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# Treatment-effect identification without parallel paths

*Vincent Vandenberghe*

**Abstract**
Imagine a region suffering from a widening income gap that becomes eligible for a generous transfer programme (the treatment). Imagine difference-in-differences analysis (DD) — a before-and-after comparison of the income-level difference — shows that the handicap has risen. Most observers would conclude to the policy's inefficiency. But second thoughts are needed, because DD rests heavily on the validity of a key assumption: parallel paths in the absence of treatment; an assumption that is often violated. To cope with this problem, economists traditionally include polynomial (linear, quadratic…) trends among the regressors, and estimate the treatment effect as a once-in-a-time trend shift. In practice that strategy does not work very well, because inter alia the estimation of the trend uses post-treatment data. What is needed is a method that i) uses pre-treatment observations to capture linear or non-linear trend differences, and ii) extrapolates these to compute the treatment effect. This paper shows how this can be achieved using a fully-flexible version of the canonical DD equation. It also contains an illustration using data on a 1994–2006 EU programme that was implemented in the Belgian province of Hainaut.

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**Keywords** Treatment-effect analysis; difference-in-differences models; EU convergence policy

**Authors**
*Vincent Vandenberghe,* ✉ IRES-UCL, Economics School of Louvain, Louvain-la-Neuve, Belgium, vincent.vandenberghe@uclouvain.be

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# 1 Introduction

This paper deals with how to properly evaluate the impact of convergence policies like Objective 1-Hainaut. At its core lies a methodological proposal. But, before turning to its full exposition, here are a few words about Objective 1 and the province of Hainaut in Belgium.

Objective 1-Hainaut is an example of a European-Union (EU)-funded transfer policy aimed at helping European regions reduce their socio-economic handicap. The policies have a relatively old history. The underpinning idea was present in the preamble to the Treaty of Rome in 1957, and has been 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 aimed at ensuring 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 to mitigate regional income disparities.[1] 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 (Rodríguez-Pose and Fratesi, 2003). 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 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 that was tied in with the establishment of the Cohesion Fund to alleviate the burdens that transition to EMU would impose on the less developed territories.

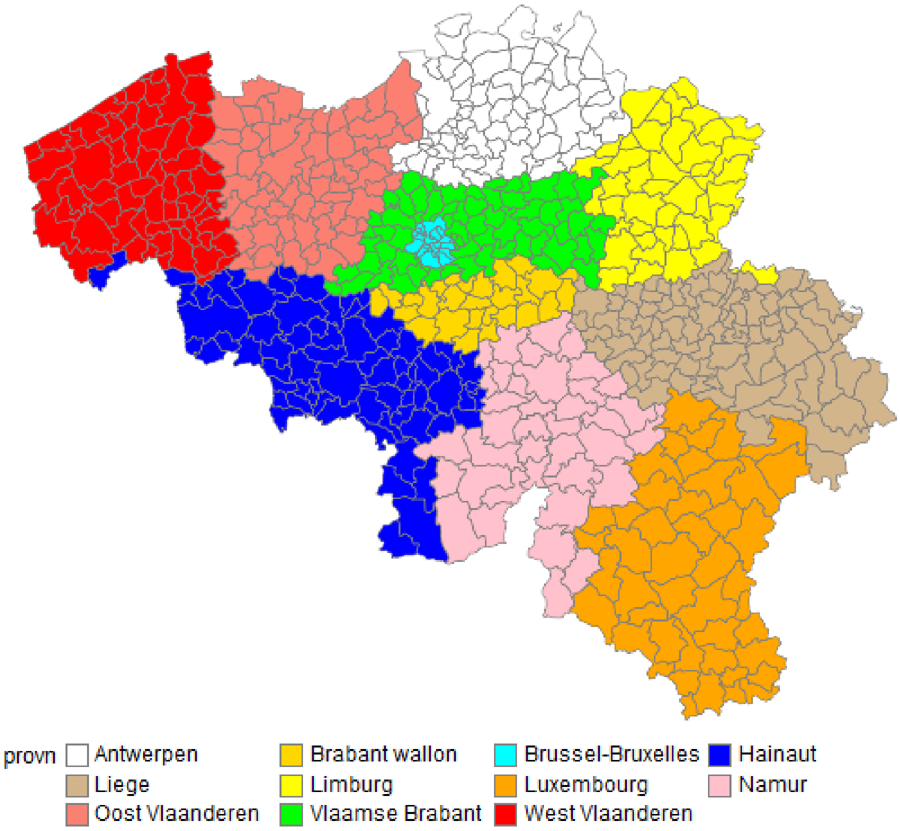
After the reform, more than two thirds of all Structural Fund expenditure have been concentrated in the so-called Objective 1 regions. These are territories whose GDP per capita, measured in purchasing power standards (pps), is less than 75% of the EU average. In the 1990s, the list comprised 64 NUT2 regions[2] (Tondl, 2007), one of them being Hainaut in Wallonia/Belgium (Figure 1). The 69 municipalities forming that province benefited from Objective 1 money between 1994 and 1999. And from 2000 to 2006 they also benefited from the "phasing out" programme.

Yet, despite their rising macroeconomic importance, questions are being raised about the capacity of European development/convergence policies in general, and of policies targeted at Objective 1 regions, 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). In that context, it is a bit surprising that there are

[1] The European Commission's focus on regional disparities has been paralleled by a renewed academic interest – both theoretical and empirical – in the economic analysis of growth and (non) convergence. From the work of Romer (1986), (1990) and Lucas (1988), a growing body of literature, known as 'new growth theories', has started to question the optimistic predictions of the traditional neoclassical model laid out by Solow (1956), which leaves little or no role to regional/convergence policy.

[2] Nomenclature of Units for Territorial Statistics (NUTS) is a geocode standard for referencing the subdivisions of countries for statistical purposes. The standard is developed and regulated by the EU, and thus only covers the member states of the EU in detail.

*Figure 1*: Hainaut and its municipalities (+ the rest of Belgium)




very few *ex post* economic evaluation studies[3] of the monetary benefits of Objective 1. More precisely, there are very few papers answering questions such as "what would be the level of income per head in region *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…), very little work has been done using microdata, in a quasi-experimental setting, to evaluate the effectiveness of Objective 1 (or other EU policies aimed fostering convergence across regions or countries). In a sense, this paper aims at filling that void. This said, at its core, lies a methodological discussion of what can (or cannot) be achieved within the canonical differences-in-differences (*DD*) estimator, and how best to address its limitations.

*DD* is a statistical technique commonly used in microeconometrics (Angrist and Krueger, 1999) that mimics an experimental research design using observational data, by studying the different evolution of 'treated' ' vs 'control' groups in a (quasi) natural experiment. It calculates

[3] There are several macroeconomic models that have been used to assess the *potential* impact of EU funds on economic growth (e.g. HERMIN model). All these models estimate growth effects from cohesion spending, but their size changes depending on the theoretical assumptions upon which the model is based.

the effect of a treatment (e.g. Objective 1) on an outcome (e.g. income per capita) by comparing *i)* the average change over time in the outcome variable for the treatment group (e.g. the municipalities of Hainaut), to *ii)* the average change over time for the control group (e.g. the municipalities forming the rest of Belgium). But the validity of that method rests heavily on the parallel-path assumption: in the absence of treatment (and in particular before its inception) the (average) outcome-level difference between the treated and the control entities (municipalities hereafter) must be time-invariant; so that the observation of a statistically significant change of the pre-treatment difference after the treatment's inception can be ascribed to the latter. Key to this paper is the idea that, whenever data permit, one should go beyond the canonical *DD* model and the parallel-path assumption underpinning its capacity to properly identify a treatment's effect. It is also that this should be done not simply via the addition of a polynomial (linear, quadratic…) time trend to the canonical *DD* model, as most authors do. A more promising avenue is to *i)* estimate the generalized, fully-flexible *DD* model proposed by Mora and Reggio (2012) *ii)* and so to account (and correct) for the absence of parallel paths, using only pre-treatment observations.

