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Can Housing Prices Be an Alternative to a Census-based Deprivation Index? An Evaluation Based on Multilevel Modeling

주택가격이 센서스에 기반한 박탈지수의 대안이 될 수 있는가?: 다수준 모델에 기반한 평가*

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Abstract

We conducted this research to examine how well regional housing prices are suited to use as an alternative to conventional census-based regional deprivation indices in health and medical geography studies. To examine the relative performance of mean regional housing prices compared to conventional census-based regional deprivation indices, we compared several multilevel logistic regression models, where the first level was individuals and the second was health districts in the Seoul Metropolitan Area (SMA) in Korea, for the sake of adjusting the regional clustering tendency of unknown factors. In these models, we predicted two dichotomous variables that represented individuals' after-lunch tooth brushing behavior and use of dental floss by individual characteristics and regional indices. Then, we compared the relative predictive performance of the models using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The results from the estimations showed that mean regional housing prices and census-based deprivation indices were correlated with the two types of dental health behavior in a statistical sense. The results also revealed that the model with mean regional housing prices showed smaller AIC and BIC compared with other models with conventional census-based deprivation indices. These results imply that it is possible for housing prices summarized using aerial units to be used as an alternative to conventional census-based deprivation indices when the census variables employed cannot properly reflect the characteristics of the aerial units.

Keywords: Deprivation Index, Housing Prices, Multilevel Model

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1. Research Background

Macintyre et al.(2002) suggested that spatial variations in health outcomes can be explained using compositional, contextual, and collective factors. “Compositional” factors refers to how a place consists of individuals of different socioeconomic backgrounds. “Contextual” factors represent the relative affluence of resources that influence health status. “Collective” factors mean the cultural heritage, shared norms, and social capital in a place. Through multilevel and ecological analyses, various studies have verified the impact of these factors on personal health. “Contextual” and “Collective” factors are generally considered through the measurement of deprivation indices in empirical research. Deprivation indices show how hard it is for an individual, group, or place to access socially desirable resources. They are calculated via principal component analyses or summations of normalized scores from a place’s census variables. Conventional census-based deprivation indices usually include income, housing quality, educational attainment, occupational class, and social disadvantage sub-indicators, which usually come from a census.[1)]

Although census-based deprivation indices have been widely used in empirical research, they have two major weaknesses. The first stems from the fact that censuses are usually conducted at 5- or 10-year intervals. Therefore, a census-based deprivation index measured in a census year cannot appropriately reflect the deprivation level of a place between the previous and next census years if the place experienced rapid demographic changes after the previous census. The second weakness is related to the modifiable aerial unit problem. Census aerial units are predefined by the government. It is impossible to redefine the aerial units used for calculating deprivation indices, so we must simply accept the government-defined ones.

Housing price data, which is available in most countries, provide new opportunities for complementing the weaknesses of census-based deprivation indices. As long as there exist strong correlations between housing prices and some of the sub-indicators used for calculating census-based deprivation indices, housing prices summarized using aerial units can be used as an alternative to census-based aerial deprivation indices.[2)] When compared with conventional deprivation indices based on census variables, summarized housing prices have two advantages. First, they can be defined in any aerial units, from individual units to any size of sub-national unit, when sales prices or assessed values of houses are available along with location information. Second, information about the sales prices or assessed values of housing is usually generated at the time of transaction or on a yearly basis.

