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ALLEVIATING SURVEYOR BIAS IN REAL ESTATE: AN APPLICATION TO VACANCY AND PROPERTY PRICES

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Abstract. Although vacancies in the real estate market have always been of key interest to both private and public stakeholders, measuring the impact of vacancy rates on property prices is challenging. This study attempts to quantify the extent of the influence of vacancy rates on the price decline of commercial properties. The dataset used in this study was collected and collated by valuation experts. We attempt to alleviate the bias inherent in the price estimates provided by the surveyors. A Bayesian multilevel estimation model was employed, and the results revealed that while some experts do not show deviations from the standard tendency of a peer group, others do diverge from this norm. Based on these findings, a bias-controlling price decline rate was derived. As many real estate statistics are produced based on survey data compiled by experts, the approach adopted in this study is expected to be applied to various real estate practices to mitigate the inherent and inevitable surveyor bias.

Keywords: surveyor bias, vacancy, property price, Bayesian estimation, multilevel model.

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1. Introduction

High vacancy rates in the commercial property market result in a loss in rental income for individual property owners. At a macro level, high vacancy rates also indicate the oversupply of properties, which forces selling prices to fall. Thus, monitoring vacancy rates in the market has always been of key interest to both individual investors and government officials.

While the inverse relationship between vacancy rates and property prices is well-known, it is challenging to quantify the extent of price decline attributable to vacancy rates. One such challenge stems from the unavailability of sales data for commercial properties with high vacancy rates in the market. Compared to the housing market, sales of commercial properties are relatively lower, but there are even fewer sales of vacant commercial properties which makes it more difficult to reliably estimate the impact of vacancies on prices in the commercial property market.

When evidence is difficult to obtain directly from the market, a common recourse is to employ experts to investigate, survey, and collect the data. This approach can help overcome the problem of data unavailability for vacant property sales; albeit with the premise that survey data obtained by experts is inevitably biased. This bias can worsen when a survey is undertaken by more than one expert, which is common in real estate projects, owing to the large number of properties that require examination.

In this study, a district in Seoul was chosen, and 100 commercial property samples were examined by valuation experts. The valuation experts surveyed the vacancy rates of the sample properties and estimated their prices. We then attempted to measure the expert bias contained in the price estimates, and alleviate it by using a Bayesian multilevel estimation model. Finally, we propose a bias-controlling price decline rate in accordance with varying vacancy rates.

While there are abundant theoretical studies on the bias generated by experts or surveyors, research that provides a practical solution to alleviate or remove the bias from the inferences is rarely found in the literature on most domains including real estate. The challenge of accurately quantifying the impact of high vacancy rates on commercial property prices persists due to the scarcity of sales data for vacant properties. By employing a Bayesian multilevel estimation model to mitigate expert bias in price estimation, this study aims to provide a practical solution to improve the accuracy of real estate statistics. As many government statistics disclosed in South Korea are based on survey data collected by real estate experts, the approach proposed by this study can be applied to many official real estate indices announced by the government, such as the rental patterns of commercial properties, the fluctuation trend of land prices, and housing price trends.

The remainder of this paper is organized as follows. First, a literature review on vacancies and expert bias is presented. Second, we explain the dataset, study area, and approach used to quantify the impact of vacancies on prices. Third, the estimation results and a solution to alleviate expert bias are proposed. Finally, the study findings are summarized and a future study path is provided.

2. Literature review

2.1. Property vacancies

Vacancy represents both macro and micro level market conditions (Couch & Cocks, 2013). On a broad scale, it can be used as an economic indicator, where low vacancies may imply strong demand for rental properties and the willingness of corporations to operate businesses in a particular area. On an individual property scale, it describes how well a particular property performs compared to the area's average vacancy rate, and presents the level of rental income that the property can command.

These vacancies lead to various problems in property management. When the vacancy rate is low, no significant damage to the properties is observed. Landowners will always experience some level of vacancy in their properties, even when demand and supply are balanced; this base-level vacancy rate is often referred to as the natural vacancy rate in the literature (Hagen & Hansen, 2010). However, when the vacancy rate rises significantly above the natural rate, for example over 30%, it can cause serious problems: it not only leads to damage or incidents such as theft, vandalism, and illegal occupation but also causes a direct decrease in rental income.

