Assessing Place-Based Policies.

The Importance of Allowing for Non-Common and Multiplicative Trends

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Abstract

Imagine an impoverished territory that becomes eligible for a generous place-based transfer programme (the treatment). Difference-in-differences analysis (DiD) shows that the level of the income per head handicap has risen. But DiD assumes that the (presumably common) trend and treatment effects are additive, whereas standard economic theory would rather assume they are multiplicative. In this paper, we first show that shifting to a multiplicative version of the DiD estimator significantly alters the initial conclusion. Beyond, a placebo analysis reveals the violation of the (multiplicative) common trend assumption: the growth rate characterising the treated region was historically smaller. Hence the need for a method that allows for (multiplicative) trend differences between treated vs. control entities before treatment, and estimates the treatment as a (multiplicative) trend difference-in-differences. The one we implement here is called Controlled Interrupted Time Series Analysis (CITS) by epidemiologists. We illustrate the relevance and strength of CITS, when combined with an exponential/multiplicative specification, by studying the medium-term impact of an EU-funded place-based policy called "Objective 1" on taxable income per capita in the Belgian Province of Hainaut, using 1997-2013 times series.

Keywords: Treatment-Effect Analysis, Multiplicative Trend, Controlled Interrupted Time Series Analysis vs. Difference-in-Differences, Place-based Policies.

JEL Codes: C52, C21, R58, P25

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1 Introduction

This paper deals with how to properly evaluate the impact of place-based policies (Neumark and Simpson, 2015) such as European Union Structural Funds targetting underperforming areas. It discusses the use of quasi-experimental methods (based on the before-and-after and treated vs control paradigm) when theory suggests trend and treatment are more adequately modelled as multiplicative (thus non-linear) and the available evidence points to no common multiplicative/log-additive trends. The paper capitalizes and extends on Puhani (2012) regarding the relevance of non-linear/multiplicative DiD, and on Vandenberghe (2018), Vandenberghe (2019) and Mora and Reggio (2019) for the way to cope with a lack of common trend. At its core lies a methodological proposal on the virtues of modelling trends (and thus treatment) multiplicatively in combination with Controlled Interrupted Time Series Analysis (CITS) to account for the lack of a common trend.

But, before turning to its full exposition of these methods, here are a few words about the type of place-based policy we use to illustrate our methodological point: the EU-funded Objective 1 convergence policy that was applied to the province of Hainaut in Belgium between 1993 and 2006. Objective 1-Hainaut is an example of a European Union (EU)-funded place-based transfer policy aimed at helping European regions reduce their socioeconomic/income handicap. The policies have a relatively old history. The underpinning idea was present in the preamble to the Treaty of Rome in 1957 and was further emphasised in the 1980s with the entry of Greece, Portugal and Spain. In 1987, with the Single European Act, the EU received explicit competence for undertaking a regional policy to ensure convergence. Over the decades, a growing political concern for the so-called "regional problem" has meant that a considerable – and increasing – amount of resources has been spent in an attempt to mitigate regional income disparities. Since the mid-1980s, the importance of EU development/convergence policies has not ceased to increase. In budgetary terms, the policies have grown from representing a mere 10% of the EU budget and 0.09% of the EU-15 GDP in 1980, to more than one-third of the budget and around 0.37% of the EU GDP as an average of the period 1998-2001 (Rodriguez-Pose, 2004). The policies have become, after the Common Agricultural Policy (CAP), the second-largest policy area in the EU. Also, every recent step towards greater economic integration at the EU level has been accompanied by measures aimed at supporting financially the lagging countries or regions. For instance, the decision in the Maastricht reform to create the Single European Currency was tied in with establishing the Cohesion Fund to alleviate the burdens that the transition to EMU would impose on the less developed territories.