2. Related Studies

Several studies in the health and medical geography fields have already proven the explanatory power of housing prices (Sohn, 2013; Coeffee et al., 2013; Rehm et al., 2012; Drenowski et al.,

Table 1. Related Studies

Article	Aerial Unit	Housing Price Measure	Disease
Sohn(2013)	Region	Regional Mean Housing Price	Obesity
Coffee et al.(2013)	Single House	Relative Location Factor	Hypertriglyceridemia and diabetes
Rehm et al.(2012)	Single House	Assessed Housing Value	Obesity
Drenowski et al.(2007)	ZIP code area	Median House Value	Obesity

2007). Sohn(2013) showed that regional mean housing prices had a negative correlation with regional obesity rates and explained the variations in regional obesity rates as well as other socioeconomic status variables such as regional poverty rate or educational attainment rate in the SMA in Korea. Coffee et al.(2013) calculated the relative location factor (RLF) using a hedonic housing price equation estimated for Adelaide, Australia. The RLF is the ratio of real sale price divided by housing price predicted using the estimated hedonic price function with the house's physical properties only. An RLF greater than 1 means the house is located in a better location. The authors spatially interpolated the calculated RLF and found that individuals living in higher-RLF locations had a lower risk of hypertriglyceridemia and diabetes. Rehm et al.(2012) found that women living in houses with higher assessed values had a lower risk of obesity in a study conducted for King County, Washington. Drenowski et al.(2007) found a negative relationship between ZIP code-based obesity rates and census-based median house values in King County, Washington.

Previous studies showed that housing prices have the power to explain variations in individual health or aerial health levels. However, these studies did not show how well housing prices explain individual and aerial health levels compared with conventional census-based deprivation indices. One exception is Sohn(2013), who compared the relative explanatory performance of some regional socioeconomic status variables with regional mean housing prices regarding variations in regional obesity rates. However, this study did not examine census-based composite deprivation indices, but rather compared some socioeconomic status variables with regional mean housing prices using ecological regression.

3. Research Objectives, Methodology, and Data

As discussed previously, housing prices have several potential advantages over conventional census-based deprivation indices. To use housing prices as an alternative to conventional census-based deprivation indices, we need to know whether housing prices can explain individual or aerial health levels as well as these indices do in a real context. In this vein, we decided to investigate the relative explanatory performance of housing prices using Korean census data, housing price data, and health survey data.

To examine the relative performance of housing prices compared to conventional census-based deprivation indices, we estimated and compared several multilevel logistic regression models, where the first level was individuals and the second was health districts in the SMA in Korea, for the sake of adjusting the regional clustering tendency of unknown factors. In these models, we intended to predict two dichotomous variables that represented individuals' after-lunch tooth brushing behavior and use of dental floss (or a dental interspace brush) based on individual characteristics and regional indices including regional mean housing price per sq. meter and different types of census-based regional deprivation index. We selected personal dental health care behaviors for the dependent variables because a previous study proved that there exists a significant contextual effect in the use of dental floss and after-lunch tooth brushing behavior in Korea using a multilevel model (Kim et al., 2013). Kim et al.(2013) used a conventional census-based deprivation index to consider regional contextual effects.[3)]

We estimated random intercept models as depicted in (1) and (2). We estimated six models, including one with regional mean housing prices and five with different types of census-based deprivation index. Definitions of the variables used are provided in Table 2. Then, we compared

Table 2. Definition of Variables

Ydfloss	1=Respondent uses dental floss, 0=otherwise.
Ylunchb	1=Respondent brushes their teeth after lunch, 0=otherwise.
Female	1=female, 0=otherwise.
Age	Age of respondent.
Single	1=Single household, 0=otherwise.
Eqincome	Equivalent income: household income divided by square root of household size.
Highedu	1=postgraduate degree, 0=otherwise.
depk1	z_p_lowedpop + z_p_lowjob + z_p_nocarhh + z_p_lowhousing
depk2	z_p_lowedpop + z_p_lowjob + z_p_single + z_p_lowhousing
depk3	z_p_lowedpop + z_p_lowjob + z_p_oldsingle + z_p_lowhousing
depk4	z_p_lowedpop + z_p_lowjob + z_p_oldsingle + z_p_nocarhh
depk5	z_p_lowedhhh + z_p_single + z_p_lowhousing
spsize11	Mean real sale price of apartment properties per sq. meter sold in 2011.
Z_p_lowedpop:	Z value, percentage of low educational attainment pop. up to middle school (19–64 yrs).
Z_p_lowedhhh	Z value, percentage of low educational attainment household heads up to middle school.
Z_ p_lowjob	Z value, percentage of low-level job pop.
Z_ p_single	Z value, percentage of single households.
Z_ p_oldsingle	Z value, percentage of old single households (over 64 yrs).
Z_p_nocarhh	Z value, percentage of no car households.
Z_p_nocarhh	Z value, percentage of low-quality housing households (no toilet or no heating).

