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# Has EU Accession Boosted Patent Performance in the EU-13? A Critical Evaluation Using Causal Impact Analysis with Bayesian Structural Time-Series Models

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**Abstract:** This paper provides new insights into the causal effects of the enlargement of the European Union (EU) on patent performance. The study focuses on the new EU member states (EU-13) and accession is considered as an intervention whose causal effect is estimated by the causal impact method using a Bayesian structural time-series model (proposed by Google). The empirical results based on data collected from the OECD database from 1985–2017 point towards a conclusion that joining the EU has had a significant impact on patent performance in Romania, Estonia, Poland, the Czech Republic, Croatia and Lithuania, although in the latter two countries, the impact was negative. For the rest of the EU-13 countries, there is no significant effect on patent performance. Whether the EU accession effect is significant or not, the EU-13 are far behind the EU-15 (countries which entered the EU before 2004) in terms of patent performance. The majority of patents (98.66%) are assigned to the EU-15, with just 1.34% of assignees belonging to the EU-13.

**Keywords:** causal analysis; European Union; patents; innovations; Bayesian structural time-series models

**JEL Classification:** O340; C11; C32; O52

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## 1. Introduction

Based on theoretical assumptions, economic integration and accession to the European Union (EU) usually bring numerous benefits. However, despite the efforts of EU policy makers, disparities exist between the EU-15 (countries which entered the EU before 2004) and EU-13 (countries that joined the EU in and after 2004) in various ways, as highlighted by many authors, e.g., [1–3]. Among other things, the EU is also polarized in terms of innovations. According to [4], data from the European Innovation Scoreboard suggest that the EU-13 lags behind the EU-15. As showed by [5], the headquarters of the EU's top 1000 R&D investors from the ICT sector are located in 16 countries, with an overwhelming concentration in EU-15 countries. Furthermore, organizations based in the EU-13 have benefited less from their participation in the European Framework Programmes (FPs) than organizations from the EU-15 [6]. Most of the time, the EU-13 can be found at the lower end of participation rankings concerning Horizon 2020 [7]. The majority of EU nations with smaller research budgets are former communist countries in central and eastern Europe, which, together with Cyprus and Malta, joined the EU after 2004 as emphasized by [8].

In recent years, there have been numerous academic and policy debates on the delivery mechanisms of EU funds in member states. Accessing large amounts of funding has often been seen as one of the main benefits of EU accession. It was hoped that European funds such as structural funds, direct payments in agriculture and rural development, and other funds would contribute towards reducing disparities between regions. Economists and regional geographers have been very interested in studying the effects of European transfers on national and regional/local economies, e.g., [9]. In various scientific literature and reports, analysis can be found assessing the impact of EU membership on different aspects such as political changes, economic reforms, political values or foreign policies, e.g., [10–13]. Analysis of "cause" and "effects" of EU accession appears occasionally in the literature. Despite this, the problem is challenging and results can be ambiguous depending on the methods used. For example, in [14], the authors concluded that "entry into the EU is positively associated with levels of the homicide rate in the 10 Eastern European countries that joined the EU in 2004 and 2007". However, in [15], the author argues that the available empirical evidence does not support the inference that accession to the EU increased homicides and highlights thatthe result of the statistical model specification was based on a number of unwarranted assumptions and data preprocessing decisions. This underlines how many challenges there are in such analyses.

Despite the research, there are different subjective views of the EU and its influence on member countries. Many of the Central and Eastern European countries have positive views of the political union in surveys; however, on the other hand, there are plenty of Eurosceptics within the EU, as the UK Brexit referendum demonstrated. Hence, it is crucial to reliably and quantitatively assess how membership impacts member states in many different aspects. Considering all aforementioned aspects of disparities between EU-13 and EU-15 leads to the natural question of: has EU-13 accession boosted the innovation of these countries? Since the question is about cause and effect, a formal causal analysis is required to answer it. However, causal impact analysis of EU enlargement on the EU-13 countries' innovations conducted in very few scientific publications. Ref. [16] investigates the relationship between innovation and EU membership using panel data on firm level, similar to [17], while [2] studied scientific collaboration between 'old' and 'new' member states. Results from the latter paper are a direct motivation for this research, as they show that collaboration between new and old member states has been affected by EU enlargement.

In the literature (e.g., [18]), innovation is presented as the most important factor in achieving economic and employment growth, and one of the main determinants of economic development in modern societies. Investing in research is considered essential for achieving smart, sustainable and inclusive growth and jobs in Europe. Investment protects R&D activities by approval of patents rights, and this can make a patent a risk-reducing factor for an investor. Given the strong connection between innovation and patents, we may expect that less innovative countries will lag behind highly innovative ones in terms of total number of patents.

International scientific co-publication is just one of the components of innovation. The number of Patent Cooperation Treaty (PCT) patents applications per billion GDP is another component of the Summary Innovation Index [4]. In this paper, we used number of patents as one key measure of innovation activity. Despite the role of patents in innovation, no studies so far have attempted to examine the dynamics of patent performance in the EU-13 over time, particularly including the effects of EU-13 accession on patent performance. This study has tried to bridge that gap and analyze the dynamical causal impact of EU accession on patent performance.

According to the European Patent Office [19], a patent is "*legal title that gives inventors the right, for a limited period (usually 20 years), to prevent others from making, using or selling their invention without their permission in the countries for which the patent has been granted*".

In an increasingly knowledge-driven economy, society invariably needs creative or inventive ideas or concepts to improve existing features, add useful new features to products or develop new products. It is worth noting that the main formal requirement for patent-granting is that the proposed technical solution be novel and inventive; however, a patent application is a bureaucratic and costly process with numerous procedural aspects that can determine whether the patent is granted or rejected [20]. European patent application statistics from 2019 ([21]) show that the top patent technology fields were digital communication, medical technology and computer technology—all highly influential and fast-growing areas of technology.

In this rapidly changing environment, patents are a long-term investment. The patent applicant can commercialize the invention at any point during the period of patent protection, either through developing products or services incorporating the patented technology, or by licensing it to others. This means patents play an increasingly important role in innovation and economic performance. There is evidence that patenting in general contributes positively to financial performance. The number of patents is a quantitative output of technologically successful R&D activities, can be seen as one of the key components of a country's innovation [22].