After the reform, more than two-thirds of all Structural Fund expenditure has been concentrated in the so-called Objective 1 regions. These are territories whose GDP per capita, measured in purchasing power standards (pps), is less than 75% of EU average. In the 1990s, the list comprised 64 NUT2 regions (Tondl, 2007), one of them being Hainaut in Wallonia/Belgium (Figure 1). The Belgian province benefited from Objective 1 money between 1994 and 1999. And from 2000 to 2006 it also benefited from the "phasing out" programme.

Yet, despite their rising macroeconomic importance, questions are being raised about the capacity of place-based policies, European regional/convergence like Objective 1 in particular, to achieve greater economic and social cohesion and to reduce income gaps. These questions are fundamentally based on rather mixed evidence about convergence following implementation (Magrini, 1999, Neumark and Simpson, 2015). In that context, it is a bit surprising that there are relatively few ex-post economic evaluation studies of the monetary benefits of Objective 1 or similar interventions. More precisely, there are very few papers answering questions such as "what would be the level of income per head in Province/Territory X had it not benefited from Objective 1 money ?". Along the same line, and in contrast with what economists and econometricians have done to evaluate other types of policy interventions (higher minimum wages, employment subsidies, active labour market or social policies...), relatively little work has been done to evaluate the effectiveness of place-based policies using the resources of quasi-experimental treatment effect analysis to analyse before and after microdata.

In a sense, this paper aims to fill that void. This said, at its core, lies a methodological discussion of what can be achieved when the linear/additive Difference-in-Differences paradigm (DiD) fails. DiD is a simple technique commonly used in microeconometrics (Angrist and Krueger, 1999). It attempts to mimic an experimental research design using observational study data, by studying the differential effect of a treatment on outcome level (Y) of a"treatment group" v.s. a "control group" in a (quasi) natural experiment, using a linear (thus additive) model. DiD quantifies the effect of a treatment (e.g. Objective 1) on the level of Y (e.g. real income per capita) by comparing the change over time of Y characterising the treatment (e.g. Hainaut) vs the control group (e.g. rest of Belgium). The resulting difference-in-differences (DiD) is driven by a time trend difference between the treated and the control group during the period that follows the treatment. Conditional of the two groups being characterised by the same/common time trend in the absence of treatment, the latter trend difference (and more precisely its impact on the outcome level) is considered a good candidate to identify and quantify the treatment effect.

The point raised by Puhani (2012) and Ciani and Fisher (2019) is that the latter trend is modelled additively, often without adequate scrutiny and preliminary discussion about the relevance of such a choice. For instance, economic theory would often recommend modelling the impact of time on income Y multiplicatively (i.e. as a common growth rate). In the same vein, many economists, particularly when it comes to place-based policies, would consider that the proper indication of a treatment effect is statistical evidence that it has translated into a multiplicative time trend difference between the treated and the control (i.e. an improvement of the income growth rate). More importantly, as will become clear after, modelling things additively while the true common trend is multiplicative leads to treatment effect estimates that are downward biased. We show hereafter that this bias can be avoided by resorting to an exponential – thus multiplicative – specification of the usual DiD model. The treatment effect can be retrieved by regressing (using OLS) lnY on the usual time, treatment and time$X$treatment variables. Alternatively, and preferably for reasons exposed by Mora and Reggio (2019), the exponential DiD model can be estimated using Poisson ML methods.

Another recurrent critique of DiD is that it relies too much on the common trend assumption in the absence of treatment/intervention. The critique applies to linear DiD where the time trend is modelled additively. But it also applies to the multiplicative version of DID. Hence the necessity of methods that allow for diverging pre-existing trends (seeVandenberghe, 2018, Vandenberghe (2019) and Mora and Reggio, 2019). The point we make here is that one of these methods is commonly used by epidemiologists. It is called Controlled Interrupted Time Series Analysis (CITS) and represents a straightforward extension of the canonical DiD. When many periods of observation before and after treatment are available, the assumption of a common trend before treatment can be verified/assessed. Moreover, the treatment effect delivered by CITS accounts for the trend difference before treatment as it consists of a trend (thus growth rate) difference-in-differences. In that sense, CITS can be considered as a more powerful design than DiD (Habib et al., 2021).

