Прикладная эконометрика, 2023, т. 72, с. 58–72.
Applied Econometrics, 2023, v. 72, pp. 58–72.
DOI: 10.22394/1993-7601-2023-72-58-72

A. Goryunov, E. Ageshina, I. Lavrentev, P. Peretyatko[1]

Estimating the effect of Russia's development policy in the Far Eastern region: The synthetic control approach

In 2014 Russian government enacted an ambitious policy of the "accelerated development" of the Far East. A number of special legal provisions, tax incentives and investment programs have been introduced as part of that policy. Several studies have since attempted to estimate the impact of the policy on the region's economy using intertemporal or interregional comparisons of outcomes, with most studies finding there to be no significant impact. We use the synthetic control method to arrive at a quantitative estimate of the policy's effect on the real per capita GRP of the Far East in 2014–2019. Using a pool of 59 regions to construct a counterfactual baseline and controlling for the overall level of higher education, share of the raw materials industry, share of investment in GRP and the share of working age population, we estimate that the policy had resulted in the creation of around 93 billion rubles of additional GRP in the Far East during 2014–2019. We also propose a procedure for estimating the statistical significance of the result in the case when Fischer's Exact Test, which is normally used with synthetic controls, is not applicable due to the composition of the treated object. Using our proposed procedure, we find that our estimate of the policy's effect is statistically significant at the 5% level.

Keywords: preferential regimes; economic incentives; tax breaks; regional development; synthetic controls.

JEL classification: H59; H39.

1. Introduction

The policy of accelerated social-economic development of the Far East takes its official start in 2014 with the declaration of the federal program for the "Social-economic development of the Far East and Baikal regions" (SED program) (Gulidov, 2021). The SED program was designed to put into action the earlier declared national strategic goal of the Far East's development. In 2012 the Russian government established a special federal Ministry for the Development of the Far East, which was tasked with designing what eventually became the SED program. Although this program came at the tail end of a long succession of similar ones, it was the first

[1] **Goryunov, Alexander** — Eastern State Planning Center, Khabarovsk, Russia; alex.goryunov@gmail.com.
Ageshina, Elena — Eastern State Planning Center, Khabarovsk, Russia; e.ageshina@vostokgosplan.ru.
Lavrentev, Igor — Eastern State Planning Center, Khabarovsk, Russia; i.lavrentiev@vostokgosplan.ru.
Peretyatko, Polina — Eastern State Planning Center, Khabarovsk, Russia; p.peretyatko@vostokgosplan.ru.

to be backed up by a clear political message and spell out implementation mechanisms for that message (Minakir, 2020).

Beside the federal program, two new federal laws were enacted in order to provide special incentives for businesses in the Far Eastern region: "territories of accelerated development" (TOR) (Federal Law 473-FZ, 2014) and "free port of Vladivostok" (SPV) (Federal Law 212-FZ, 2015). TOR and SPV regimes were designed to attract investment to the region by offering profit and wage tax breaks and a number of administrative privileges, including (in the case of TOR) exemptions from levies on access to municipal utilities and expanded quotas for foreign labor (Leonov, Tolmachev, 2020). Other prominent instruments of the policy include:

- "Far Eastern hectare" program, which promises to provide any Russian citizen with a free hectare of land in the Far East, albeit for a limited time but with an option to extend;
- "Unified subsidy" program, which simplifies the process of providing federal financing to regional programs;
- Subsidized mortgage program for the purchase of housing in the Far East.

Three new special agencies were created with the declared purpose of improving efficiency of the government participation in the region's development. Of these, two are still active today:

- "Agency for the development of human capital in the Far East" — originally tasked with connecting the residents of TOR and SPV with skilled labor;
- "Corporation for the development of the Far East" — the operator of TOR and SPV zones.

Additional resources were provided to the "Far East Development Fund", which was originally established in 2011 for financing investment projects in the region. All other existing federal programs were also amended to include a section on measures pertaining to the Far East development program.

According to the estimates in (Gulidov, 2021), over the 2015–2020 total federal and regional budgetary expenditures directed towards attracting private investment to the Far East amounted to 378 billion rubles. Of those, two thirds came in the form of various tax breaks and only a third was attributed to direct monetary spending. Minakir (2020) estimates direct monetary expenditures in 2014–2019 to be around 165 billion rubles.

With eight years having had passed since the launch of the policy, research is beginning to emerge on its effectiveness. So far, this research had proceeded along the avenues of matching achieved outcomes with expended resources and stated goals, comparing the Far East's outcomes with national averages, or measuring changes in the region's economic indicators in the periods before and after the policy's implementation. Separate line of inquiry is concerned with structural impact of the policy on the regional economy and its main industries.

Gulidov (2021) gives a comprehensive overview of the policy's results in 2015–2020 in terms of resources expended and outcomes achieved. He finds that the policy falls short of reaching its two main goals: attracting private investment and creating new jobs. Between 2015 and 2020, volume of private investment in the Far East amounted to only 44.5% of the target level and number of new jobs created was 50.8% of the target level.