Table 3. Summary Statistics

	Count	Mean	SD	Min	Max
ydfloss	33462	.3339011	.4716119	0	1
ylunchb	33462	.6387245	.4803774	0	1
female	33462	.5513418	.4973645	0	1
age	33462	44.51796	14.73015	19	101
single	33462	.0468292	.2112761	0	1
eqincome	33462	221.3433	140.3288	0	2000
highedu	33462	.0662841	.2487818	0	1
depk1	33462	-3.268066	1.766034	-7.749084	3.498782
depk2	33462	-3.636304	1.715446	-7.789646	2.947927
depk3	33462	-3.594007	1.500983	-6.448341	3.834645
depk4	33462	-3.368979	1.740328	-7.882125	1.938921
depk5	33462	-2.613289	1.197643	-5.136712	2.185851
spsize11	33462	397.6867	188.2179	156.4002	1078.069
N	33462				

the relative predictive performance of the non-nested models using AIC and BIC. When AIC and BIC are smaller, it means there is a better fit (Liu, 2016).

Level 1: Individual level

$$Logit(P_{ij}) = log(\frac{P_{ij}}{1-P_{ij}}) = \beta_{0j} + \beta_1 female + \beta_2 age + \beta_3 s \in gle + \beta_4 eqincome + \beta_5 highedu \quad (1)$$

P_{ij} =the probability of individual i form health district j using dental floss or brushing their teeth after lunch

β_{0j} =mean log odds of using dental floss or brushing teeth after lunch in health district j

β_{1-5} : coefficient(s)

Level 2: Health District level

$$\beta_{oj} = \gamma_{00} + \gamma_{01} Deprivation\, Index + u_{0j} \quad (2)$$

γ_{00} : log odds of using dental floss or brushing teeth after lunch in typical health district

γ_{01} : coefficient

u_{0j} : health-district-level error term, $u_{0j} \sim N(0, \tau_{00})$

The data about dental health behavior and individual characteristics came from the Korea Community Health Survey 2011. This survey is conducted by the Korea Ministry of Health and Welfare on a yearly basis. The Korea Community Health Survey also provides respondents' residential location information using health district codes. Local governments in Korea usually have one health office, with some rare exceptions. Each health office has its own governing area called a health district. Because health districts' boundaries are the same as the Korean census's aerial boundaries, we could calculate a census-based deprivation index for each health district. In

2011, this survey included questions such as "Did you brush your teeth after lunch yesterday?" and "Do you usually use dental floss or a dental interspace brush for dental health in addition to toothpaste and a toothbrush?" We used the respondents' answers to these questions and other surveyed personal characteristics for this research. We used the 2010 Korean census to measure five types of conventional regional deprivation index and information about geocoded apartment sales transactions that occurred in 2011 to calculate the mean regional housing price per sq. meter of each health district.[4] For the model estimations, we used only data from the SMA, which consists of Seoul, Gyeonggi, and Incheon.[5] We also used only data from respondents who lived in an apartment complex, because we calculated the regional mean housing prices based on apartment sales transactions. Any survey observations with at least one missing variable were excluded from our estimations. The summary statistics of the variables used in the analysis are provided in Table 3.

4. Results

Six multilevel logistic regression models, including one with regional mean housing prices and five with different types of census-based deprivation index, were estimated to explain individuals' use of dental floss and after-lunch tooth brushing behavior. Five types of individual-level explanatory variable (gender, age, household type, income, and educational attainment) were included in the models in addition to aerial variables including deprivation indices and housing prices.

