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Estimating the Impacts of International Bridges on Foreign Firm Locations: A Machine Learning Approach

Kazunobu HAYAKAWA[1], Souknilanh KEOLA [2]*,
Korrakoun SILAPHET[3], Kenta YAMANOUCHI[4]

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Abstract
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Keywords: International bridge, Foreign direct investment, Laos
JEL classification: O18, D25

1: Bangkok Research Center, Institute of Developing Economies; 2: Development Studies Center, Institute of Developing Economies (*corresponding author's email: souknilanh_keola@ide.go.jp), 3: Graduate School of Asia Pacific Studies, Ritsumeikan Asia Pacific University; 4: Faculty of Economics, Kagawa University.

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INSTITUTE OF DEVELOPING ECONOMIES (IDE), JETRO
3-2-2, WAKABA, MIHAMA-KU, CHIBA-SHI
CHIBA 261-8545, JAPAN

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Kazunobu HAYAKAWA[§]
Bangkok Research Center,
Institute of Developing Economies, Thailand

Souknilanh KEOLA[#]
Development Studies Center,
Institute of Developing Economies, Japan

Korrakoun SILAPHET
Graduate School of Asia Pacific Studies
Ritsumeikan Asia Pacific University, Japan,

Kenta YAMANOUCHI
Faculty of Economics, Kagawa University, Japan

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1. Introduction

Developing countries can jumpstart industrialization by participating in the international production network (Kimura and Chang, 2017). This strategy holds true in the current globalized world in which major multinational firms have greater economic powers than most developing countries. Economic growth in East Asia recently was strongly associated with foreign direct investment (FDI) and trade (Urata, 2001). An empirical study by Wang (2009) found that FDI in the manufacturing sector had a significant positive effect on economic growth in East Asian economies. Lee and Tan (2007) identified technology transfer as a major benefit of FDI in ASEAN-4 (Indonesia, Malaysia, Singapore, and Thailand), while mentioning that Singapore and Malaysia were more successful in tapping the benefits of FDI with effective strategies and policies. Similarly, Kuroiwa (2015)

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[#] Corresponding author: Souknilanh Keola; Address: 3-2-2 Wakaba, Mihama-ku, Chiba-shi, Chiba 261-8545; Tel: 81-43-299-9686; Fax: 81-43-299-9673; E-mail: souknilanh_keola@ide.go.jp

concluded that although participation in the global economy provides opportunities for industrial upgrade, the absorptive capacity of the host economies is critical when foreign capital and technology initiate the industrialization process. Regardless of the largely varied outcomes, FDI is being prioritized in the development strategies throughout Southeast Asia. The four new members of ASEAN (Cambodia, Laos, Myanmar, and Vietnam) introduced FDI-related legislation initially in their major economic reforms in the early 1990s.

Nevertheless, institutional reform is an insufficient condition for attracting substantial FDI. Using UNCTAD's worldwide bilateral FDI data, an empirical analysis by Chen and Lin (2020) found that physical connectivity (e.g., air (direct flight), port (liner shipping), railway, and land contiguity) has a significant impact on FDI. In their study, air connectivity was derived from the direct flight information collected by the International Civil Aviation Organization, while port connectivity was based on the liner Shipping Bilateral Connectivity index compiled by UNCTAD. Railway connectivity was constructed using various existing railway information networks. However, compared with the previous three indicators, land contiguity identified using the border is ambiguous. Adjacency and decent land connectivity between countries often differ. For example, land connectivity between adjacent Bhutan and China is still very high. The land border stretching for more than 1,600 km between Myanmar and India does not currently achieve decent land connectivity. Besides the difficult landscape, rivers constitute large portions of international borders (Figure 1).

=== Figure 1 ===

International bridges are essential for on-land trade across river borders. Rivers can hinder international investment, particularly in geographically small countries where detouring around the river on land is not an option. The land-locked Laos, where the Mekong River runs from north to south, falls into this category. Although Laos has Vietnam in the east, Cambodia in the south, Thailand in the west, Myanmar in the northwest, and China in the north, mountain landscapes span hundreds of kilometers, making international trade with Vietnam and China economically and traditionally unfeasible. Navigating through the Mekong River southwards to Cambodia and then to Vietnam to the sea is impossible because of more than 20 m high waterfalls spanning more than tens of kilometers. Therefore, Thailand is still the de facto gateway for international trade for Laos.[1] Although the Mekong River accounts for only about half the border line with Thailand, all four major cities in Laos are located on its east bank. International or domestic Mekong bridges are, therefore, prerequisites for on-land access to the nearest seaport near Bangkok, the capital of Thailand, for any foreign firms located in major cities in Laos.

FDI in developing countries relies on the import of locally unavailable inputs and exports of processed or final products to markets abroad. Thus, Mekong bridges can be considered critical for foreign firms in Laos involving cross-border logistics. To date, four Mekong international bridges between Laos and Thailand have been constructed and opened for traffic in 1994, 2006, 2011, and 2013. Keola (2013) concluded that the first three

[1] However, this situation is changing rapidly with the development of international freight trains that started services on the Lao-Chinese railway in December 2021.

bridges substantially increased trade and FDI to Laos. The first international bridge between Laos and Myanmar was also completed in 2015. The fifth international bridge between Laos and Thailand is under construction as of 2022. The sixth international bridge between Thailand and Laos is in the advanced stage of planning, while the discussion on the seventh international bridge is reported to have started. Concurrently, Laos was opened again to FDI, especially from the Western world, at the end of the 1980s as part of the transition from stagnant planned to market-oriented economies. According to the second economic census held in 2013, about 1,500 active foreign firms could be categorized into 10 industrial activities in nearly140 districts in Laos.

Studies of FDI determinants using observation data have existed in economic literature. For example, Chen and Kwan (2000) analyzed determinants of FDI in 29 Chinese regions from 1985 to 1995. The major explanatory variables were education, roads of different qualities, railway, wage, per capita income, Special Economic Zone (SEZ), and industrial zones. They addressed the reversal causality of wage and income using the generalized method of moments (GMM). Fukao and Wei (2008) examined location choices of Japanese multinational enterprises (MNEs) in 117 countries between 1989 and 2002. The explanatory variables include market size, tariffs, skill, country risk, distance, infrastructure, agglomeration, wage, and their various combinations. They addressed reverse causality with detailed information on the role of foreign affiliates in the Ministry of Economy, Trade and Industry, Japan. Mayer et al. (2010) examined French MNEs' choice of location within and outside France using data between 1992 and 2002. The explanatory variables were market access, distance, common language, ex-colony, GDP per capita, supply access, sectoral network, local investment (France), and a combination of local investment with productivity, employment, and advertising. They controlled for endogeneity with lagged values of supply access, sectoral network, MNE network, and country fixed-effects.

This study estimates the impacts of the international Mekong bridges on FDI in Laos by industrial activities and districts. This study faces two challenges. One is that either no regional statistics at the district level exist or obtaining those data is difficult in the least developed countries such as Laos. The other is that certain bulk of data is available at the village level (approximately 10,000) during population census every 10 years since 1985, but the decadal-scale is too long for examining the impacts of Mekong bridges completed every few years. Obtaining the information required to control for reverse causality as seen in the existing literature is difficult if not impossible. These challenges are addressed as follows. First, the data limitation is overcome by generating a set of proxy of district statistics from earth observation data. Second, we apply causal forest, a machine learning framework, which does not require explicit control for endogeneity to examine the impacts of international bridges on FDI. This study makes the following contribution to literature. This study is perhaps the first application of causal forest to examine the impact of infrastructure development on firms' location choice. Since 2016, the causal forest has been widely used to examine policy impacts on health, environment, and employment (Davis and Heller, 2017; Miller, 2020; Elek and Bíró, 2021). Second, the use of remote sensing data implies that the framework can be applied to any subnational regions and backward in time without requiring survey-based data.

The study is presented as follows. Section 2 describes causal forest, emphasizing differences, advantages, and disadvantages compared with regression-based empirical analysis. Section 3 explains our data and preprocessing method. Section 4 reports and discusses our results. Section 5 concludes.

