Steunpunt Economie en Ondernemen
Vlamingenstraat 83 bus 3550
3000 Leuven, België
www.steunpunt-economie-ondernemen.be

Beleidsrapport STORE-23-018

Impact van clusterlidmaatschap op bedrijfsprestaties (TFP)

Pierluigi Angelino [c], Dirk Czarnitzki [c] en Astrid Volckaert [a,b,c, 1]

[a] *Steunpunt Economie en Ondernemen*

[b] *Vlaams Instituut voor Economie en Samenleving (VIVES)*

[c] *Faculteit Economie en Bedrijfswetenschappen, KU Leuven*

[1]*astrid.volckaert@kuleuven.be*

22 december 2023

Samenvatting

In maart 2016 keurde de Vlaamse regering het besluit goed voor de oprichting van innovatieclusters in Vlaanderen. De eerste Speerpunt clusters (SPC) werden in 2017 opgericht. Deze clusterorganisaties brengen bedrijven en kennisinstellingen samen om aan innovatief onderzoek te doen.

Het doel van dit rapport is om na te gaan wat de economisch impact is op bedrijven die lid worden van een Speerpunt cluster. Meer bepaald wordt gekeken of bedrijven die lid worden van een cluster na hun lidmaatschap een hogere Totale Factor Productiviteit (TFP) hebben dan wat we zouden verwachten indien deze bedrijven geen lid waren geworden. Onze resultaten wijzen uit dat clusterlidmaatschap leidt tot een gemiddelde stijging in productiviteit van 2 tot 3%.

In hoofdstuk 1 wordt eerst een **literatuuroverzicht** gegeven van bestaande clusterstudies, waarbij een onderscheid gemaakt wordt tussen de analyse van geografische clusters versus clusterorganisaties. Binnen de literatuur rond clusterorganisaties wordt er een verdere verdeling gemaakt tussen beleid dat zich richt tot achtergesteld sectoren en beleid dat focust op innovatieve sectoren. Het Vlaams clusterbeleid behoort tot deze laatste categorie. In dit hoofdstuk wordt dit clusterbeleid ook in meer detail besproken.

In hoofdstuk 2 worden de gebruikte **data** verder toegelicht. Deze data omvatten enerzijds de **clusterledenlijsten**, die jaarlijks door STORE worden opgesteld (waarbij naast de betalende leden ook de 'verbonden ondernemingen' in kaart worden gebracht). Anderzijds wordt gebruik gemaakt van de Belfirst databank om de **economische gegevens** van de bedrijven te analyseren en een schatting te maken van de Totale Factor Productiviteit.

In hoofdstuk 3 wordt verder ingegaan op de gehanteerde **methodologie**. Waar een maatstaf als arbeidsproductiviteit enkel rekening houdt met arbeid als input, houdt de **Totale Factor Productiviteit** (TFP) rekening met arbeid én kapitaal als input. De econometrische methode om deze TFP voor elk bedrijf te schatten, bouwt voort op het recente werk van Gandi, Navarro, Rivers (GNR, 2020) en wordt in dit hoofdstuk en in de appendix in meer detail beschreven.

Om de impact van clusterlidmaatschap te kwantificeren wordt gebruik gemaakt van een **Difference-in-differences regressie model (DiD)**. Hierbij kijken we naar het verschil in TFP tussen bedrijven dit wel en geen lid zijn van de cluster en het verschil in TFP tussen bedrijven voor en na de start van het clusterinitiatief. Door deze beide verschillen te combineren, kunnen we het

verschil in TFP schatten van clusterleden na de invoering van het clusterinitiatief t.o.v. de TFP van deze bedrijven indien ze na de start van het clusterinitiatief geen lid waren geworden. Deze schatting geeft dus de impact weer die gelinkt kan worden aan de 'treatment', in dit geval het clusterlidmaatschap.

In een laatste deel van hoofdstuk 3 wordt verder ingezoomd op een aantal bijkomende methodologiën, zoals een matching procedure en een gespreide DiD ("staggered DiD").

In hoofdstuk 4 worden de **resultaten** weergegeven. Deze kunnen als volgt worden samengevat:

- Er is een **zelfselectie effect** waarbij de TFP van de clusterleden reeds hoger ligt dan die van de niet-clusterleden in de periode vóór het clusterlidmaatschap (zie figuur 4). Dit wijst erop dat de clusters erin slagen om de koplopers in hun sector aan te trekken. Tegelijkertijd wijst het ook op het feit dat het niet voldoende is om eenvoudigweg clusterleden met niet-clusterleden te vergelijken, aangezien beide groepen zich reeds onderscheiden vóór de start van het initiatief, waardoor de DiD methodologie noodzakelijk wordt.
- De analyses geven aan dat er een **significant positieve impact** is op TFP als gevolg van clusterlidmaatschap. Deze impact ligt tussen de 1 en 4,4 %, afhankelijk van de gebruikte specificatie (zie tabel 3 en 4).
- Deze significant positieve impact vinden we ook terug wanneer we een aantal controle testen uitvoeren. Wanneer we bijvoorbeeld een **matching procedure** uitvoeren waarbij de niet-clusterleden op een aantal eigenschappen nauwer aansluiten bij de clusterleden vinden we een impact tussen 2,1 en 3,4% (zie tabel 5). Wanneer we bij de TFP schattingen rekening houden met de **cluster classificatie** i.p.v. de sector classificatie, vinden we een impact van 1,7 tot 2,3% (zie appendix 4, tabel 11).
- Ook wanneer we rekening houden met het feit dat clusters op **verschillende momenten** zijn opgestart en bedrijven in verschillende jaren kunnen toetreden, zien we (door het toepassen van de "staggered DiD" methode) een positieve impact na toetreden, ongeacht in welk jaar deze toetreding plaatsvond (zie figuur 5). Tot slot zien we deze positieve impact **zowel bij kleine als bij grote ondernemingen** (zie figuur 6 en 7).

In hoofdstuk 5 worden de resultaten besproken en wijzen we in de richting van mogelijk **verder onderzoek**, zoals het in rekening brengen van projectparticipatie van de clusterleden.

Dit rapport maakt deel uit van academisch onderzoek en werd daarom het in het Engels opgesteld.

Do cluster initiatives boost productivity? The impact of cluster membership on firm level productivity.

Pierluigi Angelino[a]

Dirk Czarnitzki[ab]

Astrid Volckaert[abc]

[a] Faculty of Economics and Business, KU Leuven, Leuven, Belgium

[b] ECOOM - Centre for Research and Development Monitoring

[c] VIVES - Research Centre for Regional Economics (KU Leuven)

Abstract

The Flemish government launched its Spearhead Cluster (SHC) policy in 2017. The aim is to boost strategic sectors by setting up cluster initiatives which coordinate collaborative R&D initiatives. In this paper we analyze whether becoming a member of such a cluster initiative has an impact on the Total Factor Productivity (TFP) of the firm. We exploit firm-level data between 2013 and 2020 to estimate TFP and apply a Difference-in-Differences approach to assess the treatment effect of the treated firms. We find that becoming a member of a cluster has an average positive impact on firm level TFP of between 1 to 4,4 percent, depending on the econometric specification. These results are the first to provide an insight into the impact of the Flemish SHC policy on productivity.

Keywords: cluster associations, cluster policy, innovation policy, programme evaluation, total factor productivity, difference-in-difference, nonparametric matching

JEL classification numbers: D24, L25, L52, L53, O25, O38

1. Introduction

Clusters play an important role in any industrialized economy. Since the influential work by Porter (1990,1998) a vast literature on the role of clusters has emerged. Porter identifies clusters as "a geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities" (2000) which makes them closely related to the 'specialized industrial locations' already identified by Marshall (1890/1920). According to Marshall and Porter, the spatial concentration of a particular sector (such as the automobile industry in Detroit, or Silicon Valley) creates a competitive advantage thanks to the increased presence of upstream and downstream industry, returns to scale, increased competition, and also opportunities for cooperation and knowledge spillovers, amongst others.

The focus on clusters was picked up by policy makers in many regions of the world. For example, the European Commission encouraged Member States to invest in smart specialization strategies, whereby each country specializes in those areas in which they have a comparative advantage (EC, 2010). Many countries have set up so-called 'cluster initiatives' where organizations actively bring together partners that would otherwise not be connected, with the aim to exploit the advantages of geographical clusters without the need to be spatially concentrated.

Contrary to the vast literature on clusters occurring naturally, the literature on the evaluation of cluster policies (organized clusters) is more scarce (Ketels, 2013). Schmiedeberg (2010) and Uyarra and Ramlogan (2016) provide an in depth overview of cluster policy evaluation methods. More recent overviews of the literature on cluster policies can be found in Cantner et al. (2019), Smith et al. (2020), Grashof (2021) and Wilson (2022). We refer to the paper of Rothgang et al. (2021) for a review of the knowledge gap that still exists when it comes to cluster evaluation.

A number of studies look at the impact of clusters from a qualitative perspective. Anić et al. (2019, 2022) evaluate the Croatian Competitiveness Clusters based on survey data. Kiese (2019) focusses on the German regional level and argues that the real impacts are rather qualitative. N'Ghauran and Autant-Bernard (2021) concentrate on cluster policy resulting in increased collaboration and network additionality in France. Calignano et al. (2018) analyses the knowledge exchange in the aerospace district in the peripheral region of Apulia in Southern Italy. Some papers also point out the need to consider both quantitative and qualitative aspects and take account of the local context and innovative ecosystem already in place. Examples include: Aranguren et al. (2014) evaluating the Basque policy on cluster associations; Vlaisavljevic et al. (2020), analyzing the biotech industry in Spain and Lehmann and Menter (2018) assessing the Leading-edge Clusters Competition in Germany.

