are listed in table 1. This exercise had dual focal points: 1) creating a list of potential indicators which were subsequently narrowed-down by consensus between the author and research adviser and, 2) collecting and preparing the data for analyses in subsequent phases of the research project. The state of Hawaii had data missing for the year 2004. Hence, a total of 249 data points were collected for each indicator instead the maximum possible 250 data points - 5 years times 50 states. Data were prepared for analyses by tabulation into a single table arranged by year and region. The indicators in the study were coded for ease of use in the statistical analysis software. A legend showing the cross-reference between indicators and the codes used is presented in table 8 in Appendix A.

Data	Data type	Source
State population data	Census	U.S. Census Bureau
Health status indicator	Sample	U.S. Center of Disease Control Behavioral Risk Factor Surveillance
Insurance indicator	Sample	U.S. Center of Disease Control Behavioral Risk Factor Surveillance
Obesity and overweight rate indicator	Sample	U.S. Center of Disease Control Behavioral Risk Factor Surveillance
Preterm birth rate indicator	Census	U.S. Center of Disease Control Natality Data
Suicide rate indicator	Census	U.S. Center of Disease Control - National Center for Injury Prevention
Tobacco use indicator	Sample	U.S. Center of Disease Control Behavioral Risk Factor Surveillance
Articles per 1000 capita indicator	Census	U.S.Patent and Trademark Office
Patents per 1000 capita indicator	Census	U.S. National Science Foundation
Percentage of workforce in science and engineer occupation indicator	Census	U.S. National Science Foundation
Value of R&D performed as percent of GDP indicator	Census	U.S. National Science Foundation
Venture capital per $1000 of GDP indicator	Census	U.S. National Science Foundation

Table 1 : Indicator data sample type and sources

XII. Data Analysis

The research project involved quantitative data. Descriptive and inferential statistics were used for data analysis. Significance level of $p \leq 0.05$ was used to test the null hypotheses. The kurtosis and skewness values for the indicators are presented in table 2. These values are outside the range of -2 to +2. This indicates a significant departure from normality. In other words the underlying distribution of none of the indicators is normal. A natural logarithm transformation improved the kurtosis and skewness values. The results presented in table 3. It can hence be concluded, Pearson product moment correlation values could be satisfactorily calculated after applying that the natural logarithm transformation. Pearson product moment correlations and the associated p values are presented in table 4. In case of the public health indicators the highest Pearson product moment correlation, 0.711, is observed between *health status* indicator and *preterm birth rate* indicator. *Suicide rate* indicator is the only indicator which shows a low level or insignificant of correlation with other indicators. All other public health indicators share a statistically significant Pearson product moment correlation with each other. In the case of technological innovation indicators the highest Pearson product moment correlation, 0.778, is observed between *percentage of workforce in scientist and engineer occupation* indicator and *value of R&D performed as percent of GDP* indicator. All technological innovation indicators share a statistically significant Pearson product moment correlation with each other.

	HSG_EVGG	T_Y	OW_Ob	PTB_R	I_Y	S_R	Pat_PGC	Art_PGC	VC_GGDP	GERD	SE_PWF
Average	15.452	21.095	61.009	0.125	14.951	12.540	0.251	0.492	1.034	2.214	3.442
Standard deviation	3.303	3.288	3.202	0.018	4.200	3.477	0.205	0.224	1.648	1.565	1.024
Stnd. skewness	4.764	-1.176	-2.832	4.978	2.544	3.814	13.728	12.502	21.422	10.048	5.581
Stnd. kurtosis	-0.452	2.522	1.085	3.929	-0.360	1.146	21.500	21.830	40.955	8.963	1.482

Table 2 : Raw indicator data description

	ln(HSG_EVGG)	ln(T_Y)	ln(OW_Ob)	ln(PTB_R)	ln(I_Y)	ln(S_R)	ln(Pat_PGC)	ln(Art_PGC)	ln(VC_GGDP)	ln(GERD)	ln(SE_PWF)
Average	2.732	3.032	4.107	-2.083	2.664	2.463	-1.613	-0.788	-0.712	0.633	1.206
Standard deviation	0.205	0.171	0.054	0.144	0.294	0.269	0.739	0.422	1.422	0.669	0.293
Stnd. skewness	1.562	-2.099	-1.509	1.180	-1.930	-2.038	-0.316	0.236	-1.981	-0.606	0.611
Stnd. kurtosis	-1.980	1.909	1.977	0.922	-0.387	0.628	-1.543	1.225	-0.539	-1.466	-1.243

Table 3 : Transformed indicator data description

	ln(HSG_EVGG)	ln(T_Y)	ln(OW_Ob)	ln(PTB_R)	ln(I_Y)	ln(S_R)
ln(HSG_EVGG) p-value		0.519 **<0.001**	0.485 **<0.001**	0.711 **<0.001**	0.619 **<0.001**	0.067 0.294
ln(T_Y) p-value	0.519 **<0.001**		0.478 **<0.001**	0.505 **<0.001**	0.234 **<0.001**	0.172 **0.007**
ln(OW_Ob) p-value	0.485 **<0.001**	0.478 **<0.001**		0.527 **<0.001**	0.218 **0.001**	0.127 **0.046**
ln(PTB_R) p-value	0.711 **<0.001**	0.505 **<0.001**	0.527 **<0.001**		0.425 **<0.001**	**0.041** 0.525
ln(I_Y) p-value	0.619 **<0.001**	0.234 **<0.001**	0.218 **<0.001**	0.425 **<0.001**		0.476 **<0.001**
ln(S_R) p-value	0.067 0.294	0.172 **0.007**	0.127 **0.046**	**0.041** 0.525	0.476 **<0.001**	

