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IDENTIFICATION OF FACTORS INFLUENCING LAND VALUE FOR STATE'S ASSETS MASS APPRAISAL PURPOSES: EVIDENCE FROM INDONESIA

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Abstract

Land value is an important element in a decision making. The estimation of land value conducted individually based on comparables. This approach often faces difficulties due to the large quantities of such assets with limited capacity of valuers. This research aimed to build a model to effectively identify the main property attributes that shape property value and quantify the effect of unobserved variables on value. We observed 628 property data in Jakarta collected by the Directorate General of State Asset Management (DGSAM) as part of their valuation activities in 2018. The results of this study provide an evidence that structural equation model (SEM) can be effectively used to identify property attributes that significantly affect property value, particularly for valuing state-owned assets.

***Keyword**:* Land Value, Land Market, Residential Land JEL Code: R330, R210

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INTRODUCTION

The Indonesian government is required to publish annual audited financial report that contains information including assets' value. While the Minister of Finance Regulation No 111/PMK.06/2017 has mandated a valuation to comply to this task, the actual valuation process takes a long time to complete due to the sheer number of assets. A procedure to speed up the process is therefore essential.

Mass appraisal is a common technique for this purpose in ad valorem valuation (Riley, 2018). It involves the use of standardised procedure and statistical tests to value a large number of assets (Eckert, Gloudemans, & Almy, 1990, p. 303) and uses mathematical model (Riley, 2018) to replicate property market (McCluskey, 2018). Once the model building stage is completed, model accuracy is assessed under statistical procedures (McCluskey, 2018).

Another important aspect is consistency, which is considered challenging (Benjamin, Guttery, & Sirmans, 2004) when valuing properties in large quantities. Since inconsistency is generally undesirable in state-owned assets, mass appraisal can address this problem (McCluskey, 2018) through the use of standardised models (Jahanshiri, Buyong, & Shariff, 2011).

This research aimed to build a mass appraisal model for valuing state-owned assets in the form of vacant land and measuring the effect of unobserved variables on value. The research process in this paper is depicted in Figure 1 and detailed in the following section.

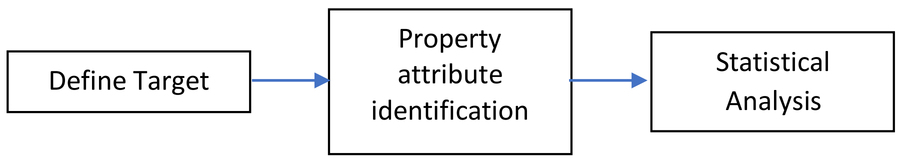

Figure 1: Research process

RESEARCH METHOD

Data Analysis Method

Regression analysis is a widely used tools in mass appraisal for its flexibility, ease of use, and acceptable accuracy level (Tretton, 2007). Unfortunately, regression analysis ignores locational attributes which significantly affect property value (Jahanshiri et al., 2011).

Another technique is the structural equation modelling (SEM). SEM is exceptional for evaluating the strength of observed variables, such as distance to CBD in representing unobserved constructs (Gallagher, Ting, & Palmer, 2008) such as location. Although widely used in social and economic studies (Gallagher et al., 2008), previous studies reported a limited application of SEM in mass appraisal (Liu and Wu, 2009; Freeman and Zhao, 2019).

Data Description

This research used 1,400 data records compiled by the Directorate General of State Asset Management (DGSAM). Unfortunately, this dataset consists of asking price with certain property attributes. The problem with asking price is that it is not the agreed arm's length price, and hence, fails to provide fair value comparison. In addition, as it represents the sellers' view, it tends to be on the higher side of the scale. Therefore, asking price per square meter that was higher than an upper fence was removed. Following Tukey (1977), the upper fence was calculated using equation (1).