Isaev (2020) uses cost-benefit analysis to study the spatial allocation of public resources from the perspective of the policy's welfare effects. Calculating the social discount rates for individual regions of the Far East, he finds that spending is overly concentrated in regions with the highest social discount rate values: Sakhalinskaya oblast and Khabarovskyi krai. This leads him to question the policy's programming.

Lomakina (2020) analyzes the policy's impact on structural composition of the Far Eastern economy. She finds that over the 2014–2020 period public investment in infrastructure had served to increase the role of the raw materials sector in the economy. She points out a feedback connection, whereby the policy's preference for the raw materials sector increases as the sector's share in the economy increases, therefore boosting the impact of the sector's economic indicators on the aggregate indicators of the economy.

Minakir (2020) matches the federal program's results with its stated goals over the period of 2014–2019 and analyses the program's resource sufficiency. He finds that the program's resource allocation is not sufficient to achieve its stated goals, since the additional financing it provides amounts to only 3% of the total public spending in the region. At the same time, he acknowledges that the resources allocated to the Far East through various sectoral programs far exceed the resources of the "main" development program, but still finds their level to be insufficient. On the matter of the program's results, Minakir finds the reality to fall short of the program's expectations: population, investment, and GRP all grew at a slower pace than projected by the development program. Gulidov (2021) further estimates the policy's impact on the real economic outcomes in the region by comparing the dynamics of nine key indicators of the region's economy in the five years prior to the start of the policy (which he takes to be in 2015) and the five years since its start. He finds that out of nine, only two indicators (investment and construction) had improved in 2015–2020 compared to 2010–2015.

To summarize, most existing research suggests that the policy so far has had a negligible effect on the region's development, while pointing out various flaws in its program design and insufficient and inefficient resource allocation. We attempt to provide quantitative causal assessment of the policy's outcome by estimating its impact on the region's real per capita gross regional product. To do so, we first construct a counterfactual scenario for the Far East's real per capita GRP dynamics in the period of 2014–2019, and then calculate the difference between the counterfactual and observed dynamics.

To construct the counterfactual Far East, we use the synthetic control method, which is described in the next section. The rest of this paper is organized as follows. The data and variables used for the estimation are presented in Section 3. Section 4 describes the estimation results; in Section 5 we present the technique we use to estimate the statistical significance of our estimate. Finally, in Section 6 we summarize and discuss our findings.

2. Method

The synthetic control method, originally proposed by Abadie and Gardeazabal (2003) (see also (Abadie, 2021) for a comprehensive overview), is a generalization of the difference-in-differences (DID) approach which has become the go-to method for estimating causal effects in social sciences. DID relies on the "parallel trends" assumption which states that in the absence of the intervention, the average outcome for the treated and untreated objects would have followed parallel trends. The average outcome for the untreated objects is estimated by controlling for common confounders which ensures that the average outcomes are comparable. The parallel trends assumption is often violated in practice and the synthetic control method addresses this problem by replacing this assumption with the requirement that a sufficiently good match exists between both the covariates and the outcomes of the treated and untreated objects in the pre-intervention period.

The synthetic control is a baseline counterfactual which the outcome of the treated object can be directly compared to in order to gauge the intervention's effect. The method constructs a "synthetic" control object, which is a weighted average of a set of objects that are similar to the treated object in terms of the pre-intervention values of covariates chosen to control for the relevant confounders. The weights are chosen to minimize the distance between the synthetic control and the treated object in the values of covariates, and an unbiased estimate should achieve a good fit between the pre-intervention values of the outcome variable of the synthetic control and the treated object. To improve the latter, we use a few linear combinations of the pretreatment values of the outcome variable as additional covariates, which is a standard trick for estimating synthetic controls. The treatment effect is then calculated as the difference between the outcomes for the treated object and the synthetic control object in the posttreatment period.

The above is a general description of the "classical" synthetic control method, as proposed by Abadie and Gardeazabal (2003). We use a somewhat modified version of the method, which is described in detail in the rest of this section. In particular, we use a two-stage approach, whereby we first "de-noise" the outcome values for both the treated object and the control pool, using a procedure proposed in (Amjad et al., 2018) and then perform the estimation of control weights.

The choice of synthetic control as the main method of evaluation of the policy in the Far Eastern Federal District requires more detailed comments.

To our knowledge the synthetic control had never been applied to a "composite" region before, meaning one that is composed as a sum of several administrative regions. This is most likely due to the fact that government policy is normally directed at administrative units (states, prefectures, cities, etc.), rather than entities which, as is the case with Russian federal districts, have no fiscal, judicial or executive functions. Therefore, on the one hand, this absence of normal administrative controls makes federal districts a kind of a statistical entity — a set of records of economic and social activities occurring within a certain territory. In this sense a difference-in-difference approach, where we estimate fixed "regional" effects for each individual Far Eastern region, would seem more appropriate.

However, on the other hand, the Far Eastern region is, to a large extent, a real entity in the economic sense. There's extensive literature in economic geography and spatial economics in Russia treating it as such (Minakir (2020) and Aganbegyan (2019) conceptualize "Far East" as a separate socio-economic object), and the original demarcation of the "Far Eastern Federal District" had largely followed the accepted contours of this economic region.