Because vacancy levels directly impact rental income generation from commercial properties, it is a key index to consider when a commercial property is evaluated or appraised (Baum et al., 2006). Several studies have quantified the extent of price discounting as vacancy rates increase. For example, Lerbs and Teske (2016) demonstrated that a doubling of the vacancy rate at the municipality level is associated with a 5–8% discount in house prices in the German market. However, it is generally difficult to quantify the impact of vacancy on property prices because properties with high vacancy rates are much less attractive to buyers than those with normal rates, and are thus rarely traded in the market. This implies that the sales prices of persistently unoccupied properties are not easily observable in the market. Therefore, it is extremely difficult to determine the market value of properties with high vacancy rates. This explains why many prior studies have relied on aggregate property data, such as median property values and vacancy rates on a county or provincial scale, instead of individual property data (Morckel, 2013; Newman et al., 2016; Manville & Kuhlmann, 2018).

2.2. Surveyor bias

Due to the low level of sales of highly unoccupied properties, researchers and practitioners often rely on alternative sources. Instead of market transaction data, valuation experts are employed to estimate the impact of vacancies on property prices. Utilizing expert knowledge has been considered a good option for overcoming the scarcity of data on sales of uncommon real estate such as vacant and special-purpose properties (mines, museums, and golf courses) (Gloudemans & Almy, 2011). However, this approach has a downside: expert bias is always present in the estimation, which can often seriously distort the inference.

In the literature, expert bias is referred to as interviewer bias or surveyor bias (Quas et al., 2007; Griffin & Wilson, 2010). As interviewer bias is often associated with a reluctance to report results that are inconsistent with previous findings or hypotheses (Wynder, 1994), this study primarily uses the term *surveyor bias*. Numerous real estate projects are undertaken with the help of valuation experts, agents, and property managers; thus, surveyor bias remains a concern for subsequent analyses in the real estate domain.

Public land survey records are important sources for reconstructing historical forest structures, but have been subject to constant criticism because of the potential bias caused by forest surveyors (Williams & Baker, 2010). This awareness of surveyor bias in forestry has led to numerous studies to solve or minimize it (Hanberry et al., 2012; Kronenfeld, 2015; Cogbill, 2023).

However, unlike the abundant studies on forestry, studies on solutions to the surveyor bias are rare in the social sciences. There is a rich body of literature on the potential impact that surveyors can have on the results of studies. For example, differences in judgments of the same population by different surveyors have long been noticed in anthropology. In a study on the impact of the market and modernization on the welfare of a foraging population (Tsimane's Amerindians in the Bolivian Amazon) (Reyes-García et al., 2005), many variables such as fish and game consumption were found to be measured differently by different surveyors (Reyes-García et al., 2005). The authors of the study used a t-test analysis to ascertain the significance of those differences, but did not present an effective solution.

National and international surveys on issues such as education and work are a popular method of data collection in the social sciences. In the European Social Survey, which covers 36 countries, Beullens and Loosveldt (2016) analyzed surveyor bias through covariance structure analysis. They demonstrated that many variables, such as the state of countries' health services and cultural diversity, contained significant surveyor bias in their regression coefficients. However, as with Reyes-García et al.'s (2005) study, they did not provide a feasible solution for this bias either.

Recently, West and Blom (2017) undertook a comprehensive literature review on surveyor bias and focused on the effects of surveyor characteristics (age, gender, experience, race, physical appearance) on the data collection process. Their findings included the observation that surveyors with more experience generally tended to produce higher response rates, for which they proposed a general approach to deal with the background characteristics of the surveyors. However, they did not provide a practical solution to eliminate the surveyor bias.

Surveyor bias can be understood from various perspectives. In the context of policy professionals, objectivity, impartiality, and accuracy are core attributes that unbiased professionals should have (Weber, 1946). The Weberian definition of bias has been widely accepted by numerous governments and organization when enlisting expertise from economists, environmental scientists, engineers, and other professionals (Banuri et al., 2019). Although these professionals in theory should conduct tasks devoid of bias, researchers have reported prevalent biases in information processing and decision-making (Langfeldt, 2004; Malmendier & Tate, 2008; Sukhera et al., 2020; Filewod et al., 2023).

Governments and public organizations employ several safeguards to prevent bias in decision-making, such as mandating post-project evaluations, peer reviews, and providing training on common biases like affinity or confirmation bias to professionals. However, these safeguards are procedural in nature, and their effectiveness remains unclear (Banuri et al., 2019; Moseley & Thomann, 2021).

