Heterogeneous Causal Impacts of Highways on Regional Economic Growth: Evidence from Japan

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Abstract

This study aims to examine the heterogeneity in the causal impact of highway development on regional economic growth. To this end, we employ causal forests, that is a machine learning algorithm for causal inference, to data on Japanese municipalities from 1971 to 2010 and estimate the conditional average treatment effect (CATE) of highway interchange (IC) openings on the growth of value-added per employee in manufacturing sector. We then find evidence that an opening of highway IC improves regional labor productivity by an average of 6.5% from 1971 to 1991, while there is no significant average effect from 1991 to 2010. This result is consistent with the fact that Japan experienced rapid growth in the former period and long stagnation in the latter period. We also identify regional characteristics that affect the heterogeneity in the causal effects for each period, and reveal that those differ between periods of economic growth and stagnation. This regional and temporal heterogeneity is likely to improve the efficiency of transportation infrastructure policies by targeting regions where significant benefits can be expected. Finally, by comparing the result of causal forests with those of regression models and propensity score matching method, we demonstrated the usefulness of the non-parametric method.

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1 Introduction

In Japan, the highway construction has been steadily progressing since the early 1960's, and has contributed greatly to social development and economic growth. However, there are criticisms that the development of the highway network has stimulated the concentration of population and capital in metropolitan areas, leading to the decline of rural areas. The impact of transportation infrastructure development on the spatial distribution of economic activity has been the subject of theoretical debate in spatial economics (e.g. Fujita et al., 1999). In recent years, there has been progress in quantitative analysis that incorporates the mechanisms of aggregation and dispersion (see Redding and Rossi-Hansberg, 2017, for a review), but empirical evidence has still not been accumulated sufficiently.

Impacts of highway development are not uniform, but vary across regions. Faber (2014) finds that new highways have lowered GDP growth in peripheral regions that were connected to the highway network compared to unconnected peripheral regions in China; mainly due to reductions in industrial output growth. Baum-Snow et al. (2020) uses data of China and observes that highway construction has a positive effect on population and GDP in major regional cities, while it has a negative effect in other cities. Baum-Snow (2007) and Baum-Snow et al. (2017) conclude that the development of radial urban highways leads to population decline in urban centers and suburbanization in the United States and China, respectively. These studies were based on a priori assumptions about the factors that cause heterogeneity of effects between regions. Therefore, the nature of heterogeneous causal effects has not been fully understood.

Recently, novel estimation approaches, using machine learning, that can incorporate heterogeneity in causal effects have been proposed (Athey and Imbens, 2019). Applying an algorithm of decision trees, causal forests (CF) enables the estimation of the average treatment effect conditioned on various attributes (Athey and Imbens, 2016; Wager and Athey, 2018). Unlike conventional approaches, CF identifies the factors of heterogeneity by exploring among multiple attribute data. Thus, It can provide detailed evidence to answer questions such as “what kinds of regional attributes bring a positive or negative significant effect?”. The accumulation of such evidence is beneficial for making place-based policies of highway development.

The rest of the paper organized as follows: we start with a brief explanation of CF and describe the context and data of this analysis in Section 2. Section 3 present the estimation results are discussion. Finally, concluding remarks is offered in Section 4.

2 Estimation strategy

2.1 Causal Forest

In this section, we provide an overview of CF . CF is a method for estimating conditional treatment effects (CATE) on covariates by applying decision tree analysis. CATE is defined as follows.

$$\tau(x) \equiv \mathbb{E}[Y_i(1) - Y_i(0)|X_i = x] \tag{1}$$

where i $(= 1, \cdots, N)$ is the index of the individual, and $Y_i(W_i)$ denotes the potential outcome variable of the individual. $W_i \in \{0, 1\}$ is the binary indicator for the treatment, with $W_i = 1$ indicating that unit i received the treatment and $W_i = 0$ indicating that unit i didn't. X_i denotes a covariate vector that is not affected by the treatment. Throughout the paper, we maintain the assumption of randomization conditional on the covariates, or "unconfoundedness" formalized as given below.

$$\{Y_i(1), Y_i(0)\} \perp W_i |\ X_i \tag{2}$$

A tree or partitioning Π which corresponds to a partitioning of the feature space $\mathbb{X}$ is denoted by;

$$\Pi = \{l_1, \cdots, l_{\#(\Pi)}\}, \text{ with } \quad \cup_{j=1}^{\#(\Pi)} l_j = \mathbb{X}, \tag{3}$$

where l_j represents the elements or leaves and $\#(\Pi)$ does the number of elements in the partition. Let $l(x; \Pi)$ denote the leaf $l \in \Pi$ such that $x \in l$.

