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THE IMPACT OF TRANSJAKARTA BUS RAPID TRANSIT ON LAND VALUE OF DKI JAKARTA PROVINCE SUBDISTRICTS

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ABSTRACT

To immediately curb severe traffic congestion, some cities choose to establish bus rapid transit (BRT) infrastructure over rail-transit. New establishment of transportation infrastructure should be followed by the increases of land value. This study mainly intents to determine the impact of TransJakarta BRT on land value of sub-districts in DKI Jakarta Province. There are two treatments in this thesis. This study utilizes difference-in-difference approach as well as score matching estimation namely Nearest Neighbor Matching (NNM). The research found that the new installation of BRT causes land value to increase around 20 – 30 percent. Hence it is correct to say that BRT impact on land value is on par with other transportation establishment such as railway. Its apparent benefit to land value can be used as basis to encourage more private and public-sector involvement in helping to fund the BRT installation..

Kata Kunci : *impact, land, Transjakarta*

A. INTRODUCTION

To immediately curb severe traffic congestion, some cities choose to establish bus rapid transit (BRT) infrastructure over rail-transit. BRT has advantages such as requires low to medium costs in implementation, needs only short time to establish, and has inherent flexibility that makes it able to reach larger areas (Cervero et al, 2011). Unlike rail-transit, BRT can take advantage from current transportation investment that is road infrastructure. It only needs exclusive median lanes to enhance its speed quality. New establishment of transportation infrastructure should be followed by the increases of land value. The area enjoys significant gains in accessibility in forms of travel-time savings and the ability to accommodate large capacity of passengers' movement. As the result the land price hikes.

There have been debates whether the increases on land value because of BRT establishment are on par of railway investments'. Levinson et al. (2002) argues that BRT investments generated land price benefits that were as big as if those were supplied by railways. Vuchic (2002), on the other side, says that rail transit will most likely to give impact to land value than BRT. Rail system has superiority in promoting land development because of its locational rigidity and permanence (Rodriguez et al, 2004). As a result, economic development is likely to occur along a rail line than along a bus-way. Because the emergence of modern BRT systems is still recent, the quantities of empirical evidence about BRT impact on land value is low. The inferiority of BRT on enhancing land development is caused by the limitation of empirical evidence on whether BRT supports or dismisses it (Deng et al, 2016).

A thorough study of BRT impacts is critical as at least it offers three benefits. First, the result could be utilized to optimize the choices of transportation technology implementation. Second, it could be used as a basis to persuade private sectors to contribute in financing the establishment. Third, its impacts on land value are beneficial to determine the proper amount of land and building tax impose.

B. METODHS

The research utilizes panel data. Its unit of analysis is sub-district in DKI Jakarta. There are 258 sub-districts. Outcome variable is land value which consist 3 (three) years data; 2013, 2014, and 2015. The data source is from Ministry of Land, Republic of Indonesia. There are two treatments in this study. They are installation of BRT route 12 and installation of extension of BRT route 2. Those installation took place during 2013 until 2015. Treatments are defined as change in distance (from center of subdistrict to nearest station) because of new BRT installation as well as BRT dummy (1 if there is change in distance for each subdistrict; 0 if the opposite).

Table 1. Number of each group

BRT Installation	Year			Total
	2013	2014	2015	
Treatment group	0	27	33	60
Control group	258	231	225	714
Total	258	258	258	

Source: own analysis

Data in this thesis is gathered through several sources. Below is the description of the data and its sources.

1. Land value data

The data is collected from the Ministry of Land, Republic of Indonesia. It is an aggregate land value data for each subdistrict. It is measured in US dollar (per kilometer square) and we also utilized CPI (Consumer Price Index) from World Bank data.

2. Distance data

Distance in this thesis means the distance to the nearest station (BRT or railway) from the subdistrict center. We plotted the stations by their coordinates using Google maps. Then we measure the distance using ArcMap software. We also utilize this software to determine center of subdistrict.