The rest of this paper is organised as follows. Section 2 exposes the difference between linear vs multiplicative DiD; and CITS as a way to cope with the absence of common trend in the absence of treatment. Section 3 presents the data used. Section 4 shows and discusses the key results. Section 5 concludes.

2 Method

2.1 Multiplicative vs additive common time trend

A representation of the canonical additive DiD is

$$Y_{i,tsi} = \alpha_1^* + \alpha_2^* TREAT_i + \beta_1^*\, tsi + \beta_2^*\, tsi \times TREAT_i + \epsilon_i^* \tag{1}$$

with $tsi = \grave{a}$ the moment just before treatment/intervention and $tsi > 0$ the time that has elapsed since the start of the intervention, $TREAT$ is a dummy variable denoting the treatment assignment (treatment or control) and β_2^* is the estimated treatment effect (TE). The common trend assumption underpinning (1) is $Y_{tsi}^k = Y_{tsi-1}^k + \beta_1^*\, tsi$ where k designates the treated vs control status.

But consider – following what economic theory would posit about the evolution of per capita income over time – that in it rather $Y_{tsis}^k = Y_{tsi-1}^k(1 + \beta_1\, tsi)$. In other words, entities grow at (common) rate β_1 without treatment. In that case, in the absence of any treatment, after 1 period, DiD estimated by β_2^* in (1) will be equal to $\beta_1 \nabla_{tsi-1}$ with $\nabla_{tsi-1} \equiv Y_{tsi-1}^{TREAT} - Y_{tsi-1}^{CONTROL}$ the initial level-difference between the two groups. After n period, the estimated DiD inflates to $\beta_1^n \nabla_{tsi-1}$. The point is that a standard additive/linear DiD modelling (eq.1) ignores the fact that for the treated entity – which starts from a lower position – the increase over time will automatically be smaller in absolute value (Ciani and Fisher, 2019). Therefore, it would underestimate the share of the change that has to be attributed to the treatment. More generally, the bias induced by the use of a linear/additive DiD model to estimate the treatment effect of a process where the common trend is multiplicative will be larger the larger *i)* the initial/pre-treatment difference between the groups and the *ii)* the larger the time over which the treatment is evaluated.

Differently, and more judiciously in the context of place-based policies, one might retain and estimate an exponential specification, where the common trend is multiplicative and where the effectiveness of the treatment/intervention is captured by the propensity of the treated group to (positively) deviate from that multiplicative common trend.

$$Y_{i,tsi} = exp(\alpha_1 + \alpha_2 TREAT_i + \beta_1\, tsi + \beta_2\, t \times TREAT_i)\eta_i \tag{2}$$

An easy way to estimate such a multiplicative model is to log-linearize it and resort to OLS. But Silva and Tenreyro (2006) and Mora and Reggio (2019), argue that the exponential

DiD model should rather be estimated using Poisson pseudo-maximum-likelihood estimator[1] The main reason is that the log-transformed error term/residual is generally not independent of the regressors X_i, also causing heteroscedasticity.[2] Also, Puhani (2012) cautions about the fact that the estimated β_2 does not estimate the treatment effect in terms of levels of Y but in terms of growth rate DiD. To retrieve the treatment effect (TE) in levels after t periods, one must compute

$$TE_t \equiv exp(\widehat{\alpha_1} + \widehat{\alpha_2} + (\widehat{\beta}_1 + \widehat{\beta}_2)\ t) - exp(\widehat{\alpha_1} + \widehat{\beta}_1\ t) \tag{3}$$

2.2 The absence of common (multiplicative) time trend and the way to cope with it

Another recurrent critique of DiD is its reliance on the common trend assumption. If data contains several pretreatment periods, it is possible to conduct a so-called "placebo" analysis. This consists of estimating the equivalent of eq.1 using only pre-treatment periods and checking that the equivalent of β_2^* is not statistically significantly different from zero. Note that the same placebo strategy can be used with the multiplicative version of the DID model (eq.2). The real question is how to cope with situations where placebo results are not supportive of the common (additive or multiplicative) trend. In what follows, we argue that a good strategy is to resort to what epidemiologists call the Controlled Interrupted Time Series Analysis (CITS) (Linden, 2015). This method allows for the common trend assumption to be verified, and, moreover, delivers a treatment effect estimator that is adjusted for differences in trend between two groups (Lopez Bernal et al., 2018).