2. Causal Forests

According to "Causal Inference in Urban and Regional Economics" by Baum-Snow and Ferreira (2015), explicit or pseudo-randomization is the preferred method for credibly estimating the treatment effects, including those related to policy evaluation, but this method is challenging in urban and regional economic settings. As the assumption that treatment is uncorrelated with unobservable or that treatment is fully randomized in observation data is unlikely, the ordinally least square method does not usually recover credible average treatment effects (ATEs). Econometrics and machine learning address this problem differently. On the one hand, when explicitly or implicitly randomized observation data are unavailable, several alternative approaches are available in econometrics, such as difference-in-differences, instrumental variables, and propensity score matching. Baum-Snow and Ferreira (2015) explained that choosing a control group whose distribution of the unobservable group is similar to that of the treatment group is imperative. They described several successful identification strategies in urban and regional economics and stated that the process was as much an art as a science. It is researchers who consider many specifications, perform various specification tests, and present the preferred model as the outcome (Athey and Imbens, 2017). Moreover, applying such an approach implies that there is a truth model imaginable, comprehensible, and agreeable by humans. Here humans try to learn and construct the correct model.

Causal inference with machine learning is an alternative approach evolved outside the field of econometrics. Machine learning attempted to build computer models of human brain behavior as proposed by Hebb (1949). Machine learning evolved into various branches with different levels of human involvement. However, as the name suggests, the search for the right model is principally tasked on the machine. Thus, whether the models are imaginable or comprehensible by humans is no longer the issue. Machine learning creates models that often predict accurately, although the mechanism models created are often not interpretable by humans.

In this section, we do not argue that causal inference with machine learning is superior. However, the application of machine learning may be preferable in some scenarios. As discussed earlier, the main reason is the exploitation of enormous data as proxies for unavailable information. If the required statistics to recover credible treatment effects are clear and available to researchers, econometrics can be used. In reality, even though methodologies to extract heterogeneous treatment effects exist in econometrics, they are rarely applied owing to data limitations, especially in developing countries. Moreover, data whose relationship with the phenomena of interest is unknown to researchers would generally be excluded from the outset. In contrast, machine learning sometimes builds highly predictive models with seemingly unrelated data. Therefore, machine learning can be useful when there is a lack of data for conventional econometric analysis or when knowledge of the true model are limited. There is a high demand for policy evaluation in both developed and developing countries. Some econometrics textbooks have included chapters on machine learning. Thus, it is beneficial to explore the benefits offered by these new tools.

Causal forest proposed by Wager and Athey (2018) applies a machine learning method called a decision tree, which is a statistical learning method that reproduces nonlinear relationships by recursively creating branches from explanatory variables to dependent variables. Figure 2 illustrates a decision tree predicting FDI in 100 districts using three explanatory variables, namely, area (land area), ntl (nighttime light), and db1t (travel time to the first international bridge), in our dataset. First, the lower panel of Figure 2 lists 100 districts by index (1–100) and the number of foreign firms they received on the vertical axis. This random sample has only one foreign firm in most districts and between two and six in a few districts. The upper panel illustrates a tree that accurately predicts the nonlinear relationship in the lower portion of Figure 2. The tree starts by asking whether the district's land area is equal to or larger than 687 m^2; if not, then proceed to the right. If the sum of nighttime light in that district is lesser than 8144, it would proceed to the left and arrive at the level of FDI equal to 5, explaining that one of four districts has received five foreign firms. The accuracy of the prediction can be observed by the number of predicted data points overlapping with the real data points (Figure 2, lower).

=== Figure 2 ===

In machine learning, the example in Figure 2 is called overfitting. Machine learning makes accurate predictions within samples. However, a model built as in Figure 2 would almost certainly fail to predict out-of-sample data. Here is where randomness becomes useful. Several trees grown on the basis of randomly selected samples constitute a random forest. A random forest grown for causal inference is a causal forest. Essentially, machine learning creates additional outcome data ex-post by building models with high predictive power, although often with an uninterpretable structure, from a large number of data.

The theoretical framework of a causal forest can be summarized as follows. Only one of two potential treated and untreated outcomes can be observed from a dataset. The difference between treated and untreated outcomes would be biased if the treated observations were not selected randomly. Rosenbaum and Rubin (1983) proposed unconfoundedness, that is, the assumption that the treatment is independent of the potential outcomes conditional on propensity (features) of observations. The continuity assumption requires nearby observations in the feature space to generate similar outcomes. If this assumption holds, nearby observations can be treated as having come from a randomized experiment. The continuity assumption generally holds in random forests as they usually produce smooth response surfaces (Bühlmann and Yu, 2002).

However, treatment effects would still vary among regions in the feature space. Wager and Athey (2018) show that consistency can be guaranteed by enforcing the leaves of trees to become small in all dimensions of the feature space. A key to this approach is the use of double random samples, one to decide the leaves and another to estimate the within-leaf treatment effect. They called it asymptotic inference with causal forests. Their methodology requires the sample to be large enough for sufficient treatment and control units near any propensity spaces.[2] The use of remote sensing data discussed in the next section is a geographically universal coverage of a large number of features.

3. Data

This section describes two main datasets: an economic census and remote sensing data. The economic census is used to represent several dependent variables, whereas the remote sensing data are selected and preprocessed into each regional unit to capture various motivations of FDI to locate (Dunning, 1998).

3.1. Economic Census

The first economic census of Laos was conducted in 2006, followed by those in 2013 and 2018. The result of the third economic census is not yet available to the public. This study uses the second economic census conducted between May 10 and May 30, 2013. The fourth international bridge was opened for traffic by late 2013 or after the second economic census. Hence, only the impacts of the first three Mekong bridges between Laos and Thailand, which were opened for traffic by 2011, can be examined. The second economic census covers all economic entities, including non-profit organizations, foreign representatives, and international organizations, regardless of the registration status. The economic census excludes family-based agriculture, shops without a fixed location, or those operating within military or police camps. The census also excludes entities that are closed or have ceased to operate for more than 3 months at the time of the surveys.

Note that only operational firms were included in the economic census. There are alternative sources of data on foreign firms, such as business registration compiled by the Ministry of Industry and Commerce or investment licenses issued by the Ministry of Planning and Investment to foreign firms. However, these data have serious drawbacks and inconsistencies. For example, not all foreign firms receiving licenses actually started operation. Periodic cancellation of a license issued to inactive applicators partly reveals the true scale of the problem. Furthermore, the administration of FDI and, therefore, the statistics of foreign firms were assigned to different ministries several times since the 1990s. Till around 2010, all foreign investments were required to file applications at the Ministry of Planning and Investment. However, applications that did not involve land concession were later moved to the Ministry of Industry and Trade. Nevertheless, investments in several SEZs were processed separately by a committee established specifically to administer SEZs. The compilation of a consistent dataset of FDI from these sources was complicated. In this study, we chose the economic census as the most consistent and ready-to-use dataset on FDI in Laos.

Locations of foreign firms are identified through the province, district, and village names provided by each surveyed entity in the economic census. In 2013, there were 17

[2] See the GRF package of R statistical language for further information on their methodology in the causal forest growing processes.

provinces, including one capital, and 140 districts. The number of villages has been decreasing recently, yet there were approximately 8,000 villages in 2013. Considering that only 328 villages have managed to attract foreign firms, a village is too small a unit to study FDI location. However, distances between villages in the same province varied from 27 km to more than 100 km. The longest distance between villages in the same province is more than 100 km in all provinces, while the maximum approaches 270 km. Considering the lack of transport infrastructure in Laos, the province is too large a unit of analysis, given the accessible range of foreign firms. In the capital, where the districts are small, the average distances between villages within the same districts varied between 2 km. In other provinces, the distances vary from 10–25 km. Although the average distance between villages is still larger than the average commuting distance in Laos, districts can be considered as the administrative unit closest to the daily operational range of general firms.