We present the estimation results in Tables 4 to 9. Tables 4 and 5 show the results when the dependent variable was the use of dental floss, while Tables 6 and 7 show the results when the dependent variable was teeth brushing after lunch. Tables 8 and 9 show the odd ratios from Tables 4 to 7. The first columns of Tables 4 to 7 show the results from the null model, which did not include any explanatory variables at levels 1 or 2.

As seen in Tables 4 and 5, in the case of the null model, between-health district variance was 0.101. Tables 6 and 7 show that between-health district variance was 0.0518. The log likelihood test, which compared the null model and ordinary logistic model, showed that these between-health district variance(s) were significantly different from 0 (=539.34, df=1, $p<0.01$ for Tables 4 and 5, =247.37, df=1, $p<0.01$ for Tables 6 and 7). The ICC from the null model was 0.0299 for Tables 4 and 5 and 0.0155 for Tables 6 and 7. This means that approximately 3(2)% of the total variance was explained by health districts in level 2.

Tables 8 and 9 report the odds ratio calculated from Tables 4 to 7. Table 8 reports the odds ratio(s) when the dependent variable was the use of dental floss. The odds ratio of females was between 1.909 and 1.910. This means that the odds of using dental floss for females was 1.9 times the odds for males, holding all other variables constant. The odds ratio for age was 0.996, which means that a one-year increase in age decreased the odds of using dental floss by 0.4%. Other discrete or continuous variables can be interpreted in a similar manner. In general, being a female, being of a younger age, not being a single family household, having a higher income, having a higher educational attainment level, and living in a lower deprived (higher housing price level) health district increased the likelihood of using dental floss.6) Table 9 reports similar results, except for the odds ratio for single family households and "depk2", which were not significant. When the dependent variable was after-lunch tooth brushing behavior, the odds ratio of females was approximately 1.42. This means that the odds of practicing after-lunch tooth brushing for females was 1.42 times the odds for males, holding all other variables constant. As in the case of dental floss, females were more likely to exhibit healthy dental behavior.

When we examined the AIC(s) and BIC(s) from the six alternative models (leaving out the null model) for the use of dental floss and after-lunch teeth brushing, we saw that the model with mean housing prices showed the smallest AIC and BIC as

Table 4. Estimation Results: Use of Dental Floss

	Model null	Model (1)	Model (2)	Model (3)
female		0.647*** (0.0246)	0.647*** (0.0246)	0.647*** (0.0246)
age		-0.00436*** (0.000841)	-0.00438*** (0.000841)	-0.00438*** (0.000841)
single		-0.222*** (0.0594)	-0.222*** (0.0594)	-0.222*** (0.0594)
eqincome		0.00133*** (0.0000888)	0.00133*** (0.0000888)	0.00132*** (0.0000888)
highedu		0.463*** (0.0469)	0.463*** (0.0469)	0.462*** (0.0469)
depk1		-0.0620*** (0.0172)		
depk2			-0.0618*** (0.0172)	
depk3				-0.0821*** (0.0179)
_cons	-0.728*** (0.0381)	-1.401*** (0.0744)	-1.423*** (0.0785)	-1.491*** (0.0802)
var(_cons)	0.101*** (0.0184)	0.0651*** (0.0127)	0.0648*** (0.0127)	0.0579*** (0.0117)
N	33462	33462	33462	33462
AIC	42089.0	40979.1	40979.2	40972.6
BIC	42105.9	41046.4	41046.5	41039.9
icc	0.0299	0.0194	0.0193	0.0173
ll	-21042.5	-20481.5	-20481.6	-20478.3