The causal impact of EU accession on patent performance was assessed by utilizing Bayesian structural time-series models. The method generalizes the widely used difference-in-differences approach to the time-series setting by explicitly modeling the counterfactual of a time series observed before and after the intervention. Hence, the research problem that guides the analysis is the assessment of the question: has EU membership significantly increased the number of patents of the EU-13 countries.

Furthermore, the paper explores the total number of patents to highlight disparities between EU-13 and EU-15 countries. The following research problems are addressed in the paper:

- To quantify the effects of accession of the EU-13, in particular, to find causalities if accession to EU has increased dynamics of patent performance in the EU-13;
- To analyze disparities between the EU-13 and EU-15.

The main contribution of this paper is an assessment of patent performance for EU-13 countries after accession to the EU using a new causal impact approach with Bayesian inference. The method generalizes the widely used difference-in-differences approach commonly used in related work to the time-series setting by explicitly modeling the counterfactual of a time series observed both before and after the intervention.

The structure of this paper is as follows. In Section 2, we provide a review of the relevant literature on patent analysis and different causal relationships in the innovation field. In Section 3, we describe the dataset and methodology. In Section 4, we report our empirical results. The results are discussed in Section 5. Section 6 summarizes and concludes with policy recommendations.

## 2. Related Work

Intellectual property law governs technological innovation. In the literature, the field of innovation has been presented by [18,23] as the most important factor to achieve economic and employment growth. Patents are a key measure of innovation activity, as patent indicators reflect the inventive performance of countries, technologies and firms [24]. They are also used to track the level of diffusion of technological knowledge and internationalization. Patent indicators can serve as a measure of R&D, output, its productivity and structure, and the development of a specific technology or industry.

As indicators, patents have the following advantages over other measures: (i) they have close link to invention; (ii) they cover a broad range of technologies on which there are sometimes few other sources of data; (iii) the contents of patent documents are a rich source of information; (iv) patent data are readily available from patent offices [25]. A popular composite indicator for measuring innovativeness at the national level is the Summary Innovation Index (SII), annually published in the European Innovation Scoreboard. One of its indicators is the number of Patent Cooperation Treaty (PCT) applications per billion GDP [4]. Another well-known composite innovation indicator, which, among other things, contains quantifiable information about patents (patent families filed in two or more offices; patent applications by origin; PCT international applications by origin), is the Global Innovation Index, published by Cornell University, INSEAD and the World Intellectual Property Organization [26].

It is not only large organizations that analyze patents. Independent scientific researchers also often utilize patents as an indicator of a country's innovation performance, e.g., [18]. Ref. [27] moves the analysis further by focusing on the different natures of national innovation systems in East Asia and Latin America. The key conclusion is that it is not scientific knowledge (academic articles), but technological knowledge (patents) that matters for economic growth. Furthermore, generating scientific knowledge does not automatically lead to the generation of technological knowledge. They noticed that technological knowledge is primarily determined by corporate research and development efforts, which used to be more lacking in Latin American countries compared to East Asia.

Companies invest in patents so that new inventions through efforts on R&D activities can be protected by approval of patents rights [28]. The patent system is one of a suite of policy levers that has been used to attempt to bring the private returns captured by inventors closer to the social value of their inventions. Patents aim to allow inventors to recoup the fixed costs of their research investments by providing inventors with a temporary period of market power [29]. A large amount of literature in economics, management, finance, law and related fields has developed over the past few decades to investigate various aspects of the patent system.

Having said that, it is worth noting that there is a contradictory role of patents in improving innovation found in the literature. On one hand, ref. [30] summarized as follows "*. . . the weight of the evidence supports the claim of a positive causal relationship between the strength of patent rights and innovation*". On the other hand, ref. [31] presents contrasting argument against patents "*The case against patents can be summarized briefly: there is no empirical evidence that they serve to increase innovation and productivity. . .*". Investigations of the relationship between the changes in patent activity and the amount of expenditure on R&D are not novel, e.g., [32]. The conclusion is that an increase in the patent activity of large enterprises can be achieved by increasing expenditure on R&D.

Ref. [33] evaluated the efficiency of R&D expenditure (data obtained from EUROSTAT) from patent activity (data obtained from EPO) in EU-28 countries for the period 1999–2013. Among the 28 EU counties, 98.07% of patents granted by the EPO in that period were given to entities belonging to the business enterprise sectors of the leading countries, which included: Germany, followed by France, the United Kingdom, Italy, Sweden, Netherlands, Finland, Austria, Denmark and Spain, while the remaining 1.93% of assignees belonged to the remaining 18 countries of the EU. The author concluded that the increase in total intramural expenditure on R&D activities in the business enterprise sectors of the 10 leading EU countries caused the increases in patenting activity of the sector in the long run. It was noted that Germany has the highest value of 0.26 of patents granted by enterprises per 1 million euros of the total intramural expenditure on R&D in the business enterprise sector across the research period, while the lowest value is that of Spain, at 0.03.

Empirical evidence on the link between firms' R&D expenditure and patent registrations in Spain was provided by [34]. A bidirectional causal relationship between R&D and patents was evidenced by the Granger causality test in a panel of Spanish manufacturing firms for the period 1990–2013. A broader study of [35] on whether patenting negatively impacts R&D activity in a panel of 88 countries over an eight-year period (1996–2003) found mixed support for the negativity of patents on R&D investment. Accumulated patents positively impact R&D intensity for the set of less developed countries, whereas no statistically significant effect emerges in the case of more developed convergence clubs. When restricting the most developed convergence club to countries with a R&D intensity above 3%, a reversed negative causality arises, corroborating the asymmetric impact of patents on R&D investment.

The review of existing studies covers different aspects of patents, e.g., interlinkages among R&D, patents and incomes in different countries, and comparative analysis between countries. Additionally, multiple reports point to the issue of under-performance in many aspects by the EU-13 in comparison with the EU-15 member states. The effects of EU accession has been studied by many authors; however, literature addressing the particular aspect of innovation was only found in a few scientific publications.

Ref. [16] investigated the relationship between innovation and EU membership using panel data at the business level with a difference-in-difference estimator considering access to the inner EU market as the treatment. The findings are that there is a significant percentage point decline in innovation efforts by firms in the new membership countries relative to the change for the control group firms. Ref. [2] found that the most significant impact, in terms of co-publication intensities, of the EU enlargement has been the major increase in the level of scientific collaboration between the EU-10 (new member states of the 2004 enlargement) and EU-2 (new member states of the 2007 enlargement). Additionally, collaboration between the new and old member states has been affected by the EU enlargement. In both papers, the authors used causal model for their analysis.

