Estimating the effects of Iberian price cap using a Bayesian multivariate synthetic control approach

Giulio Grossi

Abstract In causal inference a popular tool to assess policy effect is the synthetic control method (SCM). An undeveloped aspect is the use of SCM in complex contexts, as the estimation of causal effects on multiple outcomes simultaneously, where correlation structure across multiple outcomes can be leveraged to estimate more reliable and transparent policy effects. In this work, we propose an expansion of the current methods to deal with these complications. Our motivating application is the so-called Iberian Exception, the mechanism implemented by Spain in 2022 to set a cap for natural gas prices exploited in energy production. These interventions, starting with energy prices, have multiple impacts on other macroeconomic measures, such as GDP and unemployment. Here we evaluate the overall assessment of the policy on multiple outcomes, using a novel Bayesian multivariate approach for policy evaluation.

Keywords: energy economics, causal inference, panel data, synthetic control method

1 Introduction

During the inflation crises triggered by the record-high prices for commodities during 2021 and 2022, Spain have recently been at the forefront of a critical energy dilemma. In an unprecedented move within the European Union, Iberian nations implemented a bold policy: the implementation of a gas price cap, specifically targeting the cost of gas used for electricity generation. The crux of the issue lies in the direct impact of natural gas prices on electricity bills. Therefore, this policy serves as a critical test case in real-time economic policy-making, aiming to mitigate the immediate burden on end-users while navigating the complexities of energy market dynamics. Moreover, the relapses of the gas price cap could spread on the inflation indexes, or the other macroeconomic indicators, such as unemployment and GDP. Few to no previous work has focused on the evaluation of this policy, except for [6] and [4]. Focusing on methodological contribution, the use of synthetic control method [1], has been recognized as a pivotal method in policy evaluation literature. Usually, it is implemented focusing on a single outcome, it is a common

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occurrence across numerous fields for a policy to simultaneously affect multiple outcomes as highlighted in the work of [2]. While the standard approach in research is to conduct separate estimations for each outcome, this paper introduces a novel and flexible Bayesian semiparametric method to estimate these effects in a multivariate framework. Recent strands of literature are investigating the use of multiple outcomes estimates simultaneously [5], but these works usually do not focus on the correlation structure of the outcomes, and estimate results using classical frequentist estimators. Instead here we propose a Bayesian multivariate SC estimator exploiting Gaussian Process for priors.

2 Methods

We consider a panel data setting, with N units, observed for T times. Moreover, for each unit, in each time point, we observe K outcomes of interest. Let $W_i = (w_1, \dots, w_i, \dots, w_N), \in \{0, 1\}$ denote the binary treatment assignment for each unit, we postulate that the treatment is starting in time t_0 and units cannot revert treatment. Here we consider the first unit as treated, and all the others as controls. Thus, we observe a pre-treatment period $T^- = (1, \dots, t_0)$ during which no units are receiving the treatment and a post-treatment period $T^+ = (t_0^{+1}, \dots, T)$ in which we observe the treatment only in Spain. Under a potential outcome approach and Stable Unit Treatment Value Assumption (SUTVA) we can define a couple of potential outcomes, $Y_{i,t}^k(0)$ and estimate the causal effect as $delta_{i,t}^k = Y_{i,t}^k(1) - Y_{i,t}^k(0)$.

Let $Y_{i,t}^k = Y_{i,t}^k(w)$ denote the observed outcome for unit i at time t for the outcome k. Thus $Y_i^k = (Y_{i,1}^k, \dots, Y_{i,t}^k, \dots, Y_{i,T}^k)$ is representing the time series of outcome k for unit i, and Y_i will represent the matrix of outcome for some unit £. In SCM, the missing potential outcome $Y_k(0)$ is usually imputed as a linear combination of control outcomes as

$$\delta_{i,t}^k = Y_{i,t}^k(1) - \sum \beta_j Y_{j,t}^k \tag{1}$$

where the vector of coefficients β_i is the solution of a vertical regression problem, see for instance [3]. Usually, with multiple outcomes, the effect of the policy is inferred one at a time, which is correct, but it does not exploit the correlation structures present across the outcomes. Instead here we propose a synthetic control approach in which coefficients are estimated from the following multivariate model