Standard errors in parentheses, * p<0.05, ** p<0.01, *** p<0.001

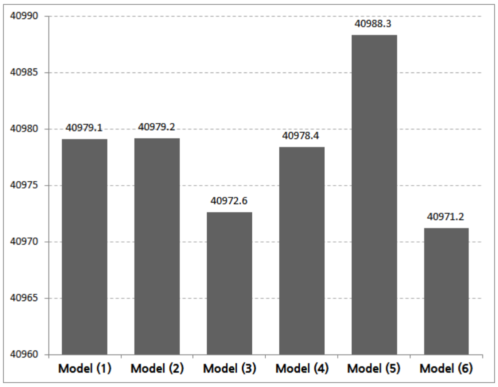

Figure 1. AIC : Estimation Results-Use of Dental Floss

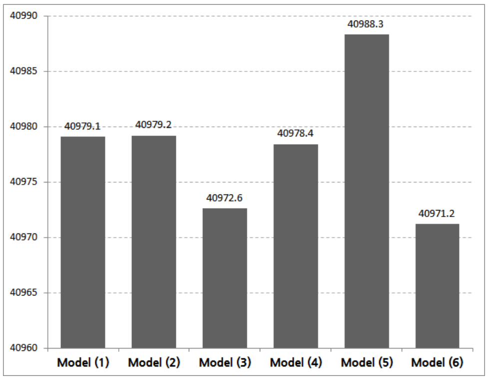

Figure 2. BIC : Estimation Results-Use of Dental Floss

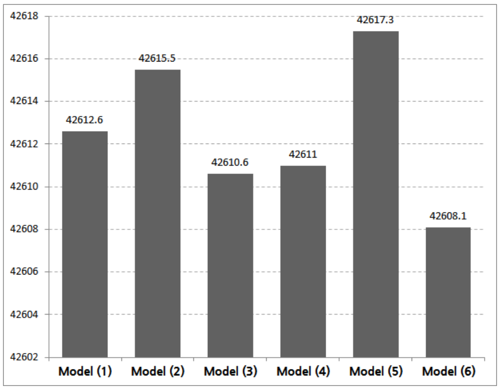

Figure 3. AIC : Estimation Results-After-Lunch Tooth Brushing

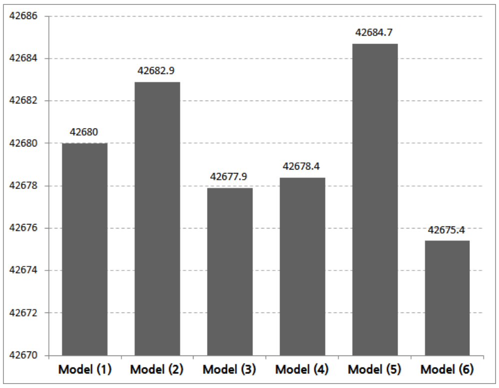

Figure 4. BIC : Estimation Results-After-Lunch Tooth Brushing

depicted in Figure 1 to Figure 4. If we rearrange the AIC(s) from Tables 4 and 5 in descending order, we get the following order: Model 5(40988.3) 〉 Model 2(40979.2) 〉 Model 1(40979.1) 〉 Model 4(40978.4) 〉 Model 3(40972.6) 〉 Model 6 (40971.2). In the case of the BIC(s), we can get the same order. Similarly, the AIC(s) from Tables 6 and 7 can be rearranged in descending order, as follows: Model 5(42617.3) 〉 Model 2(42615.5) 〉 Model 1(42612.6) 〉 Model 4(42611.0) 〉 Model 3(42610.6) 〉 Model 6(42608.1). Also, the BIC(s) shows the same pattern.