Similarly [36] examined the causal relationship between innovation, financial development and economic growth using the panel VAR approach for 27 OECD countries over the period 2001–2016. Among others, the authors conclude that the relationship between innovation and economic growth is complex, and country-specific characteristics can play an important role in fostering innovation and productivity. The paper concludes that governments can play an important role in developing a legislative framework favoring the development of innovation financing through the patent guarantee deposit.

Many additional factors have been listed in the literature that could affect innovation. Having said that, multiple findings and applications show that despite the complicated nature of innovation, patents are one of the key measurements of countries' innovation activity. To the best of the authors' knowledge, there are no other papers aimed at quantifying the causal effect of EU accession on patent performance for specific EU countries.

Causal modeling techniques are not novel and are widely used to test causal claims, both in economics and in many other areas of social sciences, e.g., [37,38]. The aforementioned papers use this method frequently. Quasi-experimental methods, such as difference-in-difference, regression discontinuity and other related methods, have had the effect of overshadowing the role of economic theory in the specification of a model. The aforementioned Granger causality is based on autoregressive (AR) processes applicable to problems of model identification, while the transfer entropy method is an information-theoretic approach that does not need assumptions on the structure of the process. It is based on the concept of Shannon entropy and is suitable for linear and nonlinear relations. Its key assumption is that the sampled data should follow a well-defined probability distribution. Both approaches are, however, essentially descriptive, as they are not based on structural modeling of the data-generating process. This approach can be found in, e.g., [34]. However, this method can have some limitations; Granger causality may not be sufficient in practice for counterfactual control, as identified by [39].

The difference-in-difference (DiD) approach is a quantitative research design for estimating causal relationships in quasi-experimental settings. It is popular, for example, in empirical economics, as well as in other social sciences, and is commonly applied when estimating the effects of certain policy interventions or institutional changes that do not affect everybody at the same time. This approach can be found in, e.g., [2]. When it comes to causal effect analysis of EU accession for a single country, this can be found in, e.g., [40], where the author utilizes the DiD method to evaluate macroeconomic outcomes in Croatia.

However, DiD is limited in several ways. (i) DiD is traditionally based on a static regression model that assumes i.i.d. data despite the temporal aspect of the data. When fit to serially correlated data, static models yield overoptimistic inferences with too narrow uncertainty intervals. (ii) Most DiD analyses only consider the point in time when the intervention happened, and no evolution of the effect can be inferred. Finally, (iii) synthetic control construction can be restricted in the case of time-series analysis.

All the issues of DiD are fixed by Google's ([41]) proposal called *CausalImpact*. This method generalizes DiD to the time-series setting by using Bayesian structural time-series models to construct a counterfactual effect estimator. The multiple advantages of the methods described in Section 3 make the method particularly suited to the needs of this paper.

## 3. Materials and Methods

In this section, we present formal methods of assessment of whether EU membership changed patent performance for new members (EU-13). The method from [41] was used in the paper as a primary causal analysis method. All causal impact calculations were performed with Google's *CausalImpact* R package.

Patent information crucial for the analysis can be obtained from different sources, from publicly available databases such as EPO, OECD or Google Patents, to the more advanced commercial ones such as Derwent, PATSTAT or Global Patent Index. The analysis reported in this paper is based on a dataset from the Organization for Economic Co-operation and Development (OECD). Our approach can be described in the following step-by-step instructions:

1. Collect the time-series you want to analyze (this is covered in Section 3.1);
2. Find another time-series related to your data of interest (such as the point above, which is covered in Section 3.1) that is available for times before and after the intervention;
3. Build the time-series model for your data, with additional covariates from the previous point, as described in Section 3.3;
4. Train the model on data before the intervention (e.g., using Bayesian inference as discussed in Section 3.4);
5. Compute the forecast after intervention and find the deviation from the actual observation. This is the causal effect, as outlined in Section 3.2.

### 3.1. Dataset

We used the OECD database [42], where patents are counted according to the inventor's country of residence. When a patent is invented by several inventors from different countries, the respective contributions of each country are accounted for in order to eliminate multiple counting of such patents (hence, fractional counts exist in the dataset). The research concerns the number of yearly patents in 28 EU countries: CY—Cyprus, MT—Malta, LV—Latvia, LT—Lithuania, EE—Estonia, HR—Croatia, BG—Bulgaria, SK—Slovak Republic, RO—Romania, LU—Luxembourg, SI—Slovenia, PT—Portugal, EL—Greece, CZ—Czech Republic, HU—Hungary, PL—Poland, IE—Ireland, DK—Denmark, ES—Spain, BE—Belgium, FI—Finland, AT—Austria, SE—Sweden, NL—Netherlands, IT—Italy, UK—United Kingdom, FR—France, DE—Germany. The analysis is carried out on patents collected over the years 1985–2017. A whole group of countries, namely, the so-called new member states that joined the European Union in 2004 (CZ, EE, HU, LV, LT, PL, SK, SI, MT and CY) 2007 (BG, RO) and 2013 (HR), will be collectively referred to as the EU-13, with EU-10, EU-2 and EU-1 denoting the subgroups, respectively. We will refer to the old member states (AT, BE, DE, DK, EL, ES, FI, FR, IE, IT, LU, NL, PT, SE, UK) as the EU-15 (because in the considered period the United Kingdom is also included in our analysis, despite it having left the EU in 2020). For each EU-13 country, the year of EU accession divides the patent dataset for that particular country into two time-series, referred to as *before accession* and *after accession*.

### 3.2. Causal Impact

Causal modeling enables reasoning about cause and effect, in contrast to correlation models, where only the association can be reasoned about [43]. The causal impact of a treatment is the difference between the observed value of the response and the value that would have been obtained under an alternative treatment, that is, the effect of the treatment on the treated. In this paper, the response variable is a time series $y_t$, so the causal effect of interest is the difference between the observed series and the series that would have been observed had the intervention not taken place. In the research reported here, the intervention is the EU accession and the response variables represent yearly patents assigned to the country. As the global political environment is not an isolated experimental environment, it is not possible to measure the counterfactual response. Thus, we applied a method proposed by [41] that uses time-series prediction to estimate the counterfactuals.