Surveyor bias is a well-recognized and acknowledged issue; but the key problem is that the extent of the bias is extremely difficult to measure and remove. In this study, we measure the impact of vacancy on property prices. As persistently vacant properties are rarely traded in the market, we use survey data collected by valuation experts, which inevitably introduces a surveyor bias into the data. Therefore, in this study, we analyze the impact of vacancy on commercial real estate prices, and simultaneously provide a solution to alleviate the surveyor bias that is present in the expert-collected data, thereby filling a longstanding research gap.

3. Data and approach

3.1. Dataset and study area

The Korea Institute of Local Financing (KILF) surveys commercial properties nationwide and assesses their taxation values. The values assessed by the KILF are often subject to criticism because they are estimated without considering vacancy rates of commercial properties (Lee & Ahn, 2020). Thus, in 2023, the KILF undertook a pilot project to solve this problem. Gwangjin-gu was chosen as the study area, 100 commercial properties were sampled, and the impact of vacancy on prices was estimated.[1] Gwangji-gu is one of 25 districts in Seoul, South Korea. Because highly vacant properties are less attractive to buyers and are rarely traded in the market, the prices of the samples were estimated by licensed valuation experts.

[1] Gwangjin-gu was chosen as the study area by the KILF. According to the KILF, the distribution of occupied and vacant properties in Gwangjin-gu is balanced, which was the primary reason for selecting it as the study area. As of 2022, the number of commercial properties in Gwangjin-gu was 5,648 (Korean Statistical Information Service, 2022), and thus, the 100 samples constitute 1.8% of the total population. Typical sample ratios in various government-disclosed statistics in South Korea are between 1.0% and 5.0%. The KILF opted for the 100 samples considering these sample ratios and the financial constraint of the budget.

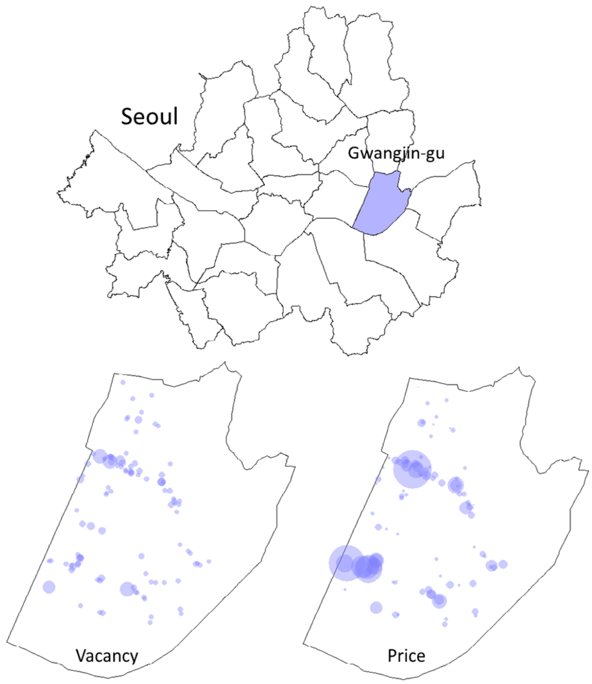
Table 1 presents the descriptive statistics of the 100 samples. A representative (median) commercial property in Gwangjin-gu has an area of 517 m^2, worth 11 billion KRW (approximately 8.4 million USD). The median and mean vacancy rates are 3% and 12%, respectively, and the difference between them is not trivial, implying that the distribution of vacancy rates is skewed.[2]

Table 1. Descriptive statistics of the 100 sample properties

	Min.	Median	Mean	Max.
Price (billion KRW)*	2	11	15	82
Vacancy (%)	0	3	12	100
Property age (year)	0	31	29	50
Site area (m^2)	167	517	637	3,062
Zone	Mid-density residence (27 samples), High-density residence (39 samples), Semi-commerce (16 samples), Commerce (18 samples)			

Note: * Estimated by valuation experts.

Figure 1 shows the location of the sample properties. The sizes of the circles in the bottom left panel of the figure are proportional to the vacancy rates. In the bottom right panel of the figure, the sizes of the circles are proportional to the prices. The sample properties appear to be evenly distributed in the study area, and those in the western region appear to command relatively high prices. The northeastern part of the study area is void of samples because it is mainly a mountainous region.



Note: The bottom-left map shows the sample locations with sizes proportional to the vacancy rate. The bottom-right map presents the sample locations with sizes proportional to the price.