5. Discussion and Conclusion

We conducted this research to examine how well regional housing prices are suited to use as an alternative to conventional census-based regional deprivation indices in health and medical geography studies. We compared several multilevel logistic regression models, where the first level was individuals and the second was health

Table 5. Estimation Results: Use of Dental Floss (Continued)

	Model null	Model (4)	Model (5)	Model (6)
female		0.647*** (0.0246)	0.647*** (0.0246)	0.646*** (0.0246)
age		-0.00435*** (0.000841)	-0.00436*** (0.000841)	-0.00443*** (0.000841)
single		-0.222*** (0.0594)	-0.223*** (0.0594)	-0.225*** (0.0594)
eqincome		0.00133*** (0.0000887)	0.00134*** (0.0000888)	0.00131*** (0.0000889)
highedu		0.463*** (0.0469)	0.465*** (0.0469)	0.459*** (0.0470)
depk4		-0.0662*** (0.0179)		
depk5			-0.0428 (0.0250)	
spsize11				0.000764*** (0.000161)
_cons	-0.728*** (0.0381)	-1.422*** (0.0772)	-1.326*** (0.0813)	-1.517*** (0.0825)
var(_cons)	0.101*** (0.0184)	0.0646*** (0.0126)	0.0749*** (0.0143)	0.0575*** (0.0114)
N	33462	33462	33462	33462
AIC	42089.0	40978.4	40988.3	40971.2
BIC	42105.9	41045.8	41055.6	41038.6
icc	0.0299	0.0193	0.0223	0.0172
ll	-21042.5	-20481.2	-20486.1	-20477.6

Standard errors in parentheses, * p〈0.05, ** p〈0.01, *** p〈0.001

districts in the SMA in Korea, for the sake of adjusting the regional clustering tendency of unknown factors. Using these models, we predicted two dichotomous variables that represented individuals' after-lunch tooth brushing behavior and the use of dental floss by individual characteristics and regional indices. We estimated six models, including one with regional mean housing prices and five with different types of census-based deprivation index.

The results of the estimations showed that the mean regional housing prices and census-based deprivation indices were correlated with the two types of dental health behavior in a statistical

Table 6. Estimation Results: After-Lunch Tooth Brushing

	Model null	Model (1)	Model (2)	Model (3)
female		0.353*** (0.0234)	0.353*** (0.0234)	0.353*** (0.0234)
age		-0.0160*** (0.000805)	-0.0160*** (0.000806)	-0.0161*** (0.000806)
single		0.100 (0.0555)	0.0999 (0.0555)	0.100 (0.0555)
eqincome		0.000937*** (0.0000937)	0.000941*** (0.0000938)	0.000929*** (0.0000938)
highedu		0.458*** (0.0525)	0.459*** (0.0525)	0.457*** (0.0525)
depk1		-0.0297* (0.0134)		
depk2			-0.0186 (0.0137)	
depk3				-0.0388** (0.0144)
_cons	0.570*** (0.0284)	0.781*** (0.0639)	0.805*** (0.0677)	0.741*** (0.0688)
var(_cons)	0.0518*** (0.0103)	0.0347*** (0.00764)	0.0367*** (0.00795)	0.0332*** (0.00742)
N	33462	33462	33462	33462
AIC	43534.9	42612.6	42615.5	42610.6
BIC	43551.7	42680.0	42682.9	42677.9
icc	0.0155	0.0104	0.0110	0.00998
ll	-21765.4	-21298.3	-21299.8	-21297.3

Standard errors in parentheses, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

sense. The results also revealed that the model with mean regional housing prices showed smaller AIC and BIC values compared with other models with conventional census-based deprivation indices. These results show that it is possible that housing prices summarized in aerial units can be used as an alternative to conventional census-based deprivation indices when the census variables employed cannot properly reflect the characteristics of the aerial units.