CITS amounts to writing the right-hand part of eq.1 or the linear index part of eq.2 as

$$\begin{aligned} &\mu_1 + \mu_2 TREAT_i + \\ &\lambda_1\ t + \lambda_2\ t \times TREAT_i + \\ &\gamma_1\ tsi + \gamma_2\ tsi \times TREAT_i \end{aligned} \tag{4}$$

where t is the data time index, covering periods before and after treatment/intervention, $tsi = \max\{0, t - \bar{t}\}$ the (positive) elapsed time that since treatment/intervention started in $\bar{t}$. The two first blocks/lines in eq.4 describe trends before intervention periods, while the third block/line characterizes what happens post-intervention. The coefficients $\mu_1, \lambda_1, \gamma_1$

[1] Available in Stata via the [poisson] command.

[2] The easiest way to show this is to consider an exponential econometric model of the type $Y_i = exp(X'\beta) + \epsilon_i$ where ϵ is well-behaved. Remembering that $ln(a+b) = ln(a(1+b/a))$, taking the log on both sides leads to $ln(Y_i) = X'\beta + ln(1 + \epsilon_i/exp(X'\beta)$, thus, to a transformed residual function of the level of X.

represent the control group, and the coefficients $\mu_2, \lambda_2, \gamma_2$ represent deviations/differences from the control group, characterising the treatment group. More specifically

- μ_2 represents the difference in the level (intercept) of the outcome variable between treatment and controls before the intervention, at the moment observation starts in the data ($t = 0$);
- λ_2 captures the difference in the slope (trend) of the outcome variable between treatment and controls pre-intervention;
- and γ_2 is the difference between treatment and control groups in the slope (trend) of the outcome variable after initiation of the intervention compared with the pre-intervention difference.

The CITS treatment effect on the level of Y in the additive case is equal to

$$\widehat{\gamma_2}\, tsi \tag{5}$$

whereas in multiplicative case it is equal to

$$\begin{aligned} &exp(\widehat{\mu_1} + \widehat{\mu_2} + (\widehat{\lambda_1} + \widehat{\lambda_2})\, t + (\widehat{\gamma_1} + \widehat{\gamma_2})\, tsi) - \\ &\quad exp(\widehat{\mu_1} + \widehat{\mu_2} + (\widehat{\lambda_1} + \widehat{\lambda_2})\, t + \widehat{\gamma_1}\, tsi) \end{aligned} \tag{6}$$

It is worth stressing that $\widehat{\lambda_2}$ delivered by CITS informs on a common trend's (non)existence before intervention/treatment.[3] What is more, $\widehat{\gamma_2}$ must be interpreted as a trend difference-in-differences. The first trend difference $[(\widehat{\lambda_1} + \widehat{\lambda_2} + \widehat{\gamma_1} + \widehat{\gamma_2}) - (\widehat{\lambda_1} + \widehat{\lambda_1}) = \widehat{\lambda_2} + \widehat{\gamma_2}]$ is the one that has emerged after the intervention and would be captured by a traditional DiD.[4]. The second trend difference $[(\widehat{\lambda_1} + \widehat{\lambda_2}) - (\widehat{\lambda_1}) = \widehat{\lambda_2}]$ is the one that pre-existed and would be captured by a placebo DiD.

Leaving aside the complications resulting from asymmetric durations before and after the intervention, the main point is that $\widehat{\gamma_2} \approx$ traditional DiD - placebo DiD. This implies that when CITS estimate the treatment effect as $\widehat{\gamma_2} * tsi$, it attributes to the treatment any change in the initial (additive or multiplicative) trend difference characterizing the treated group before the intervention, as captured by a placebo DiD or, in this case, $\widehat{\lambda_2}$.