A time-series model fitted to the observations from before intervention can predict what would have happened if the country had not joined the EU. The uncertainty of the prediction is handled by using Bayesian structural time-series models. This allows the estimation of the statistical significance of the causal impact. Since prediction intervals often grow quickly as the number of predicted steps increases, a simple time-series model is insufficient to conduct a meaningful analysis. Time-series observations from the countries not affected by the intervention (yet correlated with the analyzed time series) are crucial for the model to capture global trends. In this paper, we used patent time-series for the EU-15 to reduce prediction uncertainty for the new EU countries. Such a decision is motivated by the research of [2], where the EU-15 formed a control group in a DiD method. The next section describes the mathematical details of the time-series model used for prediction.

### 3.3. Linear Gaussian State Space Model

The Linear Gaussian State Space Model (LG-SSM) is a general family of time series models. Ref. [44] defines it as the following linear dynamical system:

$$\boldsymbol{z}_t = \boldsymbol{F}_t \boldsymbol{z}_{t-1} + \boldsymbol{R}_t \boldsymbol{\varepsilon}_t, \quad \boldsymbol{\varepsilon}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{Q}_t), \tag{1}$$

$$y_t = H_t^T \boldsymbol{z}_t + \delta_t, \quad \delta_t \sim \mathcal{N}(0, \sigma_y^2), \tag{2}$$

where $\boldsymbol{z}_0 \sim \mathcal{N}(\boldsymbol{b}_0, \boldsymbol{Q}_0)$ is the $n$-dimensional initial hidden state and $x_t \in \mathbb{R}$, $t \geq 0$ is the observed time series. Throughout, $\mathcal{N}(\cdot, \cdot)$ denotes a multivariate Gaussian distribution and the noises $(\boldsymbol{\varepsilon}_t, \delta_t)$ are independent across time $t$. The state dynamics are parameterized by the transition matrix $\boldsymbol{F}_t \in \mathbb{R}^{n \times n}$, control matrix $\boldsymbol{R}_t \in \mathbb{R}^{n \times q}$ and covariance matrix $\boldsymbol{Q} \in \mathbb{R}^{q \times q}$. The observations $x_t$ are noisy linear projections of the states $\boldsymbol{z}_t$ and are further parameterized by the observation vector $H \in \mathbb{R}^n$ and the observation noise variance $\sigma_y^2$. Many classical time-series models can be represented as an LG-SSM; this makes it a popular choice for time-series forecasting [45]. In this paper, we focus on two main components: local level and linear regression.

Mathematically, a local-level model is defined as an LG-SSM with a real hidden state, namely, a current level $l_t$. It evolves as:

$$y_t^l = l_t + \epsilon_t^y \quad \epsilon_t^y \sim \mathcal{N}(0, \sigma_y^2) \tag{3}$$

$$l_t = l_{t-1} + \epsilon_t^l \quad \epsilon_t^l \sim \mathcal{N}(0, \sigma_l^2) \tag{4}$$

where $\epsilon_t^y$ and $\epsilon_t^l$ are independent. The future depends only on the past observations of the time-series.

Often, a time series can be explained by another time series in addition to its past. In an LG-SSM, it is possible to use external observations (time series) $\boldsymbol{x}_t$ in the form of linear regression. A *static linear regression* is obtained by setting $H_t = \boldsymbol{\beta}^T \boldsymbol{x}_t$ and $z_t^r = 1$, where $\boldsymbol{x}_t$ is a vector of covariates (in our case, the EU-15 with an additional column of ones) and $\boldsymbol{\beta}$ is the vector of regression coefficients. Since the sum of LG-SSMs is also an LG-SSM, the simple components (local level and linear regression) can be summed to form a structural time-series model [44]:

$$y_t = l_t + \boldsymbol{\beta}^T \boldsymbol{x}_t + \epsilon_t^y, \tag{5}$$

where $l_t$ is the local level (4). In terms of the general representation from (1), we obtain a block-diagonal transition, control matrices and concatenated observation vectors performing the summation of the local-level and regression components in (5). Given the model parameters, the state $\boldsymbol{z}_T$ at time of intervention and the contemporaneous predictor variables after intervention $\boldsymbol{x}_{t \geq T}$, the system dynamics (1) and (2) enable forecasting for $y_{t \geq T}$. Since the model is linear and Gaussian, the forecast has a normal distribution. If the patent data were just counts, a hierarchical model with a Poisson distribution for the response variable would be required. Having said that, we emphasize that the patents in our dataset are fractional, so we use vanilla LG-SSM.

### *3.4. Bayesian Inference*

In order to fit an LG-SSM to the patent data of interest, we follow a Bayesian approach that captures uncertainty via a posterior distribution, as deeply described by [46,47]. For Bayesian inference in an LG-SSM, a joint prior distribution must be specified for the initial states and the unknown model parameters.

The prior distribution for the local level diffusion scale ($\sigma_l$) is inverse gamma interpreted as a scaled inverse-$\chi^2$ distribution (as described by [48]) with standard deviation 0.1 $\hat{\sigma}_y$ and 32 degrees of freedom, where $\hat{\sigma}_y$ is standard deviation of the time series. The prior distribution is truncated to the maximum value at $\hat{\sigma}_y$. The initial state prior distribution is normal with mean equal to the first observation $y_0$ of the time series and scale equal to $\hat{\sigma}_y$. For the regression, we used Zellner's g-prior with spike-and-slab. The prior for $\boldsymbol{\beta}$ and $\sigma_y$ is commonly expressed in terms of expected model size (in our case equal to 3), expected $R^2$ (0.8) and degrees of freedom (50). The spike-and-slab prior distribution enforces sparsity of $\boldsymbol{\beta}$; i.e., most of the values will be exactly 0. Such a prior distribution acts as a Bayesian model selection algorithm and allows the addition of multiple covariates in the model without overfitting. Only the most important covariates receive nonzero coefficients, thus, they are present in the model. All the other variables are multiplied by zero, so they are not part of the model. The hyperparameters for these distributions are set using heuristics from the *CausalImpact* package that aim to provide default prior distributions. In order to sample from the posterior distribution, we the Monte Carlo Markov chain (MCMC) [44].

## 4. Results

The results of a formal statistical causal modeling approach allows us to analyze whether EU membership has led to statistically significant growth in the number of patents in EU-13 countries compared to the counterfactual scenario in which each country did not join the EU. We rely on the patent dynamics before accession and the number of patents in the EU-15 that received no treatment to obtain accurate predictions for the counterfactual scenario. Summaries of the analysis obtained for the 20,000 MCMC samples are collected in Table 1.