The results of our estimations may have emerged for two different reasons. The first might be rapid aerial demographic change. Some areas may have experienced large-scale in- or out-migration due to the start or completion of new urban development projects. If these migrations

Table 7. Estimation Results: After-Lunch Tooth Brushing (Continued)

	Model null	Model (4)	Model (5)	Model (6)
female		0.353*** (0.0234)	0.353*** (0.0234)	0.353*** (0.0234)
age		-0.0160*** (0.000805)	-0.0160*** (0.000805)	-0.0161*** (0.000806)
single		0.100 (0.0555)	0.0988 (0.0556)	0.0980 (0.0555)
eqincome		0.000936*** (0.0000937)	0.000949*** (0.0000938)	0.000920*** (0.0000940)
highedu		0.458*** (0.0525)	0.461*** (0.0525)	0.454*** (0.0526)
depk4		-0.0355** (0.0138)		
depk5			0.00284 (0.0192)	
spsize11				0.000405** (0.000129)
_cons	0.570*** (0.0284)	0.759*** (0.0655)	0.870*** (0.0687)	0.715*** (0.0698)
var(_cons)	0.0518*** (0.0103)	0.0337*** (0.00747)	0.0382*** (0.00815)	0.0325*** (0.00720)
N	33462	33462	33462	33462
AIC	43534.9	42611.0	42617.3	42608.1
BIC	43551.7	42678.4	42684.7	42675.4
icc	0.0155	0.0101	0.0115	0.00977
ll	-21765.4	-21297.5	-21300.7	-21296.0

Standard errors in parentheses, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

occurred in 2011 rather than 2010, the 2010 ce nsus would not have captured the change. The second reason might be the inherent superiority of housing prices. For some countries like Korea, housing prices (or real estate prices) can capture what deprivation indices really want to capture: how hard it is for a place to access socially desirable resources. According to the Korea National Survey of Household Finances and Living Conditions from 2017, 69.8% of typical Korean household assets consist of real estate. Koreans have long considered real estate assets as the most important investments for the future. Thus, if they have money saved, they try to buy real estate

Table 8. Odds Ratio: Dental Floss

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
female	1.910*** (0.0469)	1.910*** (0.0469)	1.909*** (0.0469)	1.910*** (0.0469)	1.910*** (0.0469)	1.909*** (0.0469)
age	0.996*** (0.000837)	0.996*** (0.000837)	0.996*** (0.000837)	0.996*** (0.000838)	0.996*** (0.000838)	0.996*** (0.000837)
single	0.801*** (0.0475)	0.801*** (0.0476)	0.801*** (0.0475)	0.801*** (0.0475)	0.800*** (0.0475)	0.798*** (0.0474)
eqincome	1.001*** (0.0000889)	1.001*** (0.0000889)	1.001*** (0.0000889)	1.001*** (0.0000889)	1.001*** (0.0000889)	1.001*** (0.0000890)
highedu	1.589*** (0.0746)	1.589*** (0.0746)	1.587*** (0.0745)	1.589*** (0.0746)	1.592*** (0.0747)	1.583*** (0.0743)
depk1	0.940*** (0.0162)					
depk2		0.940*** (0.0161)				
depk3			0.921*** (0.0165)			
depk4				0.936*** (0.0167)		
depk5					0.958 (0.0239)	
spsize11						1.001*** (0.000161)

Standard errors in parentheses, * p<0.05, ** p<0.01, *** p<0.001

assets instead of keeping it in the bank. This behavioral pattern may result in making the prices of real estate or housing owned by households into the single most important indicator of the accessibility of socially scarce resources. We hope that this kind of research will be repeated in other countries so that the usefulness of housing prices in explaining personal and spatial variations in health status can be proven in other contexts.

In sum, this research is showing that aerial housing prices can be superior to conventional census-based deprivation indices. When housing prices are used in this way, we suggest that the study area should be limited to a single housing market. This is because each different housing market has unique price variations. The basic difference between census variables and housing prices is that the former can provide multidimensional information including demographic, economic, and social dimensions, whereas the latter cannot. So, as long as census results provide information about the real situations of areas, they