	log(Pat_PGC)	log(Art_PGC)	log(VC_GGDP)	log(GERD)	log(SE_PWF)
log(Pat_PGC)		0.490 **<0.001**	0.566 **<0.001**	0.668 **<0.001**	0.692 **<0.001**
log(Art_PGC)	0.490 **<0.001**		0.498 **<0.001**	0.625 **<0.001**	0.651 **<0.001**
log(VC_GGDP)	0.566 **<0.001**	0.498 **<0.001**		0.576 **<0.001**	0.666 **<0.001**
log(GERD)	0.668 **<0.001**	0.625 **<0.001**	0.576 **<0.001**		0.778 **<0.001**
log(SE_PWF)	0.692 **<0.001**	0.651 **<0.001**	0.666 **<0.001**	0.778 **<0.001**	

Table 4 : Pearson correlations and the associated p values for transformed indicator data

In order to test hypothesis 1 single factor ANOVA was performed for every transformed indicator with regards to the four U.S. Census regions. Statistically significant difference at 95% confidence interval is highlighted with an asterisk symbol in figure 5 in Appendix A. Furthermore, the Kruskal-Wallis median comparison tests were also performed on the untransformed data to confirm the results of the single factor ANOVA. The p-values are presented in table 5. Since all values are below 0.05 it can be concluded that there is a significant difference between the medians of the indicators for the four U.S. Census regions.

		K-W Median Test p-value
Public Health Indicators	HSG_EVGG	<0.0001
	T_Y	<0.0001
	OW_Ob	<0.0001
	PTB_R	<0.0001
	I_Y	<0.0001
	S_R	<0.0001
Technological Innovation Indicators	Pat_PGC	<0.0001
	Art_PGC	<0.0001
	VC_GGDP	<0.0001
	GERD	<0.0001
	SE_PWF	<0.0001

Table 5 : p Values of Kruskal-Wallis median comparison tests for various indicators

Box whisker plots associated with the Kruskal-Wallis median comparison tests for each indicator with regards to the four U.S. Census regions are presented in figure 6 in Appendix B. The consolidated results of the Kruskal-Wallis median comparison tests are presented in table 6. A region's performance with regards to each indicator is categorically ranked in terms of codes B, F or P. B represents the best indicator scores, P represents the poor indicator scores and F represents mid-level indicator scores. The results of the ANOVA and K-W test showed that there are statistically significant differences in both the technological innovation indicator scores and public health indicator scores with regards to the four U.S. Census regions.

		Midwest	North East	South	West
Public Health Indicators	HSG_EVGG	B	B	P	B
	T_Y	F	B	P	B
	OW_Ob	P	B	P	B
	PTB_R	F	B	P	F
	I_Y	B	B	P	P
	S_R	F	B	F	P
Technological Innovation Indicators	Pat_PGC	F	B	P	F
	Art_PGC	F	B	P	P
	VC_GGDP	P	B	P	F
	GERD	F	B	P	F
	SE_PWF	F	B	P	F
Total	B	2	11	0	3
	F	7	0	1	5
	P	2	0	10	3

Table 6 : Ranked comparison of U.S. Census regions with regards to various indicators

Data analysis showed that the South is the only U.S. Census region which has poor *health status* indicator scores. In fact the South U.S. Census region had the poorest scores for all public health and technological indicators. On the other hand the Northeast U.S. Census region had the best scores for all public health and technological indicators. The Midwest and the West U.S. Census regions did not have the best scores for any of the technological innovation indicators. The Midwest U.S. Census region had the best scores for *health status* indicator and *insurance* indicator. This region had poor scores for *obesity and overweight rate* indicator and *venture capital per $1000 of GDP* indicator. The West U.S. Census region had the best scores for *health status* indicator, *tobacco use* indicator and, *obesity and overweight rate* indicator. This region had poor scores for *insurance rate* indicator, *suicide rate* indicator and, *articles per 1000 capita* indicator.

Hence, we can reject the null hypothesis 1 based on the results of the data analysis presented above. In other words no evidence was found which supports the hypothesis that there is no statistically significant difference between median values of technological innovation indicators or median values of public health indicators for the four U.S. Census regions at the 0.05 level of significance.

The technological innovation systems and public health systems are complex (Baranger, 2001) and dynamic in nature. Hence, they exhibit scaling properties (Amaral and Ottino, 2004). The signature of a scaling property is a power law correlation between variables of the system (Katz, 2006). Mitzenmacher (2002) and Newman (2005) also asserted that power laws can be applied to a wide variety of complex phenomena. Furthermore, power law relationships "…are readily identifiable when they are plotted on a log–log scale because they appear linear" (Katz, 2005, p.896). This identifier was observed for each technological health indicator and public health indicator combination used in this study. Hence, in order to test hypotheses 2a, 2b, 2c and 2d power law regression analysis was performed on the data associated with various indicators included in the study.

The alpha (α) and beta (β) values are tabulated in table 7. The slopes, alpha (α), signify the proportionality – direct or inverse – between the dependent and independent variables. The scaling factors, beta (β), signify sub-linear or super-linear relationships between the independent and dependent variables. Natural logarithm transformation was applied to the data to normalize the wide range in the data values. The significance level, p and goodness to fit indicator R^2 for each equation are also shown in table 7. It was found that for the Midwest U.S. Census region 10 of the possible 30 combinations between technological health indicators and public health indicators share a statistically significant relationship. For the Northeast U.S. Census region 21 of the possible 30 combinations between technological health indicators and public health indicators share a statistically significant relationship. For the South U.S. Census region 28 of the possible 30 combinations between technological health indicators and public health indicators share a statistically significant relationship. For the West U.S.

