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Cluster Policy, Innovation, and Firm Productivity. An Econometric Assessment of the Flemish Spear-head Cluster Program

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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 programs' treatment effects. 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, total factor productivity, conditional difference-in-difference

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

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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.

In this paper, we investigate econometrically whether one specific, recently introduced European cluster initiative, namely the Flemish Spearhead Cluster (SHC) policy, achieves the expected competitive advantages as hypothesized, among many others, by Marshall and Porter. In the SHC, firms with common research and business concepts engage, among other initiatives, in collaborative pre-competitive research and development (R&D) activities to realize spillover effects that eventually may lead to productivity growth.

Consequently, we therefore aim at investigating whether the Flemish SHC leads to productivity growth in the firms being cluster members. We apply various Difference-in-Differences (DiD) regressions including estimators for staggered treatments in order to assess whether cluster membership has an impact on firm level total factor productivity (TFP). 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 compute 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 some conceptual background of the literature and describes the Flemish SHC policy. The third section describes the data. Section 4 explains in more detail the methodology used to estimate the TFP and describes the subsequently used DiD methodology. Section 5 presents the results and section 6 sums up the main conclusions.

2 Conceptual background

2.1 Literature

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 on cluster policy evaluation. 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 explores the impact of clusters from a qualitative perspective. Anić et al. (2019, 2022) evaluate the Croatian Competitiveness Clusters based on survey data. Kiese (2019) focuses on the German regional level and argues that the real impacts are rather qualitative. N'Ghauran and Autant-Bernard (2021) concentrates 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 while being mindful of the local context and the innovative ecosystem already in place. Aranguren et al. (2014), for instance, evaluates the Basque policy on cluster associations; Vlaisavljevic et al. (2020), analyzes the biotech industry in Spain; Lehmann and Menter (2018) provides an assessment of the Leading-edge Clusters Competition in Germany.

The quantitative impact of the cluster policy is usually measured on the performance of the participating firms. The empirical literature makes use of several performance outcomes such as the technological maturity of the firm (see Mackiewicz et al. (2022) analyzing the National Smart Specializations scheme in Poland), or the firm exports or sales. 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 seven different Czech sectors, Zizka and Stichhauerova (2022) finds mixed results amongst the different industries. Other studies consider the impact on innovation and R&D development. Falck et al. (2010) shows 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 reports an 'indirect negative effect on firms that have not primarily been related to the targeted industries'.

2.2 The Flemish Spearhead Cluster (SHC) Policy

Some cluster initiatives are linked to regional policies with the objective to boost sectors in decline or traditional sectors in need of transformation. In recent years a second wave of cluster policies aiming to promote innovation in a more spatially neutral way has taken hold (OECD, 2007). Quantitative studies linked to the former class of clusters include Martin et al. (2011), whose results indicate a negative impact of the cluster policy on the firm level productivity in the local productive systems in France. Stojčić et al. (2019) shows a positive impact of cluster associations in the wood-processing and furniture manufacturing industries in Croatia and Slovenia. Garone et al. (2015) finds a positive impact in Brazil of the Cluster Development policy, aimed to stimulate industrial agglomerations. Our study is related to the newer kind of cluster programs that feature innovation as main goal. Other initiatives in this sense are the 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), whose aim is 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 seven Spearhead Clusters have been set up. Three of them have an industrial focus: in either chemistry, food or materials. In addition, there are clusters for logistics, energy and the blue economy. The most recent cluster on innovative healthcare launched in 2021 and falls outside the scope of this research. Further information on each of the individual clusters is 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 - has the mandate 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

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.

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

The initiative to launch a new Spearhead Cluster lies in the hands of enterprises, who first have to present an ambitious competitiveness plan. Upon approval by the Flemish government, the commitments from both the industry and the government are formalized in a cluster pact. Cluster support is granted for a maximum period of 10 years.

The government commits to provide funding to these clusters in two ways. On one hand, the allocation of a yearly budget to the cluster organization covers 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 meant to cover only half of the operational expenses of the cluster association. Earlier research (Lecocq, 2019) highlights the issue of self-selection, whereby the most productive firms in a sector are more likely to join the cluster.