Table 9. Odds Ratio: After-Lunch Tooth Brushing

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
female	1.424*** (0.0333)	1.424*** (0.0333)	1.423*** (0.0333)	1.424*** (0.0333)	1.424*** (0.0333)	1.423*** (0.0333)
age	0.984*** (0.000793)	0.984*** (0.000793)	0.984*** (0.000793)	0.984*** (0.000792)	0.984*** (0.000793)	0.984*** (0.000793)
single	1.106 (0.0614)	1.105 (0.0614)	1.105 (0.0614)	1.106 (0.0614)	1.104 (0.0613)	1.103 (0.0613)
eqincome	1.001*** (0.0000938)	1.001*** (0.0000939)	1.001*** (0.0000939)	1.001*** (0.0000938)	1.001*** (0.0000939)	1.001*** (0.0000941)
highedu	1.581*** (0.0831)	1.583*** (0.0832)	1.579*** (0.0830)	1.580*** (0.0830)	1.586*** (0.0833)	1.575*** (0.0828)
depk1	0.971* (0.0130)					
depk2		0.982 (0.0135)				
depk3			0.962** (0.0139)			
depk4				0.965** (0.0133)		
depk5					1.003 (0.0193)	
spsize11						1.000** (0.000129)

Standard errors in parentheses, * p<0.05, ** p<0.01, *** p<0.001

are the most reliable information source for constructing a deprivation index. However, because of rapid demographic changes due to urban redevelopment, it may be that census-based deprivation indices cannot properly represent the real situation in some areas, so we may need to consider housing prices as an alternative.

In conclusion, nowadays, with the provision of diverse health related social survey data including respondent's location information, many studies in the area of health and medical geography try to integrate spatial data from census and other sources to investigate influences from social and natural contextual factors on individual's health outcome. In this context, the main contribution of this research is to explicitly show that spatial real estate data is another type of data worthwhile to investigate what determines individual's health.

주1. For example, Townsend index or Carstairs Index selectively uses census variables regarding unemployment, housing overcrowding, car ownership, housing ownership, and occupational class (Aveyard et al., 2002).

주2. The existence of this kind of correlation has been statistically confirmed by many studies estimating hedonic housing price functions (Kiel & Zabel, 2008; Myers, 2004; Can, 1992).

주3. We only considered dental health care behaviors as dependent variables following Kim et al. (2013). However, any individual health related outcome or behavior variables can be considered in following studies with similar research purpose and design.

주4. Apartment sales transaction data came from "http://rt.molit.go.kr".

주5. In case of housing price, the same aerial price level can have different level of relationship with census variables in different geographical housing markets. Because of this, we only used the data from a single metropolitan housing market which consists of areas geographically adjacent and well connected by transportation system.

주6. In case of census-based deprivation indices, the only exception is "depk5" which is not statistically significant.

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초 록

본 연구에서는 건강에 대한 공간적 연구에서 통상적으로 사용되는 센서스에 기반한 지역 박탈지수의 대안으로 지역 주택가격이 사용될 수 있는지 평가하였다. 평가를 위해 개인을 1수준으로, 수도권의 보건소 구역을 2수준으로 하는 다수준 로지스틱 모델이 추정되었다. 다수준 모델에는 개인의 점심식사후 칫솔질과 치간실 사용을 설명하기 위한 개인수준의 변수들과 보건소 구역을 대표하는 사회적 박탈지수 및 지역주택가격 수준이 포함되었다. 추정된 모델들의 설명력은 Akaike Information Criterion (AIC)와 Bayesian Information Criterion (BIC)를 이용하여 평가되었다. 모델의 추정결과는 사회적 박탈지수 및 지역 주택가격이 모두 개인의 치아관리 행동을 설명하는 데 기여하나 지역 주택가격을 사용한 모델의 AIC 및 BIC가 통상적인 센서스 기반 지역 박탈지수를 사용한 경우 보다 낮은 것을 보여 주었다. 본 연구결과는 센서스에 기반한 박탈지수를 생성하는 데 사용된 센서스 변수가 시점의 차이 등의 이유로 적절하지 않을 경우 지역 주택가격이 지역의 사회경제적 수준을 대표하기 위해 대안적으로 사용될 수 있음을 보여준다.

주요어 : 박탈지수, 주택가격, 다수준 모델