Thus, we chose to use the synthetic control both for the latter reason — to estimate the effect for the region that was stipulated as the target of the policy, but also as a methodological exercise, since the use of the synthetic control method in this setup creates certain obstacles for the estimation of the statistical significance of the results. We tackle this problem in Section 5 of this paper.

2.1. Synthetic control estimation

The set of all untreated objects that are combined to form the synthetic control is referred to as the *control pool*. The weights of the objects in the control pool are chosen by optimizing the objective function:

$$\underset{w}{\operatorname{argmin}} \sqrt{(x_1 - X_0 w)' V (x_1 - X_0 w)}, \quad \text{with } \sum_{i=1}^{K} w_i = 1, \tag{1}$$

where K is the number of objects in the control pool, w — vector of weights with dimension $K \times 1$, x_1 is a $M \times 1$ vector of covariates and linear combinations of the outcome variable with $M = J + R$ (J — number of covariates and R — number of linear combinations of the outcome variable), X_0 — an $M \times K$ matrix of covariates and linear combinations for the control pool. The term V is an $M \times M$ positive semi-definite matrix that is used to weigh the distance between the synthetic control and the treated object in the values of covariates and linear combinations. The weights on the main diagonal of V are chosen to lie between 0 and 1 and to minimize $\|y_1 - Y_0'w\|$, where y_1 is a $1 \times T$ vector of values of the outcome variable for the treated object, and Y_0 is a $K \times T$ matrix of values of the outcome variable for the control pool.

The weights in V can, therefore, be seen as a measure of the importance of the values of covariates and linear combinations to fitting the pretreatment value of the outcome variable. If algorithm finds some covariate not "important" for fitting the pretreatment outcome, it could result in a poor fit in that particular covariate. To address this problem, we add another term in the objective function that penalizes the distance between the synthetic control and the treated object in the values of covariates. Assigning the objective function in (1) to $L(w)$, we can rewrite the objective as:

$$\underset{w}{\operatorname{argmin}}\left(L(w) + p\sqrt{(z_1 - Z_0 w)'(z_1 - Z_0 w)}\right), \tag{2}$$

where p is a tuning parameter that controls the trade-off between the fit of the pretreatment values of the outcome variable and the fit of the pretreatment values of the covariates. The term z_1 is a $J \times 1$ vector of covariates for the treated object, and Z_0 is a $J \times K$ matrix of covariates for the control pool.

2.2. De-noising the outcome

Amjad et al. (2018) propose using singular value thresholding (see also (Chatterjee, 2015)) with a ridge regression as a way to estimate the value of w directly from the outcome, without going through covariates. Although we don't use this approach for its declared purpose, we employ it to de-noise the outcome variable in the pretreatment period for both the treated object and the control pool. This significantly improves the quality of the synthetic control, considering that the outcome variable we use (per capita GRP) can exhibit large short-term fluctuations, mostly caused by transient external shocks. This behavior is characteristic of open regional economies actively engaged in trade with the outside world and it makes the exact dynamic of a region's GRP difficult to approximate as a linear combination of other regions', as well as possibly results in the estimated effect being confounded by shocks occurring close on either side of the treatment threshold. As Amjad et al. (2018) point out, the values of the outcome variable can be presented as:

$$Y_{it} = M_{it} + \varepsilon_{it}, \tag{3}$$

where M_{it} is the deterministic mean value and ε_{it} is the zero-mean stochastic component with values independent across i and t. Therefore, M_{it} can be estimated by finding a low-rank representation of Y_{it} that discards the random fluctuations. This lower-rank representation is found by singular value decomposition of the matrix Y_0 of the outcome values for the control pool. The derived representation is then transferred to the treated object's outcome as a linear combination of the control pool's values, with coefficients estimated by a linear regression with a regularization term applied over the pretreatment period — a procedure not unlike, but simpler than the one outlined above for fitting the covariates.

Next, we present the algorithm used, while referring the reader to the original work for a discussion of theory and formal proofs.

There are two steps to the de-noising procedure[2]. The original algorithm includes a provision for filling in the missing values in the outcome variable, but we skip it since our time series are complete. Without value imputation, in the first step we compute the singular value decomposition of Y_0 — the outcome matrix for the control pool:

$$Y_0 = \sum_{i=1}^{K} s_i v_i u_i', \tag{4}$$

then we select a set S of indices of singular values that are at or above a threshold μ, i.e. $S = \{i : s_i \geq \mu\}$, and filter Y_0:

$$\hat{Y}_0 = \sum_{i \in S} s_i v_i u_i'. \tag{5}$$

We then use the portions of the treated objects and the filtered control pool outcome matrices that correspond to the pretreatment period (y_1^- and $\hat{Y}_0^-$), to estimate:

$$\hat{\beta}(\eta) = \underset{v \in R^K}{\operatorname{argmin}} \left(\| y_1^- - (\hat{Y}_0^-)' v \|^2 + \eta \| v \|^2 \right), \tag{6}$$

where η is a hyperparameter.

The estimated $\hat{\beta}(\eta)$ is then used to calculate the new value of the outcome variable for the treated object:

$$\hat{y}_1 = \hat{Y}_0' \hat{\beta}(\eta). \tag{7}$$

It should be immediately obvious that $\hat{y}_1$ is essentially a synthetic control, with $\beta(\eta)$ being the analog of w in the "classical" formulation of the method. However, we prefer to use the classical formulation, because it yields a more interpretable solution by preventing an "accidental" extrapolation of the control by using negative weights or weights that sum to more than one, as well as having a straightforward causal structure due to the use of covariates.