Lao Standard Industrial Classification (LSIC) provides the activities of the surveyed firms, which includes five-digit industry codes. We aggregated the five-digit codes at a one-digit level from 0 to 9. The description of the major type of activity found in each one-digit-level code for the second economic census is as follows:

LSIC 0: pig; chicken; fish farms, rubber; banana; coffee plantations, mining
LSIC 1: garment; wood; charcoal factories, mineral water plants
LSIC 2: construction material; electric cable manufacturers
LSIC 3: furniture manufacturers
LSIC 4: retail shops
LSIC 5: hotels, restaurants
LSIC 6: telecommunication; financial services
LSIC 7: transportation services
LSIC 8: schools, clinics, hospitals
LSIC 9: beauty; massage salons, barber shops

In 1992, 13 foreign firms were still operational in Laos. This number increased steadily but slowly during the 1990s. The number of foreign firms surpassed 100 only in 2002. In contrast, there was a tenfold increase in the number of foreign firms, from 84 in 2001 to 865 in 2010. The distribution of foreign firms by the district is illustrated in Figure 3. The green plus signs indicate the location of the Mekong bridges completed by 2011. Geographically, the districts in the capital city received the largest number of foreign firms in almost all industries, except LSIC3, which consists mainly of furniture manufacturing. Furniture is mostly produced from wood in Laos. The forest cleared before the construction of the large-scale hydroelectric dam has been the main source of wood supply of Laos since the 1990s. Foreign firms seeking this large supply of wood are often located near the dam construction sites. In contrast, retail shops (LSIC4) owned by foreigners are observed in almost all districts, similarly for beauty shops (LSIC9), although there are few foreign firms in the eastern part of the country. Foreign firms located near the second and the third international bridges are limited to LSIC1 and LSIC2, as well as the manufacturing industries in addition to the aforementioned LSIC3. Clusters of foreign firms related to plantations can be seen along the border with China and in the highlands in the southern part of the country, stretching from the border with Thailand to that of Vietnam (LSIC0).

=== Figure 3 ===

3.2. Remotely Sensed District Data

We examine various elements related to FDI motives, which include seeking resources, markets, efficiency, and strategic assets (Dunning, 1998). We match these elements with data generated from earth observation data, that is, remote sensing data and online routing systems. First, we try capturing resources with land cover observed by satellites. Natural resources above the ground, for example, forests and water, can be easily detected by satellites. The application of satellite images to detect petroleum and mineral resources dates back to the 1970s (Halbouty, 1976). In this study, we aggregate 38 types of land cover categorized by satellite images in a dataset made available by the European Space Agency. We aggregate the size in square kilometers for the 140 districts in Laos. The meaning of each type of land cover is as follows. We use land cover data as a proxy for resources that may influence FDI's decision on location in Laos.

lc10: Cropland, rainfed
lc11: Herbaceous cover
l12: Tree or shrub cover
lc20: Cropland, irrigated or post-flooding
lc30: Mosaic cropland (>50%) / natural vegetation (tree, shrub, herbaceous cover) (<50%)
lc40: Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%) / cropland (<50%)
lc50: Tree cover, broadleaved, evergreen, closed to open (>15%)
lc60: Tree cover, broadleaved, deciduous, closed to open (>15%)
lc61: Tree cover, broadleaved, deciduous, closed (>40%)
lc62: Tree cover, broadleaved, deciduous, open (15-40%)
lc70: Tree cover, needleleaved, evergreen, closed to open (>15%)
lc71: Tree cover, needleleaved, evergreen, closed (>40%);0;60;0
lc72: Tree cover, needleleaved, evergreen, open (15-40%);0;80;0
lc80: Tree cover, needleleaved, deciduous, closed to open (>15%)
lc81: Tree cover, needleleaved, deciduous, closed (>40%)
lc82: Tree cover, needleleaved, deciduous, open (15-40%)
lc90: Tree cover, mixed leaf type (broadleaved and needleleaved)
lc100: Mosaic tree and shrub (>50%) / herbaceous cover (<50%)
lc110: Mosaic herbaceous cover (>50%) / tree and shrub (<50%)
lc120: Shrubland
lc121: Shrubland evergreen
lc122: Shrubland deciduous
lc130: Grassland
lc140: Lichens and mosses
lc150: Sparse vegetation (tree, shrub, herbaceous cover) (<15%)
lc151: Sparse tree (<15%)

lc152: Sparse shrub (<15%)
lc153: Sparse herbaceous cover (<15%)
lc160: Tree cover, flooded, fresh or brakish water
lc170: Tree cover, flooded, saline water
lc180: Shrub or herbaceous cover, flooded, fresh/saline/brakish water
lc190: Urban areas
lc200: Bare areas
lc201: Consolidated bare areas
lc202: Unconsolidated bare areas
lc210: Water bodies
lc220: Permanent snow and ice

We next consider a variable to represent the market size. Head and Mayer (2004) specified the need to consider nearby regions when quantifying the market potential. The FDI data used in this study are originally at the village level. Aggregating FDI into a larger district geographic boundary assumes that the demand and supply in nearby villages are also considered by foreign firms when making location decisions. The population may be used as a proxy for a region's market size. The use of population is, however, problematic without complementing income data. Besides, no annual population data by the district as well as by gross regional products at the district level exist in Laos. Following Henderson et al. (2012), we instead use remotely sensed nighttime light as a proxy for gross regional products. No nighttime light could be observed from space by 2013 in many districts in Laos. This problem can be addressed by the crop land area discussed earlier. In fact, Keola et al. (2015) demonstrated how nighttime light along with land cover data better capture the scale of economic activities in developing countries at the district level in Mekong regions. The size of cropland derived from the aforementioned land cover data can indicate the size of agricultural activities that emit less nighttime light.

Efficiencies discussed in efficiency-seeking FDI encompass a wider range of location advantages, for example, lower production costs because of lower wage, lower logistic costs, or lower local taxes and fees. Such region-specific information is critical to a firm's operation but often difficult to obtain in developing countries at the subnational level. In this study, we use indicators specific to districts, such as longitude, latitude, and distance to international bridges by the length of road and travel time. We also add the nearest distances to the border of each surrounding country (Cambodia, China, Myanmar, and Vietnam). The location information may capture the relative efficiency of each district from the foreign investors' perspective. The indicator on strategic asset-seeking is probably the most difficult to be captured through earth observation data. Cui et al. (2013) listed advanced technology, brand, and managerial know-how as strategic assets. These intangible assets are unlikely to be observable by satellite, while it is also unlikely to exist in less developed destinations. However, tangible strategic assets such as physical infrastructures can be captured through nighttime light and land cover. Airports and seaports are almost visible from the sky at night. We use these indicators on tangible assets as those on strategic asset-seeking FDI.

4. Estimation Results

This section presents and discusses the results obtained in this study. We started with the case that pooled all samples and considered the opening of the nearest international bridge as the treatment. We then examined the impacts of each international bridge on FDI separately before verifying how the assumption of the treated districts by different distances from the international bridges affects the estimated ATE.

4.1. Basic Results

We start with a basic case where all data are included. A district is considered treated on completion of the nearest bridge, among the first to the third international bridges. The first international bridge started operation in the first quarter of 1994. The second international bridge was completed in December 2006 but opened for regular traffic in January 2007. The third international bridge started regular operation in November but was too late for FDI registered that year. Thus, the start year of our analysis is set to 1994, 2007, and 2012 for the first, second, and third international bridges, respectively. In other words, 140 districts in Laos were grouped into three based on the nearest international bridge. The districts near the first domestic bridge were excluded from the sample because they could use the domestic Mekong bridge instead of the three international bridges examined in this study. For districts near the first international bridge, the treatment value is set equal to 0 up to 1993 and 1 in 1994 when the bridge became operational, and increased by one unit each subsequent year. The treatement value is set in the same way for the second and third international bridges, although the treatment is considered to start in 2007 and 2012 respectively. Namely, following Hirano and Imbens (2004), we introduce continuous treatments in this study as our data are annual and span over two decades.

The result is reported in Table 1. As illustrated earlier, the tree (model) uses the same explanatory variable for both directions. The concept of a coefficient with a fixed sign does not exist in partition trees. The importance of variables is probably the closest concept to the coefficient of explanatory variables in regression analysis. Column "var" specifies the explanatory variables. The numbers in each column to the right indicate the importance of each variable. The importance of a variable is computed as follows. First, the weighted frequency of a variable in each depth is computed by dividing its frequency by the total frequency of all variables. The mean of the weighted frequency of a variable across all depths indicates the importance of a variable. Therefore, the higher value implies that the use of variables improves the predictive power of the model. The importance of variables sums up to 1 in each column. The variables are sorted in a descending order with a value in column "all," where the dependent variable is the sum of FDI in all industries. Columns LSIC0 to LSIC9 show the importance when FDIs by each industry are the dependent variables. The background color of each cell indicates the relative value in each column, where the darker the color, the higher the value. The gradient color background makes it easier to identify the more important variables in the same column (industry).