Figure 1. Study area and location of 100 sample properties

[2] Of the 100 samples, 46 samples have 0% vacancy rates.

3.2. Model specification from a Bayesian perspective

Four valuation experts surveyed the 100 samples. Specifically, 25 commercial properties were assigned to each expert, who examined property characteristics like vacancy rates and estimated prices.[3] These experts represent an example of a *group* variable and it is anticipated that a certain portion of the variation in the data will be attributable to these experts. This variation due to experts, or the surveyor bias can be efficiently estimated by a multilevel model that employs the expert variable as a group variable.[4]

The model is specified as follows:

$$Price_i \sim Normal(\mu_i, \sigma); \tag{1}$$
$$\mu_i = \alpha_{expert[i]} + \sum_{k=1}^{7} \beta_k x_{i,k}, \ \sigma \sim Exponential(1.0).$$

The intercepts of the four experts are designed as varying intercepts. In other words, the prior for the expert intercepts is a function of two parameters, $\bar{\alpha}$ and σ_α, which is specified as a normal distribution with mean $\bar{\alpha}$ and standard deviation σ_α, as follows:

$$\alpha_j \sim Normal(\bar{\alpha}, \sigma_\alpha) \text{ for } j = 1, 2, 3, 4, \tag{2}$$

where $\bar{\alpha}$ and σ_α themselves have priors again, as in Equation (3):

$$\bar{\alpha} \sim Normal(-1.0, 0.5), \ \sigma_\alpha \sim Exponential(1.0). \tag{3}$$

Thus, two levels of expert intercepts are specified in the model (therefore named a multilevel model). Priors for standard deviations in Equations (1) and (3), that is, σ and σ_α are specified as exponential priors with rate 1.0: this specification is commonly used in the literature (McElreath, 2018) and also followed in the study.[5]

Finally, explanatory variables other than the expert intercepts are specified at a single level, as follows:

$$\sum_{k=1}^{7} \beta_k x_{i,k} = \beta_1 Township_i + \beta_2 Vacancy_i + \beta_3 Vacancy_i^2 + \beta_4 Site\_assessed_i + \beta_5 Zone_i + \beta_6 Site\_area_i + \beta_7 Age_i; \tag{4}$$
$$\beta_1 \sim Normal(1.0, 0.6), \ \beta_2 \sim Normal(-0.6, 0.9),$$
$$\beta_3 \sim Normal(0.4, 0.9), \ \beta_4 \sim Normal(1.0, 0.2),$$
$$\beta_5 \sim Normal(-0.3, 0.2), \beta_6 \sim Normal(2.5, 0.1),$$
$$\beta_7 \sim Normal(-0.4, 0.2).$$

As shown in Equation (4), seven variables are employed to estimate property prices: the township to which a property belongs, vacancy rate (%), squared vacancy rate, assessed site value, zone to which a property belongs, site area, and property age. The specific values in the priors in Equations (3) and (4) were selected by referring to the coefficients from an ordinary regression model.

The model specified in Equations (1)–(4) was fitted to the dataset using a Bayesian estimation approach. The reason for adopting Bayesian estimation is two-fold. First, the sample size is not large (100 samples or 25 samples per expert), but the model performance can be enhanced by specifying informed priors. In this study, the coefficients from an ordinary least-squares model were referred to while specifying the priors. Second, it is difficult to estimate surveyor bias as a point value. Estimating this as a range can provide useful insights for stakeholders. Bayesian estimation always carries distributions for each parameter; thus, it is suitable for identifying the uncertainty inherent in surveyor bias.

4. Results

4.1. Estimation results and surveyor bias

Table 2 shows the estimation results of the model specified through Equations (1)–(4). The parameters in the table were estimated by Hamiltonian Monte Carlo approximation which is a more efficient sampling method than Metropolis or Gibbs sampling, when data are high-dimensional.[6] The effective number in the table is an estimate of the number of independent samples that the model obtained during estimation. Although there is no universally useful criterion, good inference is possible with as few as 200 independent samples (McElreath, 2018). $\hat{R}$ in the table is an indicator of the convergence of the model to the target distribution. It should approach 1.00 from above when the model is properly converged.