When data contain 2 or more pre-treatment periods it is easy to verify if parallel path holds. And quite often it does not. As said above, what most authors do when confronted to that problem, is to augment the canonical *DD* model (that contains a time dummy, a treatment dummy and the interaction between these two) with a polynomial (linear, quadratic…) time trend, and to estimate the treatment effect as a once-in-a-time shift of that trend (e.g. Friedberg, 1998; Autor, 2003; Besley and Burgess, 2004). In practice, that strategy does not work very well, because *inter alia* the estimation of the trend uses post treatment data.[4] Wolfers (2006) for instance explains that Friedberg's (1998) work on the legalisation of divorce is a point in case. Friedberg controls for treated vs control US State diverging trends using a sample that covers only one year before treatment and many years after. Her estimates of the State trends rely almost completely on post-treatment developments, and absorbs most of the treatment's effect. Another – less commonly used – method to correct for the absence of parallelism consists of building a synthetic control group (Abadie et al., 2010, Bélot and Vandenberghe, 2009). The idea is that a combination of control entities is likely to provide a better (i.e. more "parallel") comparison for the treated one than any single entity alone. It might indeed. But there is no absolute guarantee that the synthetic entity will display parallelism prior to treatment. And the method is quite demanding in terms of data. Its use is conditional on the availability of relatively large set of control entities, for which the outcome variable of interest has been measured in the same way as for the treated entity. By comparison, the method exposed here below consists of taking whatever data is available as control, and to adapt the canonical *DD* identification method when the control entity does move parallel to the treated.

How can the canonical *DD* model be adapted? It simply needs to be generalized. Mora and Reggio (2012) show that such a model – and the parallel-path assumption underpinning identification ($DD_{[1]}$/$Parallel_{[1]}$ hereafter) – is a particular case of a more general one that can be used to estimate a whole family of *DD* models. The nicety of the Mora and Reggio framework

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[4] Another reason has to do with what Cabras et al. (2017) call the" parametric straightjacket"; i.e. the fact that many regressions are not flexible enough to capture the true relationships as they tend to rely on arbitrary identification assumptions.

is to allow for all sorts of diverging trends verifying (or violating) $Parallel_{[1]}$, $Parallel_{[2]}$, $Parallel_{[3]}$, and even higher degrees of parallelism. Why still talk of "parallel-something" if there is divergence? Because, as will become clear in Section 2 hereafter, the identification idea remains that at the heart of the canonical $DD_{[1]}$/$Parallel_{[1]}$. model: in the absence of treatment, the differences between growth rates/$Parallel_{[2]}$, or acceleration rates/$Parallel_{[3]}$ …. should be constant. While $DD_{[1]}$ focuses on the evolution of outcome level differences, $DD_{[2]}$ tracks the evolution of outcome growth differences; and $DD_{[3]}$ that of outcome acceleration differences. The other key feature of the Mora and Reggio framework is that it solves the problem identified by Wolfers (2006) whith polynomial time-trend corrected *DD*.[5] We show hereafter that this is because – unlike what is done by authors resorting to polynomial time-trend corrections – only pre-treatment observations are used to capture trend differences, and because the estimation of the treatment effect rests on a simple extrapolation of these pre-treatment trends.[6]

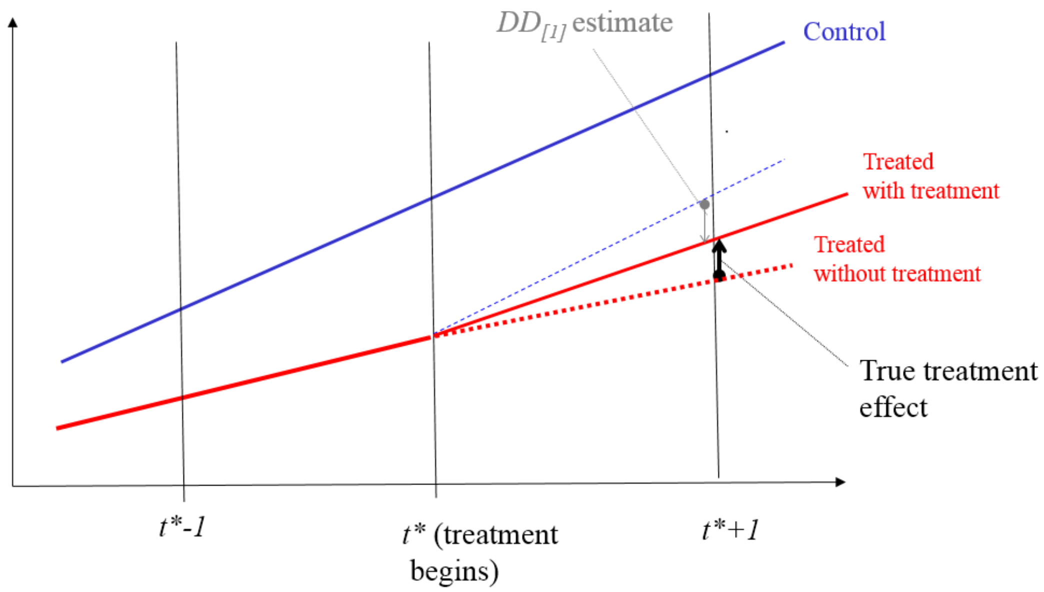
This said, the reader should be aware that the economic efficiency criteria associated with the different *DD* estimators vary dramatically. In the context of a deprived region receiving financial aid, using $DD_{[1]}$ as a treatment-evaluation method means a focus on the reduction and the initial income-***level*** difference of that region. Under $DD_{[2]}$ the requirements are intrinsically milder. Efficiency exists as soon as one detects a reduction of the pre-treatment income-***growth rate*** difference. And there is no paradox in $DD_{[1]}$ results being negative, while those delivered by $DD_{[2]}$ are positive. That simply means that the initial income-level difference has risen, but less than it would had the growth rate difference not been reduced (see Figure 2 for an illustration). By contrast, if even $DD_{[2]}$ shows no significant gains, then it means that the policy has not been very effective at all; as it has not even been able to reduce the pre-treatment growth rate difference.

In the case of Objective 1-Hainaut and its 69 treated municipalities, using per head income data and the rest of Wallonia or Belgium as a control group, our $DD_{[1]}$ results suggest a negative impact. But the analysis of pre-treatment data clearly shows that $Parallel_{[1]}$ does not hold before inception. We rather find statistically significant evidence of $Parallel_{[2]}$ (constant growth rate difference before 1994). This is thus the assumption we retain for identifying Objective 1's causal impact. And when doing so, results change considerably, as our $DD_{[2]}$ estimates are positive and statistically significant. This is supportive of the idea that Objective 1 reduced the growth rate difference that affected Hainaut before 1994. In the absence of this correction, the income-level difference increment – the one typically measured by $DD_{[1]}$ – would have been larger. Over the year 2010 horizon, we find that Hainaut experienced a rise of its income-level difference compared to the rest of Belgium of 426 euros. But we find a statistically significant $DD_{[2]}$ of 491 euros. This means is that in the absence of the growth rate (positive) correction; the income-level difference rise would have been of 426 + 491 euros.