The rows with *Stat* average (Avg.) refer to the average patents (over the time period) during the post-intervention period. The rows with *Stat* cumulative (Cum.) represent the sum of the individual yearly observations. The interpretation of our results for a given country, e.g., Poland (which could be generalized for the rest of the countries accordingly to their values) is as follows. In the post-intervention period, the response variable had an average value of approx. 312.2, as reported in column *Actual*. By contrast, in the absence of an intervention, we would have expected an average response of 101.1 (see column *Val*). The 95% interval of this counterfactual prediction is [22.4–228.6] (see columns *lower* and *upper* in the *Prediction* group). Subtracting this prediction from the observed response yields an estimate of the causal effect that the intervention had on the response variable. The same interpretation applies to entries in a row (*Cum*). In relative terms, the response variable showed an increase of +212% (see column *Val* in the *Relative* group). The 95% interval of this percentage is [+84%, +290%] (respectively, columns *lower* and *upper* in the *Relative* group ), which means that the positive effect observed during the intervention period is statistically significant.

The statistical significance of the analysis can be assessed from the last column $p$. The effect observed during the intervention period is statistically significant and unlikely to be due to random fluctuations if the probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability $p$). For countries where $p < 0.05$ (posterior prob. of a causal effect equal $1 - p >= 95\%$), the causal effect can be considered statistically significant; otherwise, the effect may be spurious and would generally not be considered statistically significant. A significant causal impact on patent performance after accession can be observed in Romania, Estonia, Poland, the Czech Republic, Croatia and Lithuania. However, as results from analysis show for Croatia and Lithuania, joining the EU caused a negative impact on patent performance. For the remaining countries—Hungary, Latvia, Cyprus, Slovakia, Slovenia, Bulgaria and Malta—joining the EU did not statistically significantly affect patent performance. An interesting result is observed for Latvia, where the percentage change increase could misleadingly suggest a significant influence after accession (above 300% increase after accession); however, the model prediction classified this increase as statistically not significant. This means that this increase came from trends before accession, so such growth was not influenced by EU membership.

**Table 1.** Summaries of causal impact analysis.

| | | | **Prediction ± 95% CI** | | | **Relative ± 95% CI** | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Stat** | **Actual** | **Val** | **Lower** | **Upper** | **Val** | **Lower** | **Upper** | ***p*** |
| RO | Avg | 54.0 | 29.3 | 20.6 | 38.5 | 85% | 53% | 114% | 0.000 |
| RO | Cum | 540.0 | 292.6 | 205.6 | 385.2 | 85% | 53% | 114% | 0.000 |
| EE | Avg | 30.4 | 13.9 | 7.1 | 23.5 | 118% | 50% | 168% | 0.000 |
| EE | Cum | 394.9 | 180.9 | 91.7 | 305.1 | 118% | 50% | 168% | 0.000 |
| PL | Avg | 312.2 | 100.1 | 22.4 | 228.6 | 212% | 84% | 290% | 0.001 |
| PL | Cum | 4058.5 | 1301.0 | 291.7 | 2971.3 | 212% | 84% | 290% | 0.001 |
| CZ | Avg | 229.6 | 126.3 | 20.5 | 223.1 | 82% | 5% | 166% | 0.018 |
| CZ | Cum | 2984.7 | 1641.5 | 266.9 | 2900.6 | 82% | 5% | 166% | 0.018 |
| HR | Avg | 19.2 | 27.9 | 18.0 | 36.7 | −31% | −63% | 5% | 0.040 |
| HR | Cum | 77.0 | 111.8 | 71.8 | 147.0 | −31% | −63% | 5% | 0.040 |
| LT | Avg | 20.1 | 33.3 | 17.3 | 46.2 | −40% | −78% | 9% | 0.047 |
| LT | Cum | 261.7 | 432.8 | 224.7 | 601.2 | −40% | −78% | 9% | 0.047 |
| HU | Avg | 183.8 | 96.1 | −105.0 | 224.1 | 91% | −42% | 300% | 0.071 |
| HU | Cum | 2388.9 | 1249.8 | −1365.3 | 2913.9 | 91% | −42% | 300% | 0.071 |
| LV | Avg | 14.1 | 9.5 | 4.3 | 18.2 | 48% | −43% | 102% | 0.115 |
| LV | Cum | 183.3 | 123.8 | 56.5 | 236.7 | 48% | −43% | 102% | 0.115 |
| CY | Avg | 8.8 | 6.3 | 1.7 | 11.0 | 40% | −35% | 113% | 0.133 |
| CY | Cum | 114.5 | 81.8 | 21.8 | 142.9 | 40% | −35% | 113% | 0.133 |
| SK | Avg | 43.3 | 33.3 | 15.7 | 55.5 | 30% | −37% | 83% | 0.217 |
| SK | Cum | 562.9 | 433.0 | 204.7 | 721.1 | 30% | −37% | 83% | 0.217 |
| SI | Avg | 101.1 | 93.9 | 53.8 | 139.4 | 8% | −41% | 50% | 0.353 |
| SI | Cum | 1314.5 | 1221.0 | 699.9 | 1812.2 | 8% | −41% | 50% | 0.353 |
| BG | Avg | 27.4 | 24.8 | −7.0 | 72.1 | 11% | −181% | 139% | 0.389 |
| BG | Cum | 273.7 | 247.7 | −70.3 | 721.2 | 11% | −181% | 139% | 0.389 |
| MT | Avg | 9.7 | 9.6 | 4.2 | 16.4 | 1% | −70% | 57% | 0.445 |
| MT | Cum | 125.9 | 124.9 | 54.0 | 213.2 | 1% | −70% | 57% | 0.445 |

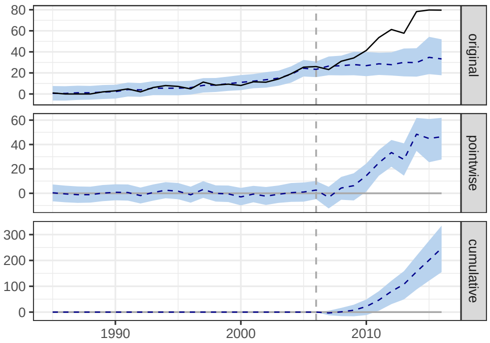
Detailed time evolutions of the inferred causal impact can be observed in Figures 1 and 2 for both groups of countries with significant and insignificant effects of EU accession on patent performance, respectively Each plot consists of three separate charts:

