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Cluster Policy, Innovation, and Firm Productivity. An Econometric Assessment of the Flemish Spearhead 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 various difference-in-differences approaches 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 around 4% roughly, robust to different econometric specifications. A mechanism analysis suggests that the benefit of the cluster policy is driven by knowledge spillovers among the cluster members because we find that the positive treatment effect is negatively moderated by the distance among cluster members.

JEL Classification: 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 (European Commission 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

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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 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).

Existing literature suggests a number of channels through which clusters lead to improved firm performance. Kerr and Robert-Nicoud (2020) mention that knowledge spillovers are a powerful source in tech clusters. In addition, high-velocity labor markets, the presence of universities, high-skilled immigration and global production linkages have been identified as mechanisms in US centers. A difference between famous US clusters such as Silicon Valley and the Flemish Spearhead Clusters is that the latter are not highly localized. The clusters span across the whole spatial area of Flanders instead of being situated in one geographic location. Silicon Valley covers an area of about 4000 km². Flanders as northern part of Belgium covers about 13,624 km² which is about the size of the US state of Connecticut. It is therefore interesting to investigate the presence of knowledge spillovers within tech clusters in the larger geographic area of Flanders. Consequently, we focus our mechanism analysis on possible spillover effects.

There are ample examples in the economic literature where scholars have hypothesized and also found empirically that knowledge spillovers are a local phenomenon, or in other words that positive spillover effects reduce with increasing distance among economic agents, such as firms or inventors (cf. e.g., Jaffe et al. 1993; Audretsch and Feldman 2004; Thompson and Fox-Kean 2005; Belenzon and Schankerman 2013; Carlino and Kerr 2015). We investigate this possible mechanism of cluster benefits in terms of knowledge spillovers by calculating the aerial distance among cluster members and find that the cluster benefits regarding TFP growth are indeed negatively moderated by the distance among cluster members. This evidence suggests the presence of spillovers as a mechanism driving (parts of) the cluster benefits.

We finally investigate whether the positive productivity effects of the cluster membership are confounded with the receipt of other public R&D grants. We therefore collected data on R&D grants from the Flemish government, the main source of public innovation support for the firms in the sample, and accounted for their receipt in the regression analysis. The results do not suggest that the cluster effects are confounded with other R&D subsidies.

Our paper makes several contributions to the existing cluster literature: we investigate Flemish tech cluster which are policy-initiated and that span over the whole geographic area of Flanders. These clusters are thus not as geographically concentrated like famous US tech clusters. It is therefore novel to conduct a mechanism analysis through incorporating the distance among cluster member in a treatment effects estimation on TFP growth of firms. Further, we are the first to use the latest econometric methods for TFP estimation and also for accounting for heterogeneous treatment effects in this strand of the literature.

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 et al. (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 and Corrocher (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'Ghaoran and Autant-Bernard (2021) concentrate on cluster policy resulting in increased collaboration and network additionality in France. Calignano et al. (2018) analyse 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, evaluate the Basque policy on cluster associations; Vlasisavljevic et al. (2020) analyze the biotech industry in Spain; Lehmann and Menter (2018) provide 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 and Pavelkova (2022) analyzing the National Smart Specializations scheme in Poland), or the firm exports or sales. Aboal et al. (2020) find a strong positive impact on exports but a weak

positive impact on sales in Uruguay. Pavelkova et al. (2021) also look 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) find mixed results amongst the different industries. Other studies consider the impact on innovation and R&D development. Falck et al. (2010) show 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) look at the spillover effects across industries in France and report 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) show a positive impact of cluster associations in the wood-processing and furniture manufacturing industries in Croatia and Slovenia. Figal Garone et al. (2015) find 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 et al. 2019) and the competitiveness cluster policy in France (Ben 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 study. Further information on each of the individual clusters is in Table 1 and in Appendix 1. The “Steunpunt Economie en Ondernemen (STORE)” —that is, 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).

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. 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.

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

TABLE 1 | Overview of the different clusters.

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

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 and Volckaert 2019) highlights the issue of self-selection, whereby the most productive firms in a sector are more likely to join the cluster.