3 Data

3.1 Cluster membership data

STORE prepares the yearly membership lists for each cluster at the level of the VAT-number. Details on the applied methodology 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 is collected directly from the cluster organizations. The 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

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

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 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.

3.2 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.

We restrict the number of firms to those that are registered in Flanders (including Brussels).[3] 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 is in Appendix 3, Table and Table. 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 10,965 unique firms, of which 623 unique firms are or have been members of a SHC (for at least 2 years). The dataset consists of 64,718 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

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

point of time joins a cluster. *Figure 1* provides an overview of the never treated and ever treated firms by year.

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

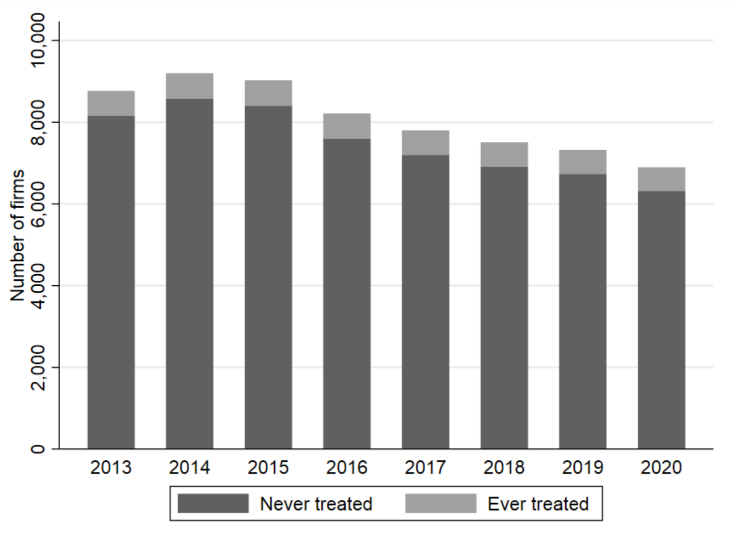


Figure 2: Firm size distribution between ever treated and never treated

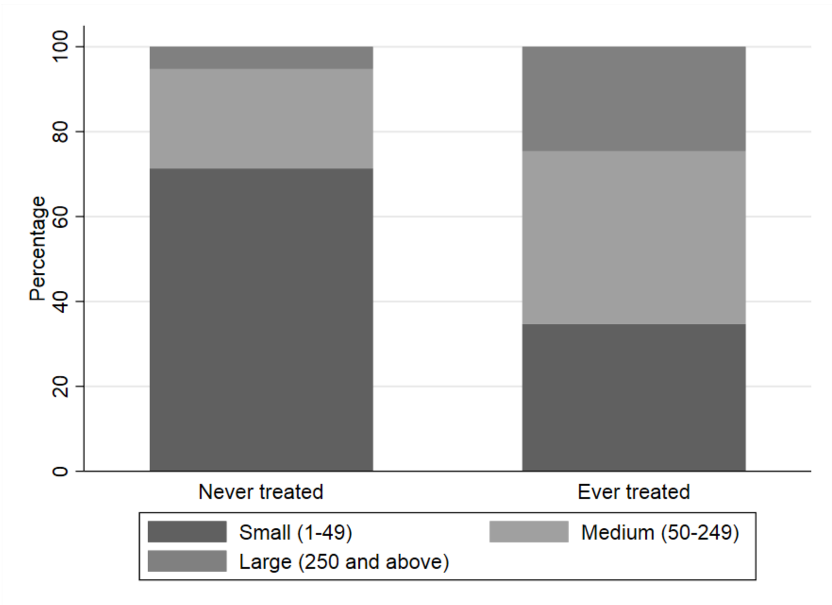


Table 2: Summary statistics

	Pre-treatment period (2013-2016)									
	Never treated (*N= 42,352*)					Ever treated (*N= 2,897*)				
	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-treatment period (2017-2020)									
	Non-treated (*N=21,528*)					Treated (*N=1,319*)				
	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

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).

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 clusters. The average employment in cluster member firms before the treatment phase amounts to 290 employees whereas the potential control firms employ 79 people, on average. 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.

Besides the variables on turnover, employment, tangible fixed assets and materials, Table 2 also includes the variables age, assets per employee and cash-flow per employee which will be used as control variables in the analysis of TFP and the treatment of cluster membership. The cluster members are, on average, older, have more assets per employee and also higher cash-flow per employee.