Given a partition Π, the conditional average treatment effects (CATE) is defined as

$$\tau(x; \Pi) \equiv \mathbb{E}[Y_i(1) - Y_i(0)|X_i \in l(x : \Pi)]. \tag{4}$$

The estimator of $\tau(x; \Pi)$ is given by

$$\hat{\tau}(x; \Pi) = \frac{\sum_{\{i:W_i=1, X_i \in l(x;\Pi)\}} Y_i}{\#(\{i : W_i = 1, X_i \in l(x; \Pi)\})} - \frac{\sum_{\{i:W_i=0, X_i \in l(x;\Pi)\}} Y_i}{\#(\{i : W_i = 0, X_i \in l(x; \Pi)\})}. \tag{5}$$

$\hat{\tau}(x; \Pi)$ is obtained as the difference between the mean of the outcome of the treatment group and that of the control group within a leaf.

The problem is how to construct the causal tree. Unlike CART, a conventional decision tree algorithm that aims to predict results, CF aims to estimate treatment effects. To this end, the following two modifications are made. First, we separate the samples for partitioning, estimation and test. Let $\mathcal{S}^{tr}$, $\mathcal{S}^{est}$ $\mathcal{S}^{te}$ denote samples for training, estimation and testing, respectively. Next, the definition of the mean squared error (MSE), which is the objective function in tree-building, is modified as

$$-\widehat{EMSE}_\tau(\mathcal{S}^{tr}, N^{est}, \Pi) \equiv \frac{1}{N^{tr}} \sum_{i \in \mathcal{S}^{tr}} \hat{\tau}^2(X_i; \mathcal{S}^{tr}, \Pi) - \left(\frac{1}{N^{tr}} + \frac{1}{N^{est}}\right) \sum_{l \in \Pi} \left(\frac{S^2_{\mathcal{S}^{tr}_{treat}}(l)}{p} - \frac{S^2_{\mathcal{S}^{tr}_{control}}(l)}{1-p} \right), \tag{6}$$

where $S^2_{\mathcal{S}^{tr}_{treat}}(l)$ and $S^2_{\mathcal{S}^{tr}_{control}}(l)$ denote the within-leaf variance for the treatment and control groups, respectively. p denotes the proportion of assignment to the treatment group. The first term on the right-hand side represents the variance of the conditional treatment effect in the training data $\mathcal{S}^{tr}$ and the second term is a penalty term for the variance of the treatment and control groups within a leaf. Thus, a causal tree is generated such that the heterogeneity of treatment effects across leaves becomes large and the within-leaf variability becomes small. This approach, called the honesty method, guarantees the consistency and asymptotic normality of the treatment effect estimates.

In CF, the conditional average treatment effect (CATE) is calculated by an ensemble procedure as follows; 1) creating a number of causal trees, 2) estimating the conditional treatment effect for each tree $\hat{\tau}(x; \Pi)$ and 3) taking the average of those values. The variable importance, which is obtained when constructing forest, indicates the degree to which the division of covariates contributes to the heterogeneity of the treatment effect. By examining the relationship between covariates with high variable importance and treatment effects, it is possible to grasp the characteristics of the heterogeneity of the effects.