In Appendix 4, we show the geographic dispersion of the cluster members in Flanders. The cluster members are distributed across the whole region of Flanders with some hubs in large cities like Brussels and Antwerp. However, the maps also show heterogeneity among the spatial distribution of the different tech clusters. We will utilize the geographic distance among cluster members to investigate the possible presence of spillover effects.

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 inconsistencies² 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 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-digit and 3-digit NACE codes is in Appendix 3, Table A1 and Table A2. 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 posttreatment period, we distinguish between two groups: the firms that will never be a cluster member and the firms that in one point of time joins 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).

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 in 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% of the never treated firms but less than 35% 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% compared to only 23% for the never treated firms). Large firms (as of 250 employees) only represent 5% of firms in the never treated sample but represent 25% of the firms in the ever treated sample.

4 | Methodology

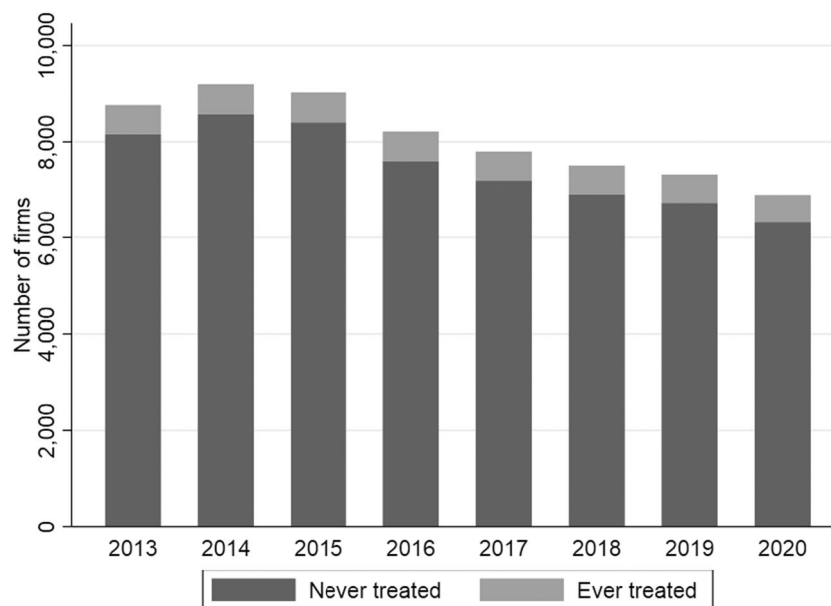
4.1 | TFP Estimation

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 et al. (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 Akerberg et al. (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) 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

TABLE 2 | Descriptive statistics.

	Pretreatment period (2013–2016)									
	Never treated (<i>N</i> = 17,692)					Ever treated (<i>N</i> = 1612)				
	Mean	St. Dev.	p25	p50	p75	Mean	St. Dev.	p25	p50	p75
Turnover (Mln. €)	438.646	1823.849	71.491	144.246	308.007	1894.583	10774.613	152.488	353.364	1049.834
Employment	117.71	659.142	17	37	75	281.492	669.991	43	107	285
Tangible fixed assets (Mln. €)	52.459	382.163	2.539	9.842	29.932	264.613	1150.892	14.209	43.801	137.107
Cost of input materials (Mln. €)	368.21	1666.843	46.595	109.758	250.867	1710.681	10776.008	100.376	256.476	889.787
Age	30.353	18.290	18	27	40	35.13	22.188	20	30	46
Assets per emp. (1000 €)	535.154	1196.933	128.593	236.843	468.732	506.849	717.862	147.037	263.313	534.786
Cashflow per emp. (1000 €)	33.197	55.691	7.198	17.485	38.385	38.996	58.548	9.279	20.713	45.541

	Posttreatment period (2017–2020)									
	Nontreated (<i>N</i> = 17,692)					Treated (<i>N</i> = 1612)				
	Mean	St. Dev.	p25	p50	p75	Mean	St. Dev.	p25	p50	p75
Turnover (Mln. €)	470.402	1894.069	75.506	156.485	340.66	2023.596	12797.634	163.458	403.956	1119.072
Employment	128.575	728.039	18	38	80	299.484	646.559	49	118	305
Tangible fixed assets (Mln. €)	60.295	442.366	2.499	9.942	31.733	311.374	1287.881	15.083	45.713	162.181
Cost of input materials (Mln. €)	395.126	1735.070	49.945	119.593	279.129	1821.687	12732.226	111.011	299.753	907.085
Age	34.353	18.290	22	31	44	39.13	22.188	24	34	50
Assets per emp. (1000 €)	581.125	1410.457	137.082	258.015	514.377	514.707	717.233	145.135	270.075	549.431
Cashflow per emp. (1000 €)	35.192	60.199	6.974	18.278	40.553	40.737	62.533	9.149	22.171	48.438

**FIGURE 1** | The number of treated and nontreated firms in the final database.

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.