To continue, we substitute the de-noised values of the outcome variables $\hat{y}_1$ and $\hat{Y}_0$ for the original values in the estimation of the synthetic control described in the previous section. The values of hyperparameters μ and η are chosen using the forward chaining procedure suggested in Amjad et al. (2018) whereby for each year t in our time series, starting from $t = 3$ (year 2002), we estimate:

$$\underset{\eta, \mu}{\operatorname{argmin}} \sum_{t=3}^{T} \| y_{1t} - \hat{y}_1(\eta, \mu) \|^2 \tag{8}$$

given $\eta \geq 0$, $\mu \geq 0$ and $\hat{y}_{1t}$ estimated setting $t-1$ to be the last year of the pretreatment period on each iteration.

2 Before de-noising we constrain the outcome values to the [–1, 1] range and recover them after. See Section 3.4.1 on page 7 in (Amjad et al., 2018) for details of the procedure.

To summarize, to estimate the posttreatment value of the outcome variable for the synthetic control, we first de-noise the values of the outcome variable for the treated object and the control pool, and then use these values to estimate the synthetic control weights w. Our model has three hyperparameters with values: $p = 0.005$, $\mu = 0.04$ and $\eta = 0.00001$. In the next section we discuss the possibility of interpolating the value of w for the Far Eastern region and the data we use for the estimation.

3. Data

Our treated object, the Far East, is comprised of 9 subjects of the Russian Federation: Amurskaya, Magadanskaya and Sakhalinskaya oblasts, Jewish autonomous oblast, Khabarovskyi, Primorskyi and Kamchatskyi krais, Republic Sakha (Yakutia) and Chukotskyi autonomous okrug. We exclude two subjects which were added to the Far Eastern Federal District only in 2018: Republic of Buryatia and Zabaikalskyi krai.

Before starting with the estimation, it was important to ensure that a synthetic control for the Far Eastern region could be arrived at by pure interpolation, i.e. that the conditions $w \geq 0$ and $\sum_{i=1}^{K} w_i = 1$ can be satisfied, given the values of covariates and linear combinations. As King and Zeng (2006) point out, counterfactuals derived for objects that lie far from the data that is used to estimate the counterfactual can have extremely high variance conditional on the model. This is especially true when using a linear model to capture a non-linear relationship between the outcome variable and the covariates: the further away from the convex hull of the data the counterfactual needs to fall to reproduce the treated object, the greater the divergence will be between the actual value of the outcome and the one predicted by the model.

As suggested by King and Zeng (2006) we confirmed that, given the covariates and linear combinations presented below, the Far Eastern region is within the convex hull of the control pool's data by checking that the solution exists for a linear programming problem with a degenerate objective function:

$$\min c'\gamma, \tag{9}$$

$$\text{s.t. } A'\gamma = b', \ \gamma \geq 0, \tag{10}$$

where A is a matrix of control pool's covariate values with dimensions $K \times (M+1)$, is a vector of covariates for the treated object with dimensions $1 \times (M+1)$, c is a $K \times 1$ vector of zeros, γ is a $K \times 1$ vector of weights. Matrix A and vector b are essentially X_0 and x_1, respectively, with a column of 1's added, which serves as the constraint $\sum_{i=1}^{K} \gamma_i = 1$.

We have chosen four covariates and three linear combinations of the outcome variable as exogenous variables for the synthetic control model:

- share of the raw materials industry in nominal GRP (mean for 2005–2014);
- share of fixed capital investment in nominal GRP (mean for 2000–2014);
- share of working age population (mean for 2010–2014);
- number of university students per 100k people (mean for 2010–2014);

- real per capita GRP for the year 2000;
- real per capita GRP for the year 2008;
- real per capita GRP for the year 2012.

When forming the control pool, we exclude all Far Eastern regions and also: Chechen Republic, Moscow, Saint-Petersburg, Zabaikalskyi krai, Arkhangelskaya and Tyumenskaya oblasts, Republic Buryatiya, Republic Dagestan, Republic Ingushetia, Kabardino-Balkarskaya Republic, Karachaevo-Cherkesskaya Republic, Republic North Osetiya-Alaniya, Stavropolskyi krai. Moscow and Saint-Petersburg were excluded as outliers, Buryatiya and Zabaikalskyi krai were excluded because since 2018 they have been part of the Far Eastern Federal District, and the North Caucasus republics enjoyed a regional development program similar to the one for the Far East, therefore had received a similar treatment. Arkhangelskaya and Tyumenskaya oblasts were excluded due to missing some of the covariate values.

The choice of covariates is standard for the literature on economic growth. For example, Abadie and Gardeazabal (2003) use real per capita GDP, investment ratio, sectoral shares, percentages of people by educational background and population density. While our set of selected variables is not identical to Abadie and Gardeazabal (2003), the chosen indicators quantify same socio-economic factors.