[5] The (linear) trend-augmented version of the canonical *DD* model writes $Y_{it} = \alpha + \sum_{\tau=t2}^{T} \alpha^{\tau} I_{\tau,t} + \alpha^{D} D_i + \eta AFTER_t.D_i + \theta\, t.D_i + \varepsilon_{it}$ with $I_{\tau,t}=1$ if $t=\tau$ and 0 otherwise, and where $Y_{it}$ is entity *i*'s outcome in time *t*, *D* the treatment dummy, *AFTER* the after treatment dummy, and here *t* is a continuous variable. Coefficient $\theta$ captures the linear trend characterizing the treated entities. And $\eta$ – a trend shift around $t=0$ – measures the treatment effect.

[6] For an illustration of how the generalized *DD* method we put forth here compares with polynomial time-trend corrected *DD*, see Vandenberghe (2018).

*Figure 2*: The inadequacy of traditional difference-in-(level) differences estimator ($DD_{[1]}$) in the presence of non-parallel paths[$]




The rest of the paper is divided into five sections. Section 2 exposes analytically the $DD_{[1]}/Parallel_{[1]}$, $DD_{[2]}/Parallel_{[2]}$… $DD_{[q]}/Parallel_{[q]}$ sequence, and how it can be implemented using OLS estimation. Section 3 briefly discusses Objective 1-Hainaut ; its particularities and the calendar of its implementation. Section 4 presents the dataset used in this paper and some descriptive statistics. Section 5 contains and comments the main estimation results. Section 6 concludes.

## 2 Beyond parallel 1

To generalise the idea of treatment effect identification via *DD*, Mora and Reggio (2012) suggest estimating a fully-flexible equation, where the right-hand part only consists of time, treatment and time*X*treatment dummies[7]

$$Y_{it} = \gamma + \sum_{\tau=t_2}^{T} \gamma_\tau I_{\tau,t} + \gamma^D D_i + \sum_{\tau=t_2}^{T} \gamma_\tau^D I_{\tau,t} D_i + \varepsilon_{it} \quad [1.]$$

with $t=t_1,\ldots T$ and $I_{\tau,t}=1$ if $t=\tau$ and 0 otherwise, covering before and after treatment periods.

[7] That equation can also be augmented by including time-varying continuous variables $X_{it}$.

The advantages of such a specification are manifold. First, conditional on the availability of many pre-treatment periods in the data, the OLS-estimated coefficients can be used to compute a whole family of difference-in-difference estimators $DD_{[p]}$, where $p=1, 2...q$ is the degree of parallelism underpinning identification. The canonical differences-in-differences model is $DD_{[1]}$, and rests on parallelism of degree 1 ($Parallel_{[1]}$), meaning that outcome levels must stay parallel in the absence of treatment.[8] Without $Parallel_{[1]}$ – as depicted on Figure 2 – one can estimate $DD_{[2]}$ that rests on $Parallel_{[2]}$, i.e. outcome growth-rate parallelism.[9] If $Parallel_{[2]}$ fails, one should turn to $DD_{[3]}$ with requires $Parallel_{[3]}$ or outcome-acceleration[10] parallelism… and so on up to degree $p=q$, if data permit. Second, Eq. [1], can capture dynamic (i.e. lagged) responses to treatment.[11] Finally – and this is something we particularly stress in the context to this paper – corrections for the violation of $Parallel_{[p]}$ rests solely on pre-treatment observations.

Consider the canonical $DD_{[1]}/Parallel_{[1]}$ estimator, with just before-and-after observations $t*$ and $t^*+1$.[12] Treatment effect corresponds to[13;14]

$$DD_{[p=1]}{}^{t*+1;t*}=(\gamma^D{}_{t*+1}+\gamma^D)-(\gamma^D{}_{t*}+\gamma^D)=\gamma^D{}_{t*+1}-\gamma^D{}_{t*}. \qquad [2.]$$

Eq. [2] can be used to assess $Parallel_{[1]}$ prior to treatment. Using 2 pre-treatment periods (say $t^*$-2, $t^*$-1), one can compute 'placebo' $DD_{[1]}$ capturing the deviation from $Parallel_{[1]}$ prior to the start of the treatment. For instance, $DD_{[1]}{}^{t*;t*-1}=\gamma^D{}_{t*}-\gamma^D{}_{t*-1}$. should not be statistically different from zero. If not, then treated and control trends diverge before treatment (as illustrated on Figure 2). And the identification of the treatment effect should rest on $Parallel_{[2]}$

The point is that this can be easily achieved by computing[15]

$$DD_{[p=2]}{}^{t*+1;\,t*-1}=DD_{[1]}{}^{t*+1;\,t*}-DD_{[1]}{}^{t*;t*-1}=(\gamma^D{}_{t*+1}-\gamma^D{}_{t*})-(\gamma^D{}_{t*}-\gamma^D{}_{t*-1})=\gamma^D{}_{t*+1}-2\gamma^D{}_{t*}+\gamma^D{}_{t*-1} \qquad [3.]$$

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8 If outcome level change by unit of time is "speed" (i.e. 1st-order derivate of outcome vis-à-vis time), then $Parallel_{[1]}$ means stable outcome level differences due to identical speeds

9 If outcome growth rate change by unit of time is "acceleration" (2nd-order derivate), then $Parallel_{[2]}$ means stable outcome growth rate differences due to same accelerations.

10 If outcome acceleration change by unit of time is "surge" (3nd-order derivate), then $Parallel_{[3]}$ corresponds to a situation where outcome acceleration differences remain stable due to identical surges.

11 The pattern of lagged effects is usually of substantive interest. We might, for example, believe that treatment effect should grow or fade as time passes.

12 Hereafter the range of periods used by the estimator appears as superscript in $DD_{[p=1]}{}^{t*+1;t*}$

13 When estimating eq. [1] with only 2 periods ($T=2$), $\gamma^D{}_{t*}$ is subsumed into the constant $\gamma^D$ and $DD_{[1]}$ is directly captured by the timeXtreatment interaction term coefficient.

14 Treatment effect' standard error must account for the fact that it is a linear combination of estimated coefficients. Variance/standard error must account for the covariance between corresponding variables. That is done e.g. by STATA `test` or `lincom` commands, that use the variance-covariance matrix of the estimated coefficients.

15 Again, when estimating eq. [1] with only 3 periods, $\gamma^D{}_{t*-1}$ is subsumed into $\gamma^D$ and $DD_{[2]}$ is computed using only 2 coefficients.

or, said differently, the difference between the OLS-estimated observed post-treatment $t^*+1$ outcome level difference i.e. $\gamma^D_{t^*+1}$ and the predicted one ($\gamma^D_{t^*}+DD_{[1]}^{t^*;t^*-1}$) given the level difference in $t^*$ and its expected rise due to growth rate difference between $t^*$ and $t^*-1$ (see Figure 3 for the link between the algebra and the graphical representation). This prediction uses only regression coefficients driven by pre-treatment observations; a major difference with the traditional polynomial time-trend corrected method mentioned in the introduction.