The quantitative impact of the cluster policy is most often measured on the performance of the participating firms. This performance is measured in different ways such as the technological maturity of the firm (see Mackiewicz et al. (2022) analyzing the National Smart Specializations scheme in Poland), or the exports or sales of the firm. Aboal et al. (2020) finds a strong positive impact on exports but a weak positive impact on sales in Uruguay. Pavelkova et al. (2021) also looks at firms in institutional and natural clusters and does not find a significant impact on the firm financial performance in the plastics and textiles industry in the Czech Republic. In a follow-up study on 7 different Czech sectors Zizka and Stichhauerova (2022) find mixed results amongst the different industries. Other studies consider the impact on innovation and R&D development. Falck et al. (2010) found a positive impact in the high tech industry in Germany and Engel et al., (2013) in the German biotech industry. Looking at the broader perspective, Audretsch et al. (2019) looks at the spillover effects across industries in France and finds an 'indirect negative effect on firms that have not primarily been related to the targeted industries'.

Some cluster policies are linked to regional policy and set up to boost sectors in decline or traditional sectors in need of transformation. More recent cluster policies aim to promote innovation in a spatially more neutral way (OECD, 2007). Quantitative studies linked to this first class of clusters include Martin et al. (2011) who found a negative impact of the cluster policy on the firm level productivity in the local productive systems in France. Stojčić et al. (2019) found a positive impact of cluster associations in the wood-processing and furniture manufacturing industries in Croatia and Slovenia. Garone et al. (2015) found a positive impact in Brazil of the Cluster Development policy, aimed to stimulate industrial agglomerations. Our study is related to the second class of clusters that focus on membership in an innovative cluster initiative. This is also the case for Denmark's Innovation Network (Daly, 2018); the Industrial Cluster Project in Japan (Nishimura and Okamuro, 2011); the Innovation Superclusters Initiative in Canada

(Doloreux and Frigon, 2022), the Leading-edge Cluster Competition in Germany (Engel and Menter, 2019) and the competitiveness cluster policy in France (Abdesslem and Chiappini, 2019).

The flagship of the Flemish cluster policy is the launch of innovative 'Spearhead Clusters' (SHC), which have the aim to boost innovation and thereby increase the competitiveness of the cluster members and the wider sector in which they are active. These cluster initiatives bring together industry, knowledge institutions and government in a triple helix structure around a particular focus area (a "strategic domain"). Each cluster is active in an internationally oriented domain, where Flanders has a comparative advantage. The cluster policy does not intend to support sectors or regions in decline but is targeted to further enhance the 'winning' industries, the 'spearheads' of the economy.

Since 2017 a total of 7 Spearhead Clusters have been set up. Three of them have an industrial focus: in either chemistry, food or materials. In addition, there is a cluster on logistics, energy and the blue economy. The most recent cluster on innovative healthcare was launched in 2021 and falls outside the scope of this research. Further information on each of the individual clusters can be found in Table 1 and in Appendix 1. The 'Steunpunt Economie en Ondernemen (STORE)' - i.e. the center of expertise for economy and development, financed by the Flemish government - was mandated to monitor these clusters on a yearly basis.[1] STORE also prepared a cluster report for each of the clusters (STORE, 2019).

Table 1: Overview of the different clusters including their strategic domain, starting year and website

Name	Strategic Domain	Starting year	Website
Catalisti	Chemistry and plastics	2017	www.catalisti.be
SIM	Materials	2017	www.sim-flanders.be
VIL	Logistics	2017	www.vil.be
Flux50	Energy	2017	www.flux50.com
Flanders' Food	Food	2018	www.flandersfood.com
De Blauwe Cluster	Blue economy	2018	www.blauwecluster.be
MEDVIA	Healthcare	2021	www.medvia.be

[1] Since 2021, STORE is a part of ECOOM, the Centre for Research & Development Monitoring (www.ecoom.be)

Despite having a particular sectoral focus area, the membership in these clusters is cross-sectoral. It also includes, amongst others, firms that are active as suppliers or downstream users, IT-providers, R&D service providers. Spearhead Clusters attract members from each of the Flemish provinces, and thereby allow for knowledge spillovers that are less likely to occur as a result of geographical clustering. The membership in each cluster is further characterized by a large heterogeneity in size and age, including the large multi-national firms with a long history as well as small start-up firms and everything in between. This unique mix creates new opportunities for innovation that might otherwise not arise.

The initiative to launch a new Spearhead Cluster lies with the business, that first needs to present an ambitious competitiveness plan. Upon approval by the Flemish government, a cluster pact is signed detailing the commitments that both the industry and the government make. Cluster support is granted for a maximum period of 10 years.

The government commitment (in the form of funding) is provided to these clusters in two ways. On the one hand, a yearly budget is allocated to the cluster organization to cover part of their operational costs, which are financed also through yearly membership fees. On the other hand, earmarked subsidies are available for cluster multi-partner R&D projects. The selected projects are identified bottom-up by the cluster members.

The role of the cluster organizations is threefold (VLAIO, 2022): (i) they act as a 'central actor' for the Flemish innovation system in the strategic domain in which they are active; (ii) they set up cooperation initiatives amongst the cluster members and (iii) they manage the cluster specific financing.

Once the cluster is established, firms can decide on a yearly and voluntary basis to join or leave one or multiple clusters. Membership is open to all firms that pay the membership fee. These fees differ for each cluster and may also depend on the size and sector of the participating member. Overall, the fees are low (below € 1000) as they are only needed to cover half of the operational expenses of the cluster association. Earlier research (Lecocq, 2019) has shown that there is a self-selection effect whereby the more productive firms in a sector are more likely to join the cluster.

In this paper we apply a Difference-in-Differences (DiD) regression method in order to assess whether cluster membership has an impact on firm level productivity. This study adds to the existing literature in three important ways. First it is, to the best of our knowledge, the first to analyze the firm level impact of the Flemish cluster policy on productivity. We also apply an innovative method to define cluster membership. In addition, we use detailed firm level data to calculate TFP through an adaptation of the non-parametric production function estimation approach proposed by Gandhi et al. (2020).

The remainder of this paper is organized as follows: section 2 presents the data, both in terms of the cluster membership, firm characteristics and financials. Section 3 explains in more detail the methodology used to estimate the TFP and carry out the DiD methodology and matching. Section 4 presents the results and section 5 sums up the main conclusions.

2 Data

2.1 Cluster membership data

STORE prepares the yearly membership lists for each cluster at the level of the VAT-number. Details on the methodology applied can be found in Goutsmet et al. (2018) and Gorrens et al. (2022). As a starting point, the list of VAT-numbers of firms that pay the annual membership fee are collected directly from the cluster organizations. This list is then checked manually for inconsistencies[2] and corrected where necessary. In a number of cases, companies have multiple VAT-numbers: for example, the headquarters, financial center and production facility each have a separate VAT-number. Only relying on the VAT-number of the firm that pays the invoice would lead to a misrepresentation of the true cluster involvement. To alleviate this concern, STORE identifies all 'related firms' for each of the paying members. These related firms are defined as those firms (VAT-numbers) that have the same Global Ultimate Owner (GUO) as the paying member. Each cluster organization then selects from this list those firms that are actually relevant for the

[2] Inconsistencies can include: typo's in the VAT numbers, duplicates, changes in VAT numbers due to M&A activities, etc.

cluster at hand. The unique combination of manual verification and direct cluster input ensures that the final list of VAT-numbers covers as closely as possible the actual participation in the cluster.

We only retain the private firms for our analysis. This means that we do not consider the knowledge institutions and other non-private firms or organizations, even though they play an important role in the cluster.

2.2 Firm level data

We use the firm level database 'Bel-first' from Bureau van Dijk to collect firm characteristics and financial variables for the period 2013-2020.[3]

We restrict the number of firms to those that are registered in Flanders (including Brussels).[4] We drop firms whose maximum number of employees in all years is less than 5. As we calculate TFP based on a gross output production function, our dataset is also limited to those firms reporting turnover in their annual accounts (large firms have the obligation to report turnover, whereas smaller firms do not). We further restrict the sample to those NACE sectors that belong to the strategic domain of one of the six clusters. An overview of the corresponding 2- and 3-digit NACE codes can be found in Appendix 3, Table 6 and Table 7. Finally, we drop the firms that are only a member during 1 year and leave afterwards as we consider their interest in and impact from the cluster to be limited.

The constructed sample finally in hand covers 10965 unique firms, of which 623 unique firms are or have been members of a SHC (for at least 2 years). The dataset consists of 64718 observations in total across all years. Table 2 presents the summary statistics. For the pre- and post-treatment period, we distinguish between two groups: the firms that will never be a cluster member and the firms that in one point of time will join a cluster. Figure 1 provides an overview of the never treated and ever treated firms by year. The total number of firms in the database is reducing over time as a consequence of dropping those firms that do not report turnover (over time, even though the overall number of firms in the economy is increasing, fewer firms are reporting turnover).

---

[3] As explained in the methodology, nominal variables are deflated by the Producers Price Index (PPI) at 2-digit NACE code level taken from the National Bank of Belgium (NBB, 2022), which provides yearly deflators for 13 different sectors.

[4] A number of firms active in the Flemish community have their registered office in Brussels.