Census region 17 of the possible 30 combinations between technological health indicators and public health indicators share a statistically significant relationship.

Midwest	Pat_PGC				Art_PGC				VC_GGDP				GERD				SE_PWF			
	α	β	R^2	p	α	β	R^2	p	α	β	R^2	p	α	β	R^2	p	α	β	R^2	p
HSG_EVGG	2.559	-0.032	1.387	0.370	2.648	0.051	1.151	0.415	2.615	-0.015	0.927	0.502	2.572	0.070	6.378	0.052	2.634	-0.019	0.066	0.846
T_Y	3.086	0.012	0.345	0.656	3.087	0.028	0.645	0.542	3.072	-0.003	0.080	0.844	3.045	0.038	3.405	0.158	3.189	-0.105	3.628	0.145
OW_Ob	4.106	-0.016	11.834	**0.007**	4.131	-0.001	0.034	0.890	4.122	-0.005	4.908	0.118	4.136	-0.008	2.697	0.210	4.156	-0.021	2.876	0.195
PTB_R	2.192	-0.048	12.776	**0.005**	-2.099	0.020	0.734	0.515	-2.128	-0.016	4.387	0.140	-2.118	0.009	0.461	0.606	-2.027	-0.073	4.086	0.121
I_Y	2.179	-0.183	28.367	<**0.001**	2.474	-0.010	0.030	0.896	2.405	-0.064	10.024	**0.024**	2.501	-0.036	1.034	0.440	2.816	-0.286	9.308	**0.018**
S_R	2.202	-0.146	24.925	<**0.001**	2.283	-0.224	19.041	**0.001**	2.345	-0.066	19.382	**0.001**	2.521	-0.138	21.357	<**0.001**	2.892	-0.385	23.186	<**0.001**
NorthEast	**Pat_PGC**				**Art_PGC**				**VC_GGDP**				**GERD**				**SE_PWF**			
	α	β	R^2	p	α	β	R^2	p	α	β	R^2	p	α	β	R^2	p	α	β	R^2	p
HSG_EVGG	2.435	-0.161	34.237	<**0.001**	2.570	-0.092	10.375	**0.031**	2.617	-0.016	1.659	0.399	2.729	-0.112	16.468	**0.006**	2.897	-0.213	12.330	**0.018**
T_Y	2.865	-0.095	24.177	**0.001**	2.937	-0.067	11.282	**0.024**	2.973	-0.022	6.782	0.084	3.059	-0.088	20.501	**0.002**	3.313	-0.260	37.322	<**0.001**
OW_Ob	4.016	-0.048	38.256	<**0.001**	4.053	-0.036	19.122	**0.003**	4.071	-0.008	5.984	0.105	4.095	-0.025	9.992	**0.034**	4.167	-0.074	18.277	**0.003**
PTB_R	-2.299	-0.079	16.422	**0.006**	-2.210	0.001	0.004	0.969	-2.214	0.021	5.994	0.105	-2.221	0.009	0.235	0.752	-2.215	0.003	0.006	0.959
I_Y	2.334	-0.090	8.304	0.055	2.341	-0.189	34.027	<**0.001**	2.439	-0.042	9.260	**0.042**	2.599	-0.163	27.095	<**0.001**	2.928	-0.374	29.636	<**0.001**
S_R	2.103	-0.066	1.655	0.400	2.086	-0.184	11.926	**0.020**	2.191	-0.112	24.797	**0.001**	2.371	-0.192	13.927	**0.012**	2.851	-0.511	20.522	**0.002**
South	**Pat_PGC**				**Art_PGC**				**VC_GGDP**				**GERD**				**SE_PWF**			
	α	β	R^2	p	α	β	R^2	p	α	β	R^2	p	α	β	R^2	p	α	β	R^2	p
HSG_EVGG	2.419	-0.223	47.411	<**0.001**	2.568	-0.340	44.094	<**0.001**	2.832	-0.056	17.427	<**0.001**	2.955	-0.208	40.149	<**0.001**	3.401	-0.463	66.460	<**0.001**
T_Y	2.906	-0.108	27.619	<**0.001**	2.971	-0.173	28.055	<**0.001**	3.078	-0.048	29.580	<**0.001**	3.170	-0.112	28.651	<**0.001**	3.409	-0.249	47.400	<**0.001**
OW_Ob	4.074	-0.033	25.936	<**0.001**	4.114	-0.032	10.018	**0.004**	4.133	-0.009	11.863	<**0.001**	4.150	-0.020	9.057	**0.007**	4.204	-0.054	22.449	<**0.001**
PTB_R	-2.137	-0.089	27.765	<**0.001**	-2.001	-0.055	4.221	0.068	-1.997	-0.042	33.815	<**0.001**	-1.935	-0.045	6.859	**0.019**	-1.767	-0.165	31.059	<**0.001**
I_Y	2.404	-0.191	16.978	<**0.001**	2.424	-0.404	30.394	<**0.001**	2.779	-0.034	3.371	0.112	2.901	-0.307	42.406	<**0.001**	3.317	-0.461	32.204	<**0.001**
S_R	2.209	-0.131	32.864	<**0.001**	2.219	-0.280	60.234	<**0.001**	2.444	-0.033	12.374	**0.002**	2.535	-0.159	47.025	<**0.001**	2.782	-0.269	44.929	<**0.001**
West	**Pat_PGC**				**Art_PGC**				**VC_GGDP**				**GERD**				**SE_PWF**			
	α	β	R^2	p	α	β	R^2	p	α	β	R^2	p	α	β	R^2	p	α	β	R^2	p
HSG_EVGG	3.601	-0.330	9.209	**0.014**	2.654	-0.026	0.723	0.501	2.584	-0.121	2.116	0.248	2.719	-0.020	0.814	0.517	2.681	0.021	0.391	0.621
T_Y	4.410	0.014	1.784	0.293	4.443	-0.004	1.640	0.313	4.469	0.023	9.446	**0.014**	4.444	0.002	0.677	0.558	4.453	-0.009	8.187	**0.022**
OW_Ob	1.750	0.427	27.736	<**0.001**	2.803	-0.084	13.969	**0.002**	2.619	-0.343	33.097	<**0.001**	2.880	-0.063	19.389	**0.001**	2.978	-0.084	11.643	**0.006**
PTB_R	3.893	0.065	9.322	**0.014**	4.067	-0.004	0.498	0.579	4.014	-0.065	17.100	**0.001**	4.065	-0.002	0.405	0.651	4.078	-0.008	1.602	0.319
I_Y	-2.484	0.121	9.388	**0.013**	-2.208	-0.038	11.495	**0.006**	-2.254	-0.114	14.326	**0.002**	-2.154	-0.042	28.100	<**0.001**	-2.130	-0.035	8.251	**0.020**
S_R	1.929	0.332	6.864	**0.035**	2.877	0.023	0.400	0.617	2.618	-0.250	6.653	**0.038**	2.840	-0.004	0.027	0.906	2.834	0.015	0.144	0.764

