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Technological innovation and its effect on public health in the United States

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Background: Good public health ensures an efficient work force. Organizations can ensure a prominent position on the global stage by staying on the leading edge of technological development. Public health and technological innovation are vital elements of prosperous economies. It is important to understand how these elements affect each other. This research study explored and described the relationship between these two critical elements/constructs.

Methods: Indicators representing technological innovation and public health were identified. Indicator data from 2000 to 2009 were collected from various US federal government sources, for the four US Census regions. The four US Census regions were then compared in terms of these indicators. Canonical correlation equations were formulated to identify combinations of the indicators that are strongly related to each other. Additionally, the cause–effect relationship between public health and technological innovation was described using the structural equation modeling technique.

Results: The four US Census regions ranked differently in terms of both type of indicators in a statistically significant manner. The canonical correlation analysis showed that the first set of canonical variables had a fairly strong relationship, with a magnitude > 0.65 at the 95% confidence interval, for all census regions. Structural equation modeling analysis provided $\beta < -0.69$ and Student's t statistic > 12.98, for all census regions. The threshold Student's t statistic was 1.98. Hence, it was found that the β values were significant at the 95% confidence interval, for all census regions.

Discussion: The results of the study showed that better technological innovation indicator scores were associated with better public health indicator scores. Furthermore, the study provided preliminary evidence that technological innovation shares causal relation with public health.

Keywords: technological innovation, public health

Introduction

The economic success of an organization depends on it competitiveness. Innovation and market competition share an inverted U relationship.[1] Novel goods and services provide monopolistic incentives to the innovators.[2] Hence, technological innovation is very important for organizations and political regions. US employers spend billions of dollars annually in health-related expenses.[3] Multiple studies have confirmed that better health results in higher productivity.[4–6] Thus, public health is also critical to the viability of organizations and political regions. 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.[7,8] However, these reports don't present a quantified relationship between the two constructs.

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Importance of the research study

Dreyfuss[9] noted that it is challenging to measure the value and impact of knowledge generated by technological innovation. One way to make this measurement is the process of technology assessment.[10] However, this method seems to be limited to assessment of specific technologies and not the complete spectrum of technological development.[11–16] Rogers[17] held that technological innovation is dynamic and iterative and that it propagates under the influence myriad of socioeconomic forces.[17] However, this theory doesn't address the collective impact of technological innovation on the society. Berwick[18] observed that decision makers need to understand all affects of innovation. Türmen and Clift[19] maintained that without access to all products of technological innovation, there is limited public health benefit. Nevertheless, the relationship between technological innovation and public health was not quantified.

Open innovation improves the effectiveness of the underlying research.[20,21] Blank spots in the prioritization of technologies implementation must be understood.[22] Moniruzzaman and Andersson[23] stressed the need to understand the relationship between innovation and health care. Hughes[24] argued that value created by a technological innovation goes beyond the preconceived individual service applications. Greenberg[25] presented many examples where technologies that were not directly geared toward healthcare had substantive public health effect. Policy makers should thus take a holistic approach to research and development-associated technological innovation.[26,27] Gill[27] recommended that this relationship should be explored at a macro level and over an extended period of time. It is pertinent to study how technological innovation, at a macro level, impacts the broad socioeconomic systems, including the public health. Hence, this study explored the relationship between technological innovation indicators and public health indicators for the four US Census regions over a period of 10 years.

Research questions

The research questions were:

1. Is there a statistically significant difference between the mean values of technological innovation indicators and the mean values of public health indicators for the four US Census regions?

2.1. What relationship, if any, exists between technological innovation indicators and public health indicators in the Midwest US Census region?

2.2. What relationship, if any, exists between technological innovation indicators and public health indicators in the Northeast US Census region?

2.3. What relationship, if any, exists between technological innovation indicators and public health indicators in the South US Census region?

2.4. What relationship, if any, exists between technological innovation indicators and public health indicators in the West US Census region?

Hypothesis

The hypotheses associated with this study were tested with a significance level of P value ≤ 0.05. The hypotheses tested were:

1. There is no statistically significant difference between the mean values of technological innovation indicators and the mean values of public health indicators associated with the four US Census regions.

2.1. There is no statistically significant relationship between technological innovation indicators and public health indicators in the Midwest US Census region.

2.2. There is no statistically significant relationship between technological innovation indicators and public health indicators in the Northeast US Census region.

2.3. There is no statistically significant relationship between technological innovation indicators and public health indicators in the South US Census region.

2.4. There is no statistically significant relationship between technological innovation indicators and public health indicators in the West US Census region.

Delimitations/limitations

Delimitations

Data from the District of Columbia and from US territories not federated as a state were not included in the study. The smallest geographical unit included in the study was a single US Census region.[28] A small number of indicators were used to describe both constructs.[29–31] The public health indicators, for this study, were selected from the 26 leading health indicators tracked by the US Department of Health and Human Services.[32] The technological innovation indicators were selected from a list of innovation indicators tracked by the Organisation for Economic Co-operation and Development[33] and studied by Reffitt and Sorenson[34] for the Michigan Department of Labor and Economic Growth. Four technological innovation indicators and five public health indicators were selected by the author.