=== Table 1 ===

In the case of aggregated FDI, the model considers that nighttime light, several types of land covers, distance to the border with China and Thailand, distance and time to the first international bridge are among the top 10 important predictors of FDI. Nighttime light, a proxy for market size, accounts for 0.29, four times larger than the second most important variable. Note that the importance is not provided for the treatment but only for explanatory variables. The ATE (within brackets) is 0.57, which means that if treated, a district is expected to attract about 0.6 foreign firms on average every year adjusted by their features based on the important variables.

The impacts by industries are as follows. Tree cover (lc170), nighttime light, area, and distance to the border with China are the top four important variables for farming activities (LSIC0), although ATE declined to 0.27. For light manufacturing industries (LSIC1), the ATE declined to about 0.017, while travel time to the first international bridge was the most important variable. The travel time and road distance to the first international bridge account for more than 40% of all important variables for FDI in light industries. This result reflects well the concentration of FDI in light industries around the capital. This finding on the role of travel time in LSIC1 can be considered a good news for policymakers since such variables (features) of a district can be changed substantially. For example, the time taken for travel from Vang Vieng district, slightly farther than 100 km to the north, to reach the capital city before the completion of the Vientiane–Vang Vieng expressway in 2021 was about 4 hours[3]. However, the travel time was reduced to about an hour with the expressway. The extension of this expressway further to China is expected to be completed in the next few years. If the model's prediction is accurate, the expressway to China's border, which will substantially reduce the access time to the first international bridge by districts in northern Laos, will increase the number of foreign firms in these districts. The same is true if districts in the southern part of Laos improve the travel time to the second and third international bridges.

Various variables (border, db1t, db1r) related to connectivity with Thailand are important in construction materials and electric cables manufacturing (LSIC2). Distance to the border with Vietnam also becomes important (0.035) for LSIC2. Market size and combination of tree cover and cropland (lc40) are important for furniture manufacture (LSIC3). As much as 80% of foreign firms in Laos are retail shops (LSIC4) in a majority of the districts. Besides the variables related to accessibility to Thailand and China, the model finds that latitude (x) and longitude (y) are also important. Market size and proximity to Chinese border are important for foreign firms in hotel and restaurant activities (LSIC5), which also has the highest ATE of approximately 0.46, compared with 0.27 in farming activities. Nighttime light, or demand, is the most important feature for the location of FDI in telecommunication and financial services (LSIC6), schools, clinics and hospitals (LSIC8), and beauty salons (LSIC9). Land area, broadleaved tree cover (lc60), cropland (lc10), and accessibility to Thailand are more important than market size for transport services (LSIC7). Approximately 30–40 features have importance greater than zero. All features correspond to tangible properties detected by earth observation or online routing system. Consequently, there is much scope for concrete policy measures.

[3] https://www.eastasiaforum.org/2021/01/15/what-next-for-laos-growth-strategy/

4.2. Results by Each Bridge

In the previous section, a district is considered treated on the opening of the nearest international bridge. Although a machine constructs the model with the data, in causal inference with causal forests, human still has to tell the machine which the treated samples are. Examining impacts of infrastructure projects is complicated. Unlike medical trials or subsidies to low-income households, identifying treated samples is not straightforward. In our case, we do not know which district would actually use the bridge and, therefore, be considered a treated sample. In this section, we examine whether changing the boundaries of the treated and control groups alters the results.

We start by growing causal trees for each bridge separately. The results for the first to the third international bridges are shown in Tables 2, 3, and 4, respectively. For the first international bridge, the two types of land cover, lc190 (urban) and lc120 (shrubland), follow nighttime light, a proxy for market size, as the three most important features when the dependent variable is the overall FDI (Table 2). Distance to the border with China is also important, along with several other types of land cover (lc40, mosaic natural vegetation, lc121, evergreen shrubland, lc20, cropland). The all-industry ATE remains almost similar to the case of basic result reported in the Table 1 (0.55 vs. 0.57). Similar to the basic result, LSIC5 (retail shops) is the largest activity to be attracted by the first international bridge. However, the ATE for FDI in farming activities declined substantially from 0.27 in the basic result to 0.06. The first international bridge is predicted to attract FDI in all industries, judging from the positive ATEs.

=== Table 2 ===

For the second international bridge, the most important feature remains the market size, followed by lc100 (mosaic tree and shrub) and lc30 (mosaic cropland/natural vegetation), as shown in Table 3. Nighttime light is the most important feature in all activities, except for LSIC6 (telecommunication and financial services). The ATEs for LSIC1 (light manufacturing), LSIC7 (transportations services), LSIC8 (schools, clinics, hospitals), and LSIC9 (beauty salons etc.) are 0, indicating that the districts closest to the second international bridge did not have sufficient demand to attract FDI in these activities by 2013.

=== Table 3 ===

For the third international bridge, the four important features are lc60 (tree cover, broadleaved, deciduous, closed to open), lc10 (rainfed cropland), travel time to the first international bridge, and lc100 (mosaic tree), as shown in Table 4. Notably, as the third international bridge is located between the first and the second international bridges, the districts in this area can choose to use the other two bridges with fewer additional costs. No firms in LSIC6 (telecommunication and financial services), in addition to LSIC1, 7, 8, and 9, are predicted to be attracted by the third international bridge. Similar to the case of the second international bridge, the causal forest builds a model with the data, but they do not predict outcomes that never happened in the sample data period. In other words, there were no FDIs in LSIC0, 6, 7, 8, and 9 in the districts near the third international bridge by 2013.

=== Table 4 ===

Next, we examine whether the range of assumed treatment alters the ATE. We change the assumed treatment boundary defined by road distance from each bridge by 10 km at each step and compute the ATE for the three bridges. The result is illustrated in Figure 4. We find that for the first international bridge, the ATE is almost stable around one, regardless of the assumed treated regions. Since the farthest district within the area of the first international bridge is about 600 km away to the border area with China, this finding predicts the impacts of the bridge to extend that far from the capital. In fact, goods entering from Thailand through the first international bridge reach districts 600 km away in the north, some of which also cross the border to China. In the opposite direction, goods entering Laos from the north arrive in the capital and cross the bridge to Thailand as well. Therefore, it is rather intuitive to look at the foreing firms handling the transit trade between Thailand and China over the bridge as the impact of the bridge.

=== Figure 4 ===

The ATE for the second and third international bridges varies by the range of assumed treated regions. The ATE for the second international bridge is approximately 10 but declines to 2 when regions up to 50 km from the bridge are considered treated. The ATE declines further and stabilizes at 1 after nearly 100 km of the assumed treated distances. The high ATE for the second international bridge likely reflects the agglomeration of firms, which are mostly Japanese affiliates, in several SEZ zones within 20 km from the bridge. The ATE of the third international bridge resembles that of the second, although it starts from slightly more than 5 instead of 10 before declining to be stable at approximately 1.

5. Concluding Remarks

This study applied the causal forest developed by Athey and co-investigators to measure the impacts of international bridges on foreign firms' locations in Laos. We also proposed using earth observation data, which are freely available and back in time in conjunction with an online routing system to overcome data limitations in developing countries. Although the structure of the causal tree itself might not be interpreted sensibly, important features (explanatory variables) that may influence the FDI were found to fit reasonably well with the findings in existing literature based on regression analysis. However, as the ATE differs with arbitrary spatial boundaries from the bridge, particulary for the second and the third bridges, we confirmed that human decisions still affect the finding using machine learning technics, although interpretable at least in this study. We argue that how subjective decision affects results is worth exploring as it would help make the findings more objective.

