Business, Management and Economics Research
ISSN(e): 2412-1770, ISSN(p): 2413-855X
Vol. 6, Issue. 10, pp: 127-134, 2020
URL: https://arpgweb.com/journal/journal/8
DOI: https://doi.org/10.32861/bmer.610.127.134

Academic Research Publishing Group

Original Research **Open Access**

Spillovers of Urban Road Infrastructure Investment and Operation: a Case Study Using Synthetic Control Method

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Article History
Received: August 31, 2020
Revised: September 25, 2020
Accepted: October 3, 2020
Published: October 7, 2020

Abstract

This study evaluates the impacts of urban road investment and operation in China, especially the spillover effect attributable to the investment of urban road projects. Using the synthetic control method and difference-in-differences technique and taking the opening of Jiaozhou Bay Bridge and its Subsea Tunnel in China on 30 June 2011 as a natural experiment, this paper investigates the causal effect between urban road investment and its economic impacts. Results show that the project has a positive externality in terms of its contribution to the output and employment: taken the industrial relative output as outcome variable, no matter whether the covariates are controlled or not, the parameters of the interactive terms are positive; taken the industrial relative employment rate as outcome variable, the gap between the treated unit and its counterpart indicates a direct program effect for the treated city as well as a spillover effect across the cities within the sample province. Furthermore, the permutation test ascertains that the probability of achieving a spillover effect as large as the treated city is around 5.88 per cent. Overall, the investment and operation of urban road transportation infrastructure has a noticeable spillover effect. Our results are robust across a series of placebo tests.

Keywords: Urban road investment; Regional economy; Spillover effect; Panel data; Synthetic control method.

1. Introduction

Spillover effect is a type of conventional externality of economic activity or process that affects those who are not directly involved. The positive spillover effect associated with a toll urban road may refer to the benefits between the treated unit, such as a city, a region or a county, and its neighboring units. It is a new trend of urbanization given the interactions among the adjacent cities in China. There are several ways to yield the spillover effect, such as the sustainable operation of an urban toll road, the opening of a newly built high-speed rail or of a brand new airline, to name just a few.

In the literature, several studies such as Zhang (2013), Canning and Pedroni (2008), Duffy-Deno and Dalenberg (1993), and Munnell and Cook (1990), have examine the impacts of transportation infrastructure investment on local or regional economy. Much rigorous research on the spillover effects of transportation infrastructure investment and operation has been conducted so far, particularly the impact of high-speed rail on various levels of economic development across the world (Cotomillan *et al.*, 2007; Froidh, 2008; Gonzalezsavignat, 2004; Gutierrez, 2001; Vickerman, 1997). Analogous situation occurs in OECD countries and other countries such as Spain: transport infrastructure investment has a positive externality associated with growth in labor productivity and total factor productivity (Farhadi, 2015). The railway infrastructure investment and operation in China also has an overall positive external effect (Gutierrez *et al.*, 2010; Yu *et al.*, 2013; Zhang, 2013; Zhou *et al.*, 2016). Specially, the spillover effects on industry output vary from industry to industry and also dissimilar across spillover channels. Transport infrastructure has significant spatial spillover effects on regional economic growth. Given a specific region in China, evidence shows that transport infrastructure in other regions has mostly positive effect but a little bit negative spatial spillover effect as well (Zhang, 2013; Zhou *et al.*, 2016). Surprisingly, no evidence of spatial positive spillovers in productivity of highways has been identified (Holtzeakin and Schwartz, 1996), though this is rarely the case in China. In the meantime, however, negative externalities of road transport including congestion, accidents, environmental damages and oil dependence also coexist and should not be ignored because they have imposed negative impacts on society (Boarnet, 1998; Calthrop and Proost, 1998; Santos *et al.*, 2010). The most relevant article to our research is the rural roads construction program spillover, which indicates employment in firms expands after the completion of the project (Asher and Paul, 2020). Nevertheless, to the best of our knowledge, there exists little empirical research measuring the spillover effects including the industrial output and employment associated with the urban roads investment program on its adjacent units.