Limitations

The data were collected from publicly available sources commissioned by governmental agencies and/or organizations. The data collected for the study were limited to the 50 US states. The interval 2000–2009 was the only contiguous period for which data are available for the identified technological innovation indicators and public health indicators. The availability of data influenced selection of the indicators. Formative path models were used for structural equation modeling, to illustrate constructs of technological innovation and public health defined in terms of the respective indicators.[35]

Definition of terms

Public health indicator

A public health indicator is a variable with characteristics used to quantify, directly or indirectly, an aspect of public health.[36] The five public health indicators included in this study were: (1) Health Status, which was the percent of people reporting that their general health is fair or poor, in the annual behavioral risk factor surveillance survey conducted by the US Centers for Disease Control and Prevention;[37] (2) Insurance, which was the percent of people reporting that they don't have any kind of health care coverage, in the annual behavioral risk factor surveillance survey conducted by the US Centers for Disease Control and Prevention;[37] (3) Obesity and Overweight Rate, which was 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 US Centers for Disease Control and Prevention;[37] (4) Preterm Birth Rate, which was the ratio of the births before 36 weeks of gestation to the total number of births, as reported in the US Centers for Disease Control and Prevention's Natality public-use data in the CDC WONDER Online Database;[38–40] and (5) Tobacco Use, which was the percent of people reporting that they are current smokers, in the annual Behavioral Risk Factor Surveillance survey conducted by the US Centers for Disease Control and Prevention.[37]

US Census region

The 50 federated states are grouped together into four census regions by the US Census Bureau:[28] (1) the Midwest, consisting of Indiana, Illinois, Michigan, Ohio, Wisconsin, Iowa, Nebraska, Kansas, North Dakota, Minnesota, South Dakota, and Missouri; (2) the Northeast, consisting of Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont, New Jersey, New York, and Pennsylvania; (3) the South, consisting of Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia, Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, and Texas; and (4) the West, consisting of Arizona, Colorado, Idaho, New Mexico, Montana, Utah, Nevada, Wyoming, Alaska, California, Hawaii, Oregon, and Washington.

Technological innovation indicator

A technological innovation indicator is a variable used to measure, directly or indirectly, an aspect of technological innovation.[36] The four technological innovations indicators included in this study were: (1) Articles per 1000 Capita, which was the number of scholarly articles published per 1000 people in a state, as reported by the US National Science Foundation's National Center for Science and Engineering Statistics;[41] (2) Patents per 1000 Capita, which was the number of patents awarded per 1000 people in a state, as reported by the US Patents and Trademarks Office;[42] (3) Percentage of Science and Engineering Degrees, which was the number of science and engineering degrees awarded as a percentage of all higher education degrees awarded in a state, as reported by the US National Science Foundation's National Center for Science and Engineering Statistics;[41] and (4) Venture Capital per $1000 of Gross Domestic Product (GDP), which was the volume of venture capital investment in a state per $1000 of the state GDP, as reported by the US National Science Foundation's National Center for Science and Engineering Statistics.[41]

Methodology

The various indicator data were collected from different US governmental agencies. Table 1 presents the indicators along with their associated codes and data type. Analysis of variance (ANOVA) multiple range tests were performed to assess whether there were significant differences between indicator scores from the four US Census regions. Canonical correlation equations were formed between the technological innovation indicators and the public health indicators. The strength of the relationship was measured in terms of the magnitude of the canonical correlation statistic. Formative structural equation modeling technique was employed to demonstrate whether a causal relationship existed between technological innovation and public health.

Results

Results of the descriptive data analysis are presented in Table 2. The standardized kurtosis and standardized skewness

Table 1 Indicator and associated codes

Indicator type	Indicator	Data type	Indicator code
Public health	Lack of health insurance	Sample	I_N
	Obese and/or overweight	Sample	OW_Ob
	Poor health status	Sample	HS
	Preterm birth rate	Census	PTB_R
	Tobacco use	Sample	T_Y
Technological innovation	Articles per 1000 capita	Census	Art_PGC
	Patents per 1000 capita	Census	Pat_PGC
	S&E degrees per 100 higher education degrees	Census	SED_PED
	Venture capital investment per $1000 of GDP	Census	VC_GGDP

Abbreviations: S&E, science and engineering; GDP, gross domestic product.

values for the indicators are presented in Table 3. These values are outside the range of –2 to +2. This indicates a significant departure from normality. A natural logarithm transformation improved the kurtosis and skewness values. These results are also presented in Table 3. It was hence determined that ANOVA and canonical correlation analyses could be performed on the transformed data.