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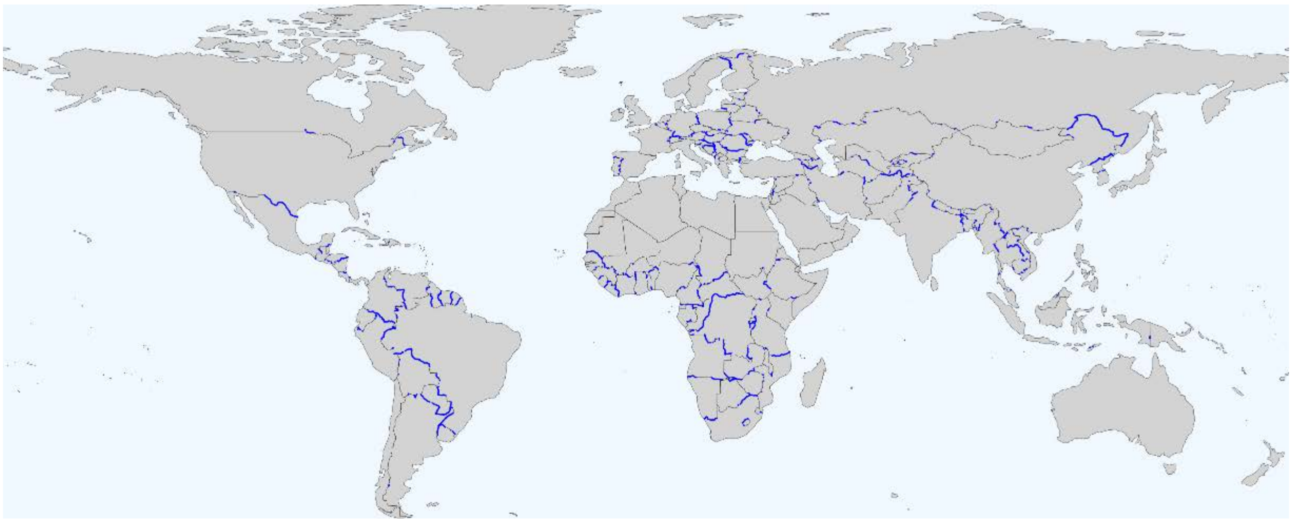
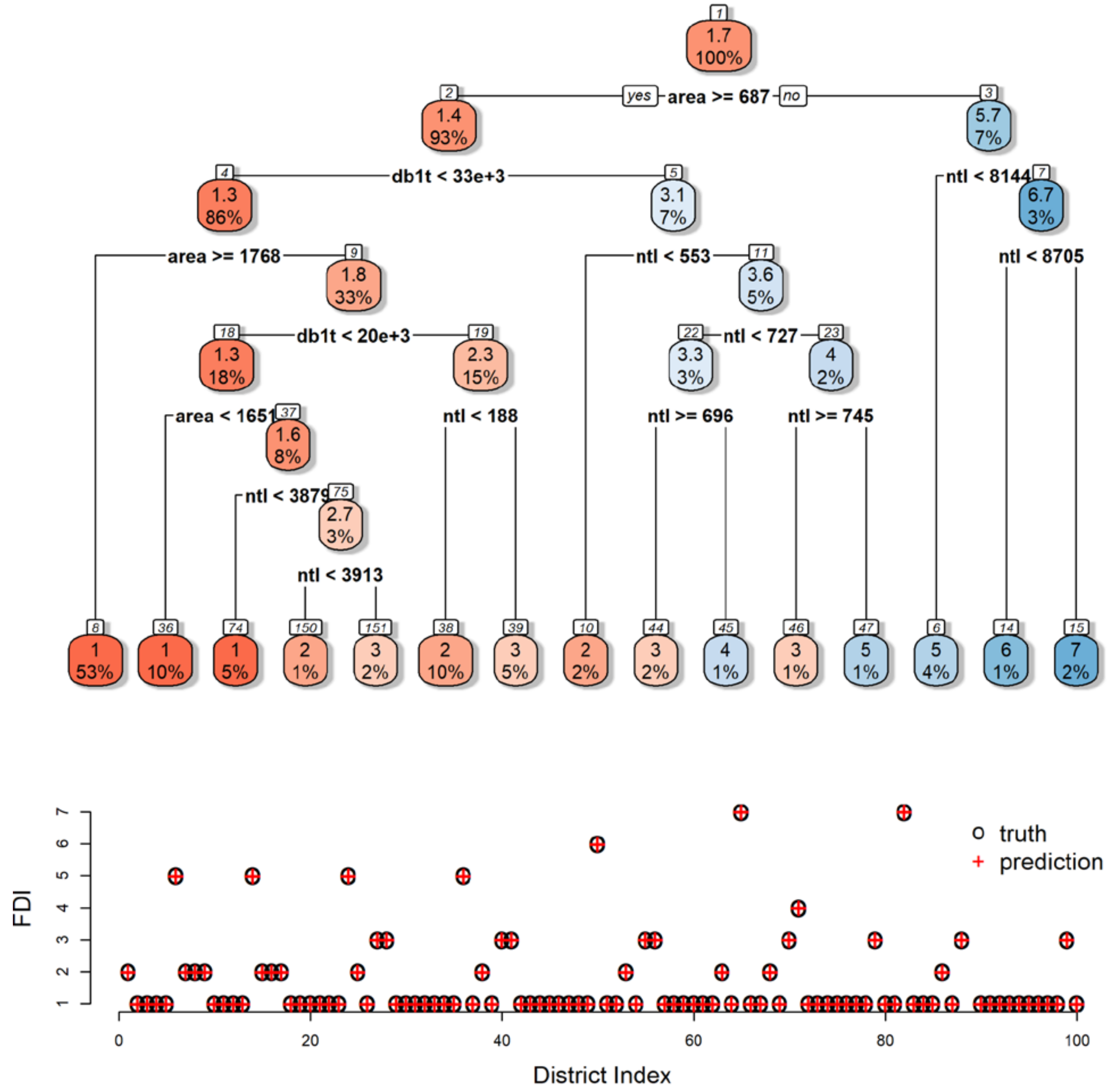
Figure 1. Global Map of the River Borders



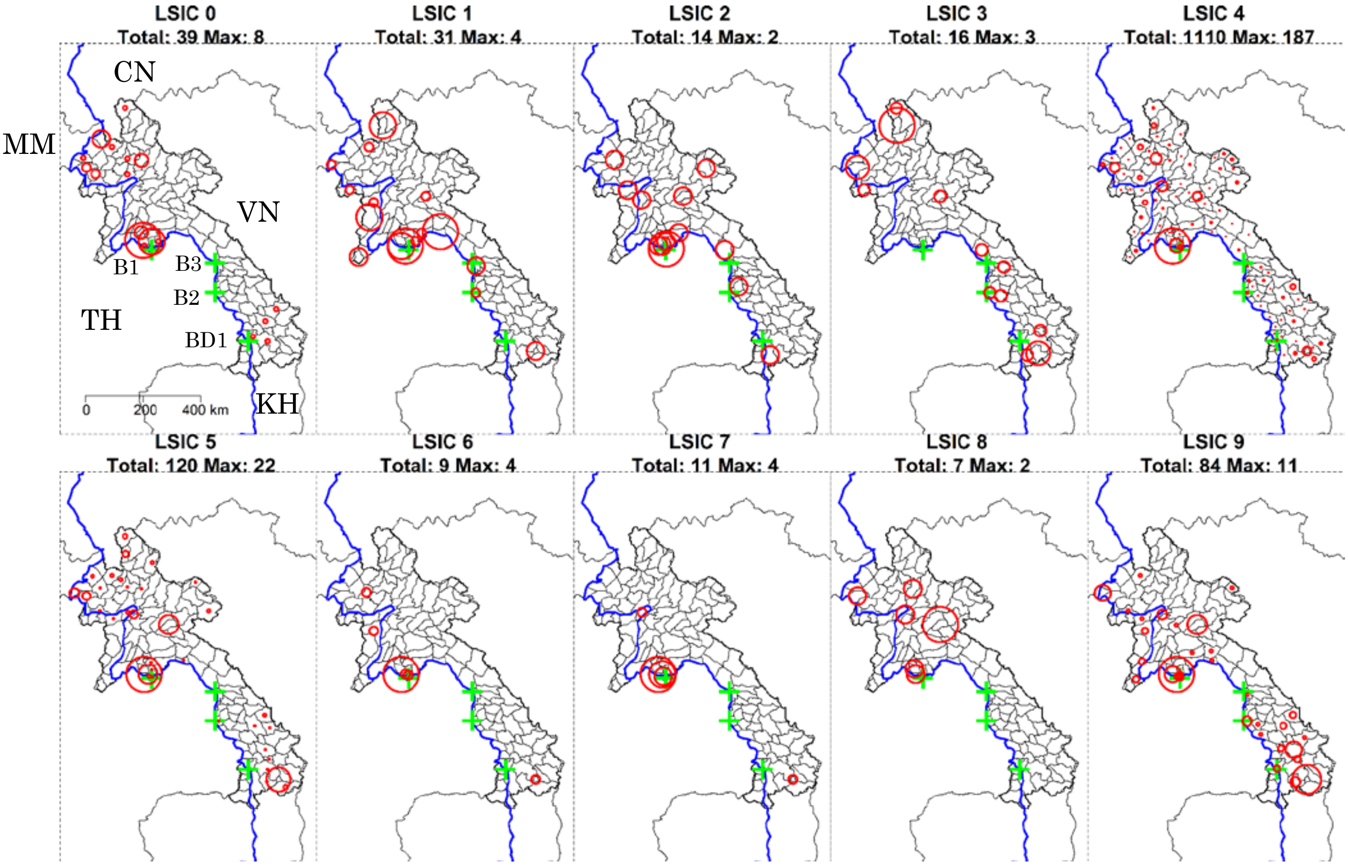
Source: Authors' drawing based on Popelka and Smith (2020) and Global Administrative Unit Layers (FAO).