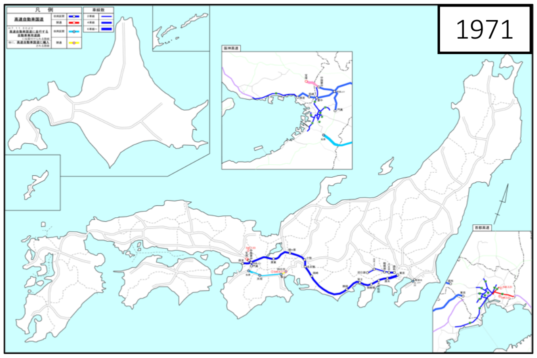
2.2 Context and data

2.2.1 Highway network development in Japan

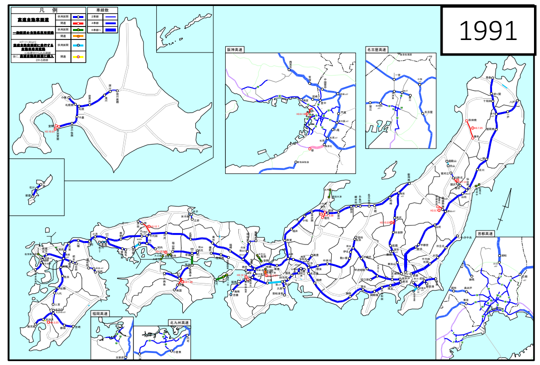
In Japan, the highway network has been steadily developed for about 60 years since the first section was constructed in 1963. This study focuses on the impacts of highway network improvements made between 1971 and 2010. Figure 1 (a), (b) and (c) show the highway network in 1971, 1991 and 2010, respectively. Only the main routes connecting Tokyo, Nagoya and Osaka were in place in 1971. In the period of 1971-1991, the highway network was developed to directly connect major cities. It was expanded and densified during the following two decades with the construction of branch lines to regional cities.

Let $W_i \in \{0, 1\}$ be a binary indicator of whether or not a new highway interchange (IC) was opened in municipality i during a given period of time, with $W_i = 1$ indicates that a new IC was opened and $W_i = 0$ indicating that it wasn't.

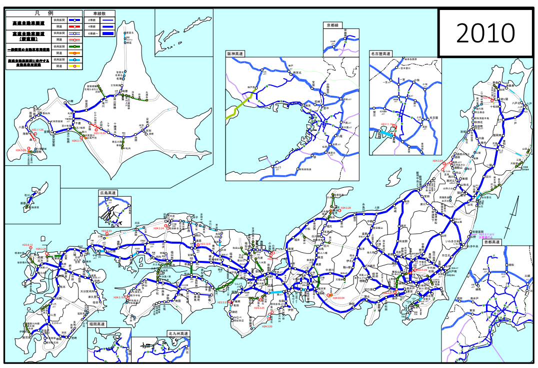
This analysis covers municipalities that belong to the urban employment zone (2015 standard) defined by Kanamoto et al.,excluding municipalities in Okinawa Prefecture.



(a) 1971 highway network



(b) 1991 highway network



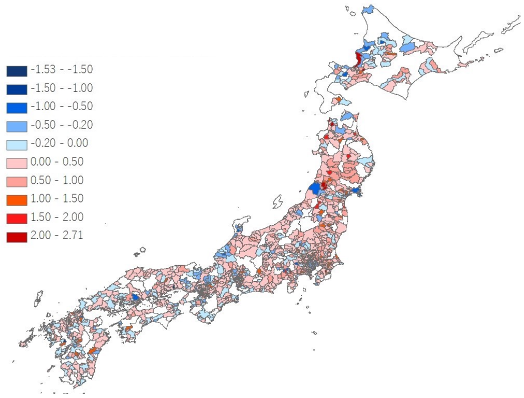
(c) 2010 highway network

Figure 1: Development of highway network

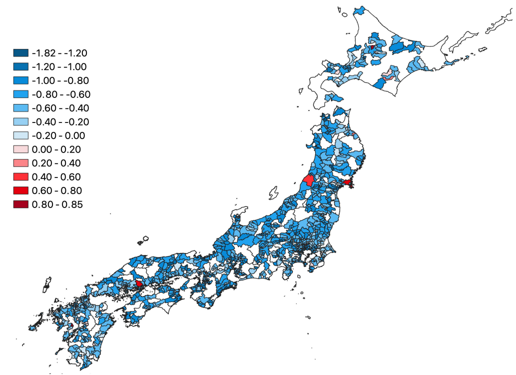
We set the entire period from 1971 to 2011 as the period of interest. We further divide the entire period into two: the first period from 1971 to 1991 and the second period from 1991 to 2011. In order to avoid including municipalities that already had ICs in the control group, only municipalities that did not have ICs in 1971 are included for the entire period and the first period, and only municipalities that did not have ICs in 1991 are included for the second period.

