4.3 Methods for Analyzing the Effect of Science, Technology, and Innovation Policy

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First Published August 28, 2018 Final Updated April 25, 2019

Abstract

Analyzing policy effectiveness clarifies the impact and significance of a given policy. This paper reviews the purpose of policy effects analysis and discusses the most popular methods used and their value in this regard. Using R&D subsidy policy as an example, this paper introduces several case studies of policy effects.

Keywords

Policy effects, policy evaluation, R&D subsidies, difference-in-difference analysis, treatment effects, matching, simulation, ex-ante evaluation, ex-post evaluation

1 Objectives of policy effectiveness analysis

Analyzing policy effectiveness clarifies the impacts of a given policy. When conducting such analysis, it is important to refer to previous studies that have analyzed the effects of similar policies. For example, consider the effects of a policy allocating R&D subsidies to firms. In this case, the purpose of such policies is to stimulate R&D activities in enterprises, thereby facilitating the development of technology, creation of innovation, and a higher rate of economic growth. The primary test of the effect of these policies is whether the R&D investments of the companies receiving the subsidies increases. As an increase in R&D

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investment affects technological development, the number of patent applications and other factors are potential indicators of outcomes. Examining the impact of a policy on innovation also involves tracing the rate of increase in productivity and whether product innovation, such as new products and services, is increasing.

When capturing the impact of R&D subsidies on economic growth, we also need to look at the policy's spillover effects. In order to achieve a detailed understanding of policy effects, we must assume a counter-factual potential outcome (Ito Koichiro, 2017; Nakamuro Makiko and Tsugawa Yusuke, 2017). In the aforementioned example of the effect of an R&D subsidy policy, ideally, it would be possible to verify the effect of the subsidy policy on R&D investment by comparing the R&D investment of a subsidized firm after receiving the subsidy with what it would have been had the firm not received the subsidy. However, in practice, we cannot observe the value of investment by companies that receive the subsidy had they not received the subsidy. The key to verifying policy effects lies in envisioning the consequences that did not actually occur but which could have occurred without the policy intervention—that is, potential counterfactual consequences—and to compare these with the actual situation.

For example, it is dangerous to simply compare Company A, which received the subsidy, and Company B, which did not receive the subsidy, and judge whether the subsidy had the effect of increasing R&D investment on this basis, even if Company A's R&D investment was greater than that of Company B. This is because differences in factors other than the subsidy—for instance, differences between Company A and Company B in terms of R&D capacity and fund-raising ability—may have given rise to this difference in R&D investment. It is also dangerous to conclude that the increase in R&D investment by Company A, which received the subsidy, is due to the effect of the subsidy, even if the amount of R&D investment increased around the time that the subsidy was received. This is because Company A may have planned to increase its R&D investment from the beginning, regardless of the subsidy. In this case, the subsidy may have covered a preplanned increase in R&D investment, or the originally planned increase in R&D investment may have been used for other purposes. There may also have been a planned reduction in funding from private financial institutions arranged before receiving the subsidy; this kind of reduction in private-sector demand for funds resulting from government spending is generally known as the "crowding out" effect.

In response to these issues, the following sections introduce typical methods of analysis for evaluating policy effects using limited data.

2 Ex-post and ex-ante evaluation of policy effects

It is important to distinguish between ex-post and ex-ante evaluation methods when analyzing policy effects. Ex-post evaluation is the process of assessing the efficacy of a policy after it has been implemented. In contrast, ex-ante evaluation is the assessment of a policy that is to be implemented in the future, that is, before its implementation.

More specifically, in ex-post evaluation, it is essential to collect and preserve the data necessary for policy evaluation before the policy is even implemented. In this process, accumulating enough data to reproduce the potential consequences of counterfactuals discussed earlier is crucial. For example, it is almost impossible to replicate the potential consequences of counterfactuals using only data on firms that actually received the subsidy. Therefore, data from companies that do not receive the subsidy should also be available for comparison. It is also difficult to verify policy effects only using data pertaining to after the subsidy was received. As such, it is necessary to collect and preserve pre- and post-policy intervention data for both the group that received the policy intervention and its comparison group.