**(original)** The observed time series (solid line) and fitted model's forecast counterfactuals (dashed line) with 95% credible interval (shaded area);

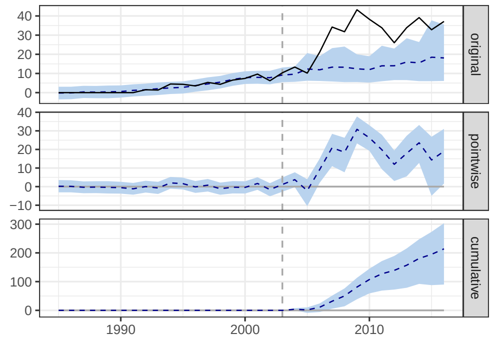
**(pointwise)** The pointwise causal effect with 95% credible interval, as estimated by the model. This is the difference between the observed outcome and the predicted outcome;

**(cumulative)** The cumulative effect with 95% credible interval—the total number of patents due to EU accession.

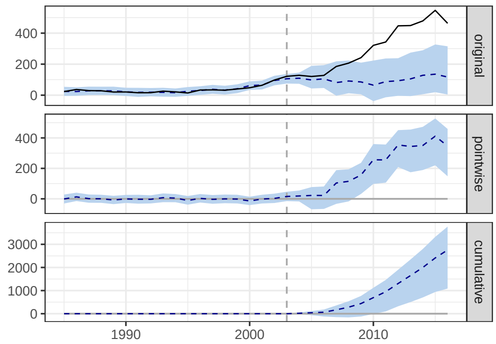
The vertical line represents EU accession year (intervention) for the particular country (2004/2007/2013). Further information that can be obtained from the plots includes (**original**) the detailed time distribution (trajectory) of EU-13 countries. (**pointwise**) The difference between observed data and counterfactual predictions is the inferred causal impact of the intervention. A key characteristic of the inferred impact series is the progressive widening of the posterior intervals (shaded area). This effect emerges naturally from the model structure, as predictions should become increasingly uncertain as we look further and further into the future. (**cumulative**) Another way of visualizing posterior inferences is by means of a cumulative impact plot. This shows, for each year, the summed effect up to that year. If the 95% credible interval of the cumulative impact crosses the zero-line after the intervention, then, at that point, we would no longer declare a significant overall effect.



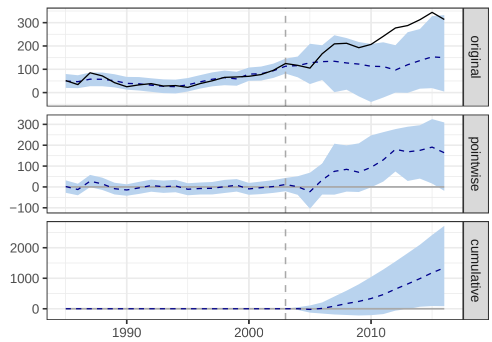

(**a**)



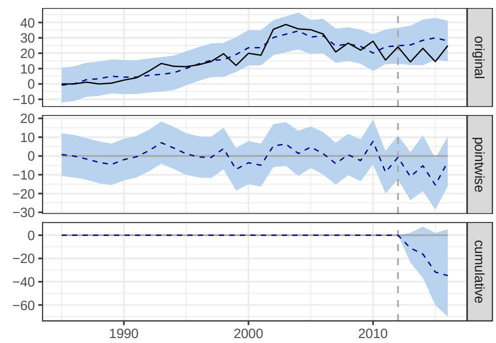

(**b**)



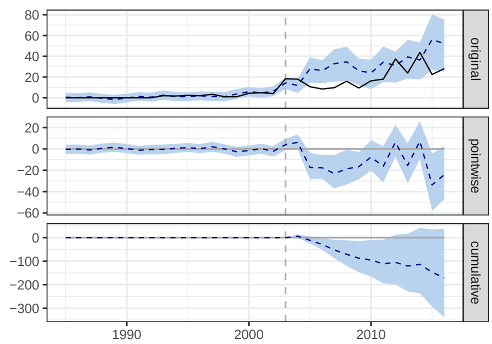

(**c**)




(**d**)

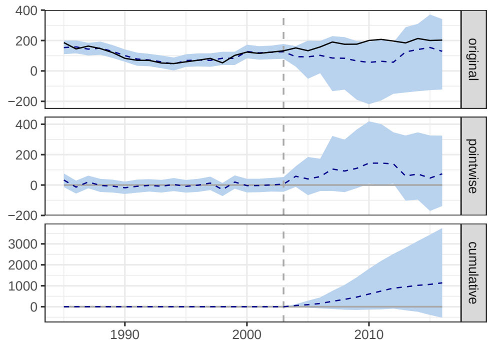



(**e**)

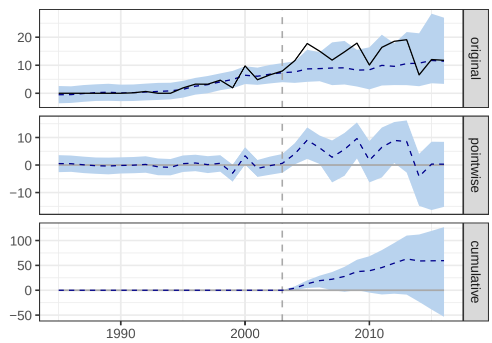



(**f**)

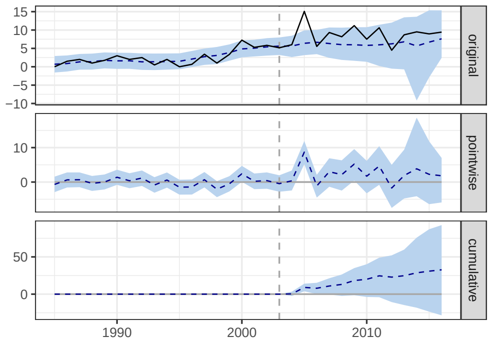
**Figure 1.** Significant causal impact. (**a**) Romania. (**b**) Estonia. (**c**) Poland. (**d**) Czech Republic. (**e**) Croatia. (**f**) Lithuania.