Both the effective number and $\hat{R}$ indicate that the model has been properly converged. Parameters also appear to be consistent with general expectations in the real estate market. For example, the coefficient of site area, β_6 is positive in both the point estimate (2.47) and 90% interval (2.32–2.62), which is plausible because a large-sized property generally commands a higher price. The coefficient of property age, β_7 is negative (–0.34) and is considered reasonable because an old property is less attractive to buyers, leading to a lower price. Figure 2 shows the goodness-of-fit of the model. The estimated prices closely follow the observed prices, showing no significant deviation from the diagonal line in the figure. Therefore, it may be concluded that the inference can be made safely based on Table 2.

The parameter of interest in this study is α_{expert}, which indicates the valuation tendency of each expert; or the upward or downward inclination of the price estimation. Fig-

[3] The KILF reached out to candidate appraisers who met the following criteria: licensed appraisers operating their businesses in Gwangjin-gu with at least five years of experience. Subsequently, four of them accepted the KILF's offer and participated in this pilot project. Each appraiser then selected 25 samples considering their locations and vacancy rates.

[4] This type of model is often referred to as a mixed-effects model in the literature and its details are succinctly described by Zuur et al. (2009).

[5] The exponential distribution with rate λ=1.0 has density: $f(x) = \lambda e^{-\lambda x} = e^{-x}$.

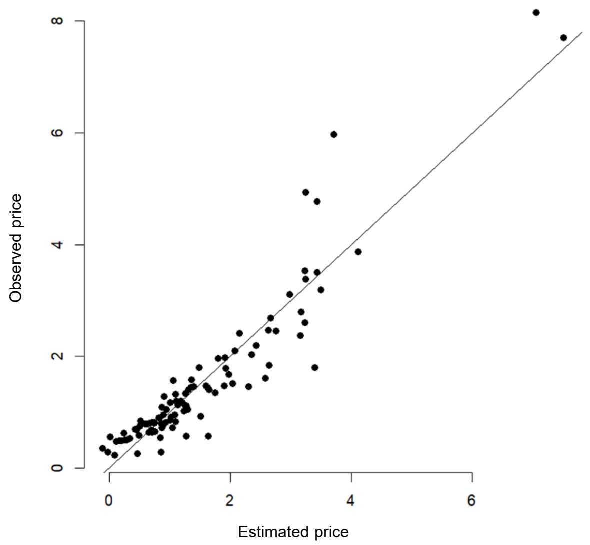
[6] Hamiltonian Monte Carlo approximation is explained in detail in Betancourt (2017).

ure 3 presents α_{expert} in Table 2 in graphical form. Experts 1 and 4 (α_1, α_4) exhibit similar valuation tendencies. They tend to arrive at almost the same price estimates if property characteristics such as township and vacancy are the same. In contrast, expert 2 (α_2) shows a clear downward or underestimation tendency compared with experts 1 and 4. Finally, expert 3 (α_3) reveals an obvious upward or overestimation tendency. Therefore, while some experts do not show severe deviations from the standard tendency of a peer group, others do demonstrate divergence from the normal tendency of a peer group, revealing a significant surveyor bias.

Table 2. Estimation results

Parameters		Mean	Standard deviation	90% interval	Effective number	$\hat{R}$
σ		0.53	0.04	0.47–0.60	1,858	1.00
α_{expert}	α_1	–1.60	0.27	–2.03– –1.17	537	1.00
	α_2	–1.88	0.28	–2.33– –1.45	557	1.00
	α_3	–1.27	0.28	–1.71– –0.83	564	1.00
	α_4	–1.61	0.28	–2.05– –1.16	552	1.00
$\bar{\alpha}$		–1.58	0.30	–2.04– –1.11	701	1.00
σ_α		0.39	0.26	0.14–0.87	1,063	1.00
Township	$\beta_1[1]$	–0.04	0.43	–0.75–0.66	1,819	1.00
	$\beta_1[2]$	1.13	0.24	0.75–1.52	563	1.00
	$\beta_1[3]$	1.11	0.26	0.69–1.51	591	1.00
	$\beta_1[4]$	1.13	0.26	0.72–1.54	627	1.00
	$\beta_1[5]$	1.07	0.24	0.69–1.46	584	1.00
	$\beta_1[6]$	0.94	0.24	0.56–1.31	547	1.00
	$\beta_1[7]$	1.61	0.29	1.14–2.06	811	1.00
Vacancy	β_2	–0.68	0.50	–1.50–0.12	1,484	1.00
Vacancy^2	β_3	0.43	0.53	–0.42–1.28	1,320	1.00
Site assessed	β_4	0.98	0.12	0.78–1.18	1,796	1.00
Zone	$\beta_5[1]$	0.04	0.13	–0.18–0.25	1,782	1.00
	$\beta_5[2]$	–0.37	0.13	–0.58– –0.15	1,503	1.00
	$\beta_5[3]$	–0.39	0.13	–0.60– –0.19	1,403	1.00
	$\beta_5[4]$	–0.48	0.14	–0.70– –0.25	1,583	1.00
Site area	β_6	2.47	0.09	2.32–2.62	2,198	1.00
Age	β_7	–0.34	0.16	–0.60– –0.08	2,300	1.00