4 Methodology

4.1 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:

$$y_{it} = f(l_{it}, k_{it}, m_{it}) + v_{it} \tag{1}$$

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[4] PPI_{nt}; $l_{it} \equiv \ln(Emp)$ measures 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; v_{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. $v_{it} = lnTFP_{it} + \varepsilon_{it}$.

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:

$$lnTFP_{it} = g(lnTFP_{it-1}) + \xi_{it} \tag{2}$$

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

[4] The time series for the Producers Price Index (PPI) at 2-digit NACE code level comes from the National Bank of Belgium (NBB, 2022), which provides yearly deflators for 13 different sectors.

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:

$$m_{it} = d_t(lnTFP_{it}, l_{it}, k_{it}), \tag{3}$$

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.

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:

$$y_{it} = f(l_{it}, k_{it}, m_{it}) + lnTFPfe_{it} + a_i + \varepsilon_{it} \quad \Leftrightarrow \quad lnTFP_{it} = a_i + lnTFPfe_{it} \tag{4}$$

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). 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). 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:

$$lnTFP_{it} = g(lnTFP_{it-1}, treatSHC_{it-1}) + \xi_{it} \qquad (5)$$

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.

4.2 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 (2008) for a general overview.

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:

$$lnTFP_{it} = \beta treatSHC_{it-1} + \gamma\, X_{it} + \lambda_i + \tau_{st} \tag{6}$$

where β is the average treatment effect on treated (ATET) 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 (*lnAssets/EMP*) and cash flow per employee[5] (*CF/EMP*).

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. The comparison group so defined, however, may be insufficient to fully rule out the endogeneity stemming from heterogeneous self-selection into treatment. For this reason, we construct a more restrictive control group using matching techniques on relevant pre-treatment covariates.

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

The reference period are the pre-policy years 2013-2016. We apply augmented k-nearest neighbors (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 firm-specific weights are assumed constant over years. 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 set of covariates employed in the matching procedure includes: age (*lnAge*), cash flow per employee (*CF/EMP*), 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] By nature of the data in hand, firms enter a cluster at different points in time and stay treated until the last sample period. Recent research indicates that a canonical DiD design fails to provide consistent ATET estimates when in a multiple period panel setting the treatment is staggered, that is differences in treatment adoption timing exist (Callaway and Sant'Anna, 2021; Roth et al., 2022; De Chaisemartin and d'Haultfoeuille, 2020). We therefore employ the heterogeneity-robust DiD estimator illustrated in De Chaisemartin and d'Haultfoeuille (2020), whose methodology compares changes in outcomes for units whose treatment status changed to other units whose treatment status remained constant over the same periods. The overall effect estimator is then a weighted sum of two DiD estimators, one related to firms switching into treatment ($DID_{joiners}$), the other pertaining treated firms switching out of treatment ($DID_{leavers}$):

$$
\begin{aligned}
DID_M &= \sum_{t=2}^{T}\left(\frac{N_{1,0,t}}{N_S}DID_{joiners} + \frac{N_{0,1,t}}{N_S}DID_{leavers}\right) \\
DID_{joiners} &= \sum_{j:\ D_{jt}=1, D_{jt-1}=0} \frac{N_{jt}}{N_{1,0,t}}\left(Y_{jt} - Y_{jt-1}\right) - \sum_{j:\ D_{jt}=D_{jt-1}=0} \frac{N_{jt}}{N_{0,0,t}}\left(Y_{jt} - Y_{jt-1}\right) \qquad (7) \\
DID_{leavers} &= \sum_{j:\ D_{jt}=D_{jt-1}=1} \frac{N_{jt}}{N_{1,1,t}}\left(Y_{jt} - Y_{jt-1}\right) - \sum_{j:\ D_{jt}=0, D_{jt-1}=1} \frac{N_{jt}}{N_{0,1,t}}\left(Y_{jt} - Y_{jt-1}\right)
\end{aligned}
$$

[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.

In (7) D_{jt} identifies the treatment dummy, Y_{jt} refers to the outcome of interest, N indicates the number of observations within a specific group of untreated or treated.