The $DD_{[2]}^{t^*+1;t^*-1}$ estimator can be generalised to the case where one wants/has de possibility to calibrate $Parallel_{[2]}$ using more than 2 adjacent pre-treatment periods. Imagine one has $v>2$ pre-treatment and 1 post-treatment observations. The estimator becomes

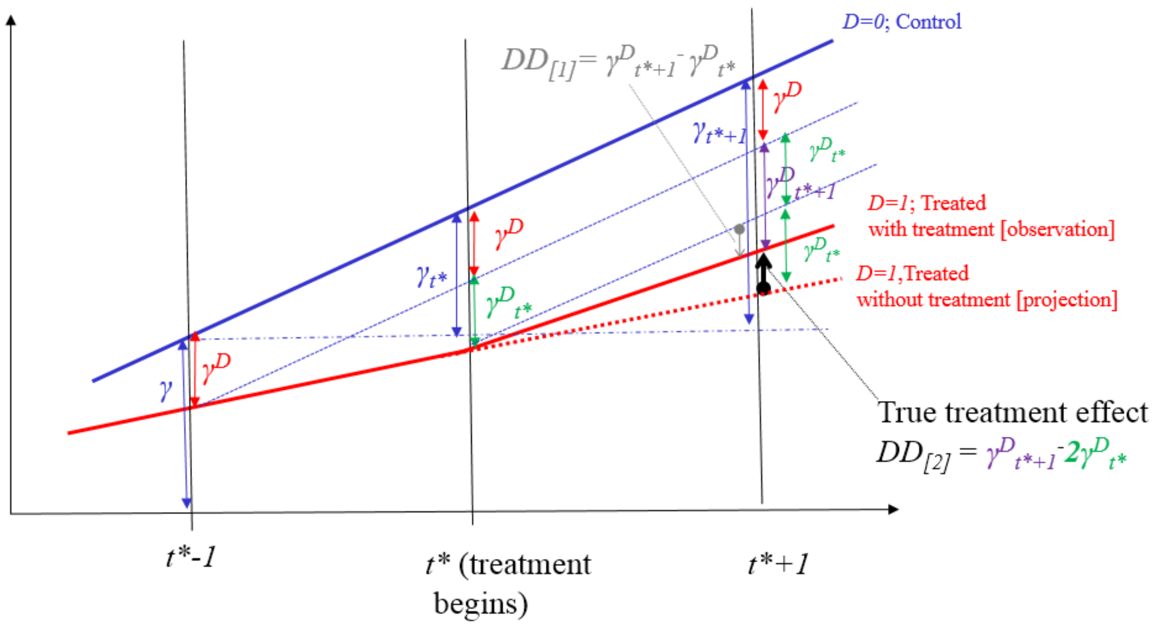
$$DD_{[p=2]}^{t^*+1/t^*-v}= DD_{[1]}^{t^*+1;\,t^*} - 1/v\; DD_{[1]}^{t^*;t^*-v} =\gamma^D_{t^*+1}- (1+1/v)\gamma^D_{t^*} \;+1/v\gamma^D_{t^*\,-v} \qquad [4.]$$

with $v\geq p-1$

One can also account for the possibility that treatment lasts more than one period or, alternatively, that its effects are lagged (i.e. it takes several periods for the treatement to deliver

*Figure 3*: How difference-in-[growth-rate] differences ($DD_{[2]/}Parallel_{[2]}$) can cope with non-parallel paths$

$$Y_{i,t}= \gamma + \gamma_t I_{t^*} + \gamma_{t+1} I_{t^*+1} + \gamma^D D_i + \gamma^D_{t^*} D_i.I_{t^*} + \gamma^D_{t^*+1} D_i.I_{t^*+1} + \varepsilon_{it}$$




$ On this figure, $t^*-1$ is the first period observed in the data. Hence, $\gamma^D_{t^*-1}$ is subsumed into $\gamma^D$ and, in contrast with [3], $DD_{[2]}$ is computed using only 2 coefficients significant effects). In $t^{*}+s\ ;s\geq 1$, the difference between the observed level difference and the expected one is

$$DD_{[p=2]}^{t^{*}+s/t^{*}-v} = \gamma^{D}_{t^{*}+s} - (1+s/v)\gamma^{D}_{t^{*}} + \boldsymbol{s/v}\,\gamma^{D}_{t^{*}-v} \qquad [5.]$$

with $v\geq p\text{-}1$

The ultimate generalisation is to assume $Parallel_{[p=q]}$. As to data, the minimal requirement is to possess $q$ pre-treatment observations, and one post-treatment observation at horizon $t^{*}+s\ ;\ s\geq 1$ . The treatment effect can then be estimated using the OLS-estimated coefficients of the $q\text{-}1$ interaction terms $D.I$ in eq. [1]. It is in fact equal to

$$DD_{[p=q]}^{t^{*}+s;t^{*}-q+1} = \gamma^{D}_{t^{*}+s} - [\gamma^{D}_{t^{*}} + s.\textstyle\sum_{\tau=1}^{q-1} DD_{[\tau]}^{t^{*};t^{*}-\tau}] \qquad [6.]$$

where $DD_{[\tau]}^{t^{*};t^{*}-\tau} = (1\text{-}L)^{\tau}\gamma^{D}_{t^{*}}$ with $L$ the lag operator[16]

Note that in eq. [6] the treatment effect remains computed as a difference between *i)* an observed (difference) in $t^{*}+s$ (i.e. $\gamma^{D}_{t^{*}+s}$) characterising the treated vs control entities and *ii)* a predicted difference, whose level is solely based on pre-treatment observations (i.e. $[\gamma^{D}_{t^{*}} + s.\sum_{\tau=1}^{q-1} DD_{[\tau]}^{t^{*};t^{*}-\tau}]$ only contains pre-treatment dummy coefficients capturing the potentially diverging trajectories of treated vs control entities).

Finally, note that when $p=q=1$ eq. [6] simplifies to

$$DD_{[p=1]}^{t^{*}+1} = \gamma^{D}_{t^{*}+1} - \gamma^{D}_{t^{*}} \qquad [7.]$$

which is equivalent to eq. [2]. And it is immediate to show that [6] also reproduces eq. [3] when $p=q=2$.

## 3 Objective 1: Hainaut Municipalities vs…

Hainaut is a province (one of the NUTS2 EU regions) situated in French-Speaking Wallonia, forming the south of Belgium. It counts 69 municipalities (Table 1) that will form our 'treated' entities hereafter. It is one of the most economically deprived parts of the country. At its heart lies the large the city Charleroi: a former bastion of the country's industrial revolution that has since endured decades of decline. In 1993, Hainaut was retained on the list of EU regions eligible to Objective 1. It benefited from that EU programme from 1994 to 2006.[17] This was

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[16] $(1\text{-}L)X_t = X_t\text{-}X_{t-1}\ ;\ (1\text{-}L)^2X_t = (1\text{-}L)(X_t\text{-}X_{t-1}) = (X_t\text{-}X_{t-1})\text{-}(X_{t-1}\text{-}X_{t-2})\ ;\ \ldots$

[17] Anecdotal evidence, but also intermediate evaluation reports commissioned by the EU (IDEA Consult, 2003), invariably point at a "slow start" due to lack of experience, an underestimation of some legal issues, the large number of stakeholders to get to agree on priorities and implementation procedures.