The spillover effects can be measured by indicators like industry output and employment rate. In searching for causal links between the investment and operation of urban road infrastructure and its economic impacts we mostly use the synthetic control method (SCM) because it is a powerful econometric strategy that has been widely used recently in this context and perhaps the first time for being used to analyze the urban road spillovers in China.

This paper aims to report on a microeconometric investigation of the spillovers associated with the Jiaozhou Bay Bridge and Jiaozhou Bay Tunnel. Regarding the former, it is currently the longest sea-crossing bridge in the world, and is 26707 meters in length, of which the sea-crossing part is 25881 meters long and 18.5 meters wide; whereas the latter is the longest subsea tunnel in China and also the third longest one in the world, it is 7797 meters in lengths, of which the subsea part is 4095 meters long and 21.5 meters wide. They are so named because both are connected to the Jiaozhou Bay and are located in Qingdao as well, a prefecture-level city of Shandong province, China; either the Jiaozhou Bay Bridge (Figure-1) or the Jiaozhou Bay Subsea Tunnel (Figure-2) has nearly the same construction period and opening time. The Subsea Tunnel got started on June 25 of 2008 and was put into use on June 30 of 2011 after nearly five years of construction, with the total investment being 4.059 bn Yuan. Due to the complex marine corrosion environment, the magnitude of endurance is much more stringent than that of other underground water and ridge tunnels, thus the structure and operation equipments must suffice to the 100-year design service life. By contrast, the Bay Bridge with the total investment being 9.04 bn yuan and a 15-year investment payback period and a twenty-five-year operation period, is less complex in terms of its construction difficulty. The major difference between them is that the bridge extends to an entrance of an inter-province highway whereas the subsea tunnel simply connects the roads across the Jiaozhou Bay.

For simplicity, we consider the mentioned bridge and tunnel as one urban road program. Prior to the opening of the tunnel and bridge, people has to commute by ferry or by highway; both are highly restricted by the weather condition such as heavy fog or/and strong wind. More importantly, the commute cost is economical, for instance, the average one-way fare for passengers was Rmb 7-12 yuan (in 2000 yuan). Let alone the toll for vehicles to go through the Jiaozhou Bay. By contrast, the current one-way ticket for each person is only 2 yuan for the same physical distance, and 10-100 yuan for different types of vehicles. On average, the present toll is only about one-fourth the previous price level; furthermore, it only takes 5-7 minutes to go through the tunnel compared to the respective 40 minutes or one and a half hours by ferry or by highway. Additionally, as of June 30, 2020, the tunnel has safely run for 9 years or 3287 days, with the accumulated passage of 0.15 billion vehicles and 0.6 billion passengers. Assuming that the yearly average passage including passengers and vehicles is 0.083 billion people per year, thus we derive the cost-effectiveness ratio that is around 48.9 yuan per person. Compared to the situation before 2011 when people could only commute by ferry or by highway, this cost-effectiveness ratio is quite low. Regarding the Jiaozhou Bay Bridge, with the cost-effectiveness ratio being about 1176 yuan per vehicle, which is also pretty low compared to the same kind of projects. To the spillover effects associated with the road program we will turn since it has surely passed the feasibility study before construction.

Figure-1. The Jiaozhou Bay Bridge

Source: https://baike.so.com/doc/2827423-2983999.html

Figure-2. An Interier of the Jiaozhou Bay Subsea Tunnel(one-way)

Source: https://baike.so.com/doc/6050988-6264007.html

2. Data and Method

The operation of Jiaozhou Bay Subsea Tunnel as well as the Jiaozhou Bay Bridge can be considered as a natural experiment. We will focuses on one city, namely Qingdao, and two outcome variables: the industry relative output and the industry relative employment rate. As donor pool, we consider 16 cities which have no such treatment during the same period. Also, we consider the year of 2011 as the timeline of treatment.

