

How can Machine Learning models contribute to agricultural policy evaluation?

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The advantages of Machine Learning algorithms

Background

Policy evaluation is critical in designing effective policies and ensuring their correct implementation. In recent years, Machine Learning (ML) models have been proposed as an extension to the agricultural economists' toolkit (Athey 2017 & 2018; Baylis et al., 2021; Mullainathan and Spiess, 2017). However, applications to analyse the Common Agricultural Policy (CAP) are still limited (Stetter et al., 2022), although there are many benefits to be expected from their adoption.

Objective

Compare the performance of different ML algorithms versus classical econometric evaluation methods. To achieve this, an extended dataset is simulated based on the EU Farm Accountancy Data Network (FADN) and a large number of factors relevant for causal inference are included. In this way, it is possible to indicate which model can be applied given certain specific circumstances.

Mind the CAP expenses

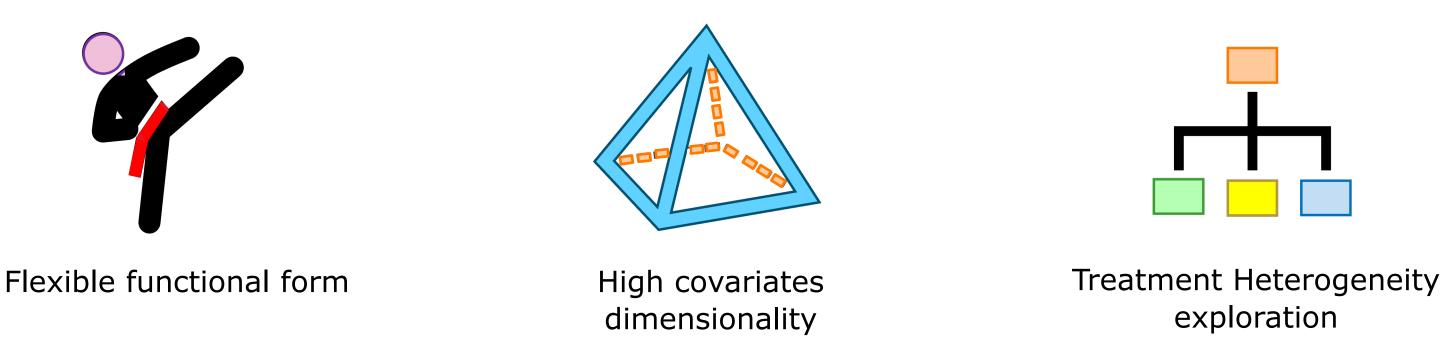
The importance of evaluating the CAP lies in the relevance of its and the budget objectives devoted to its intervention [Fig. 1]. The evaluation is often starting carried out from observational data, in particular However, FADN. this the approach comes with several obstacles to the identification of the causal effect.



2021 - 2027 CAP

CAP percentage of the

ML methods can provide useful insights for policy making thanks to 3 properties:



In this way, it is possible to find more realistic comparisons, and also understand how the treatment effect changes across farmers [Fig. 4].



Figure 4. On the left, a vineyard in the Champagne province, France; on the right, a vineyard in the Tuscany region, Italy. Both zones are characterized by limestone soils, high temperature, high exposure to sun and low altitude.

Figure 1. Budget for CAP for 2021-2027. **Source:** Council Regulation (EU, Euratom) 2020/2093



CAP expenditure



386,6

Billions

CAP budget devolved to climate action

The problem of comparing apples with oranges



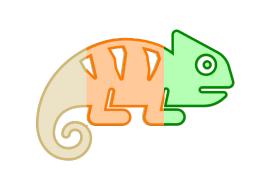


Our simulation

The simulation we develop is calibrated on the FADN dataset. In addition to that, it considers several factors relevant for causal inference [Fig. 5]. across multiple replications, so that we can assess where each model can be expected to break and how.

Factors

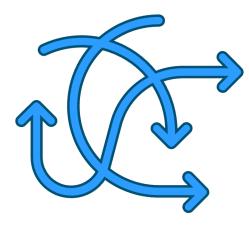




Strength of treatment

Strength of confounding

Figure 5. Factors considered in the different replications of the simulation. For each of the factor, two distinct level are considered.



Non-linearity



Heterogeneity in Treatment

Silver bullet or red herring?

Figure 2. Heroic Viticulture in the Valle d'Aosta region, Italy. Vineyards in this region are characterized by sandy soils, low temperatures, low exposure to sun and high altitude.

Figure 3. Viticulture in the Champagne province, France. Vineyards in this province are characterized by limestone soils, high temperature, high exposure to sun and low altitude.

The problems we face when evaluating the impact of a CAP intervention essentially relate to selection bias and confounding [Figs. 2-3]. Farmers receiving the treatment are not directly comparable with those who do not, as participation is voluntary and/or targeted.

So far it might seems that ML models only bring advantages to the causal inference question. However, not everything that shines is gold, and ML is often associated with 2 major disadvantages:





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