Steunpunt Economie en Ondernemen
Vlamingenstraat 83 bus 3550
3000 Leuven, België
www.steunpunt-economie-ondernemen.be

Table 2: Summary statistics

	Pre-treated period (2013-2016)									
	Never treated *N= 42352*					Ever treated *N= 2897*				
	Mean	St. Dev.	p25	p50	p75	Mean	St. Dev.	p25	p50	p75
Turnover (Mln. €)	35	163	3	10	22	187	1034	14	36	108
Employment	79	497	9	23	51	290	828	37	95	254
Tangible fixed assets (Mln. €)	5	41	0	1	2	28	115	1	4	14
Cost of input materials (Mln. €)	30	151	2	7	18	165	1023	9	26	87
Age	28	18	15	26	37	36	23	20	30	46
Assets per emp. (1000 €)	910	8719	107	212	460	1103	5417	148	290	637
Cashflow per emp. (1000 €)	49	1131	5	14	35	73	484	8	21	49

	Post-treated period (2017-2020)									
	Non-treated *N= 21528*					Treated *N= 1319*				
	Mean	St. Dev.	p25	p50	p75	Mean	St. Dev.	p25	p50	p75
Turnover (Mln. €)	47	192	5	14	31	270	1648	15	43	128
Employment	99	578	12	30	65	335	753	42	111	319
Tangible fixed assets (Mln. €)	8	64	0	1	3	40	172	1	5	18
Cost of input materials (Mln. €)	40	178	3	10	26	246	1672	11	31	102
Age	31	19	18	29	41	39	24	23	33	50
Assets per emp. (1000 €)	1089	8204	127	255	563	1267	6335	147	284	617
Cashflow per emp. (1000 €)	52	1188	5	17	42	84	461	6	21	52

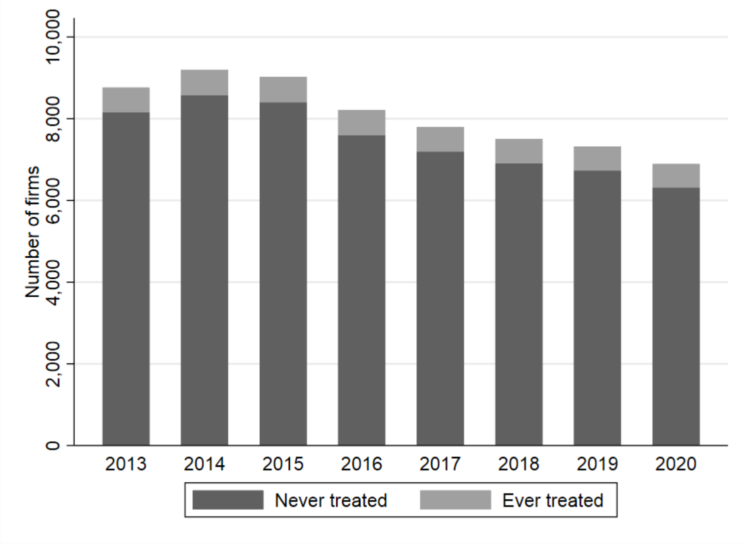

Figure 1: The number of treated and non-treated firms in the final database

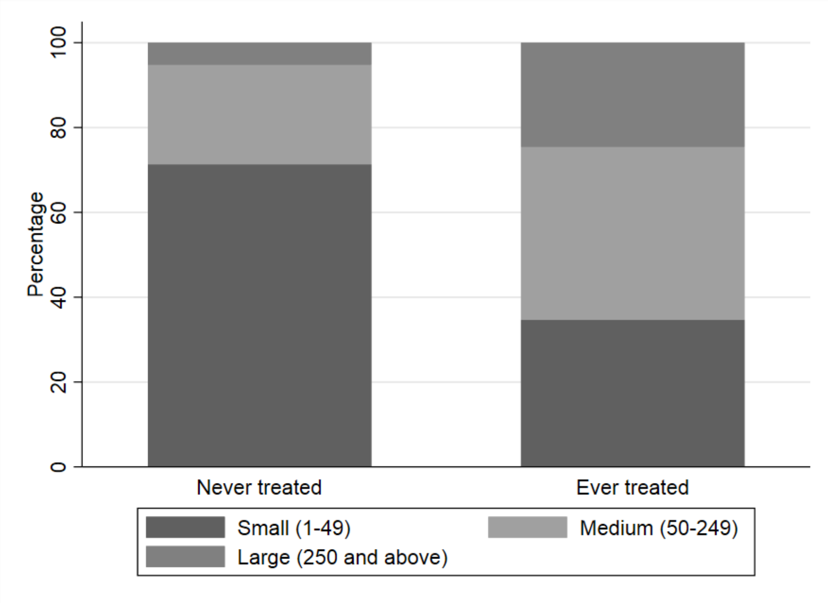

Figure 2: Firm size distribution between ever treated and never treated

As can be seen from Table 2, the firm size of cluster members and non-cluster members is different, with large firms being overrepresented in the cluster. To provide more insight is these differences, Figure 2 represents the share of firms according to their firm size for both groups. Small firms (less than 50 employees) make out 70 percent of the never treated firms but less than 35 percent of the cluster members. At the same time, the share of medium sized firms (50-249 employees) is nearly twice as large for the ever treated firms (40 percent compared to only 23 percent for the never treated firms). Large firms (as of

250 employees) only represent 5 percent of firms in the never treated sample but represent 25 percent of the firms in the ever treated sample.

3 Methodology

3.1 TFP estimation

The main outcome of interest is the total factor productivity of firms, which we estimate by adopting a control function approach and, in particular, the estimation procedure from Gandhi, Navarro and Rivers (2020) – GNR as of now. This methodology exploits an equation for the intermediate inputs elasticity to identify gross output production functions. Among its advantages, it does not impose restrictive functional assumptions as occurs, for example, in Ackerberg, Caves and Frazer (2015) – ACF henceforth – whose approach postulates a production function that is Leontief in the input materials (i.e. intermediate inputs are proportional to the output) in order to estimate a value added production function (where intermediate input does not enter the production function to be estimated). The GNR estimation procedure allows for gross output production functions to be identified. Moreover, GNR has the additional advantage of not assuming a particular parametric structure for the production function, which allows fitting the heterogeneous variety of real data with a reduced degree of measurement error compared to imposing a Cobb-Douglas parametric form as in ACF, for instance.

The GNR identification framework rests on typical assumptions. The starting foundation is perfect competition with common prices in the intermediate-input and output markets, while producers within the same industry make identical, homogenous goods.

The relationship between output and inputs is represented in real terms as:

$$y_{it} = f(l_{it}, k_{it}, m_{it}) + \nu_{it} \tag{3.1}$$

where f is a function that is differentiable across all input combinations and is strictly concave with respect to intermediate inputs m_{it}; $y_{it} \equiv \ln(Turn_{it}/PPI_{nt})$ is log revenues deflated by sectoral producers price index PPI_{nt}; $l_{it} \equiv \ln(Emp)$ features labor as log number of employees; $k_{it} \equiv \ln(TFA_{it}/PPI_{nt})$ is log capital proxied by deflated tangible fixed assets; $m_{it} \equiv \ln\,(Int.inputs_{it}/PPI_{nt})$ indicates log deflated intermediate inputs; ν_{it} is the Hicks neutral productivity that can be decomposed as a sum of a persistent shock $lnTFP_{it}$ known to the firm before making its decisions in period t and a transitory shock ε_{it} unknown at t and realized only after the decisions in period t are made, i.e. $\nu_{it} = lnTFP_{it} + \varepsilon_{it}$.

The second set of assumptions regards the firm information and decision timing. Capital and labor are predetermined and known in period t, whereas m_{it} is the flexible input. The information set $\mathcal{I}_t$ available to the firm at t includes also past and current observed production shocks $lnTFP_i$, while the ex-post shock ε_{it} is unpredictable and independent, i.e. $\varepsilon_{it} \notin \mathcal{I}_t$ and $E[\varepsilon_{it}|\mathcal{I}_t] = E[\varepsilon_{it}] = 0$.

The persistent productivity $lnTFP_{it}$ evolves according to a first-order Markov process:

$$lnTFP_{it} = g(lnTFP_{it-1}) + \xi_{it} \tag{3.2}$$

Consistently with the control function literature, scalar unobservability and strict monotonicity are postulated to obviate the transmission bias in production function estimation. Accordingly, firms are price takers and maximize expected discounted profits with respect to the flexible input m_{it}. The resulting optimal demand for intermediate inputs is an unknown function of productivity and other producer-specific observable factors:

$$m_{it} = d_t(lnTFP_{it}, l_{it}, k_{it}), \tag{3.3}$$

where the input demand function is strictly increasing in $lnTFP_{it}$, and productivity is the only econometric unobservable in the equation.

Under those key assumptions, the intermediate inputs demand can be inverted to recover productivity as a function of data and parameters, i.e. $lnTFP_{it} = d_t^{-1}(m_{it}, l_{it}, k_{it})$.

In the absence of time-series variation in flexible input prices, the ACF estimation structure is not sufficient to identify gross output production functions. In order to solve those shortcomings, GNR notes that the production function implicitly defines the intermediate input demand through the first-order condition of the firm's profit-maximization problem, and exploits that relationship as identification strategy.

In practical terms, GNR proposes a nonparametric two-step sieve M estimator of the production function. The first step concerns the estimation of an input-revenue share equation using nonlinear least squares to get the flexible input elasticity $\frac{\partial}{\partial m_{it}} f(l_{it}, k_{it}, m_{it})$. The integral of the resulting partial derivative yields the production function plus an integration constant $\mathcal{C}(l_{it}, k_{it})$. In the second step, $\mathcal{C}$ is identified through GMM estimation, which ultimately allows to retrieve $f(l_{it}, k_{it}, m_{it})$ regardless of the structure of f.