2.1. Data

In this essay, we have 17 available prefecture-level cities across Shandong province, they are Jinan, Qingdao, Zibo, Zaozhuang, Dongying, Yantai, Weifang, Jining, Taian, Weihai, Rizhao, Laiwu, Linyi, Dezhou, Liaocheng, Binzhou and Heze. Among which, Qingdao is the treated unit, while the remaining 16 cities becomes the donor pool. In addition, explanatory variables include the log of highway mileage, the log of per capita GDP, percent of finance expenditure in GDP, the log of population density, the log of year-end balance of financial institution deposits, the log of beds in hospitals of each city, the log of internet users, the industry relative employment rate of 2005, 2008 and 2010, respectively. Those predictive variables are also used to capture the demographic, and other socio-economic state.

Notice that we employ indicators such as industry relative output and its employment rate to examine the project impacts. The first indicator is each city's industrial output over the mean of the all sample cities' industrial output. Similarly, we can get the industry relative employment rate by substituting the respective number of employees and its mean for the industrial output and its mean (Gao *et al.*, 2012; Hu and Sun, 2014; Liu and Fan, 2013; Liu and Zeng, 2018; Yang and Zhou, 2013).

Given the goodness-of-fit and the robust of control unit and based upon Hu and Sun (2014) and Liu and Fan (2013), we add several relevant factors as predictors which contain highway mileage, per capita GDP, percent of finance expenditure in GDP, population density, year-end balance of financial institution deposits, number of beds in hospitals and number of internet users (Liu and Fan, 2013; Liu and Zeng, 2018). Among which the highway mileage stands for the urban road infrastructure, per capita GDP denotes city productivity, the ratio of expenditure in GDP denotes the market level, population density means the city aggregation effect, and year-end balance of financial institution deposits signals the financial level. Finally, the number of beds in hospitals and number of internet users denotes the respective medical and information level of each city.

2.2. Method

In order to measure the impact of the urban road transport program on treated unit, we mostly use the SCM as long as there is a synthetic unit for the real unit. In case there is no such synthetic unit, we then use the difference-in-differences instead. For the sake of brevity, we proceed as if simply one city or unit is exposed to the intervention. In addition, we use the terms "city" or "unit" or "counterpart", "covariate variables" or "covariates", "treatment" or "intervention" interchangeably.

The SCM is potent to extend the counterfactual methodology to evaluate program or policy effect (Abadie and Gardeazabal, 2003; Abadie *et al.*, 2010). This approach considers the missing counterfactual of a concrete treated unit as a weighted average of several control units (aka donor pool). The weights can be computed by minimizing a vector-distance between the treated unit and the control units over a series of pre-intervention covariates. Notice that this methodology implies a least square minimization, in other words, a linear conditional mean of the treated unit's covariates in the vector space spanned by the donor pool's covariates. Additionally, Giovanni (2019) put forward an extension fashion of SCM, in which the data must be well balanced. The principal difference between SCM and its extension is that the latter outperforms the former when departing from the initial of the pre-treatment period. In essence, the two types of SCM are the same because both offer a small pre-treatment prediction error, only that the extension version of SCM assumes a nonparametric estimation of the weights. Given the alternatives between SCM and the extension of SCM, we prefer to the former mainly because our panel data is somewhat unbalanced. Also, SCM is data-driven and has no requirements for sample size. With the above features, no wonder SCM has been widely employed in a variety of policy effect assessment as well as program evaluation (Bueno and Valente, 2019; Castillo *et al.*, 2017; Hsiao and Wan, 2014; Peter, 2016). In contrast, the difference-in-differences technology might be biased since it chooses control units at random, thus resulting in a biased estimator of the counterfactual. In our case, however, only when no synthetic unit of the treated city is found shall we adopt the difference-in-differences approach. Thus, the overall effect of a given program may be estimated with less bias.

Based on Abadie and Gardeazabal (2003) and Abadie *et al.* (2010), assume that we have J+1 available prefecture-level cities, without the loss of generality, suppose that simply the first city is exposed to the intervention, so that we have J remaining cities as donor pool. For simplicity, also assume that the first city is uninterruptedly exposed to the intervention of interest after initial intervention period.