In order to test Hypothesis 1, a single-factor ANOVA was performed for every transformed indicator, with regards to the four US Census regions. Statistically significant difference at 95% confidence interval is highlighted with an asterisk symbol in Table 4. The mean range tests are presented in the Figure S1. The results of the ANOVA tests showed that there were statistically significant differences in both the technological innovation indicator scores and public health indicator scores, with regards to the four US Census regions.

Data analysis showed that the South was the only US Census region that had poor Health Status scores. In fact, the South US Census region had the poorest scores for all the public health and technological indicators. On the other hand, the Northeast US Census region had good scores for all public health and technological indicators. The Midwest and the West US Census regions did not have the best scores for any of the technological innovation indicators. The Midwest US Census region fared well in terms of Health Status and Insurance. This region had poor scores for Obesity and/or Overweight rate, Science and Engineering Degrees, and Venture Capital per $1000 of GDP. The West US Census region fared well in terms of Health Status, Obesity and Overweight Rate and Tobacco Use. The West region had poor scores for Insurance and Articles per 1000 Capita. The results data analyses provided no evidence to support Hypothesis 1, at the 0.05 level of significance.

Canonical correlation

Canonical correlation analysis relates a set of dependent variables to a set of independent variables. This is achieved by defining a scalar linear combination of the dependent variables and a scalar linear combination of the independent variables. The magnitude of the correlation between the two scalars is used to quantify the relationship between the independent and dependent variables.[43] For the purposes of this study, technological innovation indicators formed the independent variables and public health indicators constituted the dependent variables. The results of the canonical correlation are presented in Table 5.

It was found that the technological innovation indicators and the public health indicators demonstrated a fairly strong relationship at the 95% confidence interval. The first combination for the Midwest region had a canonical correlation of 0.66 with a P-value of <0.001. The first combination for the Northeast region had a canonical

Table 2 Descriptive data analysis

	HS	T_Y	OW_Ob	PTB_R	I_N	Pat_PGC	Art_PGC	VC_GGDP	SED_PED
Count	500	500	500	500	500	500	500	500	500
Average	15.21	21.25	60.58	0.12	14.46	0.25	0.49	1.61	29.07
Std dev	3.30	3.58	3.67	0.02	4.24	0.20	0.22	3.34	4.44
Minimum	9.40	9.30	48.00	0.08	4.40	0.03	0.16	0.00	16.66
Maximum	25.40	32.60	70.30	0.19	28.50	1.36	1.66	37.82	40.50
Range	16.00	23.30	22.30	0.11	24.10	1.34	1.49	37.82	23.84

Abbreviations: Std Dev, standard deviation; HS, health status; T_Y, tobacco use; OW_Ob, obesity and overweight rate; PTB_R, preterm birth rate; I_N, insurance; Pat_PGC, patents per 1000 capita; Art_PGC, articles per 1000 capita; VC_GGDP, venture capital per $1000 of gross domestic product; SED_PED, percentage of science and engineering degrees.

Table 3 Raw indicator data transformation

	HS	T_Y	OW_Ob	PTB_R	I_N	Pat_PGC	Art_PGC	VC_GGDP	SED_PED	ln(HS)	ln(T_Y)	ln(OW_Ob)	ln(PTB_R)	ln(I_N)	ln(Pat_PGC)	ln(Art_PGC)	ln(VC_GGDP)	ln(SED_PED)
Stnd skewness	7.443	−7.735	−1.930	6.807	3.434	19.432	17.761	53.430	1.893	2.083	−1.462	−1.434	1.281	−1.110	−0.134	−0.027	−1.192	−1.616
Stnd kurtosis	−2.030	8.562	−0.304	5.491	−0.681	31.546	31.020	219.904	−2.243	0.297	1.702	0.857	0.871	0.133	−1.357	1.560	−0.793	0.345

Abbreviations: Stnd, standard; HS, health status; T_Y, tobacco use; OW_Ob, obesity and overweight rate; PTB_R, preterm birth rate; I_N, insurance; Pat_PGC, patents per 1000 capita; Art_PGC, articles per 1000 capita; VC_GGDP, venture capital per $1000 of gross domestic product; SED_PED, percentage of science and engineering degrees; ln, logarithm.

Table 4 ANOVA multiple range test for transformed indicator data

Contrast	Public health indicators					Technological innovation indicators			
	ln(I_N) Sig	ln(OW_Ob) Sig	ln(HS) Sig	ln(PTB_R) Sig	ln(T_Y) Sig	ln(Art_PGC) Sig	ln(Pat_PGC) Sig	ln(SED_PED) Sig	ln(VC_GGDP) Sig
Midwest – Northeast		*		*	*	*	*	*	*
Midwest – South	*		*	*	*	*	*	*	*
Midwest – West	*	*	*	*	*	*	*	*	*
Northeast – South	*	*	*	*	*	*	*	*	*
Northeast – West	*		*	*		*	*	*	*
South – West		*	*	*	*	*	*	*	*

Note: *Statistically significant difference in means (at the 0.05 level of significance).
Abbreviations: ANOVA, analysis of variance; ln, logarithm; I_N, insurance; OW_Ob, obesity and overweight rate; HS, health status; PTB_R, preterm birth rate; T_Y, tobacco use; Art_PGC, articles per 1000 capita; Pat_PGC, patents per 1000 capita; SED_PED, percentage of science and engineering degrees; VC_GGDP, venture capital per $1000 of GDP; ln, logarithm; Sig, Significant.