This prompts the question of what kind of data needs to be collected and retained. As the policy evaluation analysis will be incomplete if the necessary data for policy evaluation indicators are missing, it is necessary to align the evaluation indicator data for both the policy intervention group and the comparison group before and after the implementation of the policy intervention, while referring to the purpose of the policy's implementation and previous studies.

There are two main approaches to ex-post evaluation analysis. The first involves the estimation of treatment effects. Known as guided analysis, this approach attempts to statistically estimate the causal relationship (i.e., impact) of evaluation indicators using data from past policy interventions. The second approach uses model-based counterfactual simulations. More specifically, this approach involves constructing a theoretical model that successfully reproduces the reality in which the policy intervention took place, attempting to run this theoretical model assuming a situation in which the policy intervention did not take place, and evaluating the efficacy of the policy actually implemented by confirming the extent to which the consequences of the theoretical model differ from reality. Approaches include growth accounting analysis, computable general equilibrium (CGE) models, structural estimation, and agent-based models (ABM). Guided analysis has the advantage of being able to examine policy effects without assuming a sophisticated theoretical model. It is a so-called data-driven approach requiring a wealth of data on both the policy intervention group and the comparison group. The latter approach attempts to examine policy effects more precisely—including direct, indirect, and spillover effects—using a theoretical model (Ohashi Hiromu and Isogawa Daiya, 2013).

The procedures for ex-ante evaluation differ from those of ex-post evaluation because it is necessary to verify the effects of a policy that has yet to be implemented. The simplest method involves randomly selecting a portion of the target population for the policy intervention, attempting the policy intervention on a trial basis, collecting data on the evaluation indicators before and after the policy intervention, and attempting to verify its efficacy. As with ex-post evaluation, data are also collected for the group that did not experience the policy intervention (i.e., the comparison group), and the evaluation indicators of the group that underwent the policy intervention are compared with those of the comparison group. This method is referred to as a Randomized Controlled Trial (RCT). However, depending on the type of policy effect being tested for, it may be difficult to carry out an RCT. The application of a model-based counterfactual simulation, as described above, may be effective in such cases. Moreover, in order to improve the accuracy of model-based counterfactual simulations in the ex-ante evaluation of policy effectiveness, it is useful to use such simulations in combination with other data, such as questionnaires.

Of these analytic methods, the ex-post evaluation of policy effectiveness targets policies that have already been implemented, while ex-ante evaluation assumes that policy options are available to analysts. Meanwhile, the creation of new policy options requires a different analytical approach. The following section explains these methods of analyzing policy effects with reference to specific examples involving science, technology and innovation policy, noting the data and indicators required when applying each method.

3 Ex-post evaluation of policy effects by estimating treatment effects

The analysis of treatment effects in the ex-post evaluation of policy effectiveness involves comparing the "real" consequences of the actual implementation of the policy with the potential "counterfactual" consequences of not implementing the policy. While the real results of policy implementation can be ascertained by properly collecting data, the counterfactuals are the potential results of situations that have not occurred in reality and must thus be created hypothetically. As such, the question of how to create a plausible counterfactual result is the basis for conducting ex-post evaluation. In terms of the R&D subsidy example, if we can establish the performance of a company that received the subsidy under exactly the same circumstances but without the subsidy, and compare it to the company's actual performance after receiving the subsidy, we can accurately determine the effect of the allocation of the subsidy on the company's performance (i.e., treatment effect).

The matching method is a popular approach to obtaining counterfactuals to estimatie a policy's treatment effect. Essentially, the matching method uses the data of matched comparators as counterfactuals by assigning the most similar person from the comparison group, which did not receive the policy intervention, to each of the subjects in the group that received the policy intervention. In doing so, care should be taken to define similarity based on data collected at a point in time prior to the policy intervention. If we define similarity based on data from a point in time after the policy intervention, the data of the subjects in receipt of the policy intervention may be affected by the policy intervention, hindering the analysis of the policy effect. By assigning similar subjects prior to the policy intervention, we are attempting to estimate the difference in policy evaluation indicators (i.e., the policy effect) between the case where the policy intervention is applied to the same subject and the case where the policy intervention is not applied to the same subject.