2.2.2 Outcomes and controls

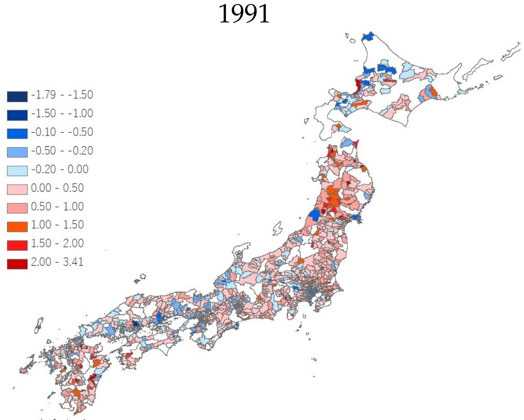
We are interested in understanding the causal impacts of the highway improvement on regional economic growth. The growth rate of the number of establishments, the number of employees and value-added per employee in the manufacturing sector are our primary outcomes. Figure 2 shows the growth rate of those outcomes 1971-1990 ((a), (c), (e)) and 1971-2010 ((b), (d), (f)). In almost all municipalities, the number of establishments and employees increased between 1971 and 1990, but decreased between 1991 and 2010. On the other hand, some municipalities experienced an increase in value added per employee in both periods.



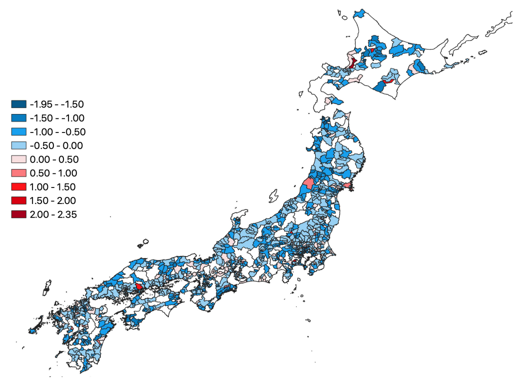
(a) Number of Establishment from 1971 to 1991



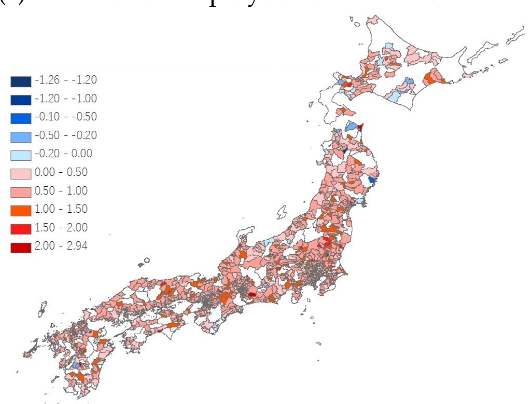
(b) Number of Establishment from 1991 to 2010



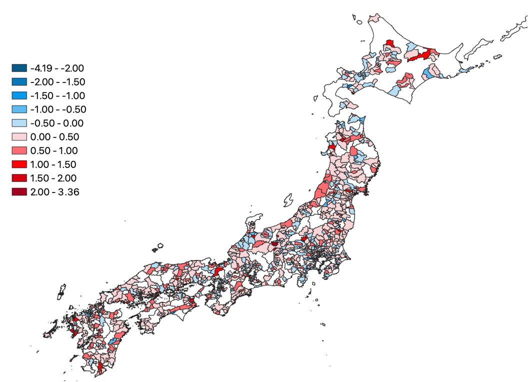
(c) Number of Employee from 1971 to 1991



(d) Number of Employee from 1991 to 2010



(e) Value-added per employee from 1970 to 1991



(f) Value-added per employee from 1991 to 2010

Figure 2: The growth rate of outcomes (logarithm)

The first period (1971-1990) was a period of stable growth with an average real economic growth rate of about 4%, despite the oil shock at the beginning of the period, as the economy underwent a structural change from heavy industries such as steel and shipbuilding to high-value-added high-tech industries such as automobiles, electrical products, and semiconductors. On the other hand, the second period (1991- 2010) has been described as "the lost decades" due to the collapse of the bubble economy and the prolonged recession that followed, and was a low-growth period with an average real economic growth rate of less than 1%. Due to the fall in international competitiveness caused by the rise of emerging economies and the relocation of manufacturing bases overseas, the domestic manufacturing industry has entered a period of decline.