Table 7 : Power law regression equation parameters for technological innovation indicators and public health indicators

Every combination between technological health indicators and public health indicators in every U.S. Census region which shares a statistically significant relationship the scaling factor β is sub-linear in nature. For a majority of combinations the scaling factor β is negative, indicating the existence of negative sub-linear relationships. This implies that as the technological innovation indicator scores move from poor to best the public health indicator scores also move from poor to best.

Based on the results of the data analysis presented above we can reject the null hypotheses 2a, 2b, 2c and 2d. In other words no evidence was found which supports the hypotheses that there is no statistically significant relationship between any technological innovation indicator and any public health indicator combination for any of the four U.S. Census regions at the 0.05 level of significance.

XIII. Structural Equation Modeling

It must also be noted R^2 values range from low to moderate for all combination between technological health indicators and public health indicators in every U.S. Census region which shares a statistically significant relationship. The highest R^2 values were 66.460 and 60.234 for *scientist and engineer occupation* indicator - *health status* indicator combination and *articles per 1000 capita* indicator – *suicide rate* indicator combination respectively in the South U.S. Census region. Relative weakness of R^2 values for individual combinations prompted a need to further explore the relationship between the two types of indicators. Structural equation modeling – SEM was employed to study linkages between the constructs of public health and technological innovation. The SEM structural model can be used to describe the causal relationships among the latent variables/constructs (Anderson and Gerbing, 1982).

SEM models consist of observed variables (also called manifest or measured, MV for short) and unobserved variables (also called underlying or latent, LV for short) that can be independent (exogenous) or dependent (endogenous)\ in nature. LVs are hypothetical constructs that cannot be directly measured, and in SEM are typically represented by multiple MVs that serve as indicators of the underlying constructs. The SEM model is an a priori hypothesis about a pattern of linear relationships among a set of observed and unobserved variables (Shah & Goldstein, 2006, p. 149)

For this research effort the covariance based partial least square – PLS technique for SEM was used to explore the relationship between public health and technological innovation.

PLS path models are formally defined by two sets of linear equations: the inner model and the outer model. The inner model specifies the relationships between unobserved or latent variables, whereas the outer model specifies the relationships between a latent variable and its observed or manifest variables. (Henseler, Ringle, & Sinkovics, 2009, p. 284)

The nonparametric bootstrap procedure can be used in PLS path modeling to provide confidence intervals for all parameter estimates, building the basis for statistical inference … The PLS results for all bootstrap samples provide the mean value and standard error for each path model coefficient. This information permits a student's t-test to be performed for the significance of path model relationships. (Henseler, Ringle, & Sinkovics, 2009, p. 305-306).

For the purposes of this research effort the constructs of technological innovation and public health have been defined in terms various indicators. Henseler, Ringle, & Sinkovics (2009) asserted that a formative measurement model "…is adequate when a construct is defined as a combination of its indicators" (p. 289). Furthermore, the PLS bootstrap path modeling algorithm allows for the computation of cause effect relationship models that employ both reflective and formative measurement models (Diamantopoulos & Winklhofer, 2001). Green & Ryans (1990), Johansson & Yip (1994), Birkinshaw, Morrison, & Hull (1995), Venaik, Midgley, & Devinney (2005), Julien & Ramangalahy (2003) and, Nijssen & Douglas (2008) maintained that the PLS could be used for data with any type of distribution and in cases with large or small sample sizes. It could hence, be inferred that the PLS SEM formative models will be adequate for data associated with this research study.