$$Upper\ fence = Q_3 + (1.5 \times IQR) \quad (1)$$

Here, Q_3 is the third quartile and IQR (inter quartile range) is the difference between the first (Q_1) and the third (Q_3) quartile. In DGSAM's dataset, Q_1 and Q_3 can be calculated as IDR 8 million and IDR 27 million, respectively, so the IQR equals to IDR 19 million. As such, using equation (1), the upper fence is IDR 55.5 million. It means that all asking prices higher than IDR 55.5 million – 321 recordsi in total – were removed. Additional outliers were also excluded based on the Mahalanobis distance criteria (Gallagher et al., 2008), leaving 628 records for analysis. It is considered sufficient because it satisfies the sample size recommended by Hair, Black, Babin, and Anderson (2013) and is larger than one used by Freeman and Zhao (2019). This process results in a set of data with asking price ranges between IDR 8.000.000/m^2 and IDR 55,147,000/m^2 (Q_2 = Rp. 20,000,000/m^2).

Model Building

This research follows the model development procedure from Gallagher et al. (2008) that includes model development, examination, and assessment.

Model Development

This research starts with a model developed by Liu and Wu (2009) and Freeman and Zhao (2019) illustrated in

Figure 3.

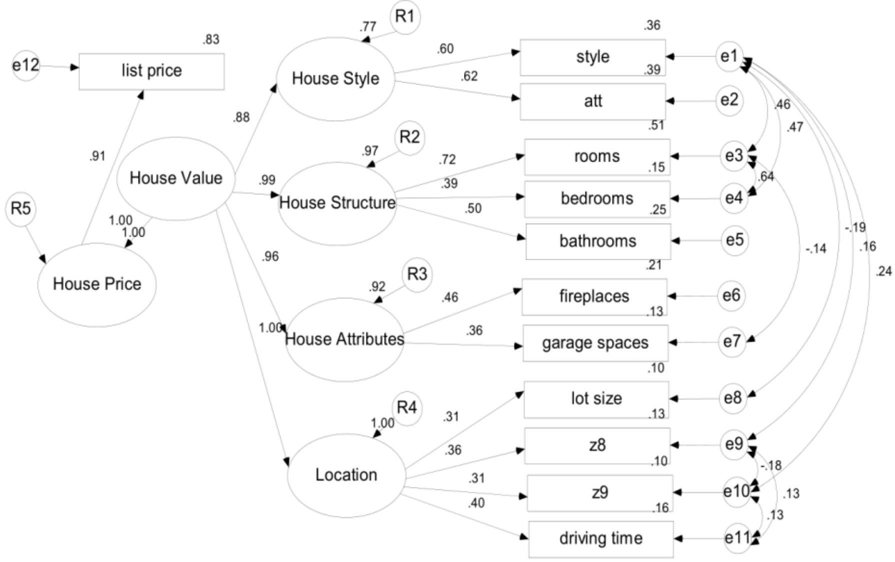

Figure 2: Base model

Source: Freeman and Zhao (2019)

Model Examination

In the DGSAM dataset, three latent variables – land structure, land attributes, and location – are chosen. Each variable comprises of at least three indicators (Table 1).

Table 1: Variable definition

Variable	Definition
	Land Structure
LS1	Area (m^2)
LS2	Slope (1. Yes, 0. No)
LS3	Elevation (1. below road 2. same with road 3. above road)
	Land Attributes
LA1	Road types (1. Residential street 2. Town road 3. City road 4. Province road 5. National road)
LA2	Road structure (1. other 2. concrete rebates 3. paving blocks 4. asphalt 5. good quality concrete)
LA3	Number of medical facilities
LA4	Waste management (0. Not available to 5. Well managed
LA5	The width of the road (in meter)
LA6	Traffic flow (1. Two way, 2. One way, 3. Two way with separator)
LA7	Road condition (1. bad 2. average 3. good)
LA8	Clean water network (1. Yes 0. No)

Variable	Definition
LA9	Noise (1 noisy 2. average 3 quite)
LA10	Air quality (1 bad 2. average 3. good)
Location	
LO1	Distance to CBD (kilometre)
LO2	Transportation easiness (1. very difficult to 5 very easy)
LO3	Distance to transportation mode (kilometres)
LO4	Number of health facilities
LO5	Number of education facilities
LO6	Number of recreation areas

The relationship of these variables is show in

Figure 3.