Let Y_{it}^{N} denote the potential outcome which could be observed for city i at time t in the absence of the intervention, for cities i = 1,⋯, J+1, and time periods t =1, ⋯,T. Let T_0 be the number of pre-intervention periods, with $1 \leq T_0 < T$. Let Y_{it}^{1} be the outcome which could be observed for city i at time t if city i is exposed to the intervention during periods T_0+1 to T. Further, we assume the intervention has no impact on the outcome prior to the implementation period, thus for $t \in \{1, \cdots, T_0\}$and $i \in \{1, \cdots, N\}$, $Y_{\mathrm{it}}^{N} = \mathrm{Y}_{\mathrm{it}}^{1}$ always holds.

Let $\alpha_{\text{it}} = Y_{it}^{1} - Y_{it}^{N}$ be the treatment effect for city *i* at time *t*, and let D_{it} be binary, taking the value 1 for treated city and 0 for control cities. Thus, the observed outcome for city *i* at time *t* is $Y_{\text{it}} = Y_{it}^{N} + \alpha_{it} D_{\text{it}}$. Our goal is to estimate the program effect $\left(\alpha_{1T_0+1}, \cdots, \alpha_{1T}\right)$. For $t > T_0$, $\alpha_{1\text{t}} = Y_{1t}^{1} - Y_{1t}^{N} = Y_{1t} - Y_{1t}^{N}$. Here we simply need to estimate Y_{1t}^{N} since Y_{1t}^{1} is observable. Assume that Y_{1t}^{N} may be given by the factor model (Abadie *et al.*, 2010; Giovanni, 2019):

$$Y_{1\text{t}}^{N} = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \varepsilon_{it} \tag{1}$$

In Eq. (1), δ_t is an unknown common factor with constant factor loadings across cities, is a （r×1）vector of observable covariates, which is unaffected by the intervention of interest. Regarding the parameters of θ_{t} , it is a （1×r）unknown vector λ_t is a （1×M）vector of unobservable common factors, and μ_{i} a（M×1）vector of unknown factor loadings. The error terms ε_{it} represent the unobservable short-term shocks at the prefecture-level with zero mean. To derive the value of Y_{1t}^{N} , the proposed SCM model is to assign weights, which is a （J×1）vector, W=（$w_{2,}$ ⋯,w_{J+1}）', to each city with $w_j \geq 0$ and $\sum_{j=2}^{J+1} w_j = 1$ .The weights are selected such that the synthetic city most closely resembles the actual treated one before intervention. Each specific value of the vector W denotes a weighted average of control cities. Thus, the value of the outcome variable for each synthetic control is

$$\sum_{j=2}^{J+1} w_j Y_{jt} = \delta_t + \theta_t \sum_{j=2}^{J+1} w_j Z_j + \lambda_t \sum_{j=2}^{J+1} w_j \mu_j + \sum_{j=2}^{J+1} w_j \varepsilon_{jt}.$$

Assume that there exists （w_2^{*}⋯,w_{J+1}^{*}） such that

$$\sum_{j=2}^{J+1} w_j^{*} Y_{j1} = Y_{11}, \sum_{j=2}^{J+1} w_j^{*} Y_{j2} = Y_{12}, \cdots, \sum_{j=2}^{J+1} w_j^{*} Y_{jT_0} = Y_{1T_0}, \sum_{j=2}^{J+1} w_j^{*} Z_j = Z_1 \tag{2}$$

(Abadie *et al.*, 2010) prove that if $\sum_{t=1}^{T_0} \lambda_t^{'} \lambda_t$ is full rank, then

$$Y_{1t}^{N} - \sum_{j=2}^{J+1} w_j^{*} Y_{jt} = \sum_{j=2}^{J+1} w_j^{*} \sum_{s=1}^{T_0} \lambda_t \left(\sum_{n=1}^{T_0} \lambda_n^{'} \lambda_n\right)^{-1} \lambda_s^{'} (\varepsilon_{js} - \varepsilon_{1s}) - \sum_{j=2}^{J+1} w_j^{*} (\varepsilon_{jt} - \varepsilon_{1t}) \tag{3}$$