In order to setup the PLS cause effect diagrams the constructs of public health and technological innovation were described in terms of following latent variables: health outcomes, innovation input and innovation output. The technological innovation indicators formed the exogenous variables. The public health indicators formed the endogenous variables. The variables, t values and the SEM for the Midwest U.S. Census region is shown in figure 1. The variables, t values and the SEM for the Northeast U.S. Census region is shown in figure 2. The variables, t values and the SEM for the South U.S. Census region is shown in figure 3. The variables, t values and the SEM for the West U.S. Census region is shown in figure 4. For data samples with degrees of freedom ≥ 60, statistical significance is demonstrated at 95%, two sided, confidence intervals if the t values ≥ 2.

Factor loadings for each indicator are also shown these figures. Discussion of results of factor analyses associated with PLS SEM is beyond the scope of this paper. However, detailed results of the PLS SEM are presented in Appendix C.

For the Midwest U.S. Census region the paths from innovation input to innovation output and from innovation output to health outcomes have t values greater than 2. For the Northeast U.S. Census region the paths from innovation input to innovation output, from innovation input to health outcomes and, from innovation output to health outcomes have t values greater than 2.

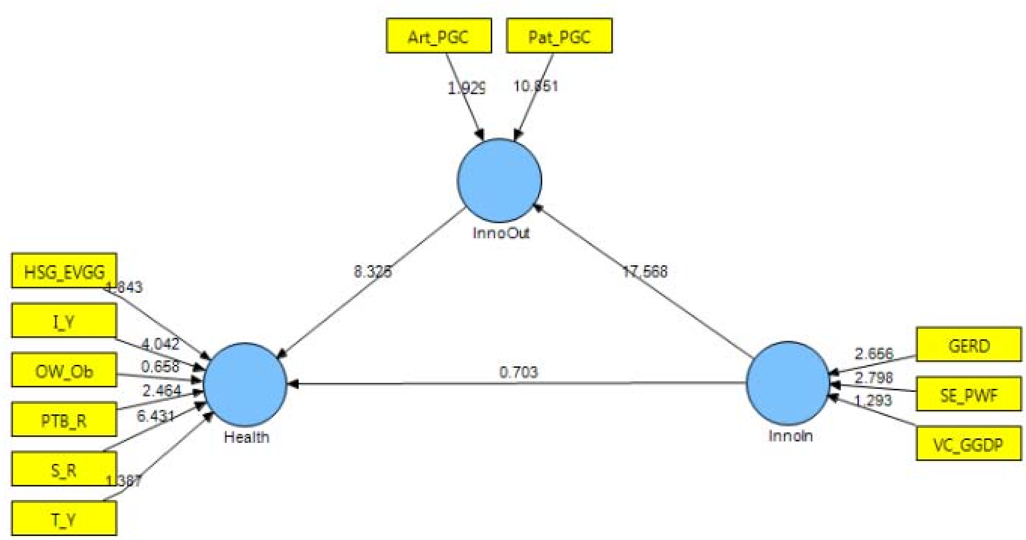

Figure 1 : SEM for Midwest U.S. Census region - Bootstrap sample rate 300

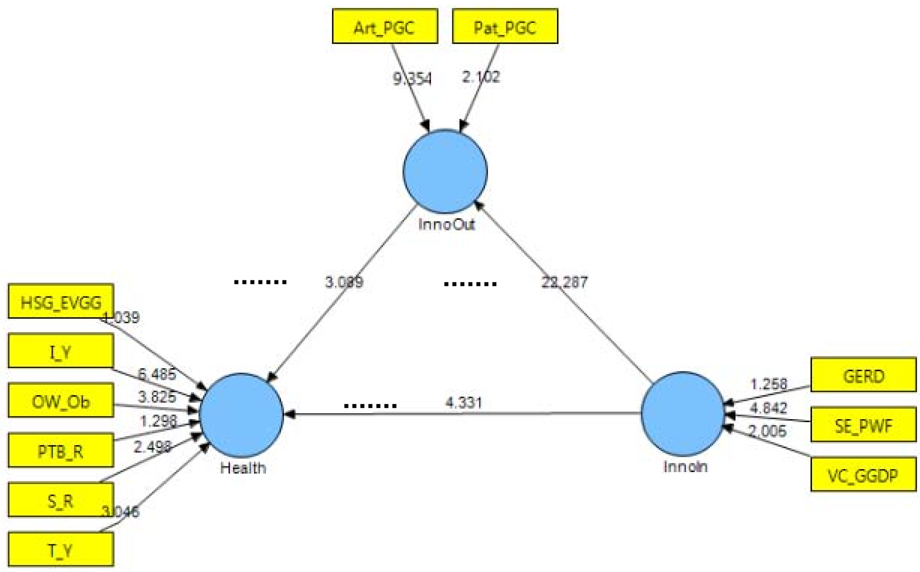

Figure 2 : SEM for Northeast U.S. Census region - Bootstrap sample rate 300

For the South U.S. Census region the paths from innovation input to innovation output, from innovation input to health outcomes and, from innovation output to health outcomes have t values greater than 2. For the West U.S. Census region the paths from innovation input to innovation output and from innovation output to health outcomes have t values greater than 2.

The results of PLS SEM provide evidence that there could be a causal relation between innovation outputs and health outcomes for all four U.S. Census regions. Additionally, the results of PLS SEM also provide evidence that there could be causal relation between innovation inputs and health outcomes for the South and Northeast regions of the U.S. Census regions.