We use socioeconomic and geographic characteristics data as covariates. The socioeconomic data used are total population, industrial employment rate, number of establishments, number of employees, total payroll, value of manufactured goods shipped, and value added. However, in order to eliminate the influence of treatment as much as possible, the oldest available data are used. As geographical data, we use the area of inhabitable land, the average elevation, the ratio of the maximum slope angle of 10 degrees, the distance to ports, the distance to the three major metropolitan areas, and the distance to government-designated cities. The average elevation, the ratio of the maximum slope angle of 10 degrees, the distance to the port, the distance to the three metropolitan areas, and the distance to the government-designated cities were all calculated using GIS. Each distance index is defined as the straight-line distance from the municipality (city hall) to the nearest port, the central city of the three metropolitan areas, and the ordinance-designated city (metropolitan government office or city hall), respectively. All covariates were taken as natural logarithms except for the variable representing proportions.

3 Estimation results and discussion

3.1 Average Treatment Effect

The estimation results of the average treatment effect (ATE) are shown in Table 1. The ATE is obtained by taking the average of the conditional treatment effect (CATE) estimated by CF. We find that an highway IC opening increased the number of manufacturing establishments in the municipality by 8.5%, the number of employees by 13.6%, and the value added per employee by 5.8% during the period 1971-2010. In the first period, they increased by 8.5%, 4.9%, and 6.5%, respectively. In contrast, none of the results were significant for the second period 1991-2010.

We also perform estimation using alternative methods; ordinary least squares (OLS) as a parametric method and propensity score matching (PSM) method as a semi-parametric method. Table 2 shows the estimation results for the value-added per employee. For the period 1971-2010, the estimates were significant for all estimation methods; for the period 1971-1991, PMS and CF estimates were significant, but OLS estimate was not significant; for the period 1991-2010, all estimates were not significant. R^2 reported in

Table 1: Average treatment effect

	(1) 1971-2011	(2) 1971-1991	(3) 1991-2011
Establishment	0.083***	0.049***	0.014
	(0.00)	(0.00)	(0.177)
Employment	0.136***	0.085**	0.010
	(0.002)	(0.031)	(0.284)
Value-added per employee	0.058**	0.065**	0.027
	(0.030)	(0.025)	(0.212)
controls	yes	yes	yes
observations	1172	1172	893

p value in Parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Results of alternative mothods

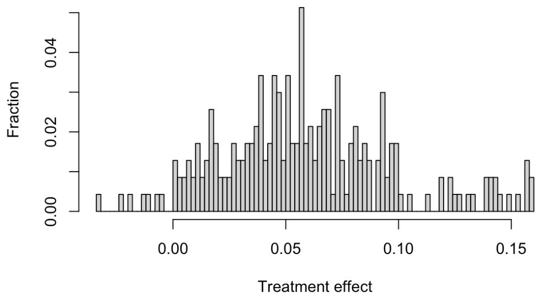
Value-added per employee	(1) OLS	(2) PSM	(3) CF
1971-2010	0.075**	0.169***	0.058**
	(0.00)	(0.001)	(0.030)
R^2	0.327	-	-
1971-1991	0.041	0.115***	0.065**
	(0.114)	(0.007)	(0.025)
R^2	0.362	-	-
1991-2011	0.021	0.044	0.027
	(0.547)	(0.406)	(0.212)
R^2	0.196	-	-
controls	yes	yes	yes

p value in Parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

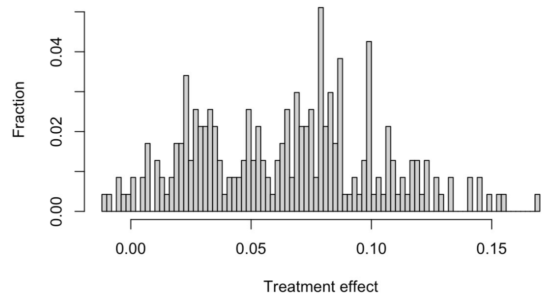
column (1) indicates that the assumption of linearity in OLS may be problematic. In all periods, the PSM estimates tend to be larger than the other estimates. PSM generally uses parametric estimators of binary response models such as the probit and logit to estimate the propensity score, which imposes strong distributional assumptions on the error term that are often violated with the underlying data.