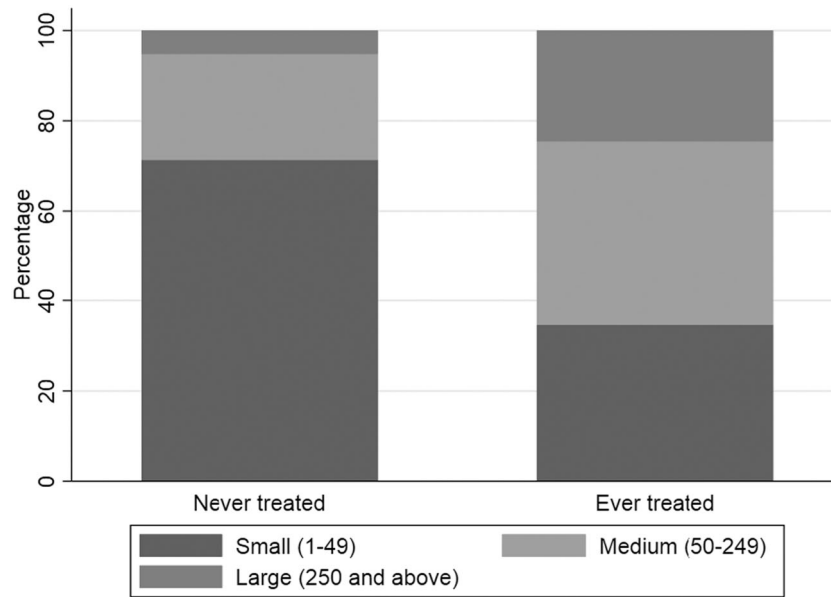


FIGURE 2 | Firm size distribution between ever treated and never treated.

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

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

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 index⁴ 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 $\ln TFP_{it}$ 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, that is, $\nu_{it} = \ln TFP_{it} + \varepsilon_{it}$.

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 $\ln TFP_{it}$, while the ex-post shock ε_{it} is unpredictable and independent, that is, $\varepsilon_{it} \notin \mathcal{I}_t$ and $E[\varepsilon_{it}|\mathcal{I}_t] = E[\varepsilon_{it}] = 0$.

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

$$\ln TFP_{it} = g(\ln TFP_{it-1}) + \xi_{it} \quad (2)$$

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:

$$m_{it} = d_t(\ln TFP_{it}, l_{it}, k_{it}), \quad (3)$$

where the input demand function is strictly increasing in $\ln TFP_{it}$, 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, that is, $\ln TFP_{it} = d_t^{-1}(m_{it}, l_{it}, k_{it})$.

In the absence of time-series variation in flexible input prices, the ACF estimation structure is not sufficient to identify gross output production functions. 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 $C(l_{it}, k_{it})$. In the second step, 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:

$$y_{it} = f(l_{it}, k_{it}, m_{it}) + \ln TFP_{it} e_{it} + a_i + \varepsilon_{it} \Leftrightarrow \ln TFP_{it} = a_i + \ln TFP_{it} e_{it} \quad (4)$$

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 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 consistent TFP estimates for that specific category, hence losing any related information.

For this reason, we aggregate all relevant 2-digit NACE sectors in 12 categories (see Table A1). 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 treatment in the Markovian process of productivity:

$$\ln TFP_{it} = g(\ln TFP_{it-1}, treatSHC_{it}) + \xi_{it} \quad (5)$$

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 (e.g., automation processes). To control for such potential sources of inconsistency, we estimate the average annual productivity considering rolling windows of 4 years, that is, we postulate a production function structure staying fixed for a maximum of 4 years.