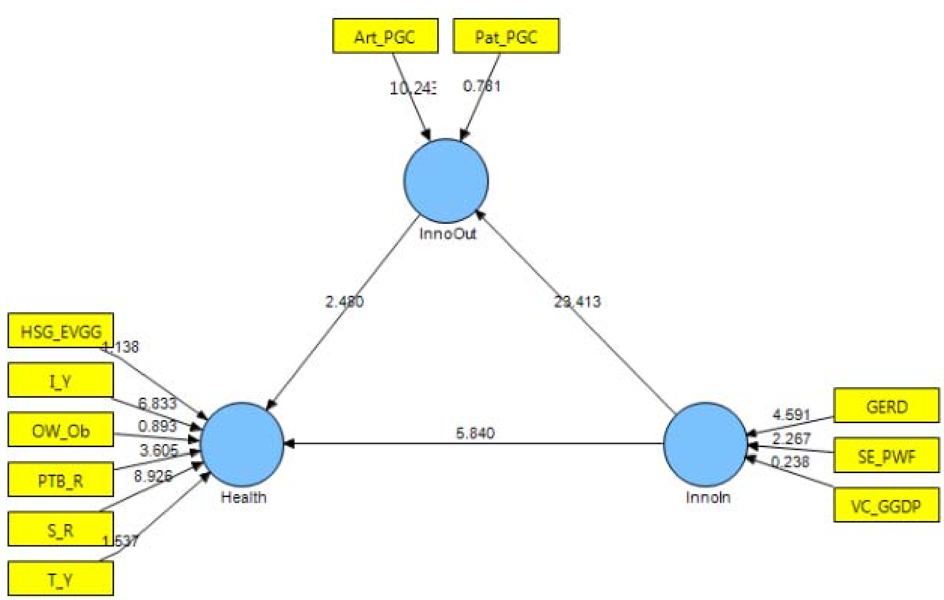

Figure 3 : SEM for South U.S. Census region - Bootstrap sample rate 300

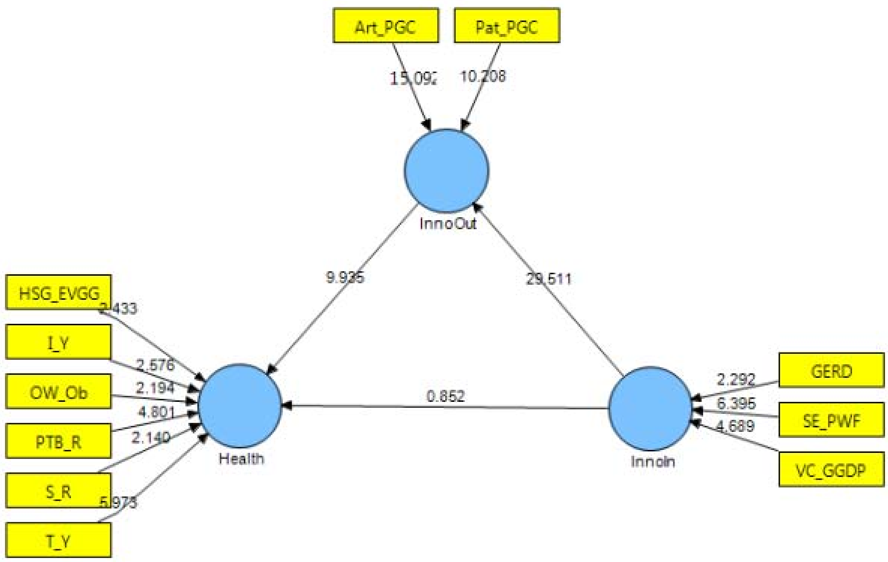

Figure 4 : SEM for West U.S. Census region - Bootstrap sample rate 300

XIV. Discussion/Conclusion

The results of the data analyses show that various U.S. Census regions fare differently in terms of technological innovation and public health. In other words technological innovation scores and public health indicator scores were at different levels for the four U.S. Census regions. It was found that the South region lagged behind other regions for both sets of indicator scores. Additionally, the Northeast regions led other regions for both sets of indicator scores. Further research should focus on studying the reasons behind this disparity between the four regions.

The relationships between the technological innovation indicators and public health indicators were quantified in terms of power law regression equations. It was found that technological innovation and public health generally share a sub-linear relation. For multiple technological innovation indicator and public health indicator combinations the relationship was negative sub-linear. Hence, it could be argued that better technological innovation is linked with better public health. The power law regression equations could serve as predictive models which could be used to calculate projected improvement in the public health indicators given a specific improvement in the technological indicators. Future studies should explore the relationship between technological innovation and public health in terms indicators not included in this study. The study should be repeated for longer periods of time to improve validity of the results. Future research could also focus on identifying the specific dimensions of technological innovation which directly impact the public health.

The results of SEM data analyses provided evidence that high levels of technological innovation were associated with better public health. Additional research, including experimental studies, is needed to confirm the causal effect of technological innovation on public health. If such a casual relation is confirmed policy makers could, for example, focus on enhancing the numbers of scientists and engineers in the work force. The scientists and engineers would in turn generate more patents and articles which in turn could lead to better public health.

The results of the data analyses also build the case that that policy makers should focus on development of the broad spectrum of technologies rather than solely focusing on health related technologies to improve public health. Additionally, this research study could serve as a guideline to compare various geographical regions - countries, states, counties - in terms of public health and technological innovation. Such a comparison provides a methodology to uncover areas in need of improvement. The methodology used in this study could be used to benchmark geographical regions with successful and synergetic technological innovation public health systems.