5 Results

5.1 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 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

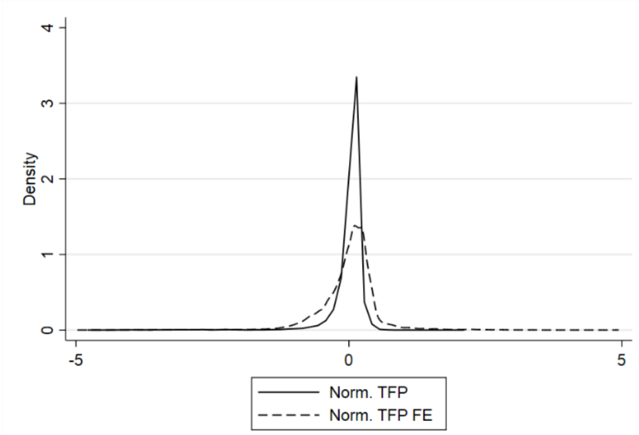
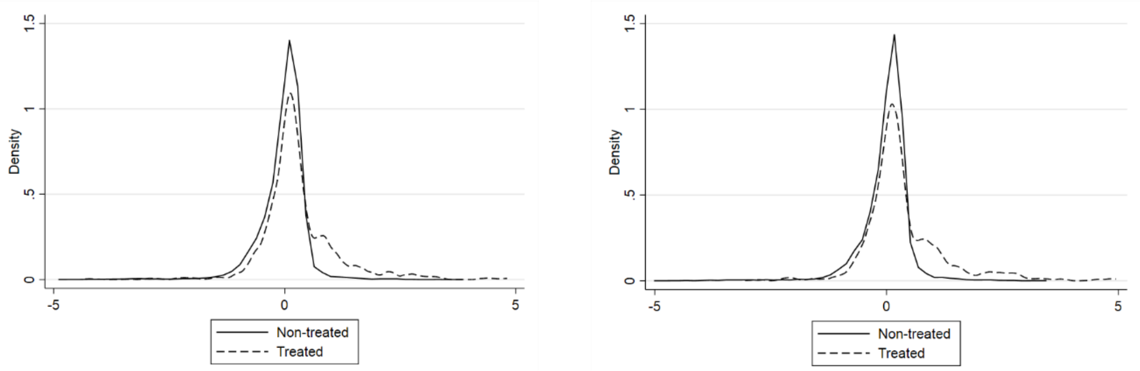


Figure 4: K-density plot between treated and non-treated firms in the pre-treatment period (LHS) and post-treatment period (RHS)



5.2 Basic Difference-in-Difference

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

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.

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

	Firm and Year FE		Firm and Industry-Year FE	
	Baseline	Common Trend Test	Baseline	Common Trend Test
	(1)	(2)	(3)	(4)
$treatSHC_{it-1}$	0.010***	0.010***	0.011***	0.010***
	(0.004)	(0.004)	(0.004)	(0.004)
$treatSHC_{it-1}$ x I(2016)		0.003		0.003
		(0.005)		(0.005)
$treatSHC_{it-1}$ x I(2015)		0.001		-0.003
		(0.006)		(0.006)
$treatSHC_{it-1}$ 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)
lnAsset/EMP	0.221***	0.221***	0.221***	0.221***
	(0.012)	(0.012)	(0.012)	(0.012)
CF/EMP	-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

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 displays the DiD regression results for TFP whose estimation includes fixed effects in the production function. 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 base on the TFP estimation including fixed effects in the production function, which allows to capture firm-level heterogeneity in technical efficiency and distance from the production frontier.

Table 4: Impact of Spearhead Cluster Membership on Log(TFPfe), basic 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)
lnAsset/EMP	0.242***	0.242***	0.242***	0.242***
	(0.011)	(0.011)	(0.011)	(0.011)
CF/EMP	-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<0.10

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 and Table. 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.