Figure 2. Overfitting Partition Tree (Target: FDI, Features: area (land area), nighttime light (ntl), and travel time to the first international bridge)



Source: Authors' computation based on the part of Economic Census 2013 (Ministry of Planning and Investment).

Figure 3. Location of Foreign Firms and the four Mekong Bridges in Laos in 2013



Source: Authors' compilation based on Economic Census 2013 (Ministry of Planning and Investment) and Global Administrative Unit Layers (FAO).

Notes: LSIC is Lao Standard Industrial Classification. Circles denote the number of firms, where the largest is equal to Max for each LSIC. Plus signs denote the location of the Mekong bridges. CN: China, KH: Cambodia, MM: Myanmar, TH: Thailand, VN: Vietnam. B1: The first international Mekong bridge, B2: the second internal Mekong bridge, B3: the third international Mekong bridge. BD1: the first domestic Mekong bridge.

Table 1. Basic Result (sample: all districts, treatment: nearest international Mekong bridge opened)

var (ATE)	all (0.578)	LSIC0 (0.274)	LSIC1 (0.017)	LSIC2 (0.014)	LSIC3 (0.009)	LSIC4 (0.011)	LSIC5 (0.462)	LSIC6 (0.047)	LSIC7 (0.005)	LSIC8 (0.003)	LSIC9 (0.002)
ntl	0.299	0.119	0.096	0.074	0.182	0.016	0.286	0.301	0.058	0.147	0.187
lc120	0.071	0.054	0.041	0.063	0.025	0.092	0.069	0.086	0.010	0.036	0.140
lc190	0.065	0.004	0.024	0.003	0.048	0.003	0.072	0.035	0.012	0.088	0.028
area	0.056	0.083	0.007	0.006	0.009	0.006	0.054	0.029	0.183	0.143	0.017
borderc	0.043	0.071	0.066	0.061	0.006	0.071	0.045	0.042	0.015	0.005	0.016
lc10	0.035	0.031	0.015	0.008	0.013	0.009	0.027	0.022	0.079	0.016	0.013
db1t	0.034	0.006	0.229	0.102	0.021	0.085	0.021	0.075	0.084	0.064	0.026
lc11	0.032	0.012	0.015	0.010	0.020	0.012	0.034	0.013	0.009	0.008	0.018
bordert	0.031	0.006	0.006	0.105	0.075	0.012	0.039	0.029	0.034	0.052	0.003
lc40	0.030	0.005	0.013	0.070	0.164	0.010	0.020	0.016	0.017	0.026	0.017
lc30	0.028	0.009	0.011	0.092	0.037	0.027	0.028	0.017	0.015	0.082	0.017
lc20	0.028	0.009	0.041	0.022	0.069	0.005	0.024	0.021	0.031	0.052	0.066
lc70	0.028	0.016	0.007	0.044	0.018	0.027	0.023	0.059	0.071	0.007	0.103
lc121	0.027	0.021	0.033	0.013	0.056	0.020	0.032	0.050	0.019	0.010	0.098
lc50	0.025	0.016	0.020	0.012	0.022	0.056	0.033	0.017	0.026	0.032	0.019
x	0.022	0.102	0.013	0.017	0.004	0.074	0.021	0.009	0.010	0.006	0.039
db1r	0.022	0.019	0.184	0.084	0.042	0.062	0.022	0.036	0.042	0.052	0.025
y	0.017	0.072	0.009	0.026	0.003	0.097	0.023	0.043	0.012	0.005	0.004
lc100	0.015	0.045	0.023	0.026	0.033	0.020	0.026	0.012	0.055	0.025	0.016
lc210	0.015	0.011	0.005	0.006	0.023	0.002	0.016	0.017	0.010	0.014	0.007
borderv	0.013	0.008	0.003	0.035	0.016	0.014	0.019	0.009	0.012	0.009	0.006
lc130	0.011	0.008	0.001	0.018	0.016	0.031	0.013	0.008	0.003	0.003	0.016
lc60	0.009	0.004	0.030	0.008	0.010	0.025	0.011	0.008	0.149	0.076	0.064
lc180	0.008	0.016	0.005	0.002	0.005	0.014	0.009	0.008	0.003	0.004	0.003
db3r	0.007	0.009	0.016	0.004	0.024	0.011	0.007	0.006	0.003	0.002	0.009
db3t	0.006	0.019	0.013	0.004	0.003	0.020	0.005	0.005	0.003	0.002	0.004
db2r	0.005	0.019	0.021	0.005	0.022	0.012	0.004	0.006	0.002	0.002	0.011
dbd1r	0.004	0.020	0.021	0.004	0.022	0.019	0.003	0.007	0.002	0.002	0.010
db2t	0.004	0.027	0.017	0.007	0.003	0.063	0.004	0.005	0.003	0.001	0.005
dbd1t	0.003	0.026	0.015	0.009	0.003	0.082	0.005	0.007	0.003	0.002	0.005
lc61	0.002	0.002	0.001	0.001	0.004	0.001	0.003	0.003	0.002	0.026	0.007
lc170	0.002	0.127	0.002	0.004	0.002	0.000	0.003	0.000	0.001	0.001	0.000
lc110	0.000	0.001	0.000	0.054	0.000	0.000	0.000	0.000	0.023	0.001	0.000
lc0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
lc12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
lc122	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
lc140	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: Authors' computation.

Notes: For column names. ATE: average treatment effect, LSIC: Laos' Standard Industrial Classification, var: explanatory variables. For row names. area: land area, border[c,k,m,v]: distance to Chinese, Cambodian, Myanmarese, Vietnamese borders, did: district code, db?r: road distance to international Mekong bridge no.?, dbd?r: road distance to domestic Mekong bridge no.?, db?t: travel time to international Mekong bridge no.?, dbd?t: travel time to domestic Mekong bridge no.?, lc?: land cover of type?, ntl: sum of nighttime light intensity, x: latitude, y: longitude.