The share of the raw materials industry is included as a proxy for a region's trade openness, while other variables proxy for the levels of human and physical capital. Descriptive statistics for the covariates of the control pool are presented in Table 1. The outcome variable's values are calculated from official statistics on nominal GRP, population sizes of regions, and the index of physical GRP. In the case of the Far East, we calculate the outcome values by first adjusting the nominal GRP of each constituent federal subject by the physical GRP index, summing together the resulting real GRP values and dividing by the sum of populations.

Table 1. Descriptive statistics for the covariates

	Share of mining (%)	Share of investment (%)	Students per 100k	Share of working age population (%)
Mean	9.015	28.191	3604	61.320
Standard deviation	15.732	7.470	1092	2.307
Minimum	0.031	16.293	0	58.713
Median	1.152	26.447	3662	61.056
Maximum	73.129	53.741	6850	70.625
Observations		60		

4. Results

The main result of estimating the synthetic control model is presented in Fig. 1 which shows the real per capita GRP of the synthetic control, estimated on the de-noised data, together with (a) de-noised and (b) untransformed real per capita GRP of the Far East and mean of the control pool. The figure demonstrates why comparisons with the mean (at least in this case) can lead to misleading conclusions. The trends of Far East's and the mean real per capita GRP had gone from diverging between 2009 and 2011, to converging between 2011 and 2014 and diverged again after 2014.

As a result, using the mean as a benchmark would yield completely different results depending on what pretreatment period one would decide to choose to calculate the baseline growth rates of the region and the mean.

The synthetic control, on the other hand, closely tracks the dynamics of the Far East during the entire pre-policy period. Importantly, it also closely corresponds to the Far East's characteristics which serve as predictors of per capita GRP. This is shown in Table 2 which presents the values of covariates and linear combinations for the Far East, its synthetic control, and the mean of the control pool. Out of the seven indicators, four are exactly equal for the Far East and its synthetic control in the third digit after the decimal point. University students per 100k of population and the share of working age population differ somewhat, but the values for the synthetic control are significantly closer to those of the Far East than are the values of the mean. Thus, we can say that the synthetic control is closely matched with the Far East not only in the outcome's dynamics but also in the characteristics relevant for the outcome. In other words, we have good reason to believe that we are drawing conclusions about the effect of the policy from comparing directly comparable objects.

The composition of the synthetic control is presented in Table 2 with covariate values for the Far East and its synthetic control provided in Table 3. Six subjects of the Russian Federation contribute 100% of the synthetic control's total weight: Komi Republic, Belgorodskaya oblast, Republic of Mordovia, Tomskaya oblast, Orenburgskaya oblast and Nenetskyi autonomous okrug.

The effect of the policy on Far East's per capita GRP can be expressed as the absolute difference between the synthetic control and the region, as well as in a more interpretable way as the policy's relative contribution to the region's per capita GRP growth over the period of 2014–2019. The former is equal to 15.5 thousand rubles or, given the region's population for each year, 95.4

Table 2. Composition of the synthetic control: regional weights

Region	Weight
Komi Republic	0.484
Belgorodskaya oblast	0.310
Republic of Mordovia	0.111
Tomskaya oblast	0.050
Orenburgskaya oblast	0.031
Nenetskyi autonomous okrug	0.013

Table 3. Covariate values for the Far East, its synthetic control and mean of the control pool

Covariate	Far East	Synthetic control	Mean
Share of raw materials industry in GRP (%)	24.156	24.156	10.328
Share of investment in GRP (%)	34.019	34.019	29.053
University students per 100k population	4056	3943	3600
Share of working age population (%)	64.059	63.254	61.823
Real per capita GRP in 2000 (thousand rubles)	44.656	45.555	40.603
Real per capita GRP in 2008 (thousand rubles)	76.682	76.682	70.648
Real per capita GRP in 2012 (thousand rubles)	86.172	86.172	74.001

billion rubles in 2000 prices. Since that number is calculated for the de-noised outcome time series, it is not directly comparable to the actual observed GRP, therefore we also calculate the policy's effect in relative terms: without the policy, the growth rate of the region's real per capita GRP over the period of 2014–2019 would have been 4.7 times lower. Adjusting for the actual (not de-noised) growth rate of Far East's per capita GRP, we estimate that without the policy's effect the region's per capita GRP would have grown only 1.9% over the period of 2014–2019, instead of 9.1%.

Finally, we calculate the estimated absolute cumulative contribution of the policy to the region's GRP in 2000 rubles over the period of 2014–2019 for the case of non-denoised data — the equivalent of the 95.4 billion rubles figure above. To do this, we calculate cumulative annual growth rates (CAGR) for the non-denoised real GRP given the 9.1% and 1.9% growth rates for the observed and counterfactual GRP, interpolate the GRP values for each year between 2014 and 2019 using the respective CAGR values and calculate the sum of the absolute differences between the resulting values for each year. We find that the policy's cumulative contribution to the region's real GRP over the period of 2014–2019 was 93.9 billion 2000 rubles.

However, considering the relatively short amount of time that has passed since the inception of the policy in our dataset, this result could be spurious. To address this concern, in the next section we perform a placebo test to estimate the statistical significance of the result.