4.2 | Difference in Differences Regressions

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 and Pischke (2008) for a general overview.

We consider the following model:

$$\ln TFP_{it} = \beta treatSHC_{it} + \gamma X_{it} + \lambda_i + \tau_t \quad (6)$$

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_t are time fixed effects. In this regard, we alternatively include basic year indicators. Among the control variables, we selected firm characteristics such as age ($\ln Age$), size ($\ln Emp$), assets per employee ($\ln Assetemp$) and cash flow per employee⁵ ($CFemp$).

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

The reference period are the pre-policy years 2013–2016. We apply augmented k-nearest neighbors matching with replacement based on the logit transformation of the estimated propensity score⁶ (LPS k-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 are constrained to be in the same 2-digit NACE industry of the respective treated firm. The set of covariates employed in the matching procedure includes: age ($\ln Age$), cash flow per employee ($CFemp$), and initial firm productivity (i.e., the earliest available instance of estimated log TFP in the pretreatment period). We then retain those firms that exist in the dataset during all periods and carry out the DiD regression applying the frequency weights.⁷ 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'Haultfœuille 2020). We therefore employ the heterogeneity-robust DiD estimator illustrated in De Chaisemartin and D'Haultfœuille (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 ($DiD_{leavers}$):

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

In Equation (7)

- j is the number of groups, that is, firms, and t is the number of periods;
- D_{jt} denotes the treatment dummy;
- N_s is the number of cells (j, t) that change treatment state from one period to another;

- $N_{1,0,t}$ is the number of cells (j, t) that change from untreated to treated (joiners);
- $N_{0,1,t}$ is the number of cells (j, t) that move from treated to untreated (leavers);
- $N_{1,1,t}$ is the number of cells (j, t) that remain treated from one period to another;
- $N_{0,0,t}$ is the number of cells (j, t) that remain untreated from one period to another;
- Y_{jt} is the outcome, TFP in our case.

5 | Results

5.1 | Total Factor Productivity

Figure 3 and Table 3 present the distribution of the estimated log TFP split for the treated and nontreated firms and normalized by removing the cluster-level mean. The left-hand side presents the pretreatment period and the right-hand side graph presents the posttreatment period.

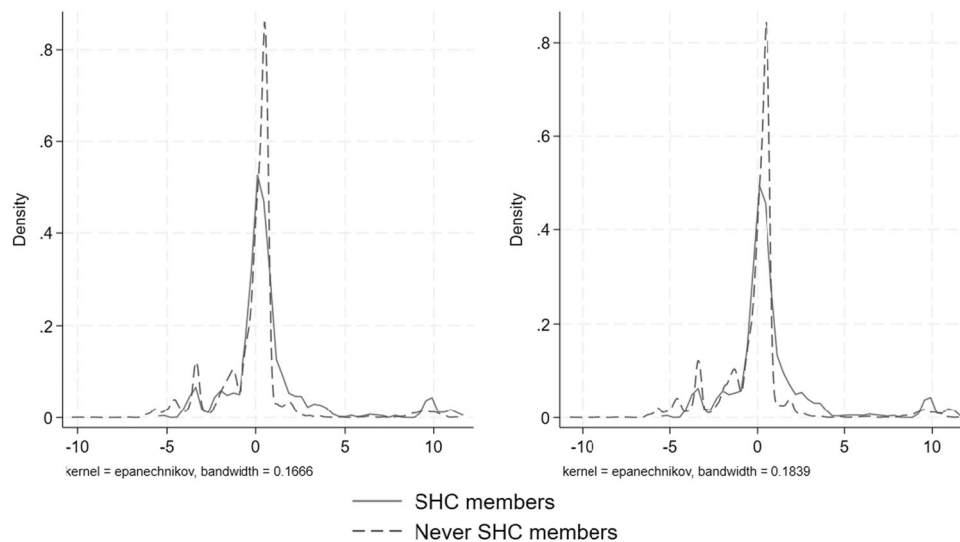


FIGURE 3 | K-density plot between treated and nontreated firms in the pretreatment period (left) and treatment period (right).

TABLE 3 | Summary statistics of estimated normalized Log(TFP).