Table 2. Result by Bridge (sample: districts in the first international Mekong bridge area, treatment: the first International Mekong bridge opened)

var (ATE)	all (0.559)	LSIC0 (0.069)	LSIC1 (0.022)	LSIC2 (0.019)	LSIC3 (0.009)	LSIC4 (0.006)	LSIC5 (0.445)	LSIC6 (0.05)	LSIC7 (0.006)	LSIC8 (0.004)	LSIC9 (0.003)
ntl	0.221	0.033	0.118	0.058	0.158	0.011	0.185	0.221	0.031	0.091	0.187
lc190	0.111	0.002	0.013	0.005	0.012	0.002	0.120	0.065	0.013	0.107	0.030
lc120	0.101	0.015	0.045	0.116	0.075	0.036	0.115	0.115	0.009	0.011	0.120
borderc	0.056	0.016	0.067	0.040	0.006	0.080	0.041	0.051	0.008	0.012	0.007
lc40	0.050	0.009	0.013	0.107	0.187	0.017	0.047	0.025	0.026	0.028	0.020
y	0.050	0.021	0.009	0.013	0.003	0.122	0.063	0.042	0.043	0.064	0.003
lc121	0.046	0.024	0.046	0.026	0.090	0.019	0.035	0.073	0.021	0.030	0.126
lc20	0.037	0.008	0.034	0.012	0.047	0.006	0.026	0.031	0.039	0.035	0.060
lc50	0.029	0.040	0.011	0.010	0.040	0.017	0.030	0.037	0.027	0.025	0.018
area	0.026	0.079	0.005	0.004	0.006	0.006	0.042	0.010	0.098	0.106	0.007
lc30	0.024	0.011	0.017	0.066	0.044	0.033	0.028	0.028	0.029	0.069	0.011
lc70	0.024	0.040	0.042	0.018	0.016	0.072	0.019	0.072	0.213	0.048	0.104
lc60	0.023	0.005	0.022	0.010	0.010	0.023	0.031	0.012	0.138	0.041	0.063
lc10	0.022	0.013	0.114	0.014	0.032	0.008	0.020	0.023	0.113	0.083	0.050
x	0.020	0.003	0.012	0.007	0.008	0.073	0.019	0.006	0.005	0.002	0.031
bordert	0.019	0.004	0.004	0.118	0.061	0.006	0.028	0.020	0.057	0.040	0.006
lc11	0.018	0.011	0.090	0.014	0.021	0.014	0.018	0.013	0.009	0.011	0.051
lc210	0.016	0.076	0.007	0.004	0.012	0.001	0.018	0.021	0.008	0.011	0.013
db1r	0.015	0.025	0.082	0.003	0.008	0.050	0.010	0.028	0.011	0.011	0.004
lc100	0.012	0.065	0.021	0.010	0.030	0.010	0.025	0.008	0.060	0.050	0.008
db1t	0.010	0.024	0.136	0.006	0.005	0.195	0.009	0.017	0.006	0.015	0.003
lc180	0.010	0.121	0.006	0.004	0.005	0.002	0.009	0.013	0.002	0.005	0.003
dbd1r	0.009	0.019	0.013	0.031	0.025	0.014	0.007	0.005	0.002	0.002	0.006
db2r	0.009	0.018	0.013	0.028	0.029	0.014	0.004	0.005	0.003	0.002	0.008
borderv	0.008	0.006	0.002	0.013	0.019	0.015	0.010	0.009	0.009	0.005	0.004
db3r	0.008	0.007	0.014	0.031	0.017	0.018	0.006	0.015	0.002	0.012	0.020
lc61	0.007	0.003	0.001	0.001	0.008	0.001	0.006	0.004	0.002	0.047	0.008
db3t	0.005	0.005	0.014	0.046	0.002	0.019	0.005	0.006	0.002	0.010	0.004
lc130	0.005	0.005	0.002	0.050	0.017	0.014	0.007	0.016	0.005	0.005	0.021
db2t	0.004	0.005	0.010	0.045	0.002	0.048	0.005	0.004	0.002	0.010	0.003
dbd1t	0.004	0.006	0.016	0.037	0.003	0.054	0.004	0.005	0.003	0.012	0.002
lc170	0.004	0.280	0.002	0.004	0.001	0.000	0.008	0.001	0.001	0.000	0.000
lc110	0.000	0.001	0.000	0.050	0.000	0.000	0.000	0.000	0.001	0.000	0.000
lc0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
lc12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
lc122	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
lc140	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: Authors' computation.

Notes: For column names. ATE: average treatment effect, LSIC: Laos' Standard Industrial Classification, var: explanatory variables. For row names. area: land area, border[c,k,m,v]: distance to Chinese, Cambodian, Myanmarese, Vietnamese borders, did: district code, db?r: road distance to international Mekong bridge no.?, dbd?r: road distance to domestic Mekong bridge no.?, db?t: travel time to international Mekong bridge no.?, dbd?t: travel time to domestic Mekong bridge no.?, lc?: land cover of type?, ntl: sum of nighttime light intensity, x: latitude, y: longitude.

Table 3. Result by Bridge (sample: districts in the second international Mekong bridge area, treatment: the second international Mekong bridge opened)

var (ATE)	all (0.875)	LSIC0 (0.902)	LSIC1 (0)	LSIC2 (-0.004)	LSIC3 (0.015)	LSIC4 (0.011)	LSIC5 (0.748)	LSIC6 (0.047)	LSIC7 (0)	LSIC8 (0)	LSIC9 (0)
ntl	0.129	0.149	0	0.198	0.075	0.099	0.136	0.094	0	0	0
lc100	0.099	0.083	0	0.019	0.028	0.037	0.094	0.039	0	0	0
lc30	0.092	0.099	0	0.052	0.030	0.070	0.127	0.059	0	0	0
lc50	0.060	0.058	0	0.080	0.016	0.045	0.048	0.117	0	0	0
lc190	0.057	0.067	0	0.128	0.042	0.094	0.055	0.022	0	0	0
y	0.053	0.040	0	0.010	0.034	0.012	0.049	0.011	0	0	0
lc10	0.049	0.054	0	0.053	0.031	0.065	0.037	0.101	0	0	0
lc121	0.047	0.047	0	0.039	0.015	0.094	0.045	0.044	0	0	0
lc120	0.045	0.043	0	0.045	0.037	0.052	0.041	0.054	0	0	0
lc60	0.040	0.044	0	0.018	0.016	0.069	0.035	0.069	0	0	0
dbd1r	0.035	0.039	0	0.009	0.009	0.009	0.049	0.020	0	0	0
lc40	0.024	0.022	0	0.039	0.054	0.045	0.030	0.056	0	0	0
lc130	0.024	0.017	0	0.024	0.032	0.024	0.017	0.054	0	0	0
db3r	0.023	0.021	0	0.011	0.025	0.006	0.022	0.010	0	0	0
area	0.023	0.016	0	0.019	0.019	0.015	0.019	0.012	0	0	0
lc20	0.021	0.023	0	0.041	0.027	0.059	0.020	0.021	0	0	0
lc180	0.020	0.016	0	0.022	0.045	0.024	0.015	0.024	0	0	0
db1r	0.020	0.018	0	0.007	0.029	0.005	0.014	0.008	0	0	0
dbd1t	0.019	0.023	0	0.002	0.008	0.009	0.022	0.016	0	0	0
lc11	0.019	0.024	0	0.039	0.068	0.071	0.027	0.031	0	0	0
lc210	0.017	0.011	0	0.040	0.018	0.019	0.012	0.018	0	0	0
borderc	0.015	0.021	0	0.006	0.035	0.007	0.020	0.016	0	0	0
x	0.011	0.012	0	0.020	0.023	0.008	0.013	0.014	0	0	0
db1t	0.011	0.009	0	0.009	0.054	0.008	0.006	0.012	0	0	0
db3t	0.011	0.007	0	0.012	0.051	0.009	0.005	0.013	0	0	0
db2r	0.010	0.011	0	0.014	0.082	0.015	0.007	0.014	0	0	0
db2t	0.008	0.008	0	0.013	0.065	0.008	0.008	0.013	0	0	0
lc70	0.007	0.006	0	0.004	0.004	0.004	0.014	0.009	0	0	0
bordert	0.005	0.005	0	0.015	0.011	0.007	0.005	0.013	0	0	0
borderv	0.004	0.006	0	0.010	0.014	0.012	0.004	0.016	0	0	0
lc170	0.001	0.000	0	0.000	0.002	0.000	0.002	0.001	0	0	0
lc61	0.000	0.000	0	0.000	0.000	0.000	0.000	0.001	0	0	0
lc0	0.000	0.000	0	0.000	0.000	0.000	0.000	0.000	0	0	0
lc110	0.000	0.000	0	0.000	0.000	0.000	0.000	0.000	0	0	0
lc12	0.000	0.000	0	0.000	0.000	0.000	0.000	0.000	0	0	0
lc122	0.000	0.000	0	0.000	0.000	0.000	0.000	0.000	0	0	0
lc140	0.000	0.000	0	0.000	0.000	0.000	0.000	0.000	0	0	0

Source: Authors' computation.

Notes: For column names. ATE: average treatment effect, LSIC: Laos' Standard Industrial Classification, var: explanatory variables. For row names. area: land area, border[c,k,m,v]: distance to the Chinese, Cambodian, Myanmarese, Vietnamese borders, did: district code, db?r: road distance to international Mekong bridge no.?, dbd?r: road distance to domestic Mekong bridge no.?, db?t: travel time to international Mekong bridge no.?, dbd?t: travel time to domestic Mekong bridge no.?, lc?: land cover of type?, ntl: sum of nighttime light intensity, x: latitude, y: longitude.