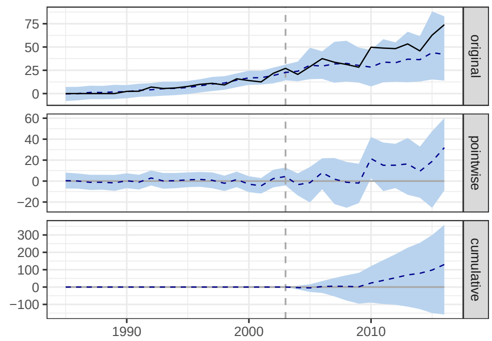

(**a**)



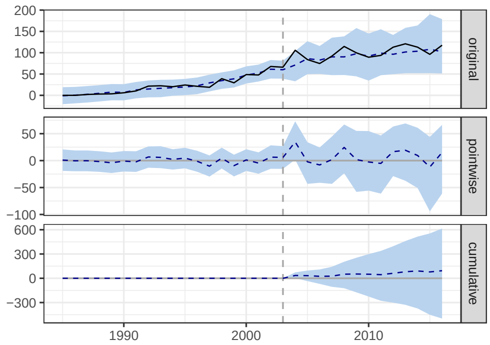

(**b**)



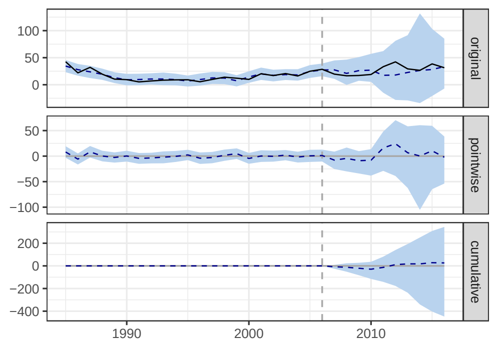

(**c**)



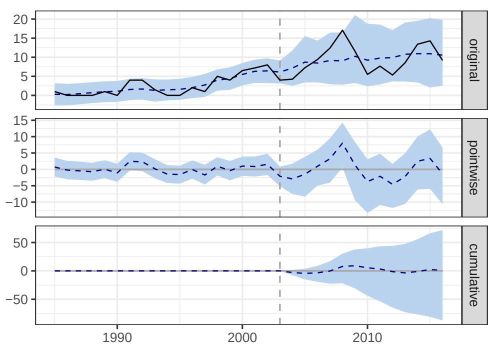

(**d**)




(**e**)




(**f**)




(**g**)

**Figure 2.** Insignificant causal impact. (**a**) Hungary. (**b**) Latvia. (**c**) Cyprus. (**d**) Slovak Republic. (**e**) Slovenia. (**f**) Bulgaria. (**g**) Malta.

The same analysis performed for combined EU-13 countries (omitted from visualization) shows a significant positive impact of accession patent performance. All EU-13 countries in total produced, on average, over 7000 patents that can be attributed to the accession. However, surprisingly, seven of the EU-13 countries have not significantly benefited from EU accession.

An interesting by-product of the causal analysis reported in this paper is a discovery of international relations in patent time series. Since coefficients in the linear regression are sparse due to the spike-and-slab prior distribution, only the most important covariates receive a nonzero coefficient. In the model, the covariates for each of the EU-13 country are the patents for the EU-15 countries. Let us consider two countries: $c \in$ EU-15 and $c' \in$ EU-13. If the coefficient $\beta_c$ is zero, it means that the patent activity of country $c$ does not explain the trend observed for country $c'$. Contrary, a nonzero value of $\beta_c$ indicates that both countries have similar dynamics of patents. The similarity may originate from different socio-political interactions, the analysis of which is far beyond the scope of this paper. We only point out the existence of these pan-European interactions.

In Figure 3, we visualized what fraction of the 20,000 MCMC samples resulted in nonzero coefficients (estimate of slab probability). The $x$-axis represents covariates ($c$), while the $y$-axis corresponds to the new EU members ($c'$). Interestingly, Luxembourg and Sweden participate very weakly in the model, while countries such as Italy or Germany are frequently selected by the Bayesian model selection.


**Figure 3.** Fraction of nonzero regression coefficients.

On the other hand, Hungary's patents are mostly explained solely by the time series for the Netherlands. Similarly, the patent activity of Romania is mostly explained by data from Spain. A deeper analysis of such relations could be helpful for policymakers in designing targeted research funds aimed at equalizing cooperation within the EU.

## 5. Discussion

One of the most important initiatives defined by the EU in its Europe 2020 strategy was to create an innovation-friendly environment that supports the generation, emergence and diffusion of innovation. Taking this into account, it is worth highlighting that patents play an increasingly important role in innovation and economic performance. In an increasingly knowledge-driven economy, society invariably needs creative or inventive ideas or concepts to improve existing features, add useful new features to products or develop new ones. Patents are widely used as an indicator of how much innovation is taking place in a given industry, which makes them an ideal candidate for causal analysis (Step 1 in our step-by-step description). Patents are also one output of technologically successful R&D activities and long-term investment. Patenting has experienced a sizeable boom in the last two decades in many fields, so let us compare a simple visual analysis to our formal results.

As Figure 4 shows, the number of patents (as a sum in years 1985–2017) among the EU member states varies greatly between countries. For better visualization, we present the EU-13 and EU-15 with a logarithmic scale (maximum number of patents for country from

EU-15 (Germany) was above 645,912 while in EU-13 (Poland) above 5000). The greatest number of patents from the EU-15 was from Germany, followed by France, the United Kingdom, Italy and the Netherlands. The greatest number of patents from the EU-13 was from Poland, Hungary and the Czech Republic. Additionally, the fraction of countries from the EU-13 (when counting the total number of patents) was negligible compared to the EU-15. In total, 98.66% (1,462,149.9) of patents during the analyzed period were allocated to the fifteen EU-15 countries, while in the EU-13 countries, only 1.34% (19,783.4) were allocated. This difference represents the huge dominance of the EU-15 in number of patents. Even accounting for the fact that countries from the EU-13 account for approximately 20% of the EU population, this is still a negligible amount. Interestingly from a visual perspective (considering two periods, before and after accession), we can observe that the fraction of patents after accession is higher (points above the diagonal line in Figure 4) in the EU-13, while for the EU-15, there was no large change (corresponding points lie nearly on the diagonal line).