For example, in the case of the R&D subsidy, the policy effect can be estimated by finding comparable companies that are as similar as possible in terms of the various indicators affecting corporate performance and R&D investment that should be focused on as policy evaluation indicators, such as the value of R&D investment, corporate performance, company size, date of establishment, and innovation activities before a company received the subsidy. These indicators can then be used to estimate the difference between the performance of the company after receiving the subsidy and the performance of the comparable company. In order to make statistically meaningful inferences, rather than using data from only one firm it is preferable to use data from as many firms as possible. In practice, it is necessary to make statistical judgments by conducting hypothesis testing and interval estimates of the magnitude of policy effects based on the average treatment effects (ATE) of the difference between each firm and its comparator. Typical matching methods include Propensity Score Matching (PSM) and matching based on Mahalanobis Distance (MD).

Several other methods are available for the ex-post evaluation of policy effects by estimating average treatment effects. For instance, the Difference in Difference (DID) analysis focuses on the difference in performance between the two groups before and after the policy intervention by removing the effect of trends common to both the intervention and control groups. Regression discontinuity design (RDD) focuses on jumps in evaluation indicators when the criteria for the policy intervention are based on continuous score cutoffs. Meanwhile, the Instrumental Variable (IV) method renders intervention and control groups comparable by using variables that affect the presence or absence of the policy intervention but do not directly affect the evaluation indicators. For more detailed explanations of these methods, see Nakamuro Makiko and Tsugawa Yusuke (2017), Ito Koichiro (2017), and Wooldridge (2010). In this respect, scholars like Czarnitzki and Delanote (2015) and Hud and Hussinger (2015) have analyzed the policy effects of R&D subsidies using PSM, while Bronzini and Piselli (2016) have used RDD and Clausen (2009) has used the IV method.

4 Examples of the ex-post and ex-ante evaluation of policy effects using counterfactual simulation

In model-based counterfactual simulation, a theoretical model that successfully reproduces the reality of a policy intervention is conducted and then run assuming that the policy intervention did not take place. The results of the model are checked to see to what extent they differ from reality, thus enabling the evaluation of the effects of the actual policy. For example, Ikeuchi Kenta et al. (2013) analyzed the effect of public R&D investment on economic growth by using the growth accounting approach to identify the causes of the decline in the productivity growth rate over the past twenty years. Meanwhile, Ohashi Hiroshi and Isogawa Daiya (2013) examined the effect of public subsidies on innovation activity-related costs using a theoretical model incorporating firms' strategic behavior and technological spillovers.

Counterfactual simulations can also be used to evaluate future policy effects. For instance, Nagata Akiya (1998) and Nagata Akiya et al. (2013) developed a simulator predicting the effects of R&D investment on future economic growth based on the standard macroeconomic model. Kuroda Masahiro et al. (2016) proposed a method to simulate the effect of future public R&D investment on economic growth using a computable general equilibrium model. Tonogi Akiyuki (2015) simulated the effect of increased public R&D investment on future economic growth using a general dynamic equilibrium model with structural estimates.

5 Ex-ante evaluation of policy effects using randomized controlled trials

Ideally, a randomized controlled trial (RCT) should be conducted for the ex-ante evaluation of policy effects. In an RCT, a portion of the target population for a policy intervention is randomly selected to pilot the policy intervention and test its efficacy. When doing so, it is important to divide the group for the policy intervention and the comparison group at random. For example, if the policy intervention group was originally biased toward poorly performing firms, it is only natural that the performance of the policy intervention group following the policy intervention would be higher than that of the control group. By selecting the policy intervention group at random, it becomes possible to estimate policy effects with greater specificity. For more detailed discussions of RCT methods, see Nakamuro Makiko and Tsugawa Yusuke (2017), Ito Koichiro (2017), and Edovald and Firpo (2016).

Although RCTs have received increasing attention from the policy side in recent years (Yamana, Kazufumi, 2017), they are not commonly implemented in science, technology, and innovation policy practice at present (What Works Centre for Local Economic Growth, 2015). One of the main reasons for this underutilization of RCTs is the lack of established procedures and consensus building surrounding the implementation of this method in policy practice. To promote the use of RCTs, it is necessary to build a consensus on their utility and develop a system to guarantee their efficacy even in instances where some subjects are disadvantaged.

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