Consider the scenario where the latter is negative ($\widehat{\lambda_2} < 0$ indicating a lower additive or multiplicative trend in the treated entity before the intervention). In such cases, $\widehat{\gamma_2}$ produces

[3] That coefficient can be related to DiD that has emerged before the intervention, i.e. $\widehat{\lambda_2}\, \bar{t}$.

[4] β_2^* in eq.1.

a treatment effect larger than the traditional DiD. To illustrate further, envision a situation where the traditional DiD yields a value of zero, interpreted as an absence of treatment effect, i.e., $\widehat{\lambda}_2 + \widehat{\gamma}_2 = 0$. Simultaneously, the CITS estimates $\widehat{\gamma}_2$ equals $0 - \widehat{\lambda}_2 > 0$, leading to the conclusion that the treatment has been successful. This is because it credits the treatment with the elimination of a pre-existing (additive or multiplicative) trend handicap.

3 Data

The data used in this paper consists of average taxable net income data (all earnings – professional and other deductible expenses) per head, provided by Statistics Belgium. These averages are available for each of Belgium's 589 municipalities (Figure 1) from 1977 to 2013; with many years before 1994 which is the year Objective 1 treatment started being effective (Figure 2); and also after 1999 (end of the first phase of Objective 1) or 2006 (end of the phasing-out period). Readily available information about the number of inhabitants at the municipal level was used as a weighting factor to capture trends that are representative at a more aggregated level; e.g.; the entirety of Hainaut (our treated entity) (Figure 1) or the rest of Belgium (our control). The advantage of this outcome variable is that it is reliable: time series on taxable income at the municipal level are amongst the oldest of Belgium's statistical apparatus. Also, taxable income is in essence an aggregate outcome variable; very close to what GDP per head captures. Using it as our main outcome variable means that we consider that the benefits of Objective 1 (whatever the precise project/programme or policy that it has financed) should ultimately show up in the sums of money earned by people residing in Hainaut (and on which they are taxed). Although some may argue in favour of other measures of outcomes (employment. . . .) we tend to favour this one because it corresponds relatively well to the goal assigned by EU decision-makers to Objective 1; but also because it is likely to capture the (monetary) spillovers of the programme (e.g. beyond net job creation or higher wages due to higher productivity (i.e. the direct benefits), an improved capacity to attract wealthier residents. . .).