Table 5 Canonical correlation analysis, by US Census region

Combination	US Census region	Eigen value	Canonical correlation	Wilks lambda	Chi-squared	*P*-value
1	Midwest	0.44	0.66	0.41	89.39	<0.001
2		0.17	0.41	0.74	30.78	0.002
3		0.07	0.27	0.88	12.42	0.053
4		0.05	0.22	0.95	4.88	0.087
1	Northeast	0.66	0.81	0.14	164.09	<0.001
2		0.50	0.71	0.42	73.35	<0.001
3		0.15	0.39	0.84	15.04	0.020
4		0.01	0.10	0.99	0.91	0.633
1	South	0.79	0.89	0.10	339.69	<0.001
2		0.46	0.68	0.46	112.87	<0.001
3		0.13	0.37	0.85	22.89	0.001
4		0.01	0.11	0.99	1.78	0.411
1	West	0.64	0.80	0.16	187.97	<0.001
2		0.38	0.62	0.46	80.72	<0.001
3		0.17	0.41	0.74	30.79	<0.001
4		0.11	0.33	0.89	11.71	0.003

correlation of 0.81 with a *P*-value of <0.001. The first combination for the South region had a canonical correlation of 0.89 with a *P*-value of <0.001. The first combination for the West region had a canonical correlation of 0.80 with a *P*-value of <0.001. Although the canonical correlation analysis provided evidence for a strong relationship between the indicators, an examination of the coefficients didn't provide a clear picture of the proportionality between the two constructs. The first combination for each region is presented in Table 6. In order to further explore the proportionality issue, the structural equation modeling technique was employed.

Structural equation modeling

The structural equation modeling (SEM) technique was employed to further study the relationship between the constructs of public health and technological innovation. The SEM technique can be employed to test causal relationships between constructs built upon measurable variables.[44] The SEM technique used for this study involved the covariance-based partial least square (PLS) path model method. 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. The outer model specifies the relationships between a latent variable and its observed or manifest variables. Latent variables are hypothetical constructs that cannot be directly measured. They are represented by multiple manifest variables 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.[35,45]

The individual path coefficients of the SEM-PLS structural path model can be interpreted as standardized β coefficients of ordinary least squares regressions. The

Table 6 First combination of canonical correlation equations, by US Census region

Region	Construct	First combination of canonical correlation equations
Midwest	Public health	$0.519864 \times \ln(HS) - 0.171572 \times \ln(T\_Y) - 0.464393 \times \ln(OW\_Ob) + 0.0546953 \times \ln(PTB\_R) - 1.12974 \times \ln(I\_N)$
	Technological	$0.535711 \times \ln(Pat\_PGC) - 0.0514066 \times \ln(Art\_PGC) + 0.56347 \times \ln(VC\_GGDP) + 0.35743 \times \ln(SED\_PED)$
Northeast	Public health	$-0.322851 \times \ln(HS) - 0.396228 \times \ln(T\_Y) - 0.736038 \times \ln(OW\_Ob) + 0.404037 \times \ln(PTB\_R) - 0.399636 \times \ln(I\_N)$
	Technological	$0.129338 \times \ln(Pat\_PGC) + 0.785715 \times \ln(Art\_PGC) + 0.151089 \times \ln(VC\_GGDP) + 0.41051 \times \ln(SED\_PED)$
South	Public health	$-0.554202 \times \ln(HS) - 0.0739683 \times \ln(T\_Y) - 0.297344 \times \ln(OW\_Ob) - 0.416647 \times \ln(PTB\_R) + 0.187316 \times \ln(I\_N)$
	Technological	$0.540725 \times \ln(Pat\_PGC) - 0.650479 \times \ln(Art\_PGC) + 0.152914 \times \ln(VC\_GGDP) + 0.899588 \times \ln(SED\_PED)$
West	Public health	$0.132727 \times \ln(HS) - 0.40142 \times \ln(T\_Y) - 0.373328 \times \ln(OW\_Ob) - 0.857425 \times \ln(PTB\_R) + 0.335358 \times \ln(I\_N)$
	Technological	$0.611958 \times \ln(Pat\_PGC) + 0.292141 \times \ln(Art\_PGC) + 0.244158 \times \ln(VC\_GGDP) + 0.302859 \times \ln(SED\_PED)$

Abbreviations: ln, logarithm; HS, health status; T_Y, tobacco use; OW_Ob, obesity and overweight rate; PTB_R, preterm birth rate; I_N, insurance; Pat_PGC, patents per 1000 capita; Art_PGC, articles per 1000 capita; VC_GGDP, venture capital per $1000 of GDP; SED_PED, percentage of science and engineering degrees.