Obs.	Mean	St. Dev.	p1	p5	p10	p25	p50	p75	p90	p99
Untreated firms, pretreatment period										
17,692	-0.072	2.258	-5.607	-3.695	-3.180	-0.565	0.222	0.557	0.756	9.758
Untreated firms, treatment period										
17,692	-0.065	2.281	-5.648	-3.696	-3.184	-0.564	0.230	0.561	0.775	9.849
Treated firms, pretreatment period										
1,612	0.727	2.726	-3.872	-3.279	-1.706	-0.231	0.283	0.863	2.893	10.904
Treated firms, treatment period										
1,612	0.778	2.751	-3.859	-3.254	-1.745	-0.194	0.302	1.013	2.984	10.956

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).

5.2 | Basic Difference-in-Difference

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 4%. We include a test on common trends among the treatment and control group by adding a dummy variable “evertreated” which is equal to 1 if the firm is at some point in time a cluster member. We then interact the dummy “evertreated” with pretreatment years to test the trends. The common trend test is satisfied for all years because neither of the interaction terms is statistically significant.

As alternative test for parallel trends assumption, we adopt the event study model of Schmidheiny and Siegloch (2023), whereby a number of leads of the treatment variable are added in the two-way fixed effects DiD regression. The resulting coefficients are then cumulated to retrieve the dynamic treatment effects for the pretreatment period.

TABLE 4 | Impact of Spearhead cluster membership on Log(TFP), basic DiD regressions.

	Baseline	Common trend test
treatSHC	0.046*** (0.011)	0.041*** (0.012)
evertreated × I(2016)		0.003 (0.008)
evertreated × I(2015)		−0.014 (0.010)
evertreated × I(2014)		−0.011 (0.007)
lnAge	−0.013 (0.021)	−0.012 (0.021)
lnAssetemp	0.254*** (0.018)	0.254*** (0.018)
CFemp/1,000,000	−0.361*** (0.054)	−0.360*** (0.054)
lnEmp	0.258*** (0.018)	0.258*** (0.018)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	38,608	38,608
Number of firms	4826	4826

Note: Standard errors clustered at firm level in parentheses.
*** $p < 0.01$.

In our setting, we consider three leads corresponding to the three pre-policy years, as well as four lags equal to the number of years of SHC program activity. Results suggest parallel trends assumption is validated, while the point estimate for the average dynamic treatment effect is 4.9% and statistically significant below 1% level (see Figure 4, Table 5).

5.3 | Conditional Difference-in-Difference

We address concerns about treatment selection bias by adopting the nearest neighbor matching technique based on logit propensity score as comparison metric (see Figure 5).

Table 6 includes the results for the unmatched sample (column 1) and the sample where the control group is established based on the distance between the logit propensity scores including 1 or 2 nearest neighbors (column 2 and 3), respectively. The positive impact of the cluster members reduces to 3%.

Figure 6 and Table 7 illustrate the Schmidheiny and Siegloch (2023) model estimates of dynamic treatment effects, using the matched firms as control group. The point estimates are slightly larger than in the full sample case, but the overall results are very similar.

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. The dynamic effect at the period -1 before entering the SHC program is normalized at zero, as commonly assumed in the event study literature (Miller 2023). Period 0 refer to the year the firms enter the cluster, then the following periods indicate the years of exposure to treatment.

The estimates on the full sample (see Figure 7, Table 8) provide a consistent positive ATET over the treatment period. The average dynamic effect across all treatment years is 4.3% and statistically significant at the 1% level. Being a member of a Spearhead cluster for more than 3 years is related to an increase in productivity equal to 11.1%. The pretreatment placebo tests are not significantly different from zero, and thus confirm statistically equal pre-trends between treated and untreated units. It is worth noticing, moreover, how the results from Schmidheiny and Siegloch (2023) model above are almost identical, suggesting that heterogeneity of treatment effects across firms and time does not have important effects and does therefore not jeopardize the validity of basic DiD estimates in our setting.