5.3 Conditional Difference-in-Difference

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 1-NN	PS 2-NN	MaD 1-NN	MaD 2-NN
	(1)	(2)	(3)	(4)	(5)
$treatSHC_{it-1}$	0.035***	0.021**	0.025***	0.034***	0.025***
	(0.008)	(0.010)	(0.010)	(0.010)	(0.010)
$treatSHC_{it-1}$ x I(2016)	0.007	0.012	0.012	0.006	0.008
	(0.008)	(0.011)	(0.010)	(0.011)	(0.010)
$treatSHC_{it-1}$ x I(2015)	-0.003	0.001	0.003	(0.014)	0.008
	(0.010)	(0.014)	(0.013)	(0.014)	(0.013)
$treatSHC_{it-1}$ 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

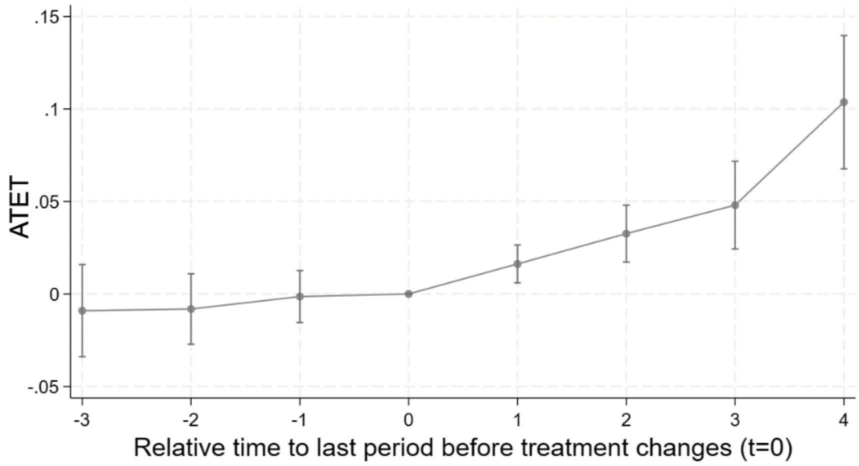
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

5.4 Heterogeneity-robust Difference-in-Difference

In addition to the canonical DiD approach, we apply also a panel event study approach to take into account staggered treatment timing. The figures below show the dynamic treatment effects before and after treatment, for the full sample and separately for subsamples containing small and large firms, respectively. 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 ATET in the treatment period, which even appear to increase over time steadily. The average dynamic effect across all treatment years is 4.1 percent and statistically significant at below 1% level.

Figure 5: De Chaisemartin and d'Haultfoeuille (2020) DiD estimates



The pre-treatment placebos are not significantly different form zero, suggesting statistically equal pre-trends between treated and untreated units. As to post-treatment trends, we perform the sensitivity analysis according to Rambachan and Roth (2023) on the policy impact in the first treatment period (Figure A1). The test gives information about the magnitude of post-treatment violations of parallel trends as a fraction of the pre-treatment differences in trends. The smaller and more negligible are the post-violations, the greater is the ratio $\bar{M}$ so that the confidence interval of the treatment effect of interest crosses zero. In our case, that happens when $\bar{M}$ is equal to 0.5: the treatment effect is then statistically significant as far as we allow the maximal post-trend violation to get as large as half the maximal pre-trend violation at most. In sum, the test results assure that the treatment effect we estimated is statistically significant, and the potential post-treatment parallel trends violation is, in comparison, too small and negligible to jeopardize the estimates; most likely there is no statistically significant violation at all given pre-treatment trend divergences are also statistically insignificant.

As a robustness check, we split the sample into small and large firms (see Figure 6 and Figure 7). Small (large) firms are firms that 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 ATET averaged across all treatment years is 3.9 percent for the SME subsample, and 4.3 percent for the large firms subsample, but 95% confidence intervals mostly overlap. Consequently, the effect heterogeneity driven by size reveals to be inexistent.