3.2 Conditional average treatment effect

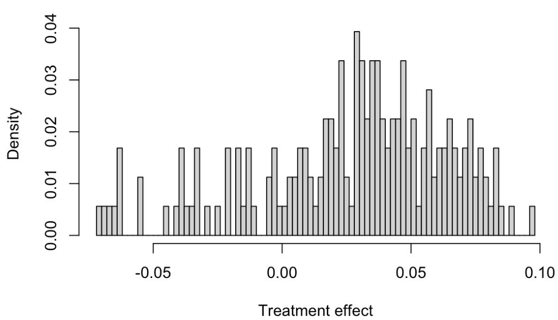
The distribution of the treatment effect is shown in Figure 3. Figure 3 (a) shows the distribution for the period 1971-2010, 3 (b) for the period 1971-1991, and 3 (c) for the period 1991-2010. The horizontal axis represents the growth rate of value-added per employee and the vertical axis does the fraction. The distribution for 1971-2010 is unimodal and almost symmetric with a median of 0.056. The distribution for the 1991-2010 appears



(a) 1971-2010



(b) 1971-1991



(c) 1991-2010

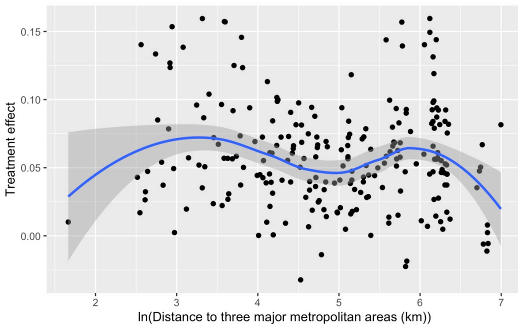
Figure 3: Distribution of the treatment effect

to be bimodal with a median of 0.068, while the distribution for 1991-2010 is unimodal with a median of 0.031 and has a slightly longer left tail.

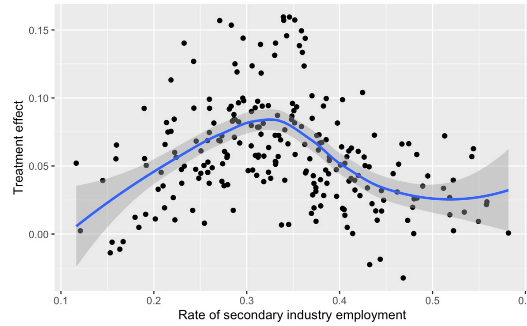
In the period 1991-2010, about 20% of the municipalities experienced a negative effect. In these municipalities, the highway connection to the metropolitan area may rather have led to the withdrawal of establishments and a decline in local productivity.

3.3 Relationship between regional attributes and treatment effect

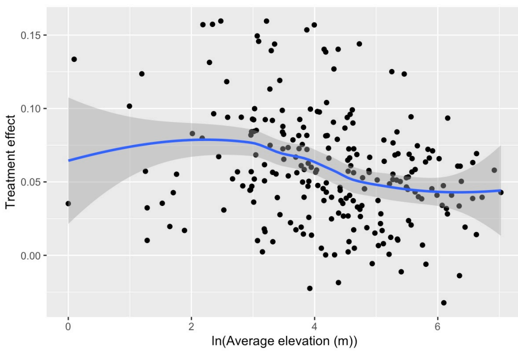
In order to identify the regional attributes that influence the heterogeneity of the causal effects, we focus on several covariates with high variable importance and examine their relationship with the treatment effect. Figure 4 depicts scatter plots and locally estimated scatterplot smoothing (LOESS) curves and their 95% confidence intervals for four covariates and the treatment effect. Figure 4(a) shows the scatter plots of distance to three major cities (Tokyo, Nagoya and Osaka) and the treatment effect. The LOESS curve has local maxima at distances of around 20km ($\ln(\mathit{distance\ to\ metropolitan\ area}\ (km)) \fallingdotseq 3$) and 400km ($\ln(\mathit{distance\ to\ three\ metropolitan\ areas}\ (km)) \fallingdotseq 6$), indicating that the re-