In Appendix O6-1 of GNR, moreover, the model is extended to account for a firm-specific permanent component of unobserved productivity, which corresponds to have fixed effects included in the production function, that is:

$$y_{it} = f(l_{it}, k_{it}, m_{it}) + lnTFPfe_{it} + a_i + \varepsilon_{it} \quad \Leftrightarrow \quad lnTFP_{it} = a_i + lnTFPfe_{it} \tag{3.4}$$

Given the empirical relevance of firm unobserved heterogeneity in TFP, neglecting this aspect may produce inconsistent estimates (Eberhardt and Helmers, 2010). For this reason, we compute productivity in both manners, i.e. excluding and including fixed effects in the production function.

Allowing for an additive term in the production function, however, may not be enough to rule out bias, especially if unobserved heterogeneity affects in a more complex way not only productivity but also the structure f and other elements relevant for firm decision-making. Assuming that businesses sharing similar characteristics, such as the industry in which they operate, have a comparable production function, we partition all firms in groups according to their NACE codes and estimate TFP for each group.

In doing so, a problematic trade-off between disaggregation and information retention appears. In fact, the more refined the grouping, the nearer to reality is the estimated production function for a specific firm category expected to be. However, it also means the more numerous are the categories and, more importantly, the smaller is the sample size of each category, which, in turn, renders the convergence of the GMM estimation procedure in the second step more likely to fail and produce no TFP estimates for that specific category, hence losing any related information.

For this reason, we consider two alternative classifications based on economic sectors. At first, we aggregate all relevant 2-digit NACE sectors in 12 categories (see Appendix 3, Table 6). As a robustness check, we apply a more restrictive classification which we refer to as ‘cluster grouping’, whereby firms are assigned to 6 categories corresponding to the sectoral strategic domain of each cluster at the 3-digit NACE level (see Appendix 3, Table 7). Regardless of the classification, we exclude from the TFP estimation those NACE industries featuring no treated firms.

The GNR framework, moreover, misses to consider endogenous drivers of productivity. It is undisputed that the SHC program may dynamically affect firm strategic behavior and outcomes. The Flemish policy is set-up in a way that cluster participation is confirmed or discarded on a yearly basis. If productivity is a state variable in the firm decision to enter, stay or exit the cluster, then structural endogeneity is even more evident. Excluding the cluster membership from TFP estimation would then inevitably yield biased causal treatment effects (De Loecker and Syverson, 2021). We therefore adapt the GNR procedure and, similarly to De Loecker (2013), we add the endogenous lagged treatment in the Markovian process of productivity:

$$lnTFP_{it} = g(lnTFP_{it-1}, treatSHC_{it-1}) + \xi_{it} \tag{3.5}$$

The detailed description of the cluster policy-augmented GNR estimator can be found in Appendix 2.

In addition, we assume that the production function structure may vary slowly but substantially over the timeframe of the panel data in hand, which span 8 years, due to complex systemic phenomena affecting firms and industries heterogeneously that are not captured by the model (for example, automation processes). In order to control for such potential sources of inconsistency, we estimate the average annual productivity considering rolling windows of 4 years, i.e. we postulate a production function structure staying fixed for a maximum of 4 years.

3.2 Difference in differences regressions

In order to estimate whether being a cluster member yields productivity gains in the short-medium term, we exploit the panel structure of our data and use a Difference-in-Differences (DiD) regression estimation framework. We refer to Angrist & Pischke for a general overview (2008).

In terms of timing, it is reasonable to assume that cluster participation exerts its benefits on firm productivity not immediately but after a learning period where the firm is supposed to have effectively incorporated the knowledge newly acquired from cluster activities into its processes. The cluster treatment variable therefore enters the model with a one-period lag.

We consider the following model:

$$lnTFP_{it} = \beta_1 treatSPC_{it-1} + \gamma\, X_{it} + \lambda_i + \tau_{st} \tag{3.6}$$

where β_1 yields the average effect of being part of an SHC versus outsider firms who were never member, X_{it} is a set of controls, λ_i refers to firm fixed effects, τ_{st} are time fixed effects. In this regard, we alternatively include basic year indicators or 2-digit NACE code industry-year fixed effects to allow for sector heterogeneity in yearly shocks. Among the control variables, we selected firm characteristics such as age (*lnAge*), size (*lnEmp*), assets per employee (*lnAssetemp*) and cash flow per employee[5] (*CFemp*).

Given the fact that firms can enter a cluster at different points in time, there is in fact a staggered treatment. Recent research (see Callaway and Sant'Anna, 2021; Roth et al., 2022; De Chaisemartin and d'Haultfoeuille, 2020), has shown that it is important to account for these timing differences. We therefore also carry out a DiD with staggered adoption in the way proposed by De Chaisemartin and d'Haultfoeuille (2020). This methodology identifies group-time averages treatment effects for different cohorts that start receiving treatment at different points in time. The parameter of interest is defined as the average treatment effect for the group of units first treated at time period g, in calendar time t (for t≥ g):

$$ATT_{(g,t)} = E\left[Y_t(g) - \ Y_t(0)\middle|G_g = 1\right] \tag{3.7}$$

3.3 Matching procedure

The group of outsider firms, the 'control group', consists of all firms that belong to a NACE sector that corresponds to the focus area of the cluster policy. This is a first step to

[5] As the cash flow per employee can be negative, we do not take the log of this variable.

eliminate selection bias in our control group. In order to account further for the selection bias, we employ different matching procedures to construct a control group that is even more similar to the treated group.

The first common step is to model the selection into a SHC program by picking a pool of meaningful observable firm characteristics. Those variables, however, may be affected by the SHC treatment. To avoid the consequent endogeneity bias, the reference period for the matching procedure is the pre-treatment years 2013-2016, and the resulting firm-specific weights are assumed constant across the sample years. We then apply augmented nearest neighbor (NN) matching with replacement, based on either the estimated propensity score (PS-NN) or the Mahalanobis distance calculated on the set of firm observables (MaD-NN). We then compute the regression frequency weights for the cases of one and two nearest neighbors, respectively. The NN procedure is augmented in the sense that the estimated propensity score is used beforehand to restrict the matching sample to common support by deleting treated firms with probabilities larger than the maximum and smaller than the minimum in the potential control group. The nearest neighbors, moreover, are constrained to be in the same 2-digit NACE industry of the treated firm of reference. The covariates that are using in the matching procedure are age (*lnAge*), cash flow per employee (*CFemp*), and initial firm productivity (i.e. the earliest available instance of estimated log TFP in the pre-treatment period). We then retain those firms that exist in the dataset during all periods and carry out the DiD regression applying the frequency weights.[6]

4 Results

4.1 Total Factor Productivity

TFP is estimated with and without fixed effects. Figure 3 presents the distribution of the normalized TFP values for each case.

Figure 4 presents the distribution of the normalized TFP (including fixed effects) split for the treated and non-treated firms. The left-hand size presents the pre-treatment period

[6] These frequency weights get a missing value when the firm is not matched. They get a value of 1 when the firm is treated or when the non-treated firm is a match. Higher values are given if the same firm is matched more with multiple treated firms.

and the right-hand side graph presents the post-treatment period. In both graphs, TFP of the treated firms is more skewed to the right, indicating that firms that will join the cluster already have a higher TFP before joining (the self-selection effect).

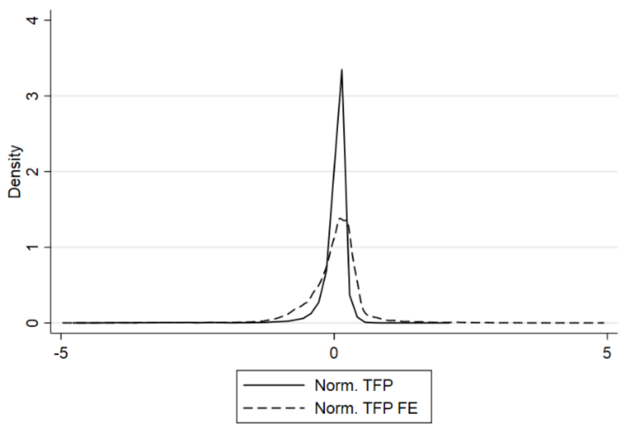

Figure 3: K-density plot of the normalized TFP estimations with and without fixed effects

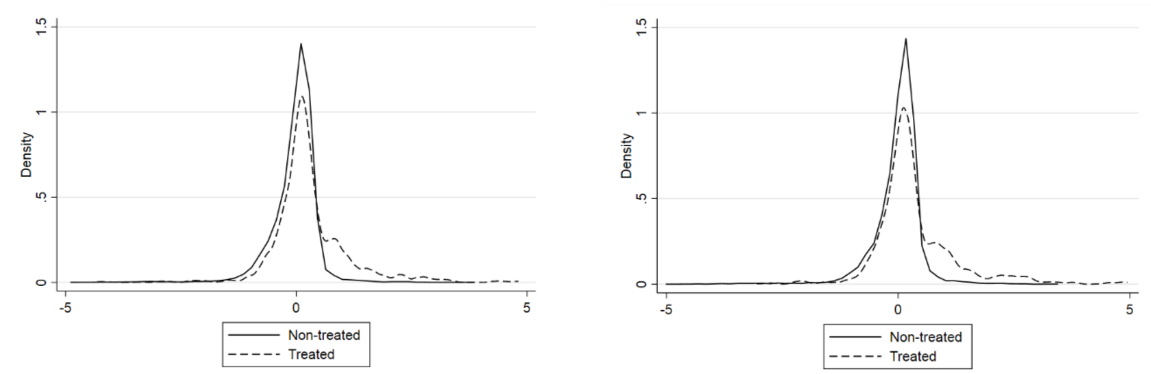

Figure 4: K-density plot between treated and non-treated firms in the pre-treatment period (LHS) and post-treatment period (RHS)

4.2 Difference-in-Differences

Table 3 presents the estimation results of the Difference-in-Differences (DiD) regression when TFP is estimated for groups classified by industry and without including fixed effects. The first two columns include firm and year fixed effects (FE), the latter two columns include firm and industry-year fixed effects.