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Appendix A

Coding for indicators

Indicator type	Indicator	Indicator code
Public Health Indicators	Health status	HSG_EVGG
	Insurance	I_Y
	Obesity and overweight	OW_Ob
	Preterm birth rate	PTB_R
	Suicide rate	S_R
	Tobacco use	T_Y
Technological Innovation Indicators	Articles per 1000 capita	Art_PGC
	Patents per 1000 capita	Pat_PGC
	Percentage of workforce in science and engineering occupation	SE_PWF
	Value of R&D performed as percent of GDP	GERD
	Venture capital per $1000 of GDP	VC_GGDP

Table 8 : Indicator and associated codes

Multiple Range Tests

HSG_EVGG

Contrast	Sig.
M - N	
M - S	*
M - W	
N - S	*
N - W	
S - W	*

T_Y

Contrast	Sig.
M - N	*
M - S	*
M - W	*
N - S	*
N - W	
S - W	*

OW_Ob

Contrast	Sig.
M - N	*
M - S	
M - W	*
N - S	*
N - W	
S - W	*

PTB_R

Contrast	Sig.
M - N	*
M - S	*
M - W	*
N - S	*
N - W	*
S - W	*

I_Y

Contrast	Sig.
M - N	
M - S	*
M - W	*
N - S	*
N - W	*
S - W	

S_R

Contrast	Sig.
M - N	*
M - S	
M - W	*
N - S	*
N - W	*
S - W	*

Pat_PGC

Contrast	Sig.
M - N	*
M - S	*
M - W	
N - S	*
N - W	*
S - W	*

Art_PGC

Contrast	Sig.
M - N	*
M - S	*
M - W	*
N - S	*
N - W	*
S - W	

VC_GGDP

Contrast	Sig.
M - N	*
M - S	
M - W	*
N - S	*
N - W	
S - W	*

GERD

Contrast	Sig.
M - N	*
M - S	
M - W	*
N - S	*
N - W	*
S - W	*

SE_PWF

Contrast	Sig.
M - N	*
M - S	
M - W	
N - S	*
N - W	
S - W	*

* denotes a statistically significant difference in means

Figure 5 : ANOVA for indicator data from various U.S. Census regions

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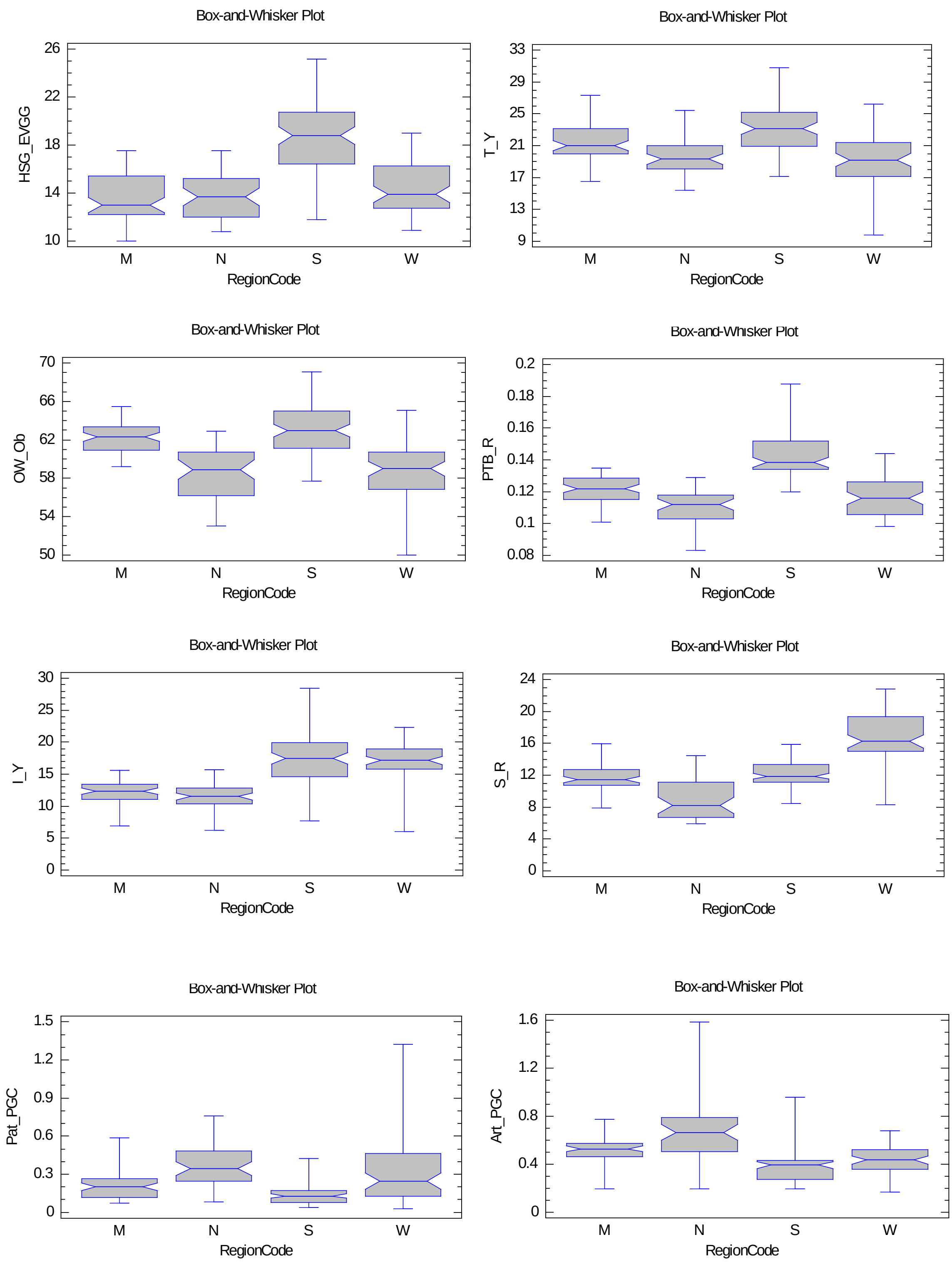
Appendix B