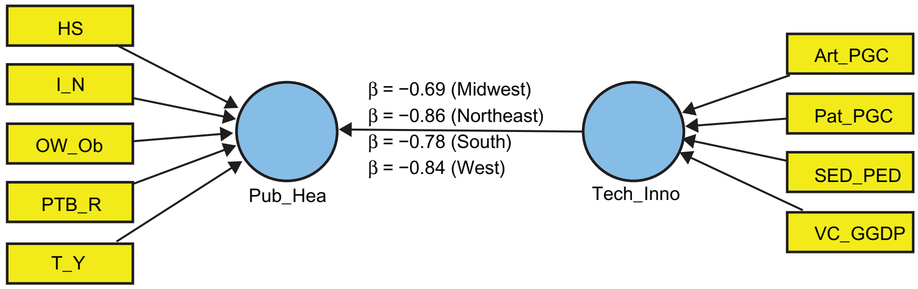

Figure 1 SEM-PLS path model for all US Census regions.
Abbreviations: SEM, structural equation modeling; PLS, partial least square path model; HS, health status; I_N, insurance; OW_Ob, obesity and overweight rate; PTB_R, preterm birth rate; T_Y, tobacco use; Art_PGC, articles per 1000 capita; Pat_PGC, patents per 1000 capita; SED _PED, percentage of science and engineering degrees; VC_GGDP, venture capital per $1000 of GDP; Pub_Hea, Public Health; Tech_Inno, Technologicial Innovation.

algebraic signs of β provide a partial empirical validation of the theoretically assumed relationships. Parameter estimates are obtained by minimizing the residual variances of dependent variables.[35]

In order to determine the confidence intervals of the path coefficients and draw statistical inference, resampling nonparametric algorithms, called bootstrapping, can be used. The SEM-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.[35] The SEM-PLS technique can be used for data with any type of distribution and in cases with large or small sample sizes.[46–51]

Henseler et al[35] asserted that a formative measurement model is adequate when a construct is defined as a combination of its indicators. Furthermore, the SEM-PLS bootstrap path modeling algorithm allows for the computation of cause–effect relationship models that employ both reflective and formative measurement models.[52] Thus, for the purposes of this study, a formative SEM-PLS path model was used. The indicator data formed the manifest variables. The constructs of technological innovation and public health formed the latent variables.

The SEM-PLS path model and β coefficients are presented in Figure 1. The Student's *t* values and bootstrap sample rates are presented in Table 7. For data samples with degrees of freedom ≥ 60, statistical significance is demonstrated at two-sided 95% confidence intervals if the I values are ≥ 2. For all US Census regions, the Student's *t* statistic was found to be greater than the threshold values for both 95% and 99% confidence intervals. The degrees of freedom associated with the threshold values were calculated from the number of data points. Furthermore, all β values were negative. These findings provide evidence that there could be a causal relationship between technological innovation and public health in all four US Census regions.

Based on the results of the canonical correlation and SEM analyses presented above, the null Hypotheses 2.1, 2.2,

Table 7 Student's *t* statistic and bootstrap sample rate used

Region	Student's t statistic	Threshold value at 95% conf interval (2 tailed)	Threshold value at 99% conf interval (2 tailed)	Number of data points	Sample rate
Midwest	14.20	>1.984	>2.626	120	100
	12.98				300
	13.39				500
	39.67				100
Northeast	40.96	>1.984	>2.626	90	300
	37.78				500
	21.80				100
South	20.30	>1.984	>2.626	160	300
	21.23				500
	27.61				100
West	28.43	>1.984	>2.626	130	300
	27.51				500

Abbreviations: Conf, confidence.

2.3, and 2.4 were rejected. In other words, no evidence was found to support the hypotheses that there is no statistically significant relationship between technological innovation and public health, for any of the four US Census regions, at the 0.05 level of significance.

Conclusion

The states of technological innovation and public health were at different levels for the four US Census regions between 2000 and 2009. The South region lagged behind other regions in terms of all the indicators studied. On the other hand, technological innovation and public health fared relatively well in the Northeast region. Further research studies should analyze this disparity with the objective of identifying and benchmarking specific enablers of higher technological innovation and better public health.

The relationships between the technological innovation indicators and public health indicators were quantified in terms of canonical correlation equations. It was found that technological innovation and public health share a fairly strong relationship. These equations could serve as predictive models to calculate the projected change in public health, given a specific change in technological innovation. The results of SEM data analyses provided evidence that high levels of technological innovation were associated with better public health. Based on the data analyses, it could be argued that better technological innovation is linked with better public health.