Moreover, under standard conditions, that is, the number of pre-intervention periods is larger than that of the post-intervention periods. Hence, the mean of the right-hand side of Eq. (3) asymptotically approaches to 0 as long as T_0 is greater than (T- T_0). This implies that the estimator of $\alpha_{1\text{t}}$ can be derived by using

$$\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^{*} Y_{jt} \quad \text{for } t \in \{ T_0+1, \cdots, T \} \tag{4}$$

In Eq. (4), it is crucial to find out the vector W* in order to compute $\hat{\alpha}_{1t}$. Let X_1 be a （k×1） vector of pre-intervention spillover effect predictors of the treated city. Let X_0 be a （k×J）matrix that includes the values of the same variables for the J possible control cities. Notice that X_1 and X_0 may likely contain pre-treatment observations of the target variable. Let V, which may also be data-driven, be a diagonal matrix with positive definite elements revealing the relative magnitude of the dissimilar one-effect predictors. By doing so, the matrix V can minimize the root of mean squared prediction error of the outcome variable. The weights vector W* is selected to minimize the objective function below:

$$\|X_1 - X_0 W\| V = \sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)}$$

This formula is used to compute the distance between X_1 and X_0W by construction. The optimal weights are those making the real outcome variable trajectory for the treated city before intervention best reproduced by the resulting synthetic control city (Abadie *et al.*, 2010; Giovanni, 2019; Hsiao and Wan, 2014; Peter, 2016).

Regarding the difference-in-differences, Eq. (1) generalizes the conventional difference-in-differences model which is mostly employed in empirical studies in program or policy evaluations. Actually, the traditional difference-in-differences model may be derived should one restrict that λt in the first Equation keep constant for all t (Abadie *et al.*, 2010). However, in case there exists no synthetic control unit for the treated, one can substitute difference-in-differences for SCM. In our case, for simplicity, we construct the model below:

$$Y_{it} = \delta_0 + \delta_1 D_1 + \delta_2 Time + \beta_1 D_i \times Time + \varphi X + \eta_i + \theta_t + \varepsilon \tag{5}$$

In Eq. (5), Y is the outcome variable; D is the dummy variable, taken the value 1 for treated city and 0 otherwise. Time represents the time dummy variable, taking the value 0 before treatment and 1 after the intervention. The parameter represents the spillover effect resulting from the previous program, η_i and θ_t denotes the respective time fixed effects and individual fixed effects, X denotes the set of urban road mileage and other covariates, and ε denotes the error term.

3. Results

Table 1 reports the predictor balance, in which it compares the pretreatment features of the actual Qingdao with that of the synthetic Qingdao, as well as with the population-weighted average of the cities in donor pool. As shown in Table 1, the averages of the cities that do not have the One Bridge One Tunnel Program in 2011-2017 does not seem to provide a suitable control group for Qingdao. Particularly, in the pre-treatment period, all the predictors were lower in the average of the 16 control cities than in Qingdao. As previously illustrated, we select V from all non-negative and diagonal matrices such that we minimize the mean square prediction error of highway mileage in Qingdao before the opening of One Bridge One Tunnel. The resulting value of the diagonal element of V relative to the log of highway mileage is pretty small, which implies that, given the other variables in Table 1, log highway mileage does not have essential power to forecast the industry relative employment rate in Qingdao prior to the operation of the One Bridge One Tunnel program. This illustrates the gap between Qingdao and its synthetic unit in terms of log highway mileage predictor.

Table-1. Predictor Balance indexed by industry relative employment rate

Variables	Real Unit	Synthetic Unit	Average of 16 Controlled Cities
ln(highway mileage)	9.48	9.43	9.08
ln(GDP per capita)	10.77	10.59	10.29
Percentage of finance in GDP	0.08	0.07	0.08
ln(population density)	6.60	6.29	6.45
ln(deposits balance)	17.18	16.55	15.03
ln (hospital beds)	10.29	10.05	9.54
ln (internet users)	4.87	4.03	3.28
relative employment rate 2005	2.58	1.69	1.03
relative employment rate 2008	2.36	1.66	1.03
relative employment rate 2010	2.17	1.63	1.01

Due to the lack of synthetic Qingdao in our data that can reproduce the relative industrial output for real Qingdao prior to 2011, we thus adopt difference-in-differences method as an alternative to estimate the program effects of One Bridge One Tunnel. Table 2 reports the traditional difference-in-differences estimation for relative industry output of Qingdao. In addition, we plot the trend of the industry relative output and replace it with its employment rate to further our evaluation.