As additional consistency check, we estimate the staggered DiD estimator considering the constructed control group according to the LPS 2-NN matching (see Figure 8). The results are greatly similar compared to those for the full sample in Figure 5, except

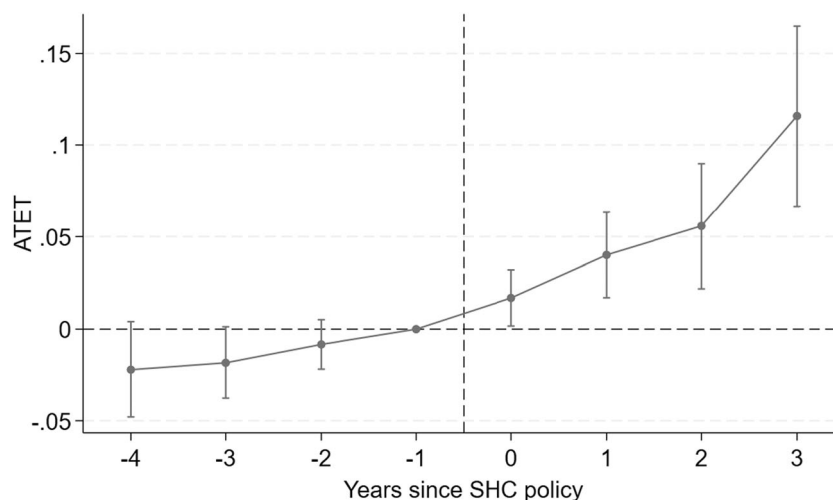


FIGURE 4 | Schmidheiny and Siegloch (2023) event study model estimates with 95% CI.

TABLE 5 | Schmidheiny and Siegloch (2023) event study model estimates.

Exposure to treatment	Coefficient	Standard errors
-4	-0.022	0.013
-3	-0.018	0.010
-2	-0.008	0.007
-1	0	
0	0.017***	0.008
1	0.040***	0.012
2	0.056***	0.017
3	0.116***	0.025
Average total effect	0.049***	0.012
Controls		Yes
Observations		38,608
Number of firms		4,826

Note: Standard errors clustered at firm level.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

TABLE 6 | Impact of Spearhead cluster membership on Log(TFP), conditional DiD regressions.

	Unmatched (1)	LPS 1-NN (2)	LPS 2-NN (3)
treatSHC	0.039*** (0.012)	0.031** (0.016)	0.036** (0.016)
evertreated × I(2016)	0.009 (0.011)	0.01 (0.014)	0.008 (0.013)
evertreated × I(2015)	-0.012 (0.013)	-0.007 (0.016)	-0.008 (0.015)
evertreated × I(2014)	-0.012* (0.007)	-0.018 (0.012)	-0.013 (0.010)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	38,608	4808	6920
Number of firms	4826	565	755

Note: Standard errors clustered at firm level in parentheses.

* $p < 0.01$; ** $p < 0.05$; *** $p < 0.10$.

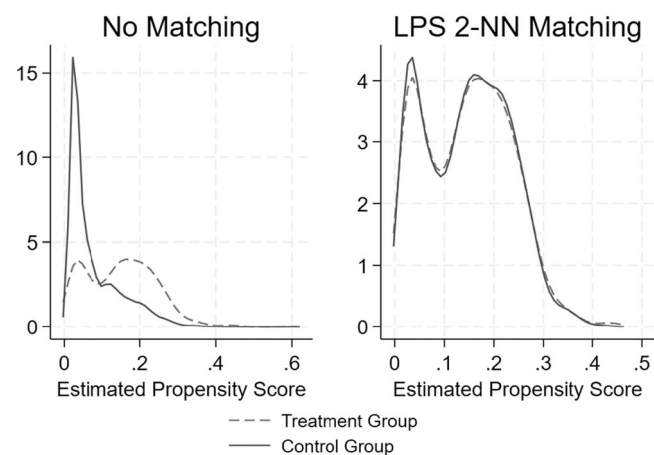


FIGURE 5 | Matching results.

for the loss of statistical significance due to the reduced sample size. The average total effect is 4.2% with 6106 observations, that is, the results are robust.

5.5 | Robustness Checks and Mechanism Analysis

5.5.1 | Estimation Results for a Small and Medium-Sized Versus Large Firms

As first robustness check, we split the sample into small and large firms to assess how the policy effectiveness varies with firm size (see Figures 9 and 10). Small (large) firms are