3. Covariates data

Covariates consist of population density, commercial area, and property tax. These data are derived from National Bureau of Statistics and Ministry of Land. We also use GDP (Gross Domestic Product) deflator from World Bank data for property tax. We utilized ArcMap software to transform spatial data to statistics data for commercial area. These covariates are suspected to affect installation of BRT.

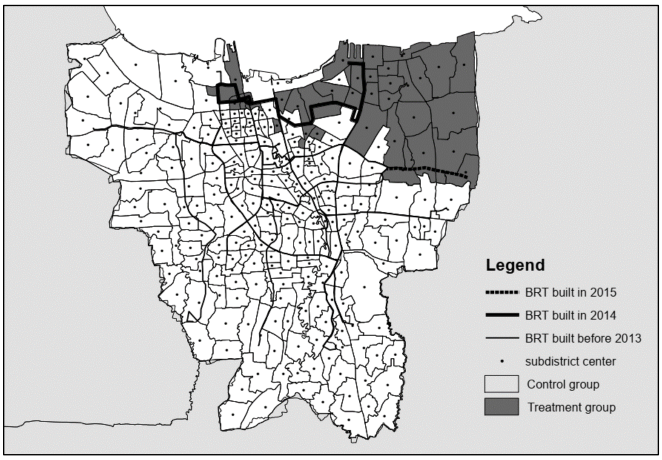

Figure 1. BRT Map
Source: own analysis

The balance check table below shows that subdistricts in treatment and control group are not balance. Variables such as land value, area, and commercial area density are very different among these two groups. It makes DID estimation strategy is not sufficient. DID strategy is based on common trend assumption. That is subdistricts are same between groups hence they will create same trend with all else being equal. Based on this, NNM becomes necessary.

Table 2. Balance check

Year 2013	Treatment (1)	Control (2)	Difference (1) - (2)
Land value (per hectare in USD with CPI)	392.1 (237.4)	825.0 (805.1)	-432.9*** [143.4]
Area (kilometers sq)	3.67 (2.68)	2.33 (1.94)	1.34*** [0.38]
Population density (1,000 persons per kilometer sq)	21.48 (15.87)	22.64 (16.23)	-1.16 [3.06]
Commercial area density (as a ratio to total land area)	0.254 (0.175)	0.185 (0.184)	0.069*** [0.035]
Property tax (per capita in USD with GDP deflator)	11.7 (16.3)	16.1 (20.8)	-4.4 [3.83]
N. of obs.	32	226	258

Notes: Standard deviations are in parentheses; while standard error are in square brackets. Data source is from World Bank, Ministry of Land, and National Bureau of Statistics, Republic of Indonesia.

This study utilizes *Difference-In-Difference* (DID) approach to determine the impact of Transjakarta BRT to subdistrict land value. For first treatment, that is installation of BRT route 12, land value year 2013 is considered as before treatment data; while land value year 2014 is regarded as after treatment data. For the second treatment, that is installation of extension of BRT route 2, land value year 2014 is considered as before treatment data; while land value year 2015 is regarded as after treatment data. Moreover, land value year 2013 is regarded as before-before treatment data.

Difference-in-difference approach uses fixed-effect model to know the causal effect of BRT and land value. It measures the impact of BRT either in form of change in distance because of new BRT installation or BRT dummy along with the year and subdistrict fixed effect using three-years panel data. Omitted variable bias that may appear because of unobserved variables that are time-invariant, and subdistrict-invariant can be eliminated by combining these two fixed-effects (Stock and Watson, 2015).

Below is the three FE models:

a. $LLandval_{i,t} = \alpha_0 + \alpha_1 Dist_{i,t} + \alpha_2 Covr_{i,t} + f_i + f_t + \mu_{i,t}$
b. $LLandval_{i,t} = \beta_0 + \beta_1 D\_BRT_{i,t} + \beta_2 Covr_{i,t} + f_i + f_t + \mu_{i,t}$
c. $LLandval_{i,t} = \gamma_0 + \gamma_1 D\_BRT_{i,t} + \gamma_2 (D\_BRT * D\_Dist)_{\ i,t} + \ \gamma_3 (D\_BRT * D\_Dist^2)_{\ i,t} + \ \gamma_4 Covr_{i,t} + f_i + f_t + \mu_{i,t}$

The subscript i refers to sub-district and the t is representation of year. Variable $LLandval_{i,t}$ in both models represents land value in log natural form. The parameter of interest α_1 in the first model measures the effect of change in distance while parameter β_1 of model 2 measures the effect of change in BRT dummy (dummy change of distance). The $Covr_{i,t}$ is covariates that consist of population density, commercial area, and property tax. Both models include subdistrict and year fixed effect which are represented by f_i and f_t respectively. The last term in both model is error term.