Future studies can validate the results of this study by exploring the relationship between technological innovation and public health using additional indicators, over extended time periods, and in other locations. Future research could also focus on isolating specific dimensions of technological innovation that have the most impact on public health. Experimental research studies could also be conducted to verify the causal effect of technological innovation on public health. Extensive verification of this relationship could help policy makers in making informed decisions about future investment in a broad spectrum of technologies, to improve public health.

Disclosure

The author reports no conflicts of interest in this work.

References

1. Aghion P, Bloom N, Blundell R, Griffith R, Howitt P. Competition and innovation: an inverted-U relationship. *The Quarterly Journal of Economics*. 2005;120:701–728.
2. Schumpeter JA. *Capitalism, Socialism and Democracy*, 3rd ed. New York: Harper & Row; 1942.
3. Stewart WF, Ricci JA, Chee E, Morganstein D, Lipton R. Lost productive time and cost due to common pain conditions in the US workforce. *JAMA*. 2003;290:2443–2454.
4. Wojcik J. Unhealthy employees cut productivity: Study. Costs of presenteeism prove greater drain than worker absence. Business Insurance; 2009. Available from: http://www.businessinsurance.com/article/20090426/ISSUE01/100027532. Accessed December 22, 2012.
5. Suhrcke M, McKee M, Stuckler D, Sauto Arce R, Tsolova S, Mortensen J. The contribution of health to the economy in the European Union. *Public Health*. 2006;120:994–1001.
6. Fuchs VR. The contribution of health services to the American economy. *The Milbank Mem Fund Q*. 1966;44(4):65–103.
7. United Nations Development Programme (UNDP). *Human Development Report 2009. Overcoming Barriers: Human Mobility and Development*. New York: Palgrave Macmillan; 2009. Available from: http://hdr.undp.org/en/reports/global/hdr2009/. Accessed November 30, 2012.
8. World Economic Forum. *The Global Competitiveness Report 2010–2011*. Geneva: World Economic Forum; 2010. Available from: http://www.weforum.org/reports/global-competitiveness-report-2010-2011-0. Accessed November 30, 2012.
9. Dreyfuss RC. Evaluating the public impact of open innovation. *Australian Economic Review*. 2011;44(1):66–72.
10. Goodman CS. Introduction to health technology assessment. National Library of Medicine; 2004 [updated September 8, 2008]. Available from: http://www.nlm.nih.gov/nichsr/hta101/ta101_c1.html. Accessed November 30, 2012.
11. Banta D. The development of health technology assessment. *Health Policy*. 2003;63(2):121–132.
12. Perry S, Thamer M. Health technology assessment: decentralized and fragmented in the US compared to other countries. *Health Policy*. 1997;40(3):177–198.
13. Abelson J, Giacomini M, Lehoux P, Gauvin FP. Bringing 'the public' into health technology assessment and coverage policy decisions: from principles to practice. *Health Policy*. 2007;82(1):37–50.
14. Royle J, Oliver S. Consumer involvement in the health technology assessment program. *Int J Technol Assess Health Care*. 2004;20(4):493–497.
15. Oliver S, Armes DG, Gyte G. Public involvement in setting a national research agenda: a mixed methods evaluation. *Patient*. 2009;2(3):179–190.
16. Cohen AB, Hanft RS. *Technology in American Health Care: Policy Directions for Effective Evaluation and Management.* Ann Arbor: University of Michigan Press; 2004.
17. Rogers EM. *Diffusion of Innovations*, 4th ed. New York: Free Press; 1995.
18. Berwick DM. Disseminating innovations in health care. *JAMA*. 2003;289(15):1969–1975.
19. Türmen T, Clift C. Public health, innovation and intellectual property rights: unfinished business. *Bull World Health Organ*. 2006;84(5):338.
20. Kenneth A Getz. Transforming R&D Through Open Innovation. *Applied Clinical Trials*. 2011;20:28.
21. Feller J, Finnegan P, Nilsson O. Open innovation and public administration: transformational typologies and business model impacts. *European Journal of Information Systems*. 2011;20:358–374.
22. Wild C, Langer T. Emerging health technologies: Informing and supporting health policy early. *Health Policy*. 2008;87(2):160–171.
23. Moniruzzaman S, Andersson R. Economic development as a determinant of injury mortality – a longitudinal approach. *Soc Sci Med*. 2008;66(8):1699–1708.
24. Hughes L. Innovation and the new landscape for public health. *Perspect Public Health*. 2011;131(13):114–115.
25. Greenberg MR. The diffusion of public health innovations. *Am J Public Health*. 2006;96(2):209–210.