Note: Township and zone are categorical variables with seven and four levels, respectively.



Note: Prices are standardized.

Figure 2. Goodness-of-fit

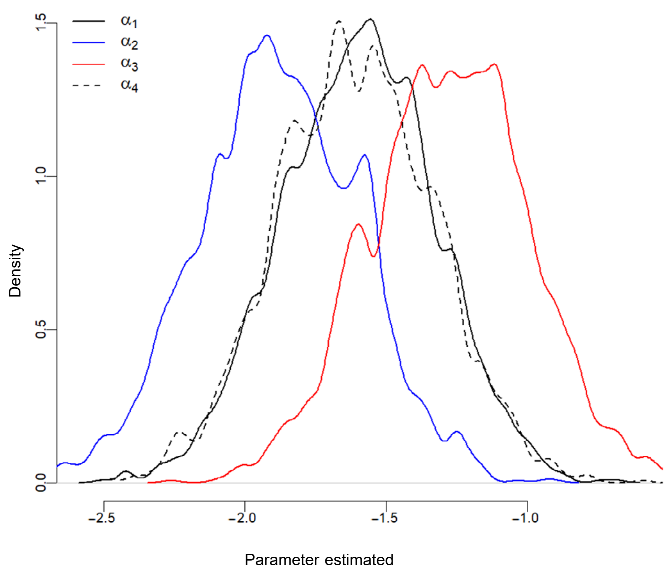


Figure 3. Parameter distribution of α_{expert}

4.2. Price decline rate proposed by the standard expert

Vacancy levels have a significant impact on the price of commercial properties. However, properties with high vacancy rates are rarely traded in the market because of disadvantages like loss of rental income, damage from vandalism, and poor management. In this study, valuation experts estimated the prices of vacant properties. This approach is effective in overcoming the lack of sales figures for these properties, but comes with the downside of the surveyor bias. To measure the extent of this bias, "expert parameters" were employed in the model. Figure 4 shows the relationship between vacancy rates and property prices as estimated by the four experts.

Figure 4 was created by varying the vacancy rate from 0% to 100% and fixing the other explanatory variables at their mean values. The curve and shade of each expert show the mean and 50% confidence region of the posterior distribution of each expert parameter, respectively. As the figure shows, the price decline gap among the experts is non-trivial. In addition, as the vacancy rate increases, the 50% confidence region widens. This is expected; the uncertainty involved in experts' price estimates will increase because properties with high vacancy rates are rarer than those with low vacancy rates.

The standard expert $\alpha_{standard}$ in the figure was created using $\bar{\alpha}$ in Equation (3). The mean of its posterior distribution was –1.58 in Table 2. This hypothetical expert's price estimate is higher than that of experts 1, 2, and 4, but lower than that of expert 3. Because the four experts' parameter estimates (α_1 through α_4) were derived from this standard expert's prior distribution in Equation (3) and the data, the standard expert's price decline rate can be considered a representative expert's opinion.

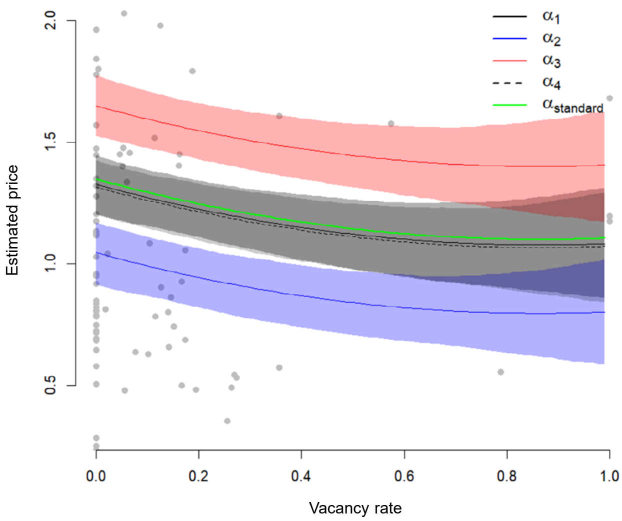
If a new property is introduced into the model for price prediction, using the standard expert's price decline rate would be a reasonable bias-controlling approach. Table 3 presents the standard expert's price decline rates from Figure 4 in a tabular form. According to this table, when a property with a 10% vacancy rate is introduced, its proper depreciation rate would be 4.4% compared to a property with a zero vacancy rate. The depreciation rate continues to increase until the vacancy rate reaches 80%, after which it remains constant (18.5%).