*Table 1*: Municipality count. Hainaut, Liège, rest of Belgium or rest of Wallonia

| | |
|---|---|
| Rest of Belgium | 520 |
| Rest of Wallonia | 193 |
| Liège | 84 |
| **Hainaut** | **69** |
| Total | 589 |

despite a GPD per capita of 77.3% of the EU reference, superior to the 75% threshold. Interestingly in the context of this paper, the Commission considered that, on top of being relatively close to the selection criteria, the province was suffering from a substantial deterioration of its economic and social situation. In other words, there was a negative income growth difference, in addition to pure income level difference; and also a severe problem of underemployment.

During the first phase (1994–1999), the sums injected in the province's economy by both the EU and Belgian authorities (due to mandatory national co-financing) were relatively high at 2.43 billion EUROS (1994 nominal), representing a bit less than 5% of the province’s GDP for each of the year ranging from 1994 to 1999.[18] Priorities ascribed to Objective 1-Hainaut were *i)* the improvement of the competitiveness of enterprises (e.g.; R& D credits) (1/3 of the total), *ii)* the attractiveness of the region (e.g. through cleaning up of old industrial sites) (1/4 of total), *iii)* prospects for tourism and research facilities (1/5 each) (for more details on the policy and its implementation see IMF, 2003; IDEA Consult, 2003).

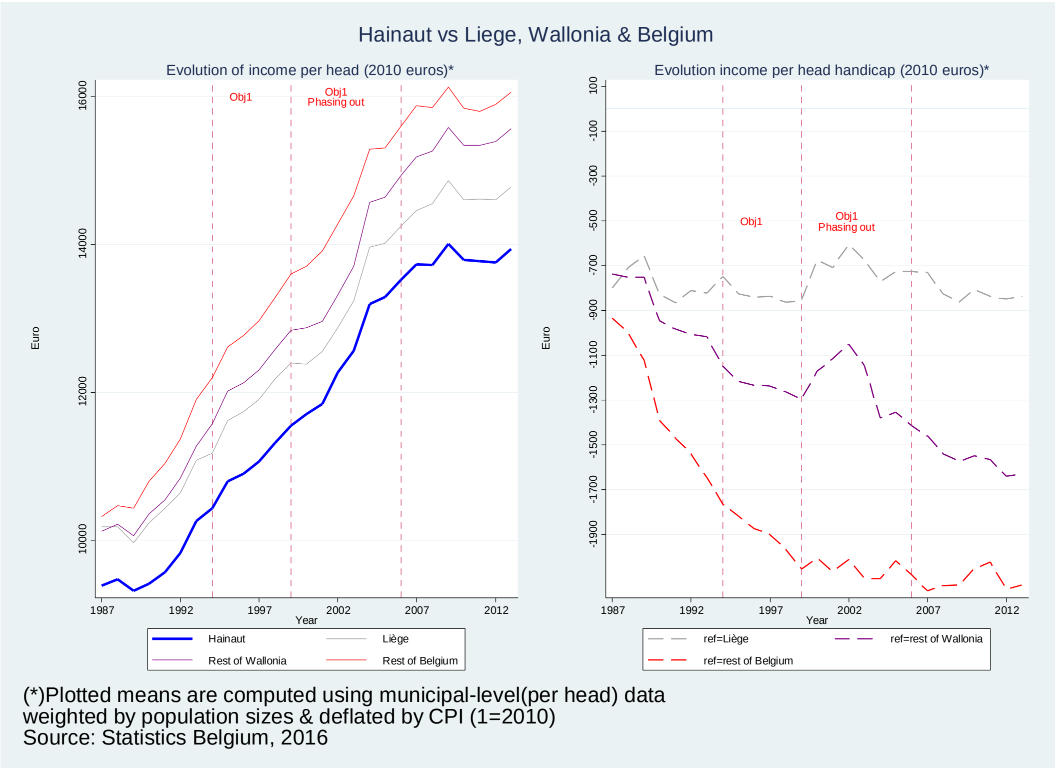
It is also worth underlying that the treatment in the form of financial support from the EU did not stopped completely in 1999. Beyond that point, the province benefited from the EU’s Objective "phasing out" programme (2000–2006), representing a total injection of an extra 2.22 billion EUROS (2000 nominal).

As to the control entities, we use three: the municipalities of the province of Liège, those located respectively in the rest of Wallonia and the rest of Belgium (Figure 4). A priori, we expected the province of Liège to be the best control territory for the implementation of the canonical $DD_{[1]}$ model. That province has many things in common with Hainaut. Although its economy was faring better in 1993 judging by the level of income (Figure 5), the province has also suffered from systematic deindustrialisation over the past decades. We had doubts about the relevance of $Parallel_{[1]}$ for the rest of Wallonia as a whole, and even more about the rest of Belgium that includes the (economically) dynamic Flemish provinces. Results largely confirm our intuition. They show that if Liège and Hainaut where approximately on parallel paths before 1994, that was not at all the case of Hainaut and the two larger control entities.

[18] Statistics Belgium estimates Hainaut's GDP (income perspective) to be of 9.497 billion in 1994 EUROS. Objective 1, over the period 1994–1999, represents a cumulative sum of 2,430 billion in 1994 EUROS injected in the province’ economy. Per year, this amounts to a push equal to 4.9 % of Hainaut’s GDP.

*Figure 4*: Hainaut vs Liège, rest of Wallonia or Belgium


*Figure 5*: Evolution of taxable income per head (2010 euros) in Hainaut municipalities (vs. Liège, rest of Wallonia, or rest of Belgium), 1997–2013



# 4 Data, descriptive statistics

The data used in this paper consist of municipal-level taxable net[19] income per head (all earnings[20] – professional and other deductible expenses), provided by Statistics Belgium. These are available for each of Belgium's 589 municipalities (Table 1) from 1977 to 2013; with many years before 1994 which is the year Objective 1 treatment started (Figure 5); 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 municipal level was used as weighting factor to capture trends that are representative at a more aggregated level; e.g.; the entirety of Hainaut (our treated entity). The advantage of this outcome variable is that it is reliable: time series on taxable income at municipal level are amongst the oldest of Belgium' 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 enhanced capacity to attract wealthier residents…).

Figure 5 (left panel) displays the evolution of (the average) income per head (in 2010 euros) for the treated vs the three sets of control municipalities used in this paper. It confirms the income-level difference of the municipalities of Hainaut (blue solid line) compare those forming the other Belgian provinces. Vertical bars help identify the calendar of implementation of Objective 1 with the initial 1994–1999 phase, followed by the "phasing out" from 2000 to 2006. The right panel of Figure 5 gives a first (purely descriptive) indication of what happened before, during and after Objective 1. The plotted dashed lines report the year-by-year evolution of the income-level difference (in 2010 euros) of Hainaut vs. each of the three control entities. These lines logically confirm the existence of an income-level difference before Objective 1 ranging from 700 to more than 1,900 euros. More to the point in the context of this paper, they suggest the income-level difference was *not constant* before Objective 1, certainly when comparing Hainaut to the rest of Wallonia or the rest of Belgium. Another interesting feature visible on Figure 5 (right panel) is the continuing rise of Hainaut's income-level difference (in constant euros) compare to these two entities, during and after Objective 1. The comparison with Liège rather suggests a stable income-level difference. But one should abstain to jump to conclusions at this early stage of the analysis. At the very least, we should question the relevance of $Parallel_{[1]}$ – except maybe when using Liège as control – to assess Objective 1's true impact on income.