Table 3: Impact of Spearhead Cluster Membership on Log(TFP), DiD Regressions

	Firm and Year FE		Firm and Industry-Year FE	
	Baseline	Common Trend Test	Baseline	Common Trend Test
	(1)	(2)	(3)	(4)
treatment t-1	0.010***	0.010***	0.011***	0.010***
	(0.004)	(0.004)	(0.004)	(0.004)
evertreated x I(2016)		0.003		0.003
		(0.005)		(0.005)
evertreated x I(2015)		0.001		-0.003
		(0.006)		(0.006)
evertreated x I(2014)		-0.003		-0.006
		(0.005)		(0.005)
lnAge	-0.024***	-0.024***	-0.027***	-0.027***
	(0.007)	(0.007)	(0.007)	(0.007)
lnAssetemp	0.221***	0.221***	0.221***	0.221***
	(0.012)	(0.012)	(0.012)	(0.012)
CFemp /1000000	-0.312***	-0.312***	-0.312***	-0.312***
	(0.026)	(0.026)	(0.026)	(0.026)
lnEmp	0.093***	0.093***	0.092***	0.092***
	(0.009)	(0.009)	(0.009)	(0.009)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
Industry x Year FE	No	No	Yes	Yes
Observations	64,718	64,718	64,711	64,711
Adj. R^2	0.994	0.994	0.994	0.994

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Columns 1 and 3 show the baseline results. Columns 2 and 4 include in addition a number of dummy variables that take the value of 1 in a given pre-treatment year (2014, 2015, 2016) for a firm that will be treated in the post-treatment period. The lack of significant coefficients in these pre-treatment years indicates that in these years the parallel trend assumption holds.

The coefficient of the variable “treatment t-1” presents the DiD estimate which corresponds to the impact that treatment has on the treated group. The impact is always significantly positive. Participation in a SHC thus results in a statistically significant increase in TFP of 1 percent.

Table 4 differs from Table 3 in that the TFP estimation includes fixed effects. The impact of cluster membership increases to around 3 percent (varying between 2,3 and 4,4 percent according to the specification). The common trend test is satisfied for all years.

Also, all control variables have a statistically significant impact. In the remainder of this paper, the results are based on the TFP estimation including fixed effects.

Table 4: Impact of Spearhead Cluster Membership on Log(TFPfe), DiD Regressions

	Firm and Year FE		Firm and Industry-Year FE	
	Baseline	Common Trend Test	Baseline	Common Trend Test
	(1)	(2)	(3)	(4)
treatment t-1	0.044***	0.039***	0.026***	0.023***
	(0.006)	(0.007)	(0.006)	(0.007)
evertreated x I(2016)		-0.002		-0.001
		(0.006)		(0.007)
evertreated x I(2015)		-0.013		-0.011
		(0.008)		(0.008)
evertreated x I(2014)		-0.013		-0.006
		(0.008)		(0.008)
lnAge	-0.032***	-0.032***	-0.029***	-0.029***
	(0.009)	(0.009)	(0.009)	(0.009)
lnAssetemp	0.242***	0.242***	0.242***	0.242***
	(0.011)	(0.011)	(0.011)	(0.011)
CFemp /1000000	-0.328***	-0.328***	-0.328***	-0.328***
	(0.031)	(0.031)	(0.031)	(0.031)
lnEmp	0.241***	0.241***	0.242***	0.242***
	(0.010)	(0.010)	(0.010)	(0.010)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
Industry x Year FE	No	No	Yes	Yes
Observations	64,718	64,718	64,711	64,711
Adj. R^2	0.997	0.997	0.997	0.997

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

As a robustness check, we change the classification of the groups for which we estimate TFP. Rather than grouping firms according to their NACE 2-digit sector ('industry grouping'), we group them according to their cluster ('cluster grouping'). The different NACE classifications can be found in Appendix 3, Table 6 and Table 7. For the industry grouping, we only consider those NACE 2-digit sectors which belong to the strategic domain of one of the clusters. Cluster grouping is sometimes specified at the NACE 3-digit level, the industry grouping is always at the 2-digit NACE level. As a result, fewer companies are included in the sample in the case of the cluster grouping. The results are given in Appendix 4. The positive impact is still significant and varies between 1,7 and 2,3 percent.

4.3 Matching results

Table 5 present the results when the control group is further restricted through a matching procedure. This table includes the results for the unmatched sample (column 1) and the sample where the control group is established based on the distance between the propensity scores (column 2 and 3) or based on the Mahalanobis distance (column 4 and 5), respectively including 1 or 2 nearest neighbors. The positive impact of the cluster members is confirmed in all specifications and ranges between 2,1 and 3,4 percent.

Table 5: Impact of Spearhead Cluster Membership on Log(TFPfe), conditional DiD Regressions, firm and year fixed effects

	Unmatched	PS NN1	PS NN2	MaD NN1	MaD NN2
	(1)	(2)	(3)	(4)	(5)
treatment t-1	0.035***	0.021**	0.025***	0.034***	0.025***
	(0.008)	(0.010)	(0.010)	(0.010)	(0.010)
evertreated x I(2016)	0.007	0.012	0.012	0.006	0.008
	(0.008)	(0.011)	(0.010)	(0.011)	(0.010)
evertreated x I(2015)	-0.003	0.001	0.003	(0.014)	0.008
	(0.010)	(0.014)	(0.013)	(0.014)	(0.013)
evertreated x I(2014)	-0.009	0.002	-0.004	-0.013	0.001
	(0.009)	(0.013)	(0.011)	(0.012)	(0.011)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	66,439	7,296	10,441	7,508	10,831
Adj. R^2	0.995	0.997	0.997	0.997	0.997

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4.4 Heterogeneity-robust Difference-in-Differences

In addition to the canonical DiD approach, we also take into account staggered treatment timing. The figures below show the Average Treatment Effect on the Treated (ATET) before and after treatment, for the full sample and separately for small and large firms. We set the time 0 at the period before the treatment changes. Period 0 therefore includes all firms that become a member of a cluster in the next year, whether this is in 2017, 2018 or later. Period 1 includes those firms that are a member for the first year. Period 4 only includes those firms that have been a member for 4 years (so the firms that joined a cluster in 2017).

When covering all firm sizes (see Figure 5), we see a consistent positive treatment effect of the treated in the post treatment period. The treatment effect in the pre-treatment period is not significantly different form zero. In the post treatment period, the treatment effect increases steadily over time. For each time period, the treatment effect is significantly positive.

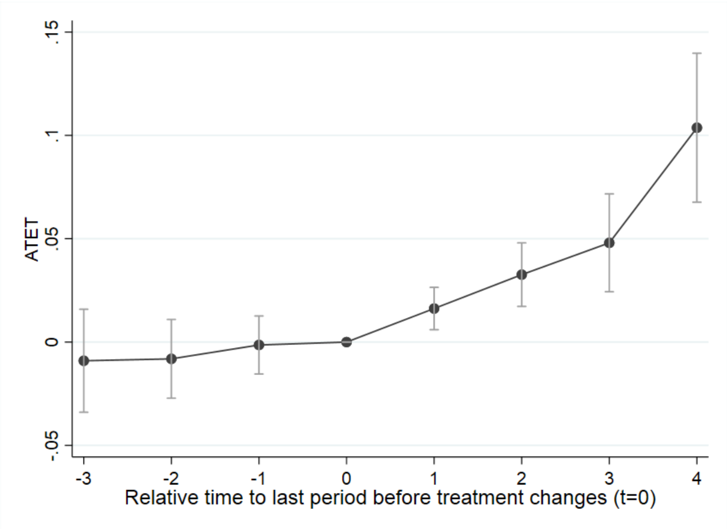

Figure 5: Event plot based on staggered DiD

As a robustness check, we split the sample into small and large firms (see Figure 6 and Figure 7). Small (large) firms are firms which have less than (at least) 250 employees in the first year that they enter the sample. For both size categories we see a pattern that is similar to the full sample presented in Figure 5: there is no treatment effect in the pre-treatment period and a significant positive and increasing effect in the post-treatment period. The positive impact of cluster membership is thus not driven exclusively by one category of firm sizes but is present in both small and large firms. Moreover, it is worth noting that the treatment effect after 3 and 4 years is higher for the smaller firms than for the larger firms.