The price decline rate presented in Table 3 can be reliably applied to the cast study area, Gwangjin-gu in Seoul. Thus, it is deduced that highly vacant properties may experience a maximum price decline of 18.5% in metropolitan areas like Seoul. In economically depressed urban areas, tax appeals by owners of vacant properties are commonplace, and local governments struggle to manage these tax complaints owing to the lack of effective methods for factoring vacancy into the valuation process. Hence, the information in Table 3 would be particularly valuable for local governments when assessing vacant properties for taxation purposes.

The Korean real estate market not only covers urban areas but also extends to rural regions. In rural settings, it remains uncertain whether the price decline occurs more rapidly or slowly compared to urban areas as vacancy rates increase. Thus, the information in Table 3 needs to be appropriately adjusted and carefully applied to rural territories.

Bias among policy professionals can be generally defined as the tendency for individuals working in policymaking to exhibit preferences or skewed perspectives that influence their decision-making process. This bias can manifest in various forms, including confirmation bias, ideological bias, availability bias, stakeholder bias, cultural bias, and overconfidence bias (Tversky & Kahneman, 1974; Stone, 2022).

Bias can be addressed through various measures, such as fostering diversity of perspectives and promoting evidence-based decision-making. Particularly, Parkhurst (2017) examined the nature of political bias with regards to evidence and illustrated how such evidence-related biases are common in policy arenas. According to Parkhurst (2017), evidence-related bias includes the inaccurate analysis of data and the misuse of data. This study focused on the accurate analysis and inference of data to alleviate bias.



Note: The dots indicate the 100 samples used in this study.

Figure 4. Vacancy rate and the corresponding price decline estimated by experts

Table 3. Price decline rate proposed by the standard expert

Vacancy rate	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%
Price (billion KRW)	13.5	12.9	12.5	12.1	11.7	11.4	11.2	11.1	11.0	11.0
Decline rate	0%	4.4%	7.4%	10.4%	13.3%	15.6%	17.0%	17.8%	18.5%	18.5%

In other words, we suggested that the bias in survey data can be identified and adjusted by using a Bayesian multilevel estimation model to yield bias-filtered evidence. Bayesian estimation is particularly useful for incorporating a surveyor's prior knowledge into statistical inference, which can help in identifying and adjusting for various sources of bias in survey data. The study findings imply that providing policy professionals with bias-filtered evidence is feasible. Objective analysis of data and provision of bias-filtered evidence enable policy professionals to make more informed decisions. In short, employing a Bayesian estimation model to identify and mitigate bias in survey data is expected to be a valuable tool for promoting evidence-based decision-making among policy professionals.

5. Conclusions

Despite the importance of vacancies in commercial properties, attempts to quantify their impact on property prices have rarely been undertaken, because persistently vacant properties are seldom traded on the market. Thus, it is difficult to determine proper sales prices for such properties. We employed valuation experts to estimate the most probable prices for vacant properties. We then attempted to alleviate the surveyor bias inherent in the price estimates and proposed a bias-controlling price decline table.

This study demonstrated how a Bayesian multilevel estimation model can be effectively utilized to identify and quantify surveyor bias in estimation. Thus, the approach adopted in this study and tools such as Bayesian estimation are expected to be widely utilized in various real estate statistics disclosed by governments. Furthermore, policy professionals are also anticipated to benefit from these findings, as bias-free translation of survey data into policy options can significantly improve policy effectiveness.

This study examined one of the 25 districts in Seoul. Seoul is a highly urbanized city that is well-known for its extremely expensive properties. To generalize the findings of this study, future research can apply the approach used here to less urbanized and rural areas.

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