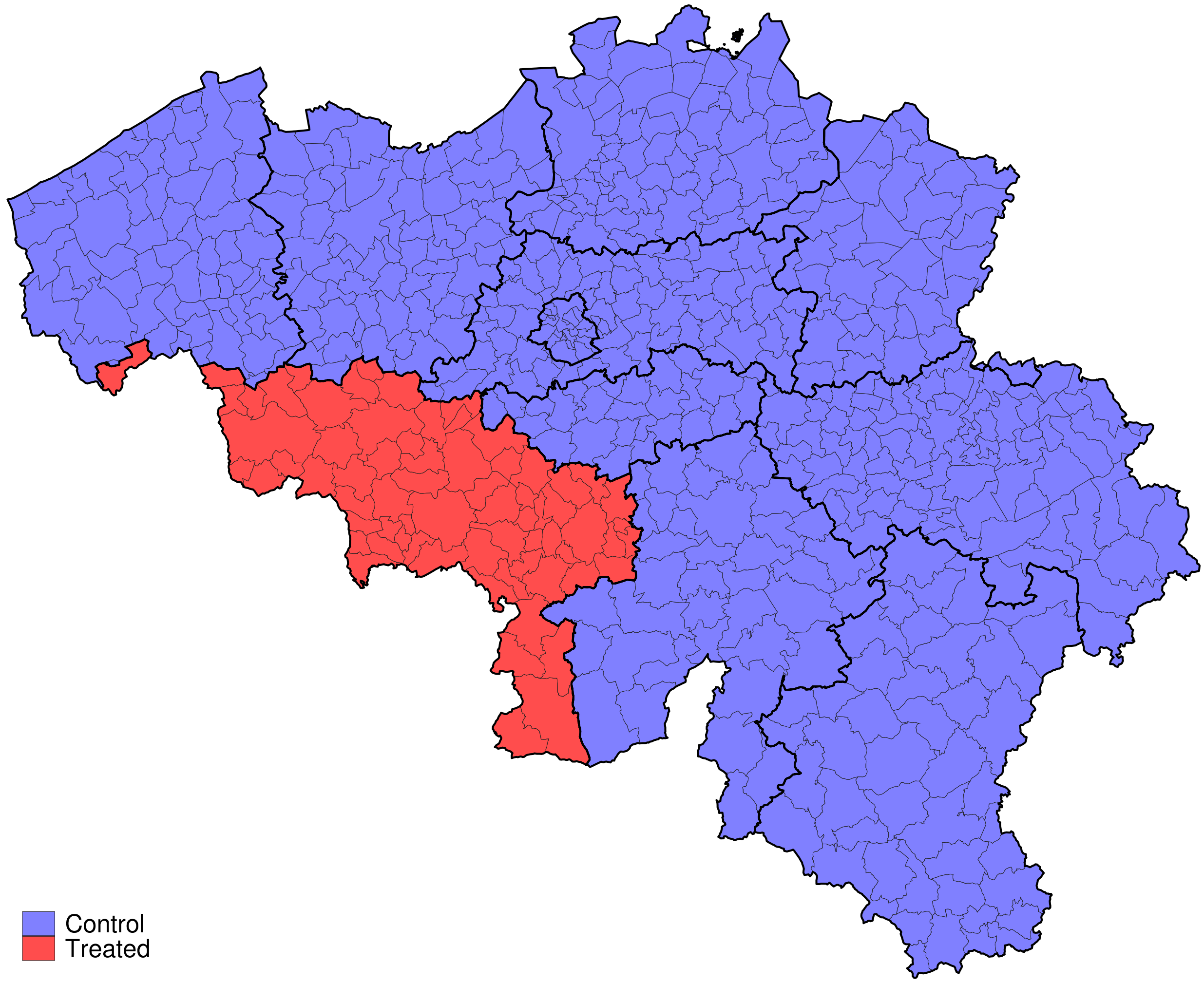

Figure 1: Objective1- Treated (Hainaut) and control (Rest of Belgium) municipalities
Source: Statbel (2016).

Figure 2 displays the evolution of the level of income per head (in 2013 euros) for the treated vs control territories used in this paper. It confirms the persistent and visually rising income-level handicap of Hainaut (dashed blue line) compared to the other Belgian provinces. Vertical bars help identify the calendar of implementation of Objective 1 with the initial 1994-1999 phase, followed by the so-called"phasing out" from 2000 to 2006. Figure 2 gives a first (purely descriptive and implicitly additive) indication of what happened before, during and after Objective 1.