[19] Of social security contribution.

[20] Earnings for employment, capital and properties and also replacement earnings.

# 5 Econometric results

We first report the results for the canonical/two periods (i.e. before and after) $DD_{[1]}$ model. Remember that Objective 1 started in 1994. We thus take $t^*$=1993 as the most immediate year before the treatment was implemented.[21] The after-treatment years are $t^*+s$=2000 (immediately after the end of Objective 1) and 2007 (immediately after the end of the phasing-out period).

Results (Table 2) are mixed. Compare to Liège, the 1993 difference was of 820 euros in 1993. In 2000, it was 177 euros smaller. And 91 euros smaller in 2007, just after end of the phasing out period. Compare to the rest of Wallonia, the difference was of 1,018 euros in 1993, but it had risen by respectively 131 and 422 euros in 2000 and 2007. And compare to the rest of Belgium, the initial difference was even larger (1,646 euros) and kept rising by 426 and 506 euros respectively at the horizon 2000 and 2007. And all these values are statistically significant at the 1% threshold.

These estimates have a descriptive value; in the sense that they accurately describe the evolution of Hainaut's income per head difference. It is much less certain, however, that they properly identify the impact of Objective 1. Remember that $DD_{[1]}$ is suitable to identify a treatment effect only if the $Parallel_{[1]}$ assumption holds. But we possess several pre-treatment points of observation in our data. And these can be used to compute $DD_{[1]}$ for a series of years *prior to* 1994. Results are plotted on Figure 6 (green solid lines). Using the municipalities forming the rest of Belgium or the rest of Wallonia as control, we clearly conclude that Hainaut was not growing at the same rate. $DD_{[1]}$ estimates are indeed significantly negative for all the years before 1993. Even in comparison with Liège, we get that $DD_{[1]}$ is slightly negative over the 1989 and 1993 period. This represents a clear violation of the $Parallel_{[1]}$ assumption.

We thus need to go beyond $Parallel_{[1]}$ in order to say something relevant about the true impact of Objective 1. Interestingly, as we possess many pre-treatment periods, we can assess the plausibility of $Parallel_{[2]}$ or $Parallel_{[3]}$ by estimating $DD_{[2]}$ or even $DD_{[3]}$ , again prior to Objective 1's inception. $Parallel_{[2]}$ consists of assuming that Hainaut and its controls where experiencing different growth rates before 1994; but that the latter difference was stable/time-invariant. We can test the plausibility of that assumption by estimating $DD_{[2]}$ for the pre-treatment years; and verifying that is it close to zero. Figure 6 (red dashed lines) suggests that was the case, at least between 1988 and 1993, for each of the three controls. The tentative conclusion is that $Parallel_{[2]}$ is a much more realistic description of the relative dynamics of Hainaut's income per head in the absence of Objective 1. And logically, the next steps of our econometric analysis will rest on $DD_{[2]}$/ $Parallel_{[2]}$.

The key results are on display on Figure 7. And the underlying numbers can be found in Table 3. On Figure 7, we confront the $DD_{[1]}^{t^*+s;t^*}$ and $DD_{[2]}^{t^*+s;t^*-1}$ estimates, where $t^*$=1993 and $t^*+s$=1994 to 2013 (from 1 to 20 years after the start of Objective 1). All of them stress the quite dramatic change of perspective induced by the shift from $DD_{[1]}$ to $DD_{[2]}$; mostly when

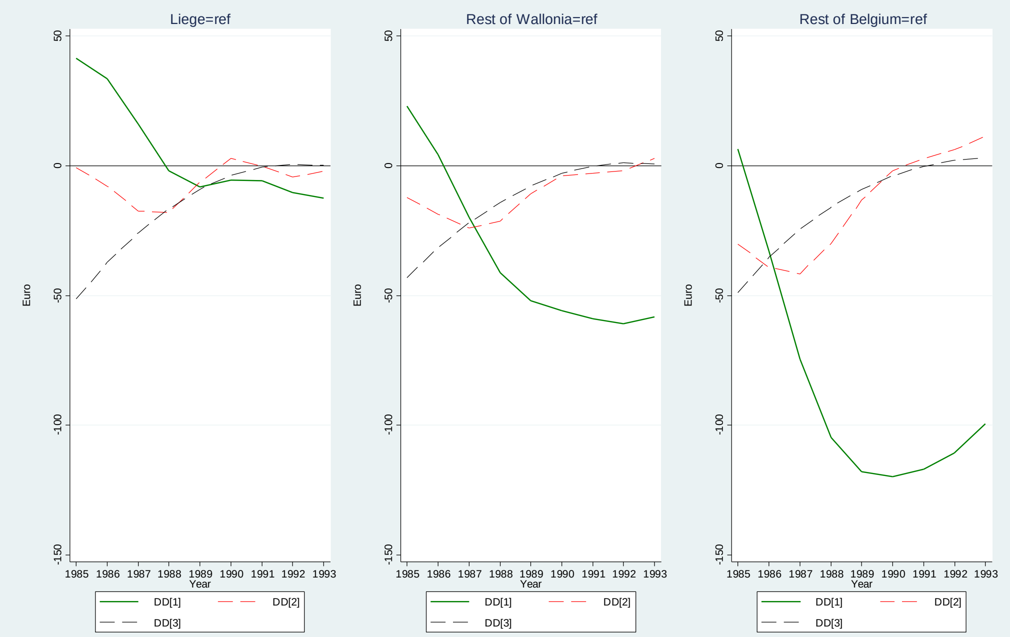
[21] We tend to believe that the usual debate about anticipation-of-treatment effects is irrelevant here. Strictly speaking Hainaut was not Objective-1 eligible, as its GDP per head was above the 75% threshold. It only got retained by the Commission after intense lobbying. Thus, until the last moment, there was a lot of uncertainty; meaning that economic agents could not reasonably anticipate the influx of money.