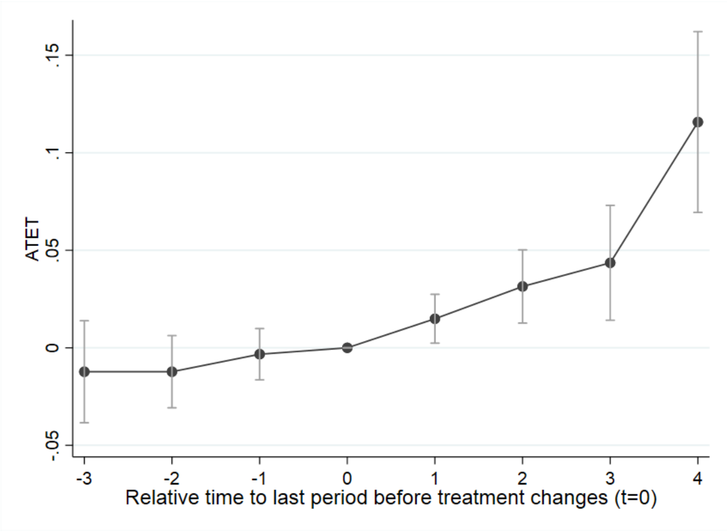

Figure 6: Event plot based on staggered DiD – SMEs only

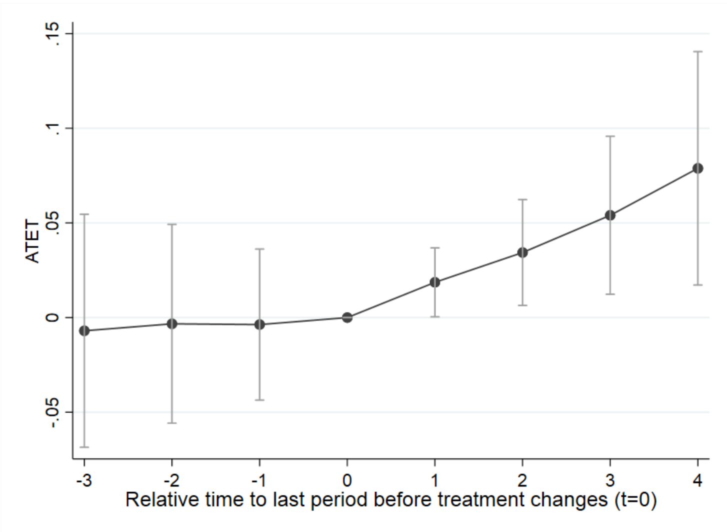

Figure 7: Event plot based on staggered DiD – large firms only

5 Discussion and conclusion

Since 2017, the Flemish government has established a cluster policy to facilitate the creation of cluster associations grouped around several strategic sectors. Within the cluster, joint R&D projects can be set-up with the partial financial support of the regional government. These organizational clusters are called 'Spearhead' Clusters, as they target the frontrunners in the industry. By stimulating innovation in these leading companies, the entire sector and its supply chain can benefit. In this paper we analyze whether firm membership in these cluster associations has an impact on the productivity of that firm.

This paper provides an important contribution to the existing literature for the following reasons: (i), to our knowledge, this is the first paper that analyzes the Flemish spearhead cluster policy. (ii) we make use of a unique and confidential database on cluster membership and (iii) we apply state-of-the-art econometrics to calculate the Total Factor Productivity which, again to our knowledge, has not been applied to Belgian data before.

For this research, we could rely on confidential cluster membership data, which does not only include the VAT-number of the firms paying the membership fee, but also all relevant branches that are involved in the cluster association. This unique database was constructed yearly by the authors in close cooperation with the cluster associations. As a measure of productivity, we use Total Factor Productivity estimated in line with the latest insights of Gandhi, Navarro, Rivers (2020). In addition to this established methodology, we also allow cluster membership to play a role in future productivity estimations by including it as an endogenous variable in the Markov process. Last but not least, we allow for the sector specific parameters to evolve over time by applying a 4-year rolling window.

We present the results of the canonical two-by-two Difference-in-Differences regression. These results indicate a positive impact of cluster membership on the productivity of the participating firms of between 2,3 and 4,4 percent on average. These results are also robust when we apply several different matching procedures (between 2,1 and 3,4 percent). When taking into account the staggered treatment in the way proposed by De Chaisemartin and d'Haultfoeuille (2020), we provide the results of an event study demonstrating a significant positive impact which is increasing over time. We also show that these results hold when addressing small and large firms separately, whereby the small firms outperform the large firms.

These results can be compared with earlier research in other countries. For example, Daly (2018) finds that "participation in the Innovation Network increases labor productivity and total factor productivity by almost 7 and 13 percent respectively after four years", with the largest benefits generated by the smaller firms.

One key mechanism through which small firms could improve their TFP more than large firms is that small firms can benefit more from the visibility and the networking that the cluster provides. Small firms are often also young firms for which brand recognition could still be improved, in contrast to large (well-known) firms that do not need a cluster to get noticed by business partners. TFP in these small firms can then improve through new or improved cooperation with upstream and downstream partners (note that even though they are not part of our analysis, these upstream and downstream industries are also invited to become members of the cluster). It should also be noted that the real impact on TFP will come from the research projects itself rather than the membership to the organization. However, the time span of our research is too short to see these effects entering into force.

This relatively short time span is one of the caveats and limitations to our current research. It should be noted that the cluster initiative only started in 2017 with two clusters only starting in 2018 whereas the most recent economic data cover the year 2020. We will have more information, including longer term impacts, in the years to come. In addition, some cluster initiatives already had a predecessor as some sectoral R&D associations already existed under a previous policy instrument. As we do not have information on the membership in these prior structures, we do not take this information into account. In our analysis, we estimate TFP based on the gross output function, we therefore only include those firms that report turnover. We also limit our analysis to those firms belonging to the strategic domain of the cluster and exclude suppliers, downstream users etc. In our analysis we also do not account for spill-over effects of member firms to non-member firms within the same sector. Finally, TFP in itself remains an estimation based on a number of key assumptions.

In the future, we envisage to extend this work and assess the impact on TFP of firms participating in a cluster-subsidized R&D project in addition to cluster membership. This is in line with recent work by Mar et al. (2021) who compares the impact of cluster membership and cluster participation in France and finds complementarity between the two types of instruments.

References

Abdesslem, A.B., & Chiappini, R., (2019). Cluster policy and firm performance: a case study of the French optic/photonic industry. *Regional Studies, 53* (5), 692–705. https://doi.org/10.1080/00343404.2018.1470324

Aboal, D., Perera, M., & Rovira, F. (2020). Cluster development policies and firms' performance: evidence from an emerging economy in Latin America. *Journal of Entrepreneurship in Emerging Economies, 12* (5), 687–726. https://doi.org/10.1108/JEEE-06-2019-0086

Ackerberg, D.A., Caves K., & Frazer G. (2015). Identification properties of recent production function estimators. *Econometrica, 83* (6), 2411–2451. https://doi.org/10.3982/ECTA13408

Angrist, J. D., & Pischke, J.S. (2008). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press. https://doi.org/10.1515/9781400829828

Anić, I.D., Corrocher, N., Morrison, A., & Aralica, Z. (2019). The development of competitiveness clusters in Croatia: a survey-based analysis. *European Planning Studies, 27* (11), 2227–2247. https://doi.org/10.1080/09654313.2019.1610726

Anić, I.D., & Corrocher, N. (2022). Patterns of value creation in policy-driven cluster initiatives: evidence from the Croatian competitiveness clusters. *Journal of Evolutionary Economics, 32* (2), 643–672. https://doi.org/10.1007/s00191-022-00766-7

Aranguren, M.J., de la Maza, X., Parrilli M.D., Vendrell-Herrero, F., & Wilson J.R. (2014). Nested Methodological Approaches for Cluster Policy Evaluation: An Application to the Basque Country. *Regional Studies, 48* (9), 1547–1562. https://doi.org/10.1080/00343404.2012.750423

Audretsch, D. B., Lehmann, E. E., Menter, M., & Seitz, N. (2019). Public cluster policy and firm performance: evaluating spillover effects across industries. *Entrepreneurship and Regional Development, 31* (1–2), 150–165. https://doi.org/10.1080/08985626.2018.1537153

Calignano, G., Fitjar, R. D., & Kogler, D. F. (2018). The core in the periphery? The cluster organization as the central node in the Apulian aerospace district. *Regional Studies, 52* (11), 1490–1501. https://doi.org/10.1080/00343404.2017.1420155

Callaway B., & Sant'Anna P. (2021). Difference-in-Differences with multiple time periods. *Journal of Econometrics, 225* (2), 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001

Cantner, U., Graf, H., & Rothgang, M. (2019). Geographical clustering and the evaluation of cluster policies: introduction. *The Journal of Technology Transfer, 44* (6), 1665–1672. https://doi.org/10.1007/s10961-018-9666-4

Daly, M. (2018). The effect of participation in Denmark's Innovation Network program. *Economics of Innovation and New Technology, 27* (5-6), 454–478. https://doi.org/10.1080/10438599.2017.1374045

De Chaisemartin, C., & d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. American Economic Review, 110(9), 2964-2996. https://doi.org/10.1257/aer.20181169

De Loecker J. (2013). Detecting Learning by Exporting. *American Economic Journal: Microeconomics, 5* (3), 1–21. https://doi.org/10.1257/mic.5.3.1

De Loecker, J., & Syverson, C. (2021). An Industrial Organization Perspective on Productivity. NBER Working Paper No. w29229. https://ssrn.com/abstract=3922503

Doloreux, D., & Frigon, A. (2022). The Innovation Superclusters Initiative in Canada: A new policy strategy? *Science & Public Policy, 49* (1), 148–158. https://doi.org/10.1093/scipol/scab071

Eberhardt, M., & Helmers, C. (2010). Untested assumptions and data slicing: A critical review of firm-level production function estimators. Economics Series Working Papers 513, University of Oxford, Department of Economics.