5. Statistical significance testing

Abadie et al. (2010, 2015) propose placebo testing as a method for estimating the statistical significance of a synthetic control. A placebo test poses the question: what would be the result of the synthetic control estimation if it was applied to a randomly selected region from the control pool? By estimating synthetic controls for all regions in the control pool we can calculate the share of regions which have a ratio of post-to-pretreatment factual-counterfactual gaps in the outcome greater than the one observed for the Far East. This procedure corresponds to Fischer's Exact Hypothesis Test. The actual test statistic proposed by Abadie et al. (2015) and accepted by most synthetic control studies (including this one) is the ratio of the posttreatment to pretreatment mean square prediction errors (RMSPE) of the outcome:

$$RMSPE_k = \frac{T_0 \sum_{t=T_0+1}^{T} (Y_{kt} - \overline{Y}_{kt})^2}{(T - T_0) \sum_{t=1}^{T_0} (Y_{kt} - \hat{Y}_{kt})^2}. \tag{11}$$

Since our treated region is a sum of constituent subregions, instead of calculating synthetic controls for the individual subregions in the control pool we form placebo regions as sums of subregions. This both provides us with placebo regions comparable in their "composite" nature to the Far East and allows us to increase the sample size for the placebo regions, by essentially performing sample bootstrapping. In forming placebo regions, we ensure that they are spatially continuous, i.e. that every subregion has a land border with at least one other subregion in the placebo. That is done to reproduce the Far East's spatial continuity.

As the first step of the algorithm for constructing placebo regions, we compile an adjacency matrix for the regions in the control pool. This is a lower triangular matrix of size $K \times K$ where

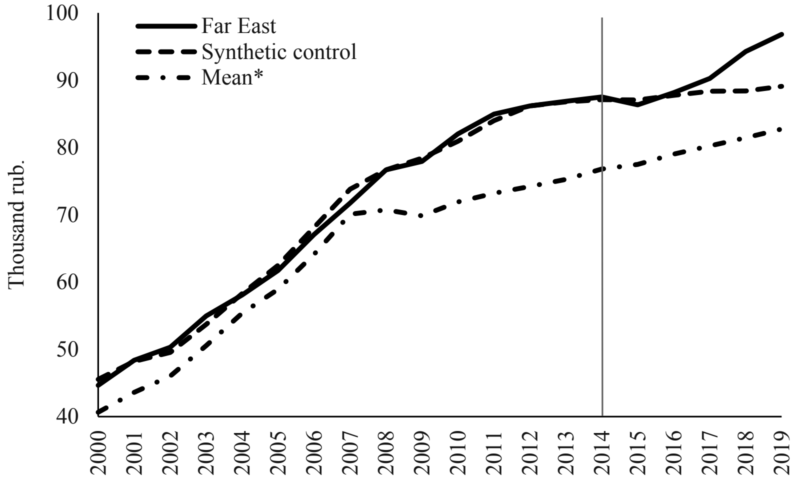

Fig. 1. Dynamics of per capita GRP for the Far East and its synthetic control (2000–2019, in thousand rubles, constant 2000 prices)

* The mean per capita GRP is calculated for the regions in the control pool only.

K is the number of regions in the control pool. Regions with a common border are denoted with 1 in the respective cell, and 0 otherwise. There are two special cases that need to be addressed at this step: Kaliningradskaya oblast, which is an exclave, and Sakhalinskaya oblast, which is an island. We get around this issue by creating artificial connections for both in the adjacency matrix. We give Kaliningradskaya oblast connections to Leningradskaya and Murmanskaya oblasts and connect Sakhalinskaya oblast with Khabarovskyi and Kamchatskyi krais and Magadanskaya oblast.

We then choose a starting location and perform 9 steps (to reproduce the size of the Far East) of a random walk on the adjacency matrix. The resulting composite region is the set of locations visited during the walk. The subregions of the Far East are included in the adjacency matrix and may enter into placebos. In this fashion we form 733 composite placebo regions and estimate a synthetic control for each of them using the same procedure as the one used for the Far East, including the estimation of the optimal value of hyperparameter μ.

Unfortunately, this algorithm for the sampling of placebo regions makes it impossible for us to use Fischer's Exact Test for the estimation of the p-value, as proposed by Abadie et al. (2015). Their estimation approach implies that the following four assumptions hold (Imbens, Rubin, 2015; Firpo, Possebom, 2018).

1. The "no spillover-single dose treatment": the potential outcome for each region is not affected by other regions receiving the treatment, and there is no other version of the same treatment which can lead to a different outcome for the region.
2. The "random assignment": the choice of the treated region is random conditional on the composition of the control pool and the observed and unobserved (controlled by fitting the outcome vector in the pretreatment period) confounders.
3. The "general population": we measure potential outcomes for all possible placebo regions, instead of a sample of some super-population of them.
4. The "uniform treatment assignment": all placebo regions have the same probability of being assigned the treatment.

Our sampling algorithm violates the third and fourth of the above assumptions. The ability to use Fischer's Exact Test rests crucially on the third assumption, since it measures the share of all placebos with a factual-counterfactual gap in the outcome greater than the one observed for the Far East. Sampling all possible paths of length 9 through the adjacency matrix of the control pool would require the order of the number of controls to the power of 9 computations of synthetic control, which is infeasible, therefore we can only sample a few hundred placebos.