*Table 2*: Canonical $DD_{[1]}$ estimation of Objective 1's impact on taxable income per head (in 2010 euros), $t^*$=1993, $t^*+s$=2000/2007 using province of Liège, rest of Belgium or rest of Wallonia as control entity

| | **Liege 2000** | **Liege 2007** | **r.of Wall. 2000** | **r.of Wall. 2007** | **r.of Bel. 2000** | **r.of Bel. 2007** |
|---|---|---|---|---|---|---|
| $\gamma_{t^*+s}$ | 1341.66*** | 3378.74*** | 1650.10*** | 3912.85*** | 1944.82*** | 3976.90*** |
| | (1.729) | (1.913) | (1.701) | (1.754) | (0.847) | (0.900) |
| $\gamma^D$ | -820.70*** | -820.70*** | -1018.05*** | -1018.05*** | -1646.08*** | -1646.08*** |
| | (1.348) | (1.348) | (1.404) | (1.404) | (1.021) | (1.021) |
| $\gamma^D_{t^*+s}$ | 177.02*** | 91.41*** | -131.42*** | -442.70*** | -426.15*** | -506.75*** |
| | (2.262) | (2.461) | (2.240) | (2.340) | (1.686) | (1.791) |
| $\gamma$ | 11076.57*** | 11076.57*** | 11273.91*** | 11273.91*** | 11901.94*** | 11901.94*** |
| | (1.036) | (1.036) | (1.108) | (1.108) | (0.547) | (0.547) |
| $R^2$ | 0.31 | 0.64 | 0.28 | 0.60 | 0.30 | 0.55 |
| $DD_{[1]}$ | 177.02 | 91.41 | -131.42 | -442.70 | -426.15 | -506.75 |
| $p\_DD_{[1]}=0$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

Standard errors in parentheses
Estimates obtained using Statistics Belgium municipal-level(per head) taxable income data, weighted by population sizes & deflated by CPI (1=2010)
$^*$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Figure 6*: Assessing $Parallel_{[1]}$ vs $Parallel_{[2]}$ and $Parallel_{[3]}$ before the start of Objective 1 ($t$=1985 to 1993)

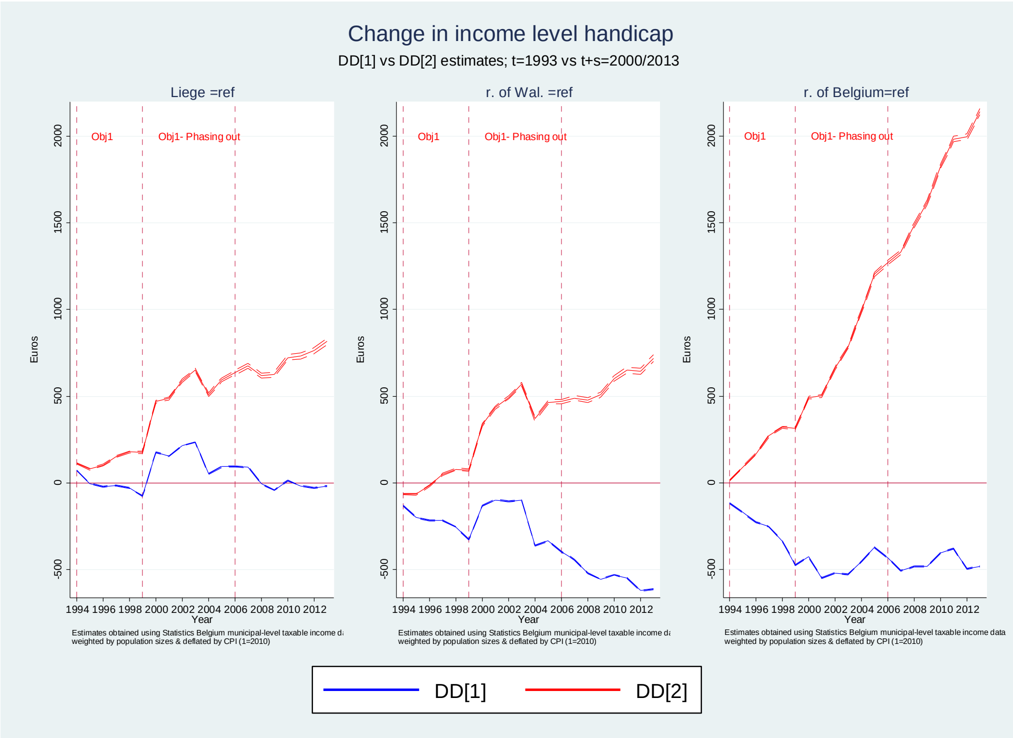


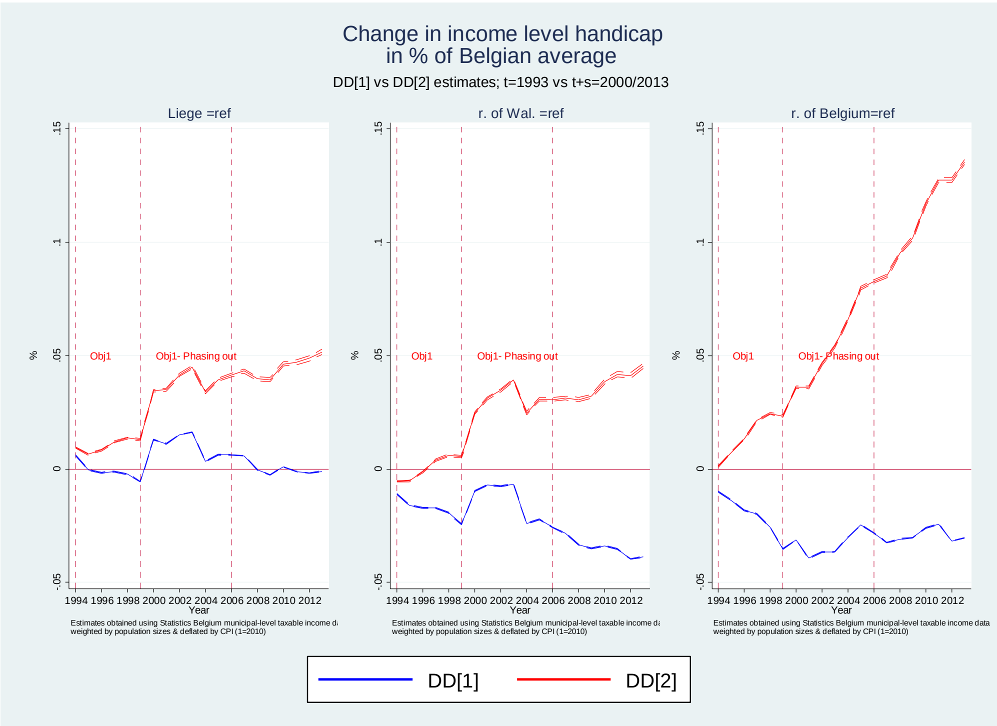

(*)Plotted means are computed using municipal-level(per head) data weighted by population sizes & deflated by CPI (1=2010)
Source: Statistics Belgium, 2016

*Table 3*: Estimates of Objective 1's impact on the level of taxable income per head (in 2010 euros), *s* periods ahead of $t^{*}$=1993; $DD_{[2]}^{t^{*}+s;t^{*}-1}/Parallel_{[2]}$ vs $DD_{[1]}^{t^{*}+s;t^{*}}/Parallel_{[1]}$, $t^{*}+s$=1994 to 2013