Table-2. Difference-in-Differences results (2005-2017) for industry relative output of Qingdao

	(1)	(2)	(3)
ATT	10.899^{***}	0.307^{**}	0.609^{***}
	(0.293)	(0.113)	(0.165)
Covariates	No	Yes	Yes
Constant	1.307^{***}	-36.257^{***}	-5.367^{***}
	(0.243)	(4.975)	(1.935)
Observations	52	48	203
Adjusted R^2	0.220	0.954	0.632

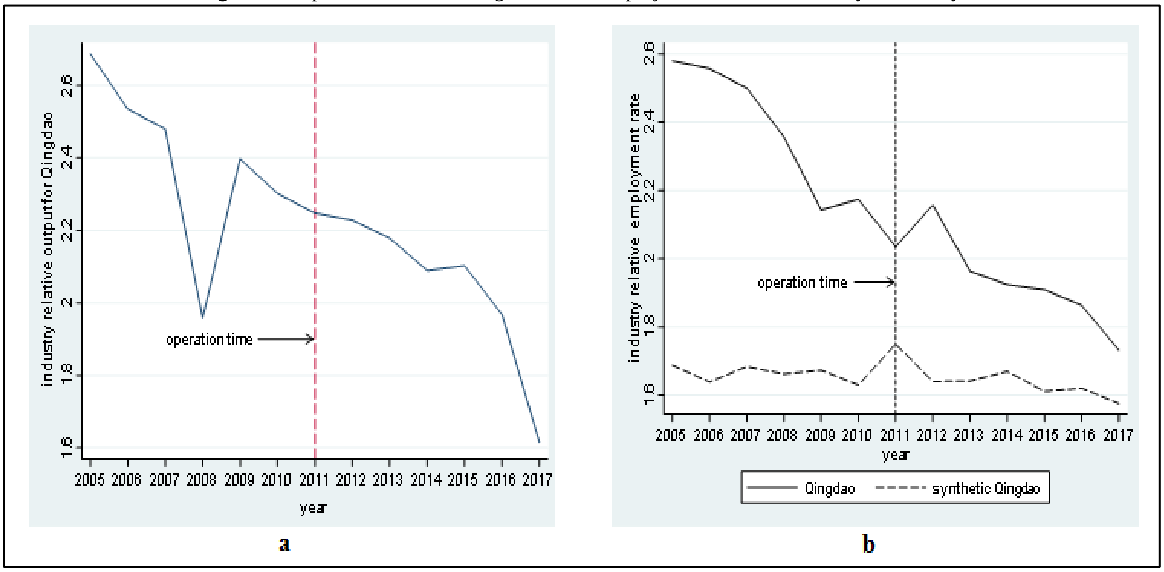
***, **, and * denote significance at the 1, 5 and 10 per cent level respectively. The value in parenthesis represents the robust standard errors

In Table 2, the difference-in-differences estimate (ATT) is given by the coefficient of the interaction between a dummy for the treated city (treated), that is, an individual fixed effect equal to 1 for Qingdao in all time periods, and a time fixed effect for the post-treatment periods (t) equal to 1 simply from 2011 onward. As mentioned before, even though this difference-in-differences estimation is probably biased due to a violation of its parallel trend assumption (Abadie and Gardeazabal, 2003), it is a complement to the loss of a synthetic counterpart of Qingdao such that we can access the spillover effect of the urban road infrastructure program more comprehensively. Column (1) and (2) both take the same 3 cities (Jinan, Yantai and Taian) as control group, only that the former does not control the covariate variables including the highway mileage while the latter controls the same covariates. Regarding column (3), we use the rest 16 cities except Qingdao as donor pool and control the same covariates as that of column (2) simultaneously. We find out that all the 3 cases provide plausible signs and magnitudes. In particular, the positive signs of parameter of the interaction term indicate that the One Bridge One Tunnel Program spurs the local industrial economy of Qingdao. Moreover, there probably has a significant spillover effect associated with the opening of the road program in the adjacent cities within Shandong province.