Figure 6: De Chaisemartin and d'Haultfoeuille (2020) DiD estimates – SMEs

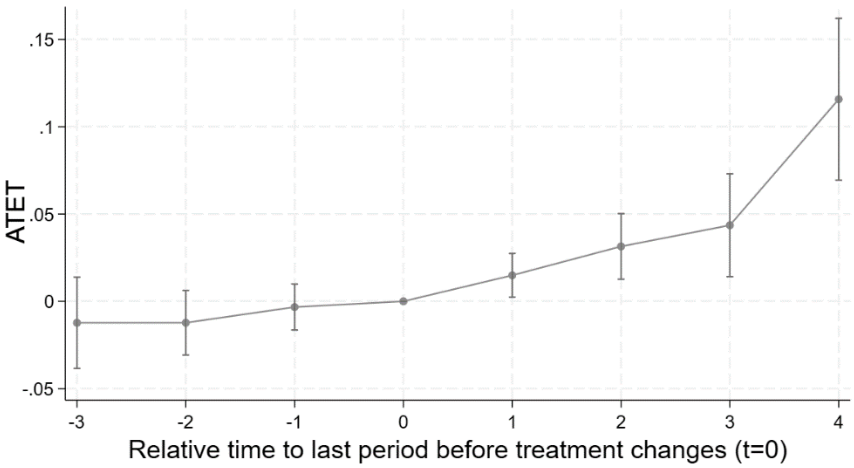
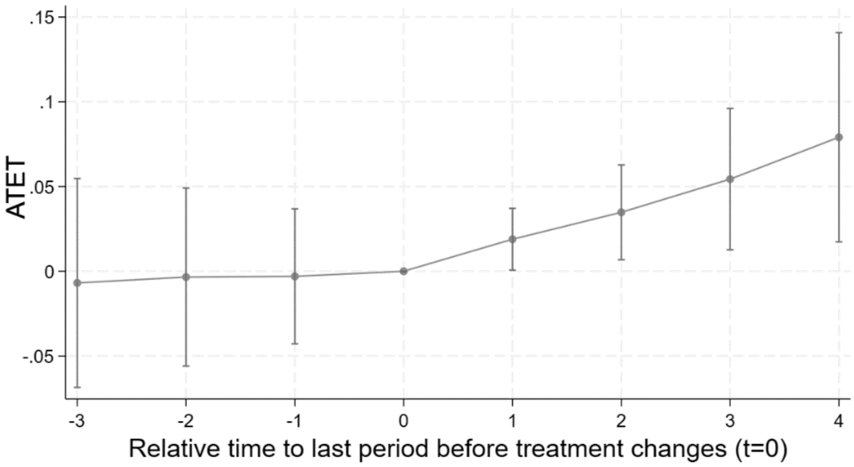
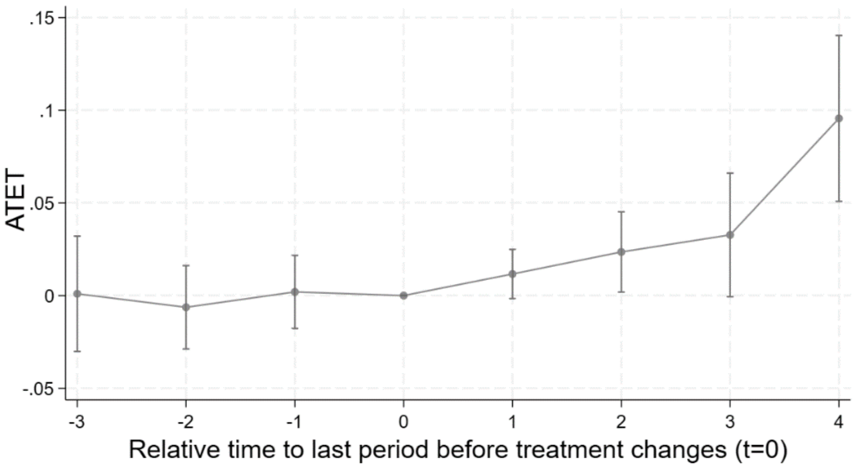


Figure 7: De Chaisemartin and d'Haultfoeuille (2020) DiD estimates – large firms



As final robustness exercise, we estimate the staggered DiD estimator considering the constructed control group according to the 1-NN matching based on the Mahalanobis distance of relevant observables (Figure 8). The results are greatly similar compared to those for the full sample in Figure 5, except for a slight loss of statistical significance due to the reduced sample size.

Figure 8: De Chaisemartin and d'Haultfoeuille (2020) DiD estimates – MD 1-NN matching



6 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 may 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 database on cluster membership and (iii) we apply state-of-the-art econometrics to calculate the TFP which 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 in close cooperation with the cluster associations. As a measure of productivity, we use TFP 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. The average dynamic effect, in fact, is around 4 percent and there is no significant impact heterogeneity driven by size.