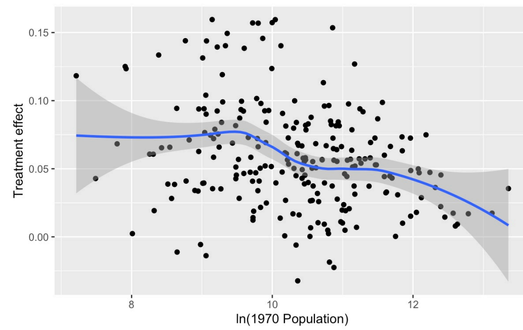
(a) Distance to 3 major metropolitan areas



(b) Rate of second industry employment



(c) Average elevation



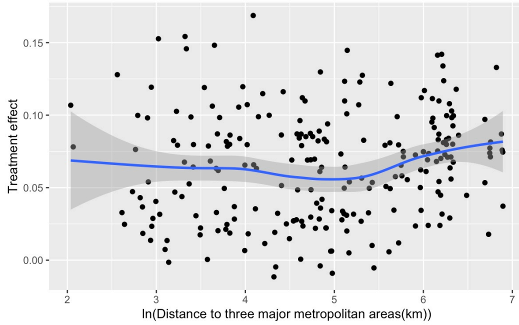
(d) 1970 population

Figure 4: Distribution of the treatment effect

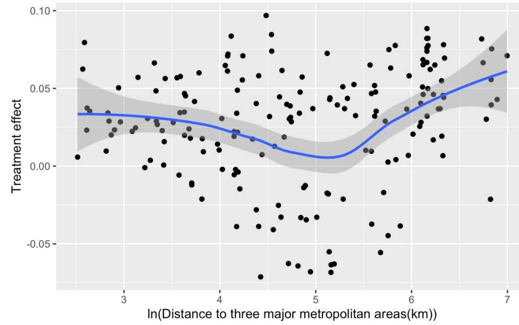
lationship is non-linear. Moreover, there are municipalities with an effect greater than 0.2 in these distance bands. Drawing a scatterplot for the distance to a government-designated city, we confirmed that most of the municipalities with a large effect of 0.2 or more are in the vicinity of a government-designated city.

Figure 4(b) describes non-linear relation between rate of second industry employment and the treatment effect. The municipalities with large effects are concentrated in the range 0.2 to 0.4, indicating that highway development increases labour productivity in regions that are already industrialized to some extent. Fig. 4(c) and (d) are scatter plots regarding average elevation and population in 1970, respectively; both LOESS curves are slightly decreasing with respect to the covariates, but no remarkable features can be found.

We also draw scatter plots separately for the period 1971-1991 and for the period 1991-2010 and examine the difference by the periods of time. Figure 5 (a) shows the scatter plots of distance to the three metropolitan areas and the treatment effect for the periods 1971-1991 (a-1) and for 1991-2010 (a-2). It is noteworthy that the patterns of plots are markedly different. In the first period 1971-1991, the LOESS curve is almost flat, and the points are scattered regardless of the distance to the three metropolitan areas. On