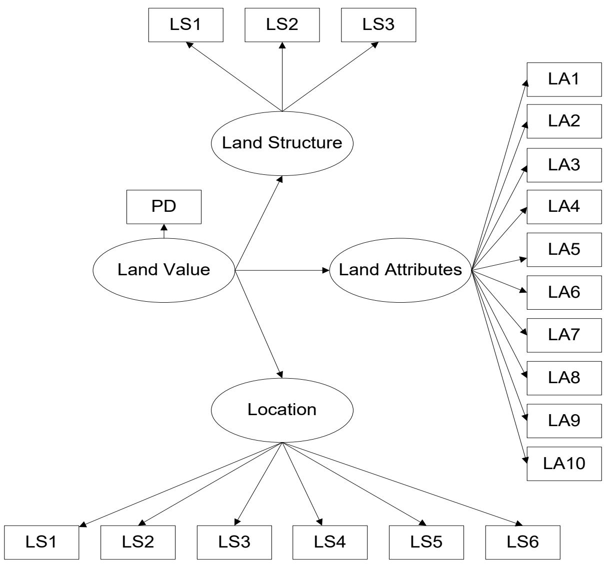

Figure 3: Final model

Model Assessment
The third step is model assessment. As seen in

Figure 3, it is hypothesised that land value is affected by land attribute, land structure, and location. These variables are latent as they cannot be directly observed and measured. SEM enables the use of latent variables without causing measurement bias (Gujarati, 2009). Using the partial least square branch of SEM,[1] this research aimed to test the following hypothesis:

H_1 : Land Style positively impact Land Value
H_2 : Land Attributes positively impact Land Value
H_3 : Location positively impact Land Value

To test the feasibility of the model, the first criterion that we looked at was discriminant validity. A construct that meets the discriminant validity criteria is one that explains a phenomenon not attributed to a different construct (Hair, Hult, Ringle, & Sarstedt, 2017) but captures the uniqueness of a construct. An indicator satisfies this criteria if it loads highest on its own construct (Hair, Sarstedt, Ringle, & Mena, 2012, p. 430). An example can be seen in Table 2 where LA1 (road type) has the highest cross loading with LAND ATTRIBUTE (0.65) compared to the rest of the constructs (for instance 0.35 for LAND STRUCTURE). Thus, we can conclude that all constructs in this research are unique.

Table 2: Cross loadings

	Land_Atribute	**Land_Structure**	**Land_Value**	**Location**
LA1	0.65	0.35	0.51	0.36
LA10	0.69	0.50	0.46	0.50
LA2	0.73	0.40	0.51	0.35
LA3	0.81	0.49	0.6	0.49
LA4	0.79	0.46	0.61	0.44
LA5	0.76	0.46	0.51	0.48
LA6	0.61	0.39	0.31	0.41
LA7	0.8	0.54	0.58	0.55
LA8	0.73	0.52	0.54	0.54
LA9	0.75	0.50	0.52	0.56
LO1	0.5	0.67	0.44	0.81
LO2	0.5	0.64	0.43	0.81
LO3	0.41	0.53	0.3	0.71
LO4	0.43	0.56	0.38	0.75
LO5	0.54	0.53	0.46	0.75
LO6	0.49	0.47	0.35	0.7

[1] This approach is taken as it allows smaller sample size and does not rely on a strict assumption (Hair, Sarstedt, Hopkins, & Volker, 2014).

LS1	0.45	0.76	0.34	0.52
LS2	0.43	0.85	0.36	0.64
LS3	0.64	0.89	0.57	0.70
PD	0.71	0.53	1.00	0.53

Secondly, we looked at the model's outer loadings. Hair et al. (2017) stated that indicators with high outer loadings tend to have more in common; hence, indicators with a factor loading of less than 0.4 should be excluded whereas those with an outer loading at least 0.7 should be retained. Lastly, indicators with an outer loading in between are acceptable for exploratory studies (Hair et al., 2012, p. 429), such as one reported in this paper. Thus, indicators used in this research satisfy these requirements (Table 3).