By running the corresponding code using Stata, we obtain Figure-3, in which the vertical dotted line represents the opening time of 2011, the solid curve represents the real Qingdao, and the dotted curve represents the synthetic

Qingdao. Figure-3 indicates the impacts of the One Bridge One Tunnel program associated with the operation of the program on June 30 of 2011:

Figure-3. Impacts of the One Bridge One Tunnel project on the treated and synthetic city



As Figure-3 suggests, overall, Qingdao's industry relative output is on its noticeable downward trend (Figure-3a). So it is with Qingdao's industry relative employment rate (Figure-3b). There are two possible reasons to shed light on the common trend. Firstly, it is because of the impact of the outbreak of global financial crisis in 2007 which also affects Chinese economy, as such a V shape appeared in period 2007-2009. Under this circumstance, the One Bridge One Tunnel Program started construction so as to stimulate the local economy. Secondly, after the opening of the One Bridge One Tunnel in 2011, the economic gap between the south and the north within China mainland began to diverge noticeably. In this context, Shandong lags far behind other Chinese provinces, though Qingdao places first in GDP among the cities within Shandong province, still it is smaller than that of other counterparts in terms of economic growth rate. Even so, this is not to say that the urban road traffic program has no effect in boosting urban industry economy, just that the effect is less sizable when compared to the effect before the regional economic gap.

With regard to industry relative employment rate after 2011, the line of real Qingdao sits on the top of the synthetic Qingdao with the peak appearing in 2012, while the line for synthetic Qingdao mostly levels off. The implications for this are twofold: first, the discrepancy between the two lines suggests a positive program effect of the One Bridge One Tunnel on industry relative employment rate. Besides, Figure-3 suggests that One Bridge One Tunnel Program has a spillover effect on industry relative employment rate across cities in Shandong, and this effect appears remarkably around 2016 as the gap between the two lines gets smaller simultaneously. The magnitude of the estimated impact is substantial, it is the positive externality associated with the project.

The SCM provides an ordinary fit for industry relative employment rate in Qingdao prior to the operation of the One Bridge One Tunnel Program. The pretreatment root of mean squared prediction error (RMSPE) in Qingdao, that is, the average of the root of the squared discrepancy between industry relative employment rate in Qingdao and in its synthetic counterpart over the period 2005-2010, is about 0.74, revealing that the SCM can provide a fair fit for industry relative employment rate before 2011 for most cities in the donor pool. However, the gap between Qingdao and synthetic Qingdao becomes smaller after 2011, which means the spillover effect grows larger due to the opening of the program. Notice that, as long as no evidence that might bring a negative impact on urban economic development is found, even if the One Bridge One Tunnel Program effect is less significant, still it should be considered as having a causal effect (King and Zeng, 2006).

4. Discussion

To access the significance of our estimates, we come up with the central question whether our results could be driven by accident. How often could we achieve results of this magnitude were we to select a city arbitrarily rather than Qingdao? We employ placebo tests to answer this question. Akin to Abadie and Gardeazabal (2003), we conduct the placebo tests by applying the SCM to cities without the One Bridge One Tunnel Program during the sample periods. Only if the placebo studies reveal that the estimated discrepancy for Qingdao is large relative to that of the city which does not build the aforementioned program, can we hold that our analysis provide significant evidence of a positive spillover effect associated with the One Bridge One Tunnel Program in treated city. According to Liu and Zeng (2018), we simply conduct the placebo tests for city that has a smaller goodness-to-fit prior to the treatment. Therefore, we just do the robust check for industry relative industry employment rate of Qingdao. Figure-4 shows the outcome of the placebo test, in which the vertical dotted line denotes the opening time of 2011, the solid line denotes the real Qingdao, and the grey lines denote the 16 cities whose RMSPE are smaller than that of Qingdao.