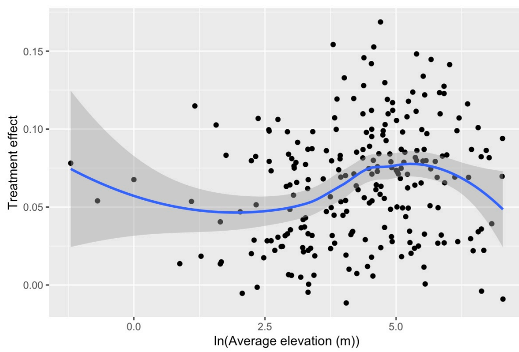


(a-1) 1971-1991

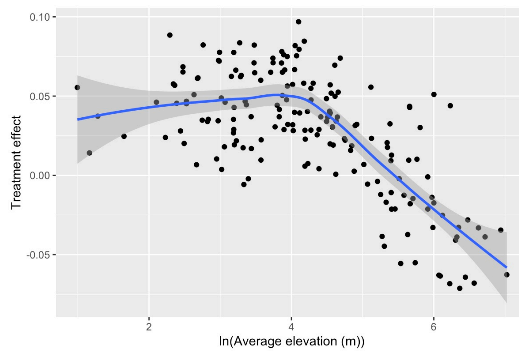


(a-2) 1991-2010

(a) Distance to three major metropolitan areas

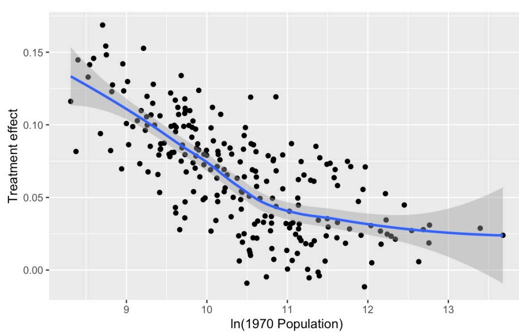


(b-1) 1971-1991

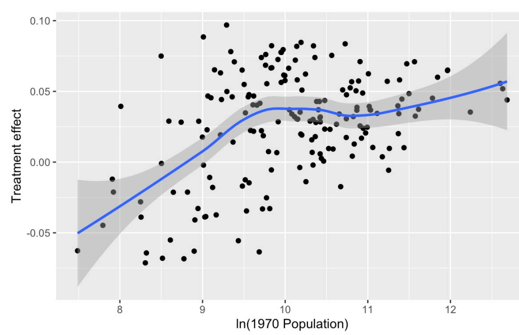


(b-2) 1991-2010

(b) Average elevation



(c-1) 1971-1991



(c-2) 1991-2010

(c) 1970 population

Figure 5: The growth rate of outcomes (logarithm)

the other hand, in the second period 1991-2010, the LOESS curve has a local minimum at about 150km ($\ln(\textit{distance to three metropolitan areas } (km)) \fallingdotseq 5$), and there are many municipalities showing a negative effect in the distance range of 55km to 400km ($4 < \ln(\textit{distance to three metropolitan areas } (km)) < 6$).

Figure 5(b) illustrates the relationship between average elevation and treatment effect: for the first period (b-1), municipalities with high effect are observed around 150m elevation ($\ln(average\ \ elevation\ (m)) \doteqdot 5$); for the period 1991-2010 (b-2), a positive effect occurs below 150m elevation, while a negative effect occurs above 150m elevation. Japan is a small and mountainous country, and highway routes often pass through mountainous areas. In the first period, the construction of highways led to firms moving into rural and mountainous areas, which increased the production efficiency of these areas, while in the second period, it may have led to firms withdrawing from these areas.

Figure 5 (c) shows the relationship between population in 1970 and the treatment effect. In the period 1971-1991 (c-1), the LOESS curve is monotonically decreasing and the effect is larger in municipalities with smaller populations, while in the period 1991-2010 (c-2), municipalities with fewer than 22,000 inhabitants ($\ln(1970\ population) < 10$) received a negative effect.

The above results indicate that (1) during the period of economic growth, the manufacturing industry spread out to rural areas and employment was partly transferred from urban areas to rural areas, and (2) during the period of economic stagnation, small municipalities about 150km from the three metropolitan areas received negative effects from highway development.

4 Concluding remarks

This study analyses the effects of highway development on regions using Causal Forest, a causal inference method based on machine learning. We identified heterogeneity of the effects of highway development and reveal that the factors of the heterogeneity differ between periods of economic growth and stagnation.

Further detailed examination is needed to verify whether and how transportation infrastructure investment widens regional disparities. This analysis employed a binary variable indicating whether a new IC was built or not as a treatment variable, but it is desirable to use an accessibility index to measure highway network improvement more appropriately . Decisions on highway development may often be endogenous. In such cases, it is necessary to estimate using an instrumental variable method.

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