Kruskal -Wallis median comparison per indicator by Region



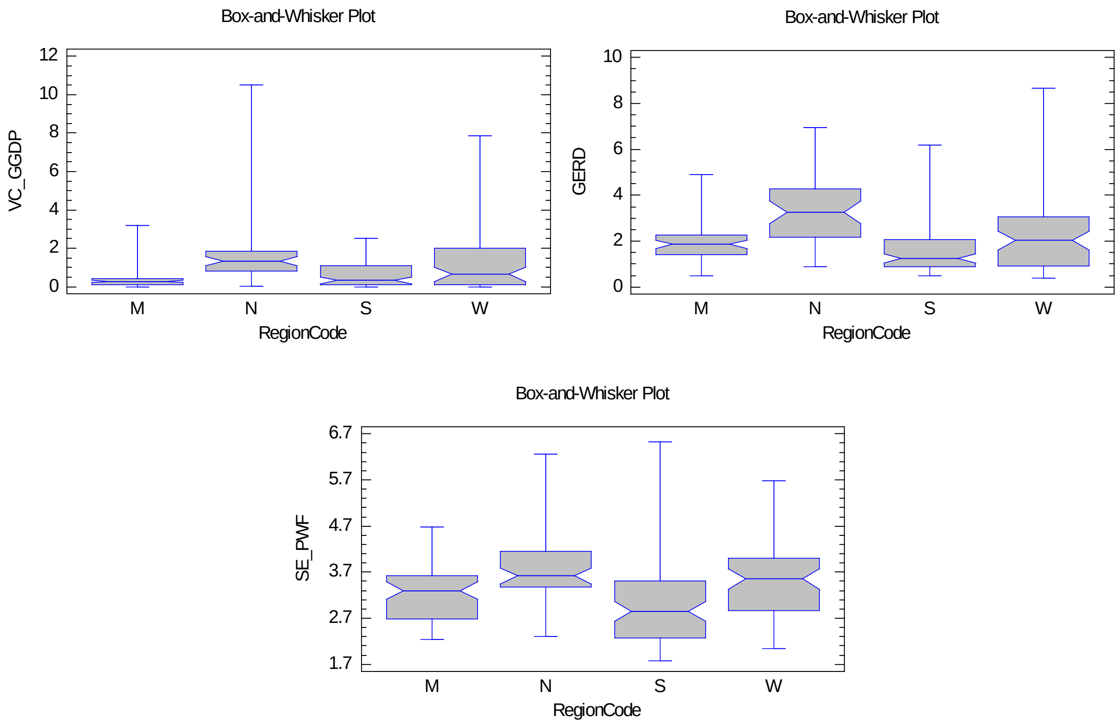


Figure 6 : Box whisker plots associated with the Kruskal-Wallis median comparison tests for the four U.S. Census regions with regards to each indicator

Appendix C

PLS SEM results

Table 9 shows path coefficients for the Midwest U.S. Census region. Table 10 shows path coefficients for the Northeast U.S. Census region. Table 11 shows path coefficients for the South U.S. Census region. Table 12 shows path coefficients for the West U.S. Census region.

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	T Statistics (|O/STERR|)
InnoIn -> Health	0.1058	0.1288	0.1417	0.1417	0.7465
InnoIn -> InnoOut	0.7591	0.7771	0.0421	0.0421	18.0246
InnoOut -> Health	-0.9126	-0.9358	0.1073	0.1073	8.5055

Table 9 : PLS SEM path coefficients for Midwest U.S. Census region – Bootstrap sample rate 200

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	T Statistics (|O/STERR|)
InnoIn -> Health	-0.5196	-0.5296	0.1315	0.1315	3.9518
InnoIn -> InnoOut	0.8626	0.8558	0.0381	0.0381	22.6555
InnoOut -> Health	-0.3893	-0.3818	0.1366	0.1366	2.8493

Table 10 : PLS SEM path coefficients for Northeast U.S. Census region – Bootstrap sample rate 200

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	T Statistics (|O/STERR|)
InnoIn -> Health	-0.6302	-0.6403	0.0948	0.0948	6.6459
InnoIn -> InnoOut	0.8496	0.8494	0.0366	0.0366	23.2259
InnoOut -> Health	-0.281	-0.2735	0.1004	0.1004	2.7991

Table 11 : PLS SEM path coefficients for South U.S. Census region – Bootstrap sample rate 200

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	T Statistics (|O/STERR|)
InnoIn -> Health	0.1041	0.0906	0.1247	0.1247	0.8346
InnoIn -> InnoOut	0.769	0.775	0.0266	0.0266	28.8883
InnoOut -> Health	-0.9474	-0.9436	0.0961	0.0961	9.8603

Table 12 : PLS SEM path coefficients for South U.S. Census region – Bootstrap sample rate 200

It must be noted that PLS SEM was run at 4 sample rate vis-à-vis the bootstrap algorithm: 200, 300, 500 and, 800 samples. The resultant t values for each sample rate point to the same conclusions described in the Structural Equation Modeling section.