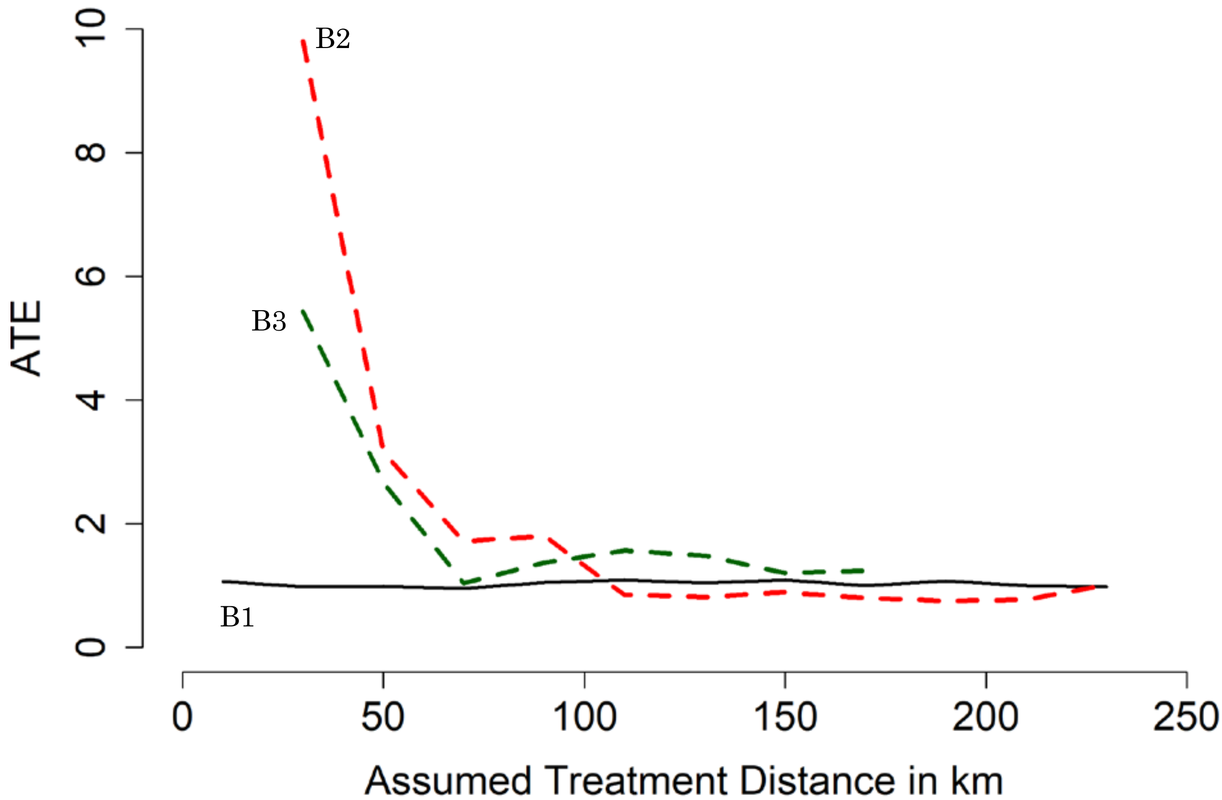
Table 4. Result by Bridge (sample: districts in the third international Mekong bridge area, treatment: the third international Mekong bridge opened)

var (ATE)	all (1.186)	LSIC0 (1.114)	LSIC1 (0)	LSIC2 (0.017)	LSIC3 (0.023)	LSIC4 (0.052)	LSIC5 (1.1)	LSIC6 (0)	LSIC7 (0)	LSIC8 (0)	LSIC9 (0)
lc60	0.119	0.140	0	0.054	0.065	0.026	0.084	0	0	0	0
lc110	0.095	0.038	0	0.067	0.041	0.058	0.050	0	0	0	0
db1t	0.080	0.038	0	0.029	0.000	0.000	0.105	0	0	0	0
lc100	0.060	0.038	0	0.031	0.055	0.095	0.047	0	0	0	0
lc30	0.058	0.013	0	0.072	0.014	0.051	0.050	0	0	0	0
dbd1r	0.053	0.000	0	0.029	0.000	0.000	0.000	0	0	0	0
lc10	0.047	0.034	0	0.053	0.014	0.013	0.021	0	0	0	0
lc130	0.042	0.063	0	0.000	0.118	0.064	0.097	0	0	0	0
dbd1t	0.040	0.013	0	0.056	0.044	0.000	0.042	0	0	0	0
y	0.040	0.013	0	0.011	0.014	0.013	0.031	0	0	0	0
db3t	0.038	0.063	0	0.022	0.014	0.020	0.061	0	0	0	0
lc210	0.038	0.009	0	0.000	0.022	0.000	0.010	0	0	0	0
lc50	0.035	0.068	0	0.011	0.041	0.038	0.042	0	0	0	0
lc20	0.033	0.025	0	0.040	0.000	0.013	0.000	0	0	0	0
ntl	0.029	0.000	0	0.045	0.069	0.128	0.000	0	0	0	0
lc180	0.027	0.000	0	0.045	0.028	0.064	0.000	0	0	0	0
lc40	0.027	0.063	0	0.084	0.043	0.040	0.087	0	0	0	0
lc120	0.022	0.025	0	0.056	0.093	0.045	0.000	0	0	0	0
lc80	0.022	0.013	0	0.000	0.028	0.013	0.000	0	0	0	0
lc70	0.016	0.034	0	0.066	0.016	0.025	0.021	0	0	0	0
borderv	0.013	0.050	0	0.000	0.000	0.058	0.031	0	0	0	0
db1r	0.013	0.038	0	0.000	0.000	0.013	0.021	0	0	0	0
db2t	0.013	0.050	0	0.033	0.000	0.013	0.071	0	0	0	0
db3r	0.013	0.021	0	0.000	0.000	0.007	0.010	0	0	0	0
lc11	0.013	0.025	0	0.029	0.069	0.026	0.000	0	0	0	0
lc121	0.013	0.055	0	0.033	0.057	0.085	0.000	0	0	0	0
area	0.000	0.000	0	0.000	0.049	0.026	0.010	0	0	0	0
borderc	0.000	0.000	0	0.018	0.000	0.000	0.010	0	0	0	0
bordert	0.000	0.013	0	0.029	0.022	0.013	0.000	0	0	0	0
db2r	0.000	0.013	0	0.033	0.049	0.000	0.031	0	0	0	0
lc0	0.000	0.000	0	0.000	0.000	0.000	0.000	0	0	0	0
lc12	0.000	0.000	0	0.000	0.000	0.000	0.000	0	0	0	0
lc122	0.000	0.000	0	0.000	0.000	0.000	0.000	0	0	0	0
lc140	0.000	0.000	0	0.000	0.000	0.000	0.000	0	0	0	0
lc150	0.000	0.000	0	0.000	0.000	0.000	0.000	0	0	0	0
lc151	0.000	0.000	0	0.000	0.000	0.000	0.000	0	0	0	0
lc152	0.000	0.000	0	0.000	0.000	0.000	0.000	0	0	0	0

Source: Authors' computation.

Notes: For column names. ATE: average treatment effect, LSIC: Laos' Standard Industrial Classification, var: explanatory variables. For row names. area: land area, border[c,k,m,v]: distance to the Chinese, Cambodian, Myanmarese, Vietnamese borders, did: district code, db?r: road distance to international Mekong bridge no.?, dbd?r: road distance to domestic Mekong bridge no.?, db?t: travel time to international Mekong bridge no.?, dbd?t: travel time to domestic Mekong bridge no.?, lc?: land cover of type?, ntl: sum of nighttime light intensity, x: latitude, y: longitude.

Figure 4. Basic Result (sample: districts within 250 km of each international Mekong bridge area, treatment: nearest international Mekong bridge opened)



Source: Authors' computation.
Notes: ATE: average treatment effect. B1: The first international Mekong bridge, B2: the second internal Mekong bridge, B3: the third international Mekong bridge.