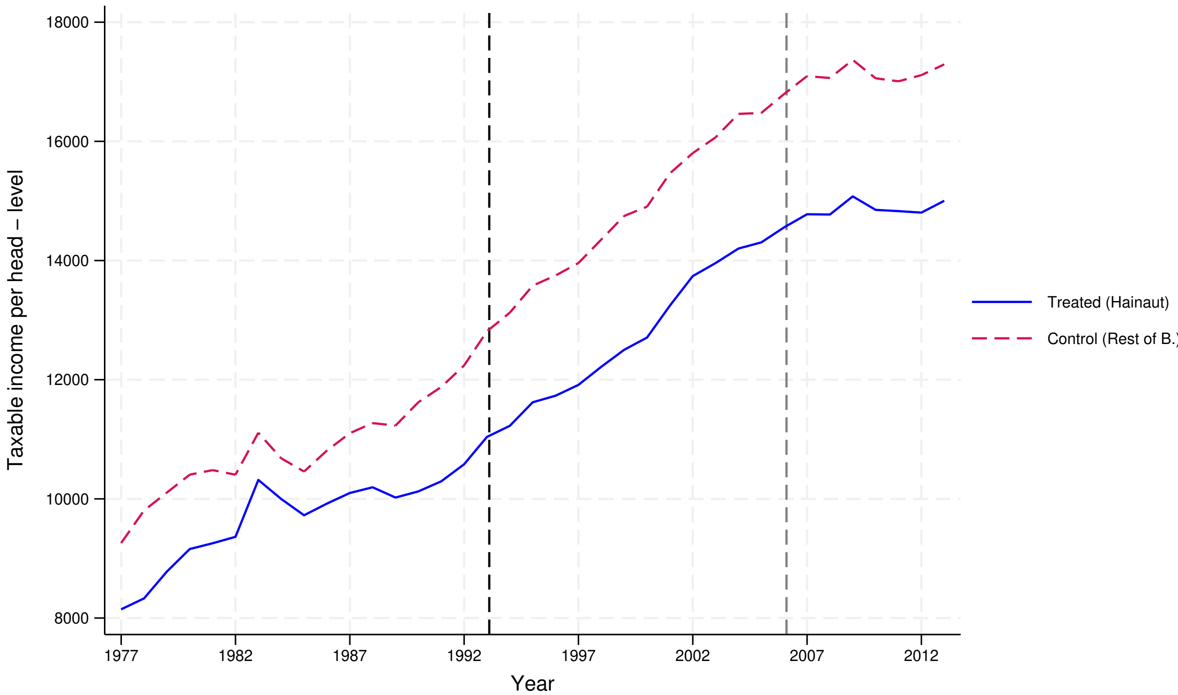

Figure 2: Objective1- Level differences in 2013 euros
Statbel (2016). Calculated using municipal-level (per head) taxable income data (in 2013 euros), weighted by population sizes

4 Results

The key econometric results of the paper are displayed in Table 1. The first two columns report the results when the time trend is modelled as additive, while the last two columns replicate them for the exponential model, where it is multiplicative and amounts to a growth rate. Columns 1 and 3 report the result of a traditional DID analysis carried out over the 1993-2013 period (1993 being the only year before treatment used), and where the coefficient of the time variable interacted with the treatment dummy captures the effect of the treatment assuming common trend in the absence of treatment. Columns 2 and 4 report the results of the more robust CITS analysis, with in particular the coefficient of the time elapsed since intervention interacted with the treatment dummy $tsi \times TREAT$ delivering a treatment effect estimate as a trend difference-in-differences.

At the bottom of Table 1, we present the treatment effects estimates (in 2013 euros) derived from the econometric results reported above. The canonical additive DiD analysis (Col. 1) estimates the treatment effect to be -356 euros by the year 2013. However, replicating this analysis using the multiplicative exponential model—estimated (using the

Poisson pseudo-maximum-likelihood estimator in Stata) reveals a contrasting result of +344 euros. This stark difference highlights the significant impact of adopting a multiplicative vs additive specification: modelling things additively when the common trend is more likely to be multiplicative leads to downward-biased DiD estimates.

Another noteworthy result is the difference between CITS compared to DiD. In Column 2, we present the outcomes delivered by a CITS using the entire before and after time series (1977-1993, 1994-2013). Pay special attention to the $t \times TREAT$ coefficient. It suggests that the assumption of an (additive) common trend is not valid. At the bottom of the table, we report the level equivalent of this (additive) trend handicap for 16 years — i.e. the time elapsed between 1993 and 2013 — as -1075 euros. Moreover, as explained earlier, the coefficient $tsi \times TREAT$ accounts for trend differences before Objective 1, leading to the conclusion that the policy has had a (small) positive impact on income per head of +17 euros.