Engel, D., Mitze, T., Patuelli, R., & Reinkowski, J. (2013). Does cluster policy trigger R&D activity? Evidence from German biotech contests. *European Planning Studies, 21* (11), 1735–1759. https://doi.org/10.1080/09654313.2012.753689

Engel, D., Eckl, V., & Rothgang, M. (2019). R&D funding and private R&D: empirical evidence on the impact of the leading-edge cluster competition. *The Journal of Technology Transfer, 44* (6), 1720–1743. https://doi.org/10.1007/s10961-017-9609-5

European Commission (2010). *Regional Policy Contributing to Smart Growth in Europe, COM(2010)553* Brussels, European Commission

Falck, O., Heblich, S., & Kipar, S. (2010). Industrial innovation: Direct evidence from a cluster-oriented policy. *Regional Science and Urban Economics, 40* (6), 574–582. https://doi.org/10.1016/j.regsciurbeco.2010.03.007

Gandhi, A., Navarro, S., Rivers, D.A. (2020). On the identification of Gross Output Production Functions. *Journal of Political Economy, 128* (8), 2973–3016. https://doi.org/10.1086/707736

Garone, L. F., Maffioli, A., de Negri, J. A., Rodriguez, C. M., & Vázquez-Baré, G. (2015). Cluster development policy, SME's performance, and spillovers: evidence from Brazil. *Small Business Economics, 44* (4), 925–948. https://doi.org/10.1007/s11187-014-9620-2

Gorrens, B., Konings, J., Putseys A., Reynaerts, J., Van Esbroeck, D., Vanschoonbeek, J., Volckaert, A. (2022). Speerpuntclusters in Vlaanderen. Methodologie voor het berekenen van kernindicatoren. Beleidsrapport STORE-22-017.

Goutsmet, D., Lecocq, C., Volckaert, A. (2018). Methodologie voor het beschrijven van speerpuntclusters in Vlaanderen. Beleidsrapport STORE-17-005

Grashof, N. (2021). Putting the watering can away – Towards a targeted (problem-oriented) cluster policy framework. *Research Policy*, *50* (9), 104335. https://doi.org/10.1016/j.respol.2021.104335

Ketels, C. (2013). Recent research on competitiveness and clusters: what are the implications for regional policy? *Cambridge Journal of Regions, Economy and Society*, *6* (2), 269–284. https://doi.org/10.1093/cjres/rst008

Kiese, M. (2019). Regional cluster policies in Germany: challenges, impacts and evaluation practices. *The Journal of Technology Transfer, 44* (6), 1698–1719. https://doi.org/10.1007/s10961-017-9589-5

Lecocq, C., & Volckaert, A. (2019). Speerpuntclusters in Vlaanderen. Een analyse op basis van de kernindicatoren 2018. Beleidsrapport STORE-19-007

Lehmann, E. E., & Menter, M. (2018). Public cluster policy and performance. *The Journal of Technology Transfer, 43* (3), 558–592. https://doi.org/10.1007/s10961-017-9626-4

Mackiewicz, M., & Pavelkova, D. (2022). Clusters and innovation: The relationship between membership in clusters organisations and technological maturity of companies in Poland. *Technological and Economic Development of Economy, 28* (6), 1854–1870. https://doi.org/10.3846/tede.2022.18005

Mar, M., & Massard, N. (2021). Animate the cluster or subsidize collaborative R&D? A multiple overlapping treatments approach to assess the impacts of the French cluster policy. *Industrial and Corporate Change*, *30* (4), 845–867. https://doi.org/10.1093/icc/dtab002

Marshall, A. (1920). *Principles of economics* (8th ed.). London: Macmillan. (Original work published 1890)

Martin, P., Mayer, T., & Mayneris, F. (2011). Public support to clusters: A firm level study of French 'local productive systems'. *Regional Science and Urban Economics, 41* 2), 108–123. https://doi.org/10.1016/j.regsciurbeco.2010.09.001

NBB (2022) Producer price index (PPI) (available at https://stat.nbb.be/)

N'Ghauran, K. A., & Autant-Bernard, C. (2021). Assessing the collaboration and network additionality of innovation policies: a counterfactual approach to the French cluster policy. *Industrial and Corporate Change, 30* (6), 1403–1428. https://doi.org/10.1093/icc/dtab017

Nishimura, J., & Okamuro, H. (2011). R&D productivity and the organization of cluster policy: an empirical evaluation of the Industrial Cluster Project in Japan. *The Journal of Technology Transfer, 36* (2), 117–144. https://doi.org/10.1007/s10961-009-9148-9

OECD (2007). *Competitive Regional Clusters: National Policy Approaches*. OECD Reviews of Regional Innovation, OECD Publishing, Paris. https://doi.org/10.1787/9789264031838-en

Pavelkova, D., Zizka, M., Homolkav, L., Knapkova, A., & Pelloneova, N. (2021). Do clustered firms outperform the non-clustered? Evidence of financial performance in traditional industries. *Economic Research-Ekonomska Istraživanja 34* (1), 3270–3292. https://doi.org/10.1080/1331677X.2021.1874460

Pecze, M. (2020). The benefits of membership in policy-stimulated clusters in Hungary. *European Planning Studies, 28* (8), 1493–1512. https://doi.org/10.1080/09654313.2019.1673322

Porter, M. E. (1990). *The competitive advantage of nations*. Free Press.

Porter M. E. (1998) Clusters and the new economics of competition. *Harvard Business Review, 76* (6):77–90.

Porter, M. E. (2000). Location, Competition, and Economic Development: Local Clusters in a Global Economy. *Economic Development Quarterly, 14* (1), 15–34. https://doi.org/10.1177/089124240001400105

Roth J., Sant'Anna P., Bilinski A., & Poe J. (2022). What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics, 235* (2), 2218–2244. https://doi.org/10.1016/j.jeconom.2023.03.008

Rothgang, M., Lageman, B., & Scholz, A.M. (2021). Why are there so few hard facts about the impact of cluster policies in Germany? A critical review of evaluation studies. *Review of Evolutionary Political Economy, 2* (1), 105–139. https://doi.org/10.1007/s43253-021-00034-7

Schmiedeberg, C. (2010). Evaluation of Cluster Policy: A Methodological Overview. *Evaluation*, *16* (4), 389–412. https://doi.org/10.1177/1356389010381184

Smith, M., Wilson, J. R., & Wise, E. (2020). Evaluating clusters: Where theory collides with practice. *Regional Science Policy & Practice*, *12* (3), 413–430. https://doi.org/10.1111/rsp3.12279

Stojčić, N., Anić, I.D., Aralica, Z. (2019). Do firms in clusters perform better? Lessons from wood-processing industries in new EU member states. *Forest Policy and Economics, 109,* 102043. https://doi.org/10.1016/j.forpol.2019.102043

STORE (2019). http://www.steunpunt-economie-ondernemen.be/p/STORE-16-20 (accessed on 15 June 2022)

Uyarra, E., & Ramlogan, R. (2016). *The impact of cluster policy on innovation.* Handbook of Innovation Policy Impact, 196–238. Edward Elgar Publishing. https://doi.org/10.4337/9781784711856.00014

Vernay, A.L., D'Ippolito, B. & Pinkse, J. (2018). Can the government create a vibrant cluster? Understanding the impact of cluster policy on the development of a cluster. *Entrepreneurship and Regional Development, 30* (7-8), 901–919. https://doi.org/10.1080/08985626.2018.1501611

VLAIO (2022) Clusterorganisaties – Het clusterbeleid www.vlaio.be/nl/clusterorganisaties/het-clusterbeleid/speerpuntclusters (accessed on 15 June 2022)

Vlaisavljevic, V., Medina, C. C., & Van Looy, B. (2020). The role of policies and the contribution of cluster agency in the development of biotech open innovation ecosystem. *Technological Forecasting & Social Change, 155*, 119987. https://doi.org/10.1016/j.techfore.2020.119987

Wilson, J., Wise, E., & Smith, M. (2022). Evidencing the benefits of cluster policies: towards a generalised framework of effects. *Policy Science 55*, 369–391. https://doi.org/10.1007/s11077-022-09460-8

Zizka, M., & Stichhauerova, E. (2022). Effect of cluster initiatives and natural clusters on business performance. *Competitiveness Review*, *Vol. ahead-of-print*, No. ahead-of-print. https://doi.org/10.1108/CR-02-2022-0021

Appendices

Appendix 1: Cluster background

Catalisti

The strategic domain of the cluster Catalisti is the chemistry and plastics industry. The ambition of the cluster is to realize “a sustainable and competitive chemical & plastics converting industry in Flanders achieved by an innovative power of world class”. According to the cluster, the chemicals and life sciences sector counted in 2017 nearly 60 000 direct and 100 000 indirect jobs, with a turnover of € 42 bln. and yearly R&D expenses of € 1.5 bln. The sector can count on the import of excellent raw materials (thanks to the presence near the Port of Antwerp), highly skilled employees and the presence of large firms and R&D centra in the sector. Some of the largest firms in the cluster include BASF Antwerpen, Covestro and Oleon.

SIM

SIM stands for Strategic Initiative on Materials. It is the ambition of SIM to contribute to the competitive position of the materials industry in Flanders and to bring innovative materials to the market that can bring an answer to some of the grand challenges, such as energy or the circular economy. The cluster Roadmap is in line with the European KET (Key Enabling Technologies) for Advanced Materials. The strategic domain of the materials is broad and covers metals, minerals and organic raw materials (such as plastics and textile) as well as composite materials and nano-materials. According to the industry, the sector represents 17 000 jobs directly (and 200 000 jobs indirectly) and has a turnover of € 7 bln directly (€ 63 bln indirectly). Some of largest firms in the cluster include ArcelorMittal Belgium, CNH Industrial Belgium and Atlas Copco Airpower.