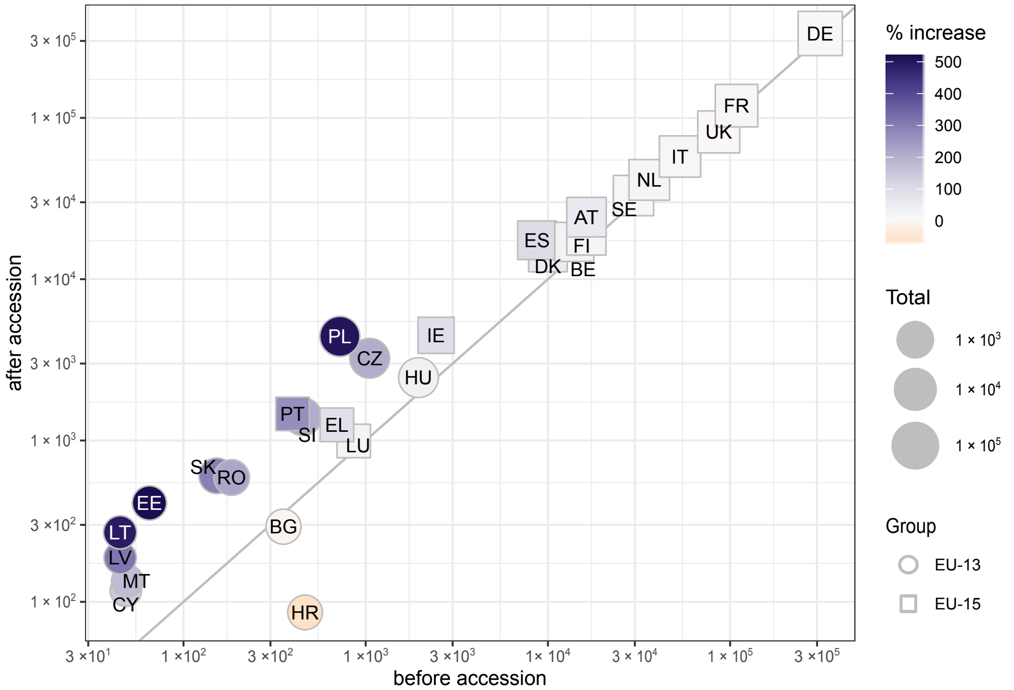



**Figure 4.** Number of patents before and after accession with the percentage of increase for a given country. The diagonal line marks zero change due to accession.

A simple analysis of the total number of patents before accession and after accession in terms of percentage increase reveals that the highest increase of patents occurred in EU-13 countries, suggesting that EU accession affected patent performance in those countries; see Figure 4. A decrease was noticed (points lying below the diagonal line) for Bulgaria (−17) and the United Kingdom (−5.4). The result for Croatia is incomparable because of an uneven period of 1985–2012 versus 2013–2017. The lowest increases were observed for Germany (6.8), Italy (8.5) and France (9.8). The number of patents increased over the two periods, especially in Estonia (+530), Poland (+512) and Lithuania (+500). In general, the highest increases in patent performance during the period considered were in the EU-13, and the lowest were in EU-15 countries. However, from this visual examination, it cannot be inferred with statistical precision whether the growth can be explained by the overall increasing trend over the last decades or whether joining the EU caused the changes. With a causal impact, we precisely quantified the strength of this effect and pointed out countries where the effect was significant. We can conclude that, for those countries, the accession was highly beneficial for innovation.

Despite the importance of innovation in the knowledge-driven economy, it is also worth highlighting that significant disparities of innovation occur between EU member states, in particular, between the EU-15 and EU-13 . In terms of the Summary Innovation Index, the majority of the EU-13 are below the EU average. Our analysis also clearly showed that the total number of patents in the years 1985–2017 among the EU member states varies greatly between countries, by up to a few orders of magnitude. From the analysis, a manifestation of the Pareto principle is observed; i.e., most patents are issued by only a few countries. Accordingly, the greatest number of patents was assigned in Germany, followed by France, the United Kingdom and Italy. Having said that, we do confirm that the growing trend is similar in both groups, as confirmed in our influence relation analysis.

There are many explanations for the underperformance of the EU-13 in patenting. In [6], the authors pointed out problems in the EU-13 such as a low focus on R&D in policy and business, lack of funds to initiate international meetings that enhance international collaborations and lower numbers of excellent researchers and research institutions in the EU-13 than in the EU-15. Additionally, by analysis, some selected indicators of the Summary Innovation Index [49] can be observed and generalized; in EU-13 countries, indicators such as human resources, attractive research systems, finance and support, firm investment and enterprise spending on R&D have lower positions. This could affect patent performance; however, further analysis is needed to prove this statement with statistically significant results.

## 6. Conclusions

EU membership can bring benefits for member states, e.g., boosted trade in goods or non-tariff trade costs. The process of EU accession also affects patents, the main driver for companies to undertake R&D activity, in multiple ways, e.g., granting more effective legal protection, enhancing the prospects of generating profits or providing funding for appropriate graduate training. However. there are different views on the EU and its influence on member countries. Hence, it is crucial to have a reliable and quantitative assessment of how much membership influences member states. The influence of EU enlargement with causal analysis on innovations could be found in very few scientific publications.

In our research, we examined the dynamics of patent performance in the EU-13 over time, in particular, the impact of EU-13 accession on patent performance. Despite the disparities in the EU, the global dynamics are similar; thus, the dataset for the EU-15 helps in constructing reliable forecast models for the EU-13 (Step 2 in the proposed analysis).

The proposed approach, based on causal impact using a Bayesian structural time-series model (Steps 3 and 4), indicates a conclusion that joining the EU has brought a statistically significant impact on patent performance in Romania, Estonia, Poland, the Czech Republic, Croatia and Lithuania. Having said that, it is worth noting that in Croatia and Lithuania, the effects were negative, although barely significant. For the remaining countries—Hungary, Latvia, Cyprus, Slovakia, Slovenia, Bulgaria and Malta—we did not find any evidence that joining the EU has significantly affected their patent performance. Most importantly, there is no sign of a significant decrease in patenting.

It is worth noting that some preparatory processes for accession, including innovation activity in the EU-13, were conducted before the accession date, which makes it difficult to specify an exact point in time. However, the accession triggers some legal possibilities and, despite it being a form of model simplification, it is commonly used in literature as a proper intervention. Another limitation of our analysis is the dataset, because data were available only until 2017. An enhanced database could enable a causal impact model of the changes in patent cooperation between EU countries after and before accession. This could provide further useful information. Nevertheless, the presented approach, which utilized Google's Causal Impact, could be widely used for the assessment of many aspects of EU-13 accession or any other political event. The results from our analysis could be a valuable source of assessment of European enlargement on patent performance, and provide further helpful information for policymakers in reforming government subsidies concerning innovation in the new member states of the EU.

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