However, these results rely on the (presumably inadequate) additive trend assumption. Our preferred model is presented in column 4, where we combine the multiplicative trend assumption with CITS. Firstly, the $t \times TREAT$ coefficient confirms the violation of the (multiplicative) common trend assumption before the inception of Objective 1. In other words, it indicates that the treated entity (Hainaut) was growing at a slower rate than the rest of Belgium before it began benefiting from Objective 1. At the bottom of the table, we report the level equivalent of this (multiplicative) trend handicap for 16 years as -704 euros. Note that this value is logically less than the additive handicap, as additive modelling biases DiD estimates downwards. Finally, and more importantly, the $tsi \times TREAT$ coefficient is positive and statistically significant. This suggests that Objective 1 has been effective in the sense that it has (more than) eliminated a pre-existing multiplicative trend (i.e., growth rate) handicap affecting Hainaut. We estimate the level equivalent of this improvement to be +885 euros.

Table 1: Econometric results: sensitivity of treatment effect estimation to the use of additive vs multiplicative trend, and traditional DiD vs Controlled Interrupted Time Series Analysis (CITS)

	Additive trend		Multiplicative trend[a]	
	Traditional DiD	CITS	Traditional DiD	CITS
cons	13272.4***	9331.4***	9.5018***	9.1483***
	(0.283)	(0.293)	(0.000)	(0.000)
t	235.79***	218.20***	0.01509***	0.02007***
	(0.027)	(0.026)	(0.000)	(0.000)
$TREAT$	-1974.3***	-852.92***	-0.1599***	-0.09884***
	(0.573)	(0.804)	(0.000)	(0.000)
$t\ X\ TREAT$	-17.823***	-53.763***	0.001105***	-0.002848***
	(0.055)	(0.072)	(0.000)	(0.000)
tsi		50.142***		-0.002693***
		(0.041)		(0.000)
$tsi\ X\ TREAT$		17.135***		0.002869***
		(0.115)		(0.000)
Nobs	12,366	21,832	12,366	21,832
Treatment	-356.467	342.700	344.691	885.796
pvalue	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Placebo DiD[b]		-1075.253		-704.150
pvalue		(0.0000)		(0.0000)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Source: Statbel (2016), our calculus
Coefficient Standard errors in parentheses
Estimates obtained using Statistics Belgium municipal-level (per head) taxable income (2013 euros) data, weighted by population sizes
[a]: Estimated using the Poisson pseudo-maximum-likelihood estimator in Stata.
[b]: Computed using CITS estimates of trend/slope differences during 16 pre-interventions years.

5 Conclusion

Evaluating the response of income per head in impoverished territories to place-based programmes aimed at fostering income convergence poses challenges. In this paper, we contend that resorting to the canonical Difference-in-Differences analysis (DiD) is inappropriate due to two assumptions unlikely to be met in this context. Firstly, DiD assumes additive time trends, whereas standard economic theory would posit multiplicative trends. Secondly, the common trend assumption is typically unverified. Thus, there is a need for a method allowing for trend differences between treated and control entities before treatment, and estimating the treatment as a multiplicative trend difference-in-differences.

The method we implement here, in combination with an exponential (thus multiplicative) model, is referred to as Controlled Interrupted Time Series Analysis (CITS) by epidemiologists. We illustrate its relevance using time series data on the evolution of taxable income per head between 1977 and 2013 for Hainaut vs. the rest of Belgium. While the canonical (additive) DiD yields a treatment effect estimate of -356 euros for the 1993-2013 period, our preferred exponential CITS method concludes with a +885 euros gain. Two factors contribute to this reversal. The first is that, in the presence of a common growth rate (i.e., multiplicative trend), the canonical additive DiD confounds the treatment effect and the mechanical rise of initial level differences. Second, unlike DiD, CITS credits the treatment/intervention for the benefits corresponding to the reduction of a pre-existing trend handicap.

Declarations

Availability of data and materials

Data supporting the findings of this study are available from the author on request.

Competing interests

We have no conflicts of interest to disclose.

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