VIL

VIL is the Flemish logistics cluster. Its aim can be summarized as “Making Flanders the European powerhouse in a global supply chain, driven by digitalization, sustainability and agility.” The logistics sector is the backbone of many economic activities. At the same time, Flanders is an important logistics hub in Europe (thanks to its harbors, airports and multimodal transport infrastructure). The challenges and opportunities for the sector lie with new technological developments (such as digitalization, automation and e-commerce) as well as the need to become more sustainable (with alternative fuels, cradle-to-cradle and shared warehouses). Some of the largest cluster members include Bpost, Brussels Airlines and UPS Europe.

Flux50

The cluster Flux50 focusses on the energy sector and describes its mission as to "Internationally excel in selected segments in the new energy system and by doing so tap into worldwide growth markets." The energy sector is in full transition towards a two-way ecosystem where renewable energy, prosumers, and digitalization play an important role. The cluster focusses on 5 innovator zones: energy harbors, microgrids, multi-energy systems at community level, energy cloud applications and intelligent renovation. The strategic domain includes the energy and building sector. Some of the drivers behind the cluster are: Electrabel, Luminus and Besix.

Flanders' Food

Flanders' Food is the cluster representing the agri-food industry, an important economic activity in Flanders, both in term of employment and turnover. Flanders is a world player the area of food and beverages and home to a number of important multinationals. Given the high employment and energy costs it is imperative to produce high quality and innovative products to remain competitive. Some of the largest members of the cluster are Cargill, Barry Callebaut Belgium and FrieslandCampina Belgium.

De blauwe cluster

"It is the blue clusters' mission to plug into the existing blue landscape and make use of several specific opportunities that are under-exploited today. Focusing on integration within specific projects will inevitably lead to blue growth that would otherwise not take place." Flanders has a relatively short coastline with the North-Sea but is a world player when it comes to harbors, dredging and off-shore wind energy. The blue economy can play an important role in the energy transition and climate policy, notably through renewable energy sources, the fight against water pollution and sustainable food production. A wide number of economic activities belong to the strategic domain, ranging from tourism, over fishery to energy production. Some of the largest members of the cluster are: Jan De Nul, Fabricom and Siemens.

Appendix 2: GNR adjusted for endogenous cluster policy

This appendix illustrates how the GNR estimation procedure has been adapted to account for the cluster policy treatment as endogenous determinant of productivity.

Following the original paper, both the intermediate input partial differential equation and the integration constant are approximated by a quadratic polynomial sieve:

$$\mathcal{S}\left(\frac{\partial}{\partial m_{it}} f(l_{it}, k_{it}, m_{it})\right) = \sum_{0 \le \tau_k + \tau_l + \tau_m \le 2} \gamma'_{\tau_k,\tau_l,\tau_m} k_{it}^{\tau_k} l_{it}^{\tau_l} m_{it}^{\tau_m} \tag{3.8}$$

$$\mathcal{C}(l_{it}, k_{it}) = \sum_{0 < \tau_k + \tau_l \le 2} \alpha_{\tau_k,\tau_l} k_{it}^{\tau_k} l_{it}^{\tau_l} \tag{3.9}$$

On the other hand, the structure of the productivity Markovian process accounting for endogenous cluster policy takes form of a polynomial of degree 2 instead of 3 to facilitate computation given the addition of the policy indicator:

$$lnTFP_{it} = \sum_{0 < a_\omega + a_{SHC} \le 2} \delta_{a_\omega, a_{SPC}} lnTFP_{it-1}^{a_\omega} \, treatSHC_{it-1}^{a_{SHC}} + \xi_{it} \tag{3.10}$$

Compared to the expression (24) in GNR paper, the model identification then changes into:

$$\begin{aligned} \mathcal{Y}_{it} = \sum_{0 < a_\omega + a_{SHC} \le 2} \delta_{a_\omega, a_{SPC}} \left(\mathcal{Y}_{it-1} + \sum_{0 < \tau_k + \tau_l \le 2} \alpha_{\tau_k,\tau_l} k_{it-1}^{\tau_k} l_{it-1}^{\tau_l} \right)^{a_\omega} treatSHC_{it-1}^{a_{SHC}} \\ - \sum_{0 < \tau_k + \tau_l \le 2} \alpha_{\tau_k,\tau_l} k_{it}^{\tau_k} l_{it}^{\tau_l} + \xi_{it} \end{aligned} \tag{3.11}$$

The moments employed for GMM estimation stay the same:

$$\begin{aligned} E\left[\xi_{it} k_{it}^{\tau_k} l_{it}^{\tau_l}\right] = 0 \\ E\left[\xi_{it} \mathcal{Y}_{it-1}^{a}\right] = 0 \end{aligned} \tag{3.12}$$

Regarding the case featuring firm fixed effects a_i in the production function to control for unobserved heterogeneity, the productivity dynamic process becomes:

$$lnTFPfe_{it} = \delta_\omega lnTFPfe_{it-1} + \delta_{SPC} treatSHC_{it-1} + \xi_{it} \tag{3.13}$$

It is worth reminding that the Markov process must be linear in order to eliminate a_i from the proxy equation through first-differencing, otherwise all the input choices would be correlated with a_i hence violating the assumption of scalar unobservability.

Given (A6), the model identification strategy summarized in equation (O.11) in the Appendix O6-1 of GNR changes into:

$$
\begin{aligned}
\hat{\mathcal{Y}}_{it} - \hat{\mathcal{Y}}_{it-1} = & - \sum_{0<\tau_k+\tau_l\leq 2} \alpha_{\tau_k,\tau_l} k_{it}^{\tau_k} l_{it}^{\tau_l} + \delta(\mathcal{Y}_{it-1} - \mathcal{Y}_{it-2}) \\
& +(\delta_\omega + 1)\left(\sum_{0<\tau_k+\tau_l\leq 2} \alpha_{\tau_k,\tau_l} k_{it-1}^{\tau_k} l_{it-1}^{\tau_l} \right) - \delta_\omega \left(\sum_{0<\tau_k+\tau_l\leq 2} \alpha_{\tau_k,\tau_l} k_{it-2}^{\tau_k} l_{it-2}^{\tau_l} \right) \\
& +\delta_{SPC}(treatSHC_{it-1} - treatSHC_{it-2}) + (\xi_{it} - \xi_{it-1})
\end{aligned} \tag{3.14}
$$

The parameters (α, δ) in model (A7) can be estimated exploiting the same moments as in the original model:

$$
\begin{aligned}
E\left[(\xi_{it} - \xi_{it-1}) k_{it-\iota}^{\tau_k} l_{it-\iota}^{\tau_l}\right] = 0, \text{for } \iota \geq 1 \\
E\left[(\xi_{it} - \xi_{it-1}) \hat{\mathcal{Y}}_{it-\iota}^{a}\right] = 0, \text{for } \iota \geq 2
\end{aligned} \tag{3.15}
$$

Appendix 3: TFP grouping categories

Table 6: Industry grouping

Categories	NACE codes
Agriculture, Mining	1-9
Manufacturing:	
- Food, Beverages	10, 11
- Textiles, Leather, Wood, Paper, Printing, Furniture, Other manufacturing	13-18, 31, 32
- Chemicals, Plastics	20, 22
- Minerals, Metals	23-25
- Electronics, Electrical equipment	26, 27
- Machinery, Motor vehicles, Repair of machinery	28-30, 33
Utilities	35-39
Construction	41-43
Wholesale and retail trade	45-47
Transportation and storage	49-53
Administrative and support service activities	75, 77-82

Table 7: Cluster grouping

Categories	NACE codes
Catalisti	20, 22.2
Sim	13, 20.2-20.6, 22.2, 23.0-23.6, 24-30, 32, 33.1
VIL	49-53
Flux50	35, 41-43
Flanders' Food	10, 11
Blue Cluster	3, 8, 10.2, 26, 30, 33, 42, 46.5, 46.9, 50, 52, 77

Appendix 4: DiD results (grouping by cluster instead of industry)

Table 8: Impact of Spearhead Cluster Membership on Log(TFP) (by Cluster), DiD Regressions

	Firm and Year FE		Firm and Industry-Year FE	
	Baseline	Common Trend Test	Baseline	Common Trend Test
	(1)	(2)	(3)	(4)
treatment t-1	0.023***	0.021***	0.019***	0.017**
	(0.005)	(0.005)	(0.005)	(0.005)
evertreated x I(2016)		<0.001		<0.001
		(0.006)		(0.006)
evertreated x I(2015)		-0.003		-0.004
		(0.008)		(0.008)
evertreated x I(2014)		-0.008		-0.009
		(0.005)		(0.006)
lnAge	-0.034***	-0.034***	-0.035***	-0.035***
	(0.011)	(0.011)	(0.011)	(0.011)
lnAssetemp	0.255***	0.255***	0.255***	0.255***
	(0.019)	(0.019)	(0.019)	(0.019)
CFemp/1000000	-0.345***	-0.345***	-0.345***	-0.345***
	(0.041)	(0.041)	(0.041)	(0.041)
lnEmp	0.109***	0.109***	0.109***	0.109***
	(0.014)	(0.014)	(0.014)	(0.014)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
Industry x Year FE	No	No	Yes	Yes
Observations	30,173	30,173	30,167	30,167
Adj. R^2	0.993	0.993	0.994	0.994

Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1