The fourth assumption is violated by the fact that the formation of placebos results in a non-uniform distribution of subregions: based on their centrality in the adjacency matrix, subregions have different sampling probabilities. Since the outcome for the composite placebo depends on the outcomes for its constituent subregions, this means that some outcomes will be sampled more frequently than others. In other words, some ranges of RMSPE values in our sample will be over-, while some relatively underrepresented.

To remedy the problem with the third assumption, we propose to estimate the distribution of the RMSPE values (the test statistic) for the placebo regions using a continuous distribution function. The oversampling problem can be addressed by using inverse probability weighting to adjust the RMSPE values for the placebo regions. We define an *adjusted RMSPE* value for a placebo region as:

$$aRMSPE_k = \frac{RMSPE_k}{p_k}, \tag{12}$$

where p_k is the probability of sampling the k-th placebo, and $RMSPE_k$ is the original, unadjusted value of RMSPE for the k-th region.

To estimate the adjusted RMSPE values we obviously need some way to learn the probability of sampling a particular placebo region p_k. In the general case, for a placebo region formed by the following walk:

$$s_1^{(0)} \to s_2^{(1)} \to s_3^{(2)}, \tag{13}$$

where s_k denotes a subregion and the superscript in brackets denotes the step of the random walk, the sampling probability is:

$$p(r) = p(s_1^{(0)}) \cdot p(s_2^{(1)} \mid s_1^{(0)}) \cdot p(s_3^{(2)} \mid s_2^{(1)}). \tag{14}$$

We know the value of $p\left(s_1^{(0)}\right)$ to be equal to $1/K$, where K is the total number of regions. Conditional probabilities $p\left(s_k^{(t+1)} \mid s_{k-1}^{(t)}\right)$ can, in general case, be calculated using the transition matrix of the Markov process underlying the random walk. However, in our case, the transition matrix would need to be recalculated for each subregion $s_k^{(0)}$, because the rules of the sampling algorithm prohibit visiting the same location twice in the same walk. This makes the transition matrix directed, with directionality of connections changing depending on which node the walk begins from.

Given this complication we chose to use a conceptually and algorithmically simpler approach to calculating probabilities of sampling subregions. We perform a search of the map defined by the adjacency matrix, retrieving all paths of length 9 starting from each subregion that are valid according to the spatial continuity rule. For each subregion we then calculate the probability of it being sampled in the placebo-generating process as the ratio of the number of paths the subregion appears on to the total number of paths discovered. The probability of sampling a placebo region k is then calculated as the joint probability of sampling all subregions it is composed of.

To address the problem of using a sample instead of the entire population, we use the Gamma distribution to model the probability density of sampling the adjusted RMSPE values, with probability density function:

$$f(x \mid \alpha, \beta) = \frac{x^{\alpha-1}\beta^{-\alpha}}{\Gamma(\alpha)} \exp\left(-x/\beta\right). \tag{15}$$

Parameters α and β are estimated using the maximum likelihood estimator (MLE) with a sample of $\log(aRMSPE)$ values for 733 placebo regions. We use the logarithms of the adjusted RMSPE values to improve the convergence of the MLE algorithm. Initial values of parameters α and β for MLE estimation were calculated as:

$$\alpha_0 = \bar{x}^2 / \mathrm{V}(x),\ \beta_0 = \mathrm{V}(x)/\bar{x}, \tag{16}$$

where $\mathrm{V}(x)$ is the sample variance.

The fit of the Gamma distribution to the sample can be seen in Fig. 2.

Given the estimated distribution parameters ($\alpha = 0.623$, $\beta = 16.068$) and the value of $\log(aRMSPE)$ for the Far East (48.032), we can estimate the p-value as the probability of randomly sampling a placebo region with a $\log(aRMSPE)$ value greater than the value of the Far East as $1 - F\left(aRMSPE_{FE} | \alpha, \beta\right)$, where $F(\cdot \mid \alpha, \beta)$ is the CDF of the Gamma distribution. This corresponds to a one-tailed p-value test with $\log(aRMSPE)$ serving as a test statistic. As a result, we obtain p-value of 0.021 which makes the estimate statistically significant at the 5% level.

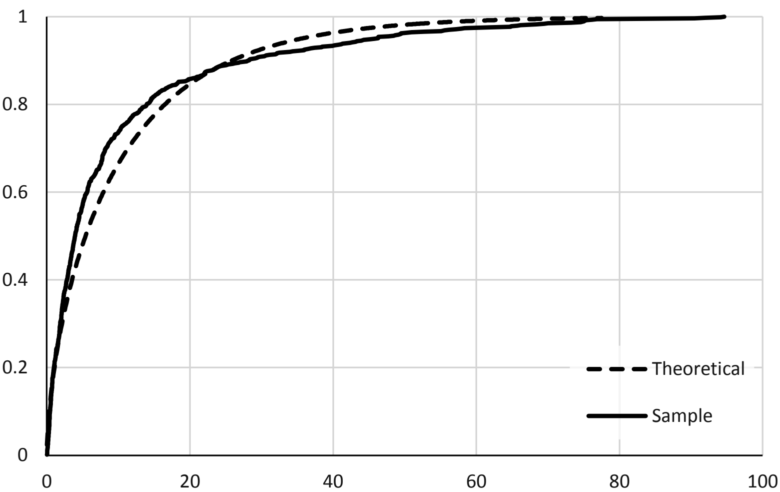

Fig. 2. Cumulative probabilities of $\log(aRMSPE)$ values for a sample from the Gamma distribution and the placebo synthetic controls sample (CDF parameters: $\alpha = 0.623$, $\beta = 16.068$)