$$\mathbf{Y}_1 = \mathbf{B}\mathbf{Y}_{2:N} + \varepsilon_i \tag{2}$$

where $\mathbf{B}$ is the $K \times (N - 1)$ matrix of coefficients, in which each column is the coefficients for control unit i across the outcomes, $Y_{2:N}$ is a $T \times K \times (N - 1)$ matrix with all the k outcomes for the control units $i \in 2, \dots, N$ and ε_i is a $T \times K$ matrix of idiosyncratic error for the treated unit. We argue that the effect starts from an affected outcome and has effects on other macroeconomic outcomes. Thus, the outcomes that are more correlated with the treated outcomes should have coefficients that describe the missing potential outcomes quite similarly, and this similarity should vary smoothly as the correlation decreases. We can exploit this additional structure by using a Bayesian regression model, using Gaussian processes as prior for the columns of the coefficients matrix.

$$
\begin{aligned}
&P(\mathbf{Y}_1|\mathbf{Y}_{2:N},\mathbf{B},\alpha_i,\rho_i,\alpha_\varepsilon,\rho_\varepsilon,D,\eta_\varepsilon) \sim \\
&N\mathbf{B}\mathbf{Y}^0, K(D,\alpha_\varepsilon,\rho_\varepsilon)+\eta_\varepsilon I \\
&\beta_i \sim GP(\mathbf{0}, K(D,\alpha_i,\rho_i)) \\
&\alpha_\varepsilon,\rho_\varepsilon,\alpha_i,\rho_i \sim \Gamma^{-1}(1,1)
\end{aligned}
\tag{3}
$$

In such a model, we posit as a prior for the coefficients a Gaussian process, and its covariance K is a function of the distance between outcomes D, and the hyperpriors α_i, ρ_i.

3 Estimating Macroeconomics effects from Iberian exception

Our interest is in estimating not only the reduction in the energetic price index due to the price cap but also (and mainly) the positive or negative relapses that this intervention has on the Spaniard economy as a whole. We highlight aside from the energy price index, six other dimensions: food price index, CPI, Core inflation, Unemployment rate, Business confidence index, and Consumer confidence index. All of these variables are monthly data, from March 2020 to September 2023, obtained from OECD. The intervention takes place on July 2022, and thus we have $T_0 = 29$ pretreatment period and $T_1 = 14$ post-treatment period. We consider one treated unit, Spain, and $N_0 = 17$ control units, other countries in the OECD pool. Some of these countries have implemented some form of price reduction for energy bills, so in this work, we can only evaluate the effect of the Iberic price cap vs. other interventions or no interventions. Figure 1 shows the results. The Iberian price cap demonstrably impacted not only Spanish energy prices, leading to a significant decrease, but also other macroeconomic indicators. While the price cap's influence on the Consumer Price Index (CPI) and core inflation materialized initially, neither reached statistically significant levels. However, the policy potentially played a role in unemployment reduction, which showed a statistically significant decrease following its implementation. This suggests that the avoided rise in energy prices may have created space for additional job creation. Additionally, the consumer confidence index rose, indicating that the gas price reduction likely bolstered consumer spending in the subsequent months. These findings align with expectations and emphasize the importance of a comprehensive evaluation of policies.

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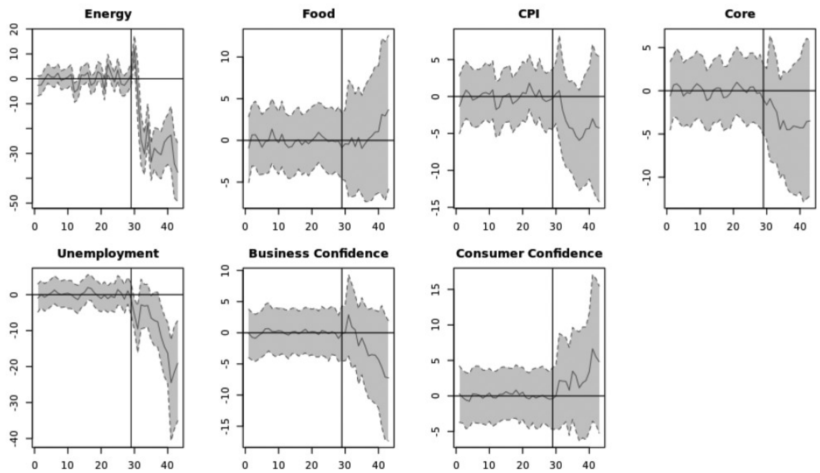

Fig. 1: Causal effects for multiple outcomes after treatment, shaded area: 95% BCI.

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