Figure-4. Placebo test: Qingdao and 16 control cities

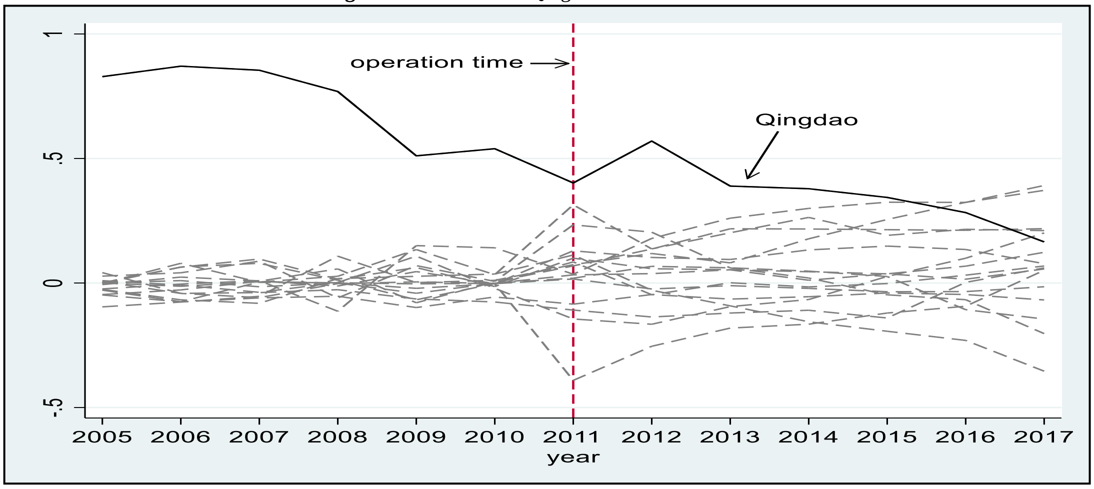


Figure-4 plots the results for the placebo test. We remain all the 16 cites in control group since no city has a pre-treatment RMSPE higher than that of Qingdao. The superimposed solid line marks the estimated gap for Qingdao. The grey lines mark the gap associated with each of the 16 runs of the test. That is, the grey lines indicate the difference in industry relative employment rate between each city in the donor pool and its corresponding synthetic counterpart. As is shown in Figure-4, the estimated gap for Qingdao over the period 2011-2017 is not that large compared with the distribution of the gaps for the cities in the donor pool. Evaluated by the distribution of the gaps for the 16 control cities in Figure-4, the gap for Qingdao appears relatively large. Because this figure contains 16 control units, given arbitrary permutation of the intervention in our data, the probability of estimating a gap of the magnitude of Qingdao would be 1/17, or 5.88 per cent, a test level commonly used in traditional tests of statistical significance.

Conversely, however, Figure-4 indicates that the spillover effect becomes large except for 2012, which is likely because the road infrastructure program investment has a time lag to showcase its corresponding positive investment multiplier effect. In particular, the spillover is remarkable in the order of 2015 where the two lines converge. Therefore, placebo tests indicate that the program has a statistically significant spillover effect on the industry relative employment rate for at least 10 cities including Qingdao in terms of their respective pre-treatment RMSPE, but this does not hold for the rest of the cities. Hence, if one city were to assign to the intervention in the data arbitrarily, the probability of achieving a spillover effect as large as Qingdao's is around 5.88 per cent.

5. Conclusion

By using the SCM and difference-in-differences if conditions fail to hold for SCM, we estimated the One Bridge One Tunnel Program's direct effects as well as its indirect effect in China, that is, the resulting spillover effect induced by the urban road transportation program. Results show that it does have a causal effect between the urban road program and regional industry economy. Particularly, the One Bridge One Tunnel Program has a spillover effect on industry relative employment rate across cities in Shandong, and this effect increases over time. Our conclusion is consistent with most of the similar research (Yu *et al.*, 2013; Zhang, 2013). Further placebo tests indicate that the program has the probability of achieving a spatial spillover effect as large as that of Qingdao is approximately 5.88 per cent.

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