6. Conclusion

Using the synthetic control method to construct a control region for the Far East, we have estimated the size of the causal effect of the Far East social-economic development policy on the region's real per capita GRP during 2014–2019. We have found that the policy had a positive and statistically significant effect. We estimate that the policy added around 93 billion rubles (in constant 2000 prices) to the region's GRP during the period.

Our use of the synthetic control method is novel in that we have applied it to a "composite" object — a super-region composed of several subregions. This gave rise to a number of challenges for the estimation of the result's statistical significance, which we tried to address by using a random sampling algorithm to generate a finite set of placebo regions and estimating the p-value using inverse probability weighted values of the test statistic.

Our conclusions appear to contradict the general consensus regarding the effectiveness (or lack thereof) of the Far East development policy. However, most other studies so far had used multiple indicators and various heuristic methods to gauge the policy's effect. In contrast, we use a causal method and restrict our estimation to a single indicator — the per capita GRP. The latter is a useful and widely accepted in the literature indicator of overall economic performance, yet it certainly doesn't reflect the full spectrum of the policy's economic and social impacts.

Nevertheless, our results appear substantial and, from the methodological point of view, demonstrate the danger of estimating effects based on comparisons with the mean and intertemporal comparisons made without regard to confounders. We propose that more attention is paid to the use of valid comparison methods for the estimation of causal effects both at the policy planning and evaluation stages.

Code availability statement. Quantitative methods used in this research were implemented using the Python programming language and freely available and open-source libraries: Numpy, Pandas, CVXPY and Scipy. The robust synthetic control method was implemented in Python with PyTorch by the authors, with code available at https://github.com/agoryuno/robust_control.

References

Abadie A. (2021). Using synthetic controls: Feasibility, data requirements, and methodological aspects. *Journal of Economic Literature*, 59 (2), 391–425. DOI: 10.1257/jel.20191450.

Abadie A., Gardeazabal J. (2003). The economic costs of conflict: A case study of the Basque country. *American Economic Review*, 93 (1), 113–132. DOI: 10.1257/000282803321455188.

Abadie A., Diamond A., Hainmueller J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American Statistical Association*, 105 (490), 493–505. DOI: 10.1198/jasa.2009.ap08746.

Abadie A., Diamond A., Hainmueller J. (2015). Comparative politics and the synthetic control method. *American Journal of Political Science*, 59 (2), 495–510. DOI: 10.1111/ajps.12116.

Aganbegyan A. (2019). Development of the Far East: A national program in the context of national projects. *Spatial Economics*, 15 (3), 165–181 (in Russian). DOI: 10.14530/se.2019.3.165-181.

Amjad M., Shah D., Shen D. (2018). Robust synthetic control. *Journal of Machine Learning Research*, 19, 1–51.

Chatterjee S. (2015). Matrix estimation by universal singular value thresholding. *The Annals of Statistics*, 43 (1), 177–214. DOI: 10.1214/14-aos1272.

Firpo S., Possebom V. (2018). Synthetic control method: Inference, sensitivity analysis and confidence sets. *Journal of Causal Inference*, 6 (2). DOI: 10.1515/jci-2016-0026.

Gulidov R. (2021). On the matter of appraisal of public policy towards the development of the Russian Far East. *Spatial Economics*, 17 (4), 143–167 (in Russian). DOI: 10.14530/se.2021.4.143-167.

Imbens G., Rubin D. (2015). *Causal inference for statistics, social, and biomedical sciences: An introduction*. Cambridge: Cambridge University Press. DOI: 10.1017/CBO9781139025751.

Isaev A. (2020). Social efficiency indicators of public investment: The case of the Far Eastern regions. *Spatial Economics*, 16 (4), 23–43 (in Russian). DOI: 10.14530/se.2020.4.023-043.

King G., Zeng L. (2006). The dangers of extreme counterfactuals. *Political Analysis*, 14 (2), 131–159. DOI: 10.1093/pan/mpj004.

Leonov S., Tolmachev V. (2020). Territories of advanced development and the free port of Vladivostok as a tools for implementing regional policy in the Khabarovsk territory. *Regionalistica*, 7 (6), 49–65 (in Russian). DOI: 10.14530/reg.2020.6.49.

Lomakina N. (2020). State incentivizing of investment activity in the resource region: Far East of Russia variant. *Spatial Economics*, 16 (4), 68–90 (in Russian). DOI: 10.14530/se.2020.4.068-090.

Minakir P. (2020). Political value of expectations in economy. *Spatial Economics*, 16 (3), 7–23 (in Russian). DOI: 10.14530/se.2020.3.007-023.

Received 19.05.2023; accepted 31.07.2023.