From the balance check table, we know that treatment and control group is not balance. Difference in difference procedure requires subdistricts to be balance so that common trend assumption is satisfied. Because this is not satisfied, we need to employ another estimation strategy that is score matching estimation namely *nearest neighbor matching* (NNM). This type of estimation is derived from *propensity score matching* (PSM) method. However, because covariates in the treatment and control group are really different, we decide to use only distance variable as the covariates for matching; thus, the name of nearest neighbor matching. The procedure is to match subdistricts in the treatment group and subdistricts in the control group by the same observed characteristics; that is distance to the nearest station. It is expected that the difference in the outcome variable between the two should be due to the treatment status.

The works of a propensity score is matching on a single index (propensity score), reflecting the probability of having BRT. It could achieve consistent estimates of the treatment effect in the same way as matching on all covariates. This single index contains all the relevant information contained in the independent variables X. Matching on this index is equivalent to matching X; i.e for a given value of the index the distribution of X should be the same for subdistricts in the treatment group and in the control group.

C. RESULTS AND DISCUSSION

We run ordinary least square (OLS) to know what will happen if we don't control region invariant covariates. Results show that there is negative correlation between land value and distance. Its magnitude is 25 percent. The second estimation strategy uses fixed effect to control region invariant covariates. Compared to OLS estimation results, DID results are extremely different. Using continuous treatment that is distance, BRT causes land value to increase around 23 percent. Compared to OLS result, the percentage decreases a bit. This shows that BRT was installed in already low in land value sub-districts. If we subset the impact by including heterogenous time trend, the impact decreases to around 13 – 14 percent (see appendix 1).

For binary variable of BRT installation, using OLS there is still negative correlation but a bit higher that is around 26 percent. If this dummy is interacted with reduction in distance variable, the magnitude becomes around 22 percent but still negative correlation. BRT supposed to make land value in treatment group to be higher than in control group. Looking at OLS result, this is not what is happening (see appendix 2).

Using binary treatment, BRT increases land value around 35 – 36 percent. Compared to OLS estimation, DID result is completely different. This shows that employing OLS will be misleading. Using fixed effect, BRT indeed makes land value in treatment group to become higher than in control group. Allowing for heterogenous time trend, the impact is subset to become 31 percent. Below is the depiction of linear combination of interaction between binary treatment and reduction in distance. The impact of BRT in land value is the largest at around 1.5 kilometers of reduction in distance.

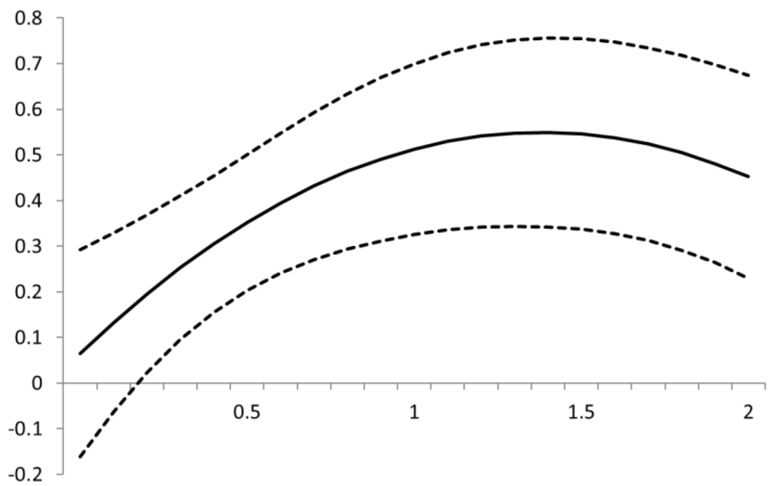

Figure 2. Linear Combination
Source: STATA results

We also run robustness check for fixed effect estimation. We did it by including interaction term between binary treatment and subdistrict area in year before the treatment.