26. Varey P. Spend to save: synergy and innovation in public health. *Perspect Public Health*. 2011;131(3):112–114.
27. Gill PS. 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. *Global Journal of Medical Research.* 2012;12(6):63–81.
28. US Census Bureau. *Census Regions and Divisions of the United States*. Washington: US Census Bureau; 2000. Available from: http://www.census.gov/geo/www/us_regdiv.pdf. Accessed June 10, 2012.
29. Chatterjee S, Sorenesen E. A Pareto-like effect in regression? *Total Qual Manag*. 1998;9:681–687.
30. Cummings GG. How many indicators does it take to measure a concept? Virginia Henderson International Nursing Library; 2004. Available from: http://hdl.handle.net/10755/152758. Accessed December 13, 2012. Abstract.
31. Mizell L. *Governing Regional Development Policy: The Use of Performance Indicators*. Paris: Organisation for Economic Co-operation and Development; 2009. Available from: http://www.oecd.org/gov/governingregionaldevelopmentpolicytheuseofperformanceindicators.htm. Accessed November 30, 2012.
32. healthypeople.gov [homepage on the Internet]. 2020 LHI (Leading health indicators). US Department of Health and Human Services. updated March 29, 2012. Available from: http://www.healthypeople.gov/2020/LHI/2020indicators.aspx. Accessed November 30, 2012.
33. oecd-ilibrary.org [homepage on the Internet]. OECD Regional statistics. Organisation for Economic Co-operation and Development (OECD); 2012. Available from: http://www.oecd-ilibrary.org/urban-rural-and-regional-development/data/oecd-regional-statistics_region-data-en. Accessed November 30, 2012.
34. Reffitt M, Sorenson C. *Innovation indicators: Report to the Council for Labor and Economic Growth*. Lansing: Michigan Department of Labor and Economic Growth; 2007. Available from: http://www.doleta.gov/Programs/2006ReportsAndPlans/Economic_Analysis_Reports/MI-2.pdf. Accessed December 22, 2012.
35. Henseler J, Ringle CM, Sinkovics RR. The use of partial least squares path modeling in international marketing. *Advances in International Marketing*. 2009;20:277–319.
36. Gruskin S, Ferguson L. Using indicators to determine the contribution of human rights to public health efforts. *Bull World Health Organ*. 2009;87(9):714–719.
37. cdc.gov/brfss [homepage on the Internet]. Behavioral risk factor surveillance system: Prevalence and trends data. Centers for Disease Control and Prevention; updated August 6, 2012. Available from: http://apps.nccd.cdc.gov/BRFSS/index.asp. Accessed July 30, 2012.
38. wonder.cdc.gov [homepage on the Internet]. CDC WONDER: Natality information, 2007–2009. Centers for Disease Control and Prevention; updated March 15, 2012. Available from: http://wonder.cdc.gov/natality.html. Accessed August 25, 2012.
39. wonder.cdc.gov [homepage on the Internet]. CDC WONDER: Natality information, 2003–2006. Centers for Disease Control and Prevention; updated March 15, 2012. Available from: http://wonder.cdc.gov/natality.html. Accessed August 25, 2012.
40. wonder.cdc.gov [homepage on the Internet]. CDC WONDER: Natality information, 1995–2002. Centers for Disease Control and Prevention; updated March 15, 2012. Available from: http://wonder.cdc.gov/natality.html. Accessed August 25 2012.
41. nsf.gov [homepage on the Internet]. Science and engineering indicators 2012 state data tool. National Science Foundation; updated Jan 2012. Available from: http://www.nsf.gov/statistics/seind12/c8/interactive/start.cfm. Accessed November 30, 2012.
42. uspto.gov [homepage on the Internet]. Patents by country, state, and year – Utility patents (December 2011). US Patent and Trademark Office (USPTO); updated March 27, 2012. Available from: http://www.uspto.gov/web/offices/ac/ido/oeip/taf/cst_utl.htm. Accessed November 30, 2012.
43. Gatignon H. *Statistical Analysis of Management Data*, 2nd ed. New York: Springer; 2010.
44. Anderson JC, Gerbing DW. Some methods for respecifying measurement models to obtain unidimensional construct measurement. *Journal of Marketing Research.* 1982;19:453–460.
45. Shah R, Goldstein SM. Use of structural equation modeling in operations management research: Looking back and forward. *Journal of Operations Management*. 2006;24(2):148–169.
46. Green DH, Ryans AB. Entry strategies and market performance causal modeling of a business simulation. *Journal of Product Innovation Management*. 1990;7(1):45–58.
47. Johansson JK, Yip GS. Exploiting globalization potential: US and Japanese strategies. *Strategic Management Journal*. 1994;15(8):579–601.
48. Birkinshaw J, Morrison A, Hulland J. Structural and competitive determinants of a global integration strategy. *Strategic Management Journal*. 1995;16(8):637–655.
49. Venaik S, Midgley DF, Devinney TM. Dual paths to performance: the impact of global pressures on MNC subsidiary conduct and performance. *Journal of International Business Studies*. 2005;36(6):655–675.
50. Julien PA, Ramangalahy C. Competitive strategy and performance of exporting SMEs: an empirical investigation of the impact of their export information search and competencies. *Entrepreneurship Theory and Practice*. 2003;27(3):227–245.
51. Nijssen EJ, Douglas SP. Consumer world-mindedness, social-mindedness, and store image. *Journal of International Marketing*. 2008;16(3):84–107.
52. Diamantopoulos A, Winklhofer HM. Index construction with formative indicators: an alternative to scale development. *Journal of Marketing Research.* 2001;38(2):269–277.