| | | In 2010 euros | | | | | | In 2010 euros relative to Belgium average income | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***t*+s*** | ***s*** | **Control=Liège** | | **Control=rest of Wallonia** | | **Control=rest of Belgium** | | **Control=Liège** | | **Control=rest of Wallonia** | | **Control=rest of Belgium** | |
| | | $DD_{[1]}$ | $DD_{[2]}$ | $DD_{[1]}$ | $DD_{[2]}$ | $DD_{[1]}$ | $DD_{[2]}$ | $DD_{[1]}$ | $DD_{[2]}$ | $DD_{[1]}$ | $DD_{[2]}$ | $DD_{[1]}$ | $DD_{[2]}$ |
| 1994 | 1 | 72.2 | 113.8 | -130.8 | -64.2 | -118.2 | 13.0 | 0.60% | 0.95% | -0.99% | 0.11% | -1.09% | -0.54% |
| 1995 | 2 | -3.8 | 79.6 | -198.7 | -65.5 | -171.6 | 90.7 | -0.03% | 0.64% | -1.39% | 0.73% | -1.60% | -0.53% |
| 1996 | 3 | -21.1 | 103.8 | -215.4 | -15.7 | -227.4 | 166.1 | -0.17% | 0.83% | -1.81% | 1.33% | -1.72% | -0.13% |
| 1997 | 4 | -14.5 | 152.1 | -217.3 | 49.0 | -253.2 | 271.4 | -0.11% | 1.20% | -1.99% | 2.13% | -1.71% | 0.38% |
| 1998 | 5 | -30.0 | 178.3 | -254.0 | 78.9 | -335.2 | 320.5 | -0.23% | 1.36% | -2.56% | 2.45% | -1.94% | 0.60% |
| 1999 | 6 | -75.0 | 174.9 | -325.9 | 73.6 | -473.2 | 313.7 | -0.56% | 1.30% | -3.52% | 2.34% | -2.43% | 0.55% |
| **2000[a]** | **7** | **177.0** | **468.6** | **-131.4** | **334.6** | **-426.1** | **491.9** | **1.30%** | **3.45%** | **-3.14%** | **3.62%** | **-0.97%** | **2.46%** |
| 2001 | 8 | 153.6 | 486.8 | -97.8 | 434.8 | -547.9 | 501.3 | 1.10% | 3.50% | -3.94% | 3.60% | -0.70% | 3.13% |
| 2002 | 9 | 215.1 | 590.0 | -106.3 | 492.9 | -519.7 | 660.7 | 1.51% | 4.15% | -3.66% | 4.65% | -0.75% | 3.47% |
| 2003 | 10 | 235.0 | 651.5 | -97.9 | 567.9 | -528.3 | 783.2 | 1.62% | 4.50% | -3.65% | 5.41% | -0.68% | 3.93% |
| 2004 | 11 | 51.2 | 509.4 | -361.9 | 370.4 | -452.5 | 990.2 | 0.34% | 3.39% | -3.01% | 6.59% | -2.41% | 2.46% |
| 2005 | 12 | 94.0 | 593.9 | -334.6 | 464.3 | -371.8 | 1202.0 | 0.62% | 3.94% | -2.47% | 7.98% | -2.22% | 3.08% |
| 2006 | 13 | 94.9 | 636.4 | -395.9 | 469.6 | -433.3 | 1271.6 | 0.62% | 4.15% | -2.82% | 8.29% | -2.58% | 3.06% |
| **2007[b]** | **14** | **91.4** | **674.6** | **-442.7** | **489.4** | **-506.8** | **1329.3** | **0.59%** | **4.32%** | **-3.24%** | **8.51%** | **-2.83%** | **3.13%** |
| 2008 | 15 | -4.8 | 620.0 | -520.9 | 477.8 | -482.0 | 1485.3 | -0.03% | 3.98% | -3.09% | 9.53% | -3.34% | 3.06% |
| 2009 | 16 | -41.2 | 625.2 | -556.1 | 509.1 | -481.1 | 1617.3 | -0.26% | 3.94% | -3.03% | 10.19% | -3.50% | 3.21% |
| 2010 | 17 | 14.8 | 722.9 | -529.6 | 602.3 | -405.0 | 1824.5 | 0.09% | 4.63% | -2.60% | 11.70% | -3.39% | 3.86% |
| 2011 | 18 | -17.2 | 732.6 | -547.6 | 650.8 | -378.0 | 1982.7 | -0.11% | 4.71% | -2.43% | 12.75% | -3.52% | 4.18% |
| 2012 | 19 | -28.4 | 763.0 | -620.9 | 644.1 | -497.0 | 1994.8 | -0.18% | 4.88% | -3.18% | 12.76% | -3.97% | 4.12% |
| 2013 | 20 | -17.1 | 816.0 | -612.5 | 719.1 | -480.8 | 2142.2 | -0.11% | 5.16% | -3.04% | 13.55% | -3.87% | 4.55% |

*Figure 7*: Estimates of Objective 1's impact on the level of taxable income per head (in 2010 euros), *s* periods ahead of $t^{*}$=1993; $DD_{[2]}^{t^{*}+s;t^{*}-1}/Parallel_{[2]}$ *vs* $DD_{[1]}^{t^{*}+s;t^{*}}/Parallel_{[1]}$, $t^{*}+s$=1994 to 2013



comparing Hainaut to the rest of Wallonia and the rest of Belgium. On the lower part of Figure 7, results are normalized by the average taxable income per head of the whole of Belgium. Qualitatively, the results are unaffected. In particular $DD_{[2]}$ estimates suggest that Objective 1 has had a *positive* impact on the growth-rate difference that Hainaut was suffering from before 1994. That positive effect is particularly visible beyond 1999, in comparison with Liège and the rest of Wallonia. In the absence of this correction, the rise of the income-level difference (captured by $DD_{[1]}$) would have been larger. Over the year 2000 horizon (Table 3), Hainaut experienced a rise of its income level difference compared to the rest of Belgium of 426.1 euros. What $DD_{[2]}^{t^{*}+s}$ = 491.9 euros means is that in the absence of a growth rate difference positive correction; that rise would have been of 426.1 + 491.9 euros.

## 6 Concluding remarks

The traditional difference-in-differences $DD_{[1]}$ model – and the parallel-paths $Parallel_{[1]}$ assumption on which it rests – seems to be particularly irrelevant in the case of Objective1-Hainaut; and perhaps also for other EU rust-belt regions that became eligible to Ojective1. Remember that Hainaut got selected by the EU expressly because "*it was suffering from a substantial deterioration of its economic and social situation*". This statement hints at a development path that was not parallel to that of other EU or Belgian regions. We show in this paper that this was indeed the case before the introduction of Objective 1. And this is something that disqualifies $DD_{[1]}$ to be a proper treatment-effect identification strategy. From a methodological point of view, we also show that if data contain more than one point of observation before treatment, it is very easy to drop $Parallel_{[1]}$ – i.e. the parallel-paths assumption on which $DD_{[1]}$ is based – and implement $DD_{[2]}/Parallel_{[2]}$ ; or even models allowing for higher degree of parallelism. In a nutshell, $Parallel_{[2]}$ *i)* allows for (time-invariant) growth-rate differences in the absence of treatment and *ii)* ascribes to the treatment (the outcome effect of) any change of the *ex ante* growth difference. The paper also shows that the estimation of treatment outcome under $Parallel_{[2]}$, or higher degree of parallelism, can be achieved via OLS applied to a generalized version the canonical linear *DD* equation. Last, and not least, the correction for trend divergences between treated and control only rests on pre-treatment observations; and the estimation of the treatment effect is based on a simple extrapolation of pre-treatment trends: an improvement in comparision with can be achieved by resorting to polynomial time-trend corrected *DD*.

This being said, as our Hainaut-Objective 1 results clearly show, $DD_{[2]}/Parallel_{[2]}$ [or higher order] estimates are much more likely to lead to the conclusion that the treatment has been effective: all it takes is a small reduction of the pre-treatment growth rate difference to conclude that treatment has generated economic gains. And in the case of Hainaut, we show that this has happened against a background of a steadily rising income level difference; i.e. something that most people would probably interpret as an absence of convergence.

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