Table 3. Robustness check

Treatment	**BRT installation (Binary)**
Model	**DID**
BRT installation	0.261**
	(0.115)
BRT installation*Region Area	0.0273
	(0.0297)
Other covariates	No
N	774
Adj. R-sq.	0.514

Notes: Clustered robust standard errors are in parentheses. Dependent variable is natural log of land value. All models include region- and year-fixed effects. Significance levels are * for $p<0.10$, ** for $p<0.05$, and *** for $p<0.01$.

For running nearest neighbor matching (NNM) estimation, we need to omit 3 (three) sub-districts from the dataset. These sub-districts have distance more than 6.3787 kilometers. This is more than the longest distance in the control group. Thus, these subdistricts in the treatment group do not have matches in the control group. The outcome in NNM is the difference of land value in 2013 and 2015.

Table 4. NNM result

```
Treatment-effects estimation                   Number of obs      =        255
Estimator      : nearest-neighbor matching     Matches: requested =          1
Outcome model  : matching                                     min =          1
Distance metric: Mahalanobis                                  max =          1
------------------------------------------------------------------------------
             |              AI Robust
  d_l_landval |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
 treat_dummy |
   (1 vs 0)  |   .2910685   .0897373     3.24   0.001     .1151865    .4669504
------------------------------------------------------------------------------
```

Source: STATA result

Table 5. Covariate balance summary

Covariate balance summary

	Raw	Matched
Number of obs =	255	58
Treated obs =	29	29
Control obs =	226	29

	Standardized differences Raw	Standardized differences Matched	Variance ratio Raw	Variance ratio Matched
distance	.9250915	-.001869	1.86357	.9927602

Source: STATA result

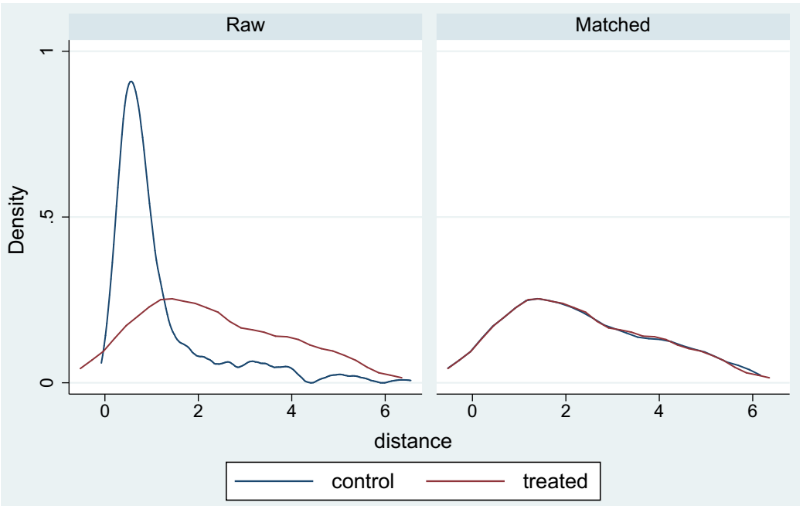

Figure 3. NNM Balance Plot
Source: STATA result

The table result shows that the difference level of land value because of BRT installation between the treatment and control group is 29 percent. This result is consistent with DID result.

D. CONCLUSION

It is clear that the increase of land value in subdistricts with BRT is higher than subdistrict without BRT. The new installation of BRT causes land value to increase around 20 – 30 percent. This magnitude is high. Hence it is correct to say that BRT impact on land value is on par with other transportation establishment such as railway. Subdistricts with BRT will not be less developed compared to subdistricts with railway for example. Its apparent benefit to land value can be used as basis to encourage more private and public sector involvement in helping to fund the BRT installation.

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