Supplementary figure

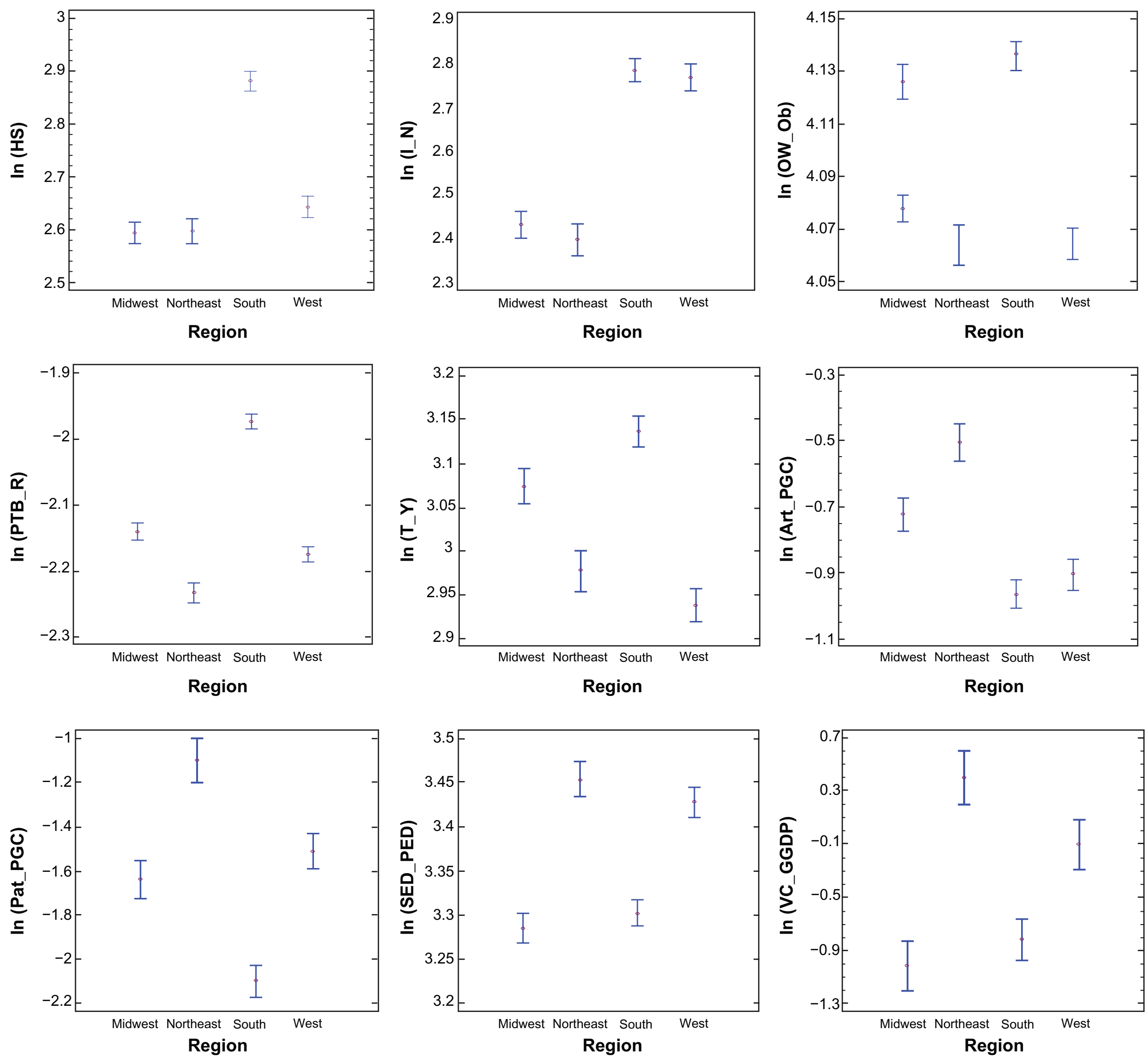

Figure S1 Multiple range tests.

Abbreviations: ln, logarithm; HS, health status; I_N, insurance; OW_Ob, obesity and overweight rate; PTB_R, preterm birth rate; T_Y, tobacco use; Art_PGC, articles per 1000 capita; Pat_PGC, patents per 1000 capita; SED_PED, percentage of science and engineering degrees; VC_GGDP, venture capital per $1000 of GDP.