Table 3: Outer loadings

	Land_Atribute	**Land_Structure**	**Land_Value**	**Location**
LA1	0.65			
LA10	0.69			
LA2	0.73			
LA3	0.81			
LA4	0.79			
LA5	0.76			
LA6	0.61			
LA7	0.80			
LA8	0.73			
LA9	0.75			
LO1				0.81
LO2				0.81
LO3				0.71
LO4				0.75
LO5				0.75
LO6				0.70
LS1		0.76		
LS2		0.85		
LS3		0.89		

	Land_Atribute	Land_Structure	Land_Value	Location
PD			1.00	

Another criterion is the Average Variance Extracted (AVE). This measure explains how far indicators' variance is explained by their constructs. Hence, if an AVE of a certain construct is below 50%, the model is unable to satisfactorily explain the variance of the indicators because most of it remains in the model's error (Hair et al., 2017). Following this logic, therefore, EVA should at least be 0.5 (Hair et al., 2012, p. 429). Table 4 shows that the EVA of the model is at least 0.54. As such, we can conclude that the model proposed in this paper satisfies convergent validity as each construct explains most of the variance in their indicators.

Table 4: Average Variance Extracted

	AVE
Land_Atribute	0.54
Land_Structure	0.69
Land_Value	1.00
Location	0.57

Another important indicator is the composite reliability that measures an internal consistency of the model. Its values vary between 0 and 1. Hair et al. (2012) recommends to use 0.6 to 0.7 as a guide of an acceptable reliability value. This research therefore satisfies this criterion (Table 5).

Table 5: Composite reliability

	Composite Reliability
Land_Atribute	0.92
Land_Structure	0.87
Land_Value	1.00
Location	0.89

Table 6 presents the coefficients for each construct, indicating that all constructs significantly affect asking price (t = 1.96, n = 628).

Table 6: Coefficients for each latent variable

	Original Sample (O)	t statistics
Land_Value → Land_Atribute	0.71	15.66

	Original Sample (O)	t statistics
Land_Value → Land_Structure	0.53	6.84
Land_Value → Location	0.53	7.06

These results are consistent with the literature. For instance, location has been recognised as one of the most important factors affecting property value. Property can be seen as a place where activities are conducted (Fanning, 2014). As one activity relates to another, property with easy access to other property is highly sought as it drives customers' preference (Thanaraju, Khan, Juhari, Sivanathan, & Khair, 2019), which leads to a higher demand and an increase in property value. It is therefore unsurprising that location affects house price significantly (Olanrewaju, Lim, Tan, Lee, & Adnan, 2018). Distance to transportation is another important feature in property location (Suhaimi, Maimun, and Sa'at, 2021). Similarly, other constructs reported in Table 6 have found support from the literature (Adair, Berry, & McGreal, 1996; Randeniya, Ranasinghe, & Amarawickrama, 2017). The main contribution of this paper is demonstrating a procedure to measure the effect of unobserved variables (e.g., location and land attributes) on land value, which is generally difficult to measure using popular tools, such as regression analysis. Next section provides a brief future research direction and concludes this paper.

CONCLUSION

This study provides statistical evidence that found – based on the sample included in this study – land attributes, land structure, and location are highly significant in affecting the state-owned land value. As such, DGSAM is suggested to adopt these variables in their proposed mass appraisal model. This paper also demonstrates that it is now possible to quantitatively measure the effect of unobserved variables like location or property attributes. Such measurement is difficult to accomplish using popular model building techniques, e.g., multiple regression analysis. The model in this paper can, however, benefit from more data transaction. Additional data should cover areas outside of Jakarta to test and improve the reliability of the model.

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