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Econometric Methods for Evaluation of Agricultural Policy

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The most important task of evidence-based policy making is the estimation of the causal impacts of policies. In Kawasaki (2020, 2021, 2022), we provided detailed reviews of three econometric methods, namely, regression discontinuity design, difference-in-differences, and instrumental variable methods, that can be used to estimate policy impacts. This note provides a brief summary of these three methods.

1. Causality

Consider the impact of agriculture policy on a selected outcome, for example, farm income or acreage of abandoned farmland. The causal impact of a policy is defined as $Y_1–Y_0$, where Y_1 is an outcome achieved by participating a policy and Y_0 is an outcome by not participating a policy. The problem is that one can never observe both Y_1 and Y_0. For farms who have participated a policy, we can observe Y_1 but not Y_0 as the latter is an outcome under counter-factual situations. Thus, some methods are needed to estimate Y_0.

The simplest method would be before-and-after comparisons, assuming the outcome before and after policy participation as Y_0 and Y_1, respectively. Such comparisons, however, would not reveal policy effects because conditions other than policy, such as weather and market conditions, are likely to differ by year.

How about comparing the average outcome of farmers not participating a policy (control group) with that of farmers participating a policy (treated group)? However, this method may also be misleading because both groups may differ systematically in terms of farm characteristics, such as farm size and skills. That is, it is impossible to distinguish policy effects from effects due to differences in farmers' characteristics.

The most promising method to estimate policy effects is randomized control trials (RCTs). Under RCTs, farmers are randomly allocated into treated and control groups. Randomization ensures that the two groups have the same characteristics on average. Thus, policy effects can be estimated by simply comparing the outcomes of the two groups. However, RCTs are not always feasible as implementable costs tend to be high, especially in developed countries.

2. Regression discontinuity design

The regression discontinuity design (RDD) can be applied when there is a discontinuity or cut-off point in participant eligibility. For example, if a policy requires participants to be younger than 50 years, then farmers' characteristics will be almost the same around the cut-off age (e.g., 49 vs 51 years), so the observed differences would be likely caused by the policy rather than farm characteristics.

Kawasaki (2020) reviewed various applications of RDD in agricultural fields, and found that previous studies used discontinuities in farm size, regional boundary, distance, time, income, and population. More recent studies focused on discontinuity in time to clarify the effects of COVID-19 upon vegetable prices (Ruan et al., 2021; Dang and Trinh, 2021), or discontinuity in space (national boundaries) to estimate the effects of fertilizer on crop yields (Wuepper et al. 2020).

The applications of RDD are relatively limited compared to the other two methods, because policies should have discontinuities in eligibility criteria, and farm-level data are often required to use RDD.

3. Difference-in-differences method

The difference-in-differences (DID) method can be applied when one can measure outcomes before and after policy introduction for both treated and control groups.

As reviewed by Kawasaki (2021), DID has been widely used in the literature to estimate the impacts of subsidies on food consumption, organic certification, environmental subsidies, agricultural land policy, health effects of pesticides, and entry effects of corporate companies in agriculture. Recently, DID is also used for trade agreements (Chi et al., 2022) and medical insurance for farmers (Kandilov and Kandilov, 2022).

One key requirement to use DID is parallel trend assumption. When this assumption fails, one can alternatively use the synthetic control method. Kawasaki (2021) reviewed a study which used this method to evaluate sugar tax, while more recent studies focused on forest conservation programs (West et al., 2020) and the effect of wearing masks on the suppression of COVID-19 outbreaks (Mitze et al., 2020).

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4. Instrumental variable method

Variables that do not directly affect outcomes, while correlating with policy participation, are called instrumental variables (IVs). Kawasaki (2022) reviewed the use of IVs in agricultural fields.

The most common IV in the literature is distance. For instance, previous studies used distance to regional agriculture extension offices, supermarkets, and neighboring countries as IVs. Regional or macroeconomic conditions are also possible candidates of IVs. Examples include the percentage of nearby farmers adopting certain technology, local policy, weather conditions, latitude, GDP, and prices. In some cases, eligibility of policy participation can be also used as IVs. Recently, Brucker et al. (2022) estimated the impacts of social security on food consumption using the IV method.

Finding IVs is always challenging. If valid IVs are not available, one can use the partial identification approach. Kawasaki (2022) reviewed a study that applied this approach to the food assistance program in the United States.

5. Conclusion

Most studies reviewed by Kawasaki (2020, 2021, 2022) were from foreign countries. To promote more empirical studies in Japan, we must not only nurture data scientists, but also mitigate barriers in performing empirical research. For example, it would be effective to add subsidy beneficiary information and geographic information to existing statistics. Estimations of policy effects are impossible if there is no control group, as is common for national policies where all farmers are eligible. Thus, empirical analysis would become much easier if trial policies are implemented in selected regions, or if detailed data of local policies become available. That is, collaboration between researchers and administrative and statistical offices is essential to realize evidence-based policy making.

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