The evidence of a clear productivity premium for spearhead cluster members is a signal the Flemish cluster policy is soundly implemented. In fact, the cluster institutions not only provide R&D subsidies for collaborative innovation projects, but they offer also a wide array of complementary services (consultancy, coordination, networking, R&D project assistance) covering several material needs of its participants. In sum, the policy features highlight the importance of designing an adequate mix of policy tools following a systemic perspective, while bearing in mind the specific necessities and potential of the local environment under the policy microscope.

Our study's 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 themselves rather than the membership to the organization. However, the time span of our research is too short to see those long-term dynamics coming into play.

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 have to ignore this information. 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.

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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:

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

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

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:

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

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

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

The moments employed for GMM estimation stay the same:

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

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:

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

Appendix 3: TFP grouping categories

Table A1: 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 A2: 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

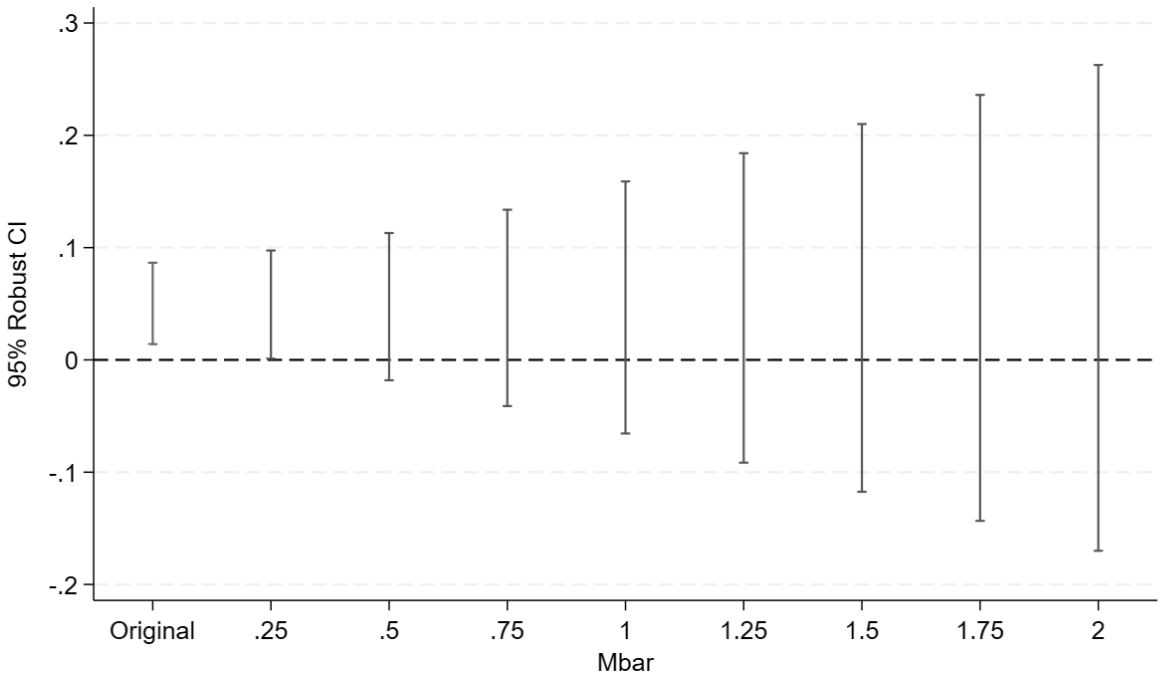
Appendix 4: DiD results (grouping by cluster instead of industry)

Table A3: 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)
$treatSHC_{it-1}$	0.023***	0.021***	0.019***	0.017**
	(0.005)	(0.005)	(0.005)	(0.005)
$treatSHC_{it-1}$ x I(2016)		0.001		0.001
		(0.006)		(0.006)
$treatSHC_{it-1}$ x I(2015)		-0.003		-0.004
		(0.008)		(0.008)
$treatSHC_{it-1}$ 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)
lnAsset/EMP	0.255***	0.255***	0.255***	0.255***
	(0.019)	(0.019)	(0.019)	(0.019)
CF/EMP	-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

Figure A1: Rambachan and Roth (2023) parallel trends sensitivity analysis on De Chaisemartin and d'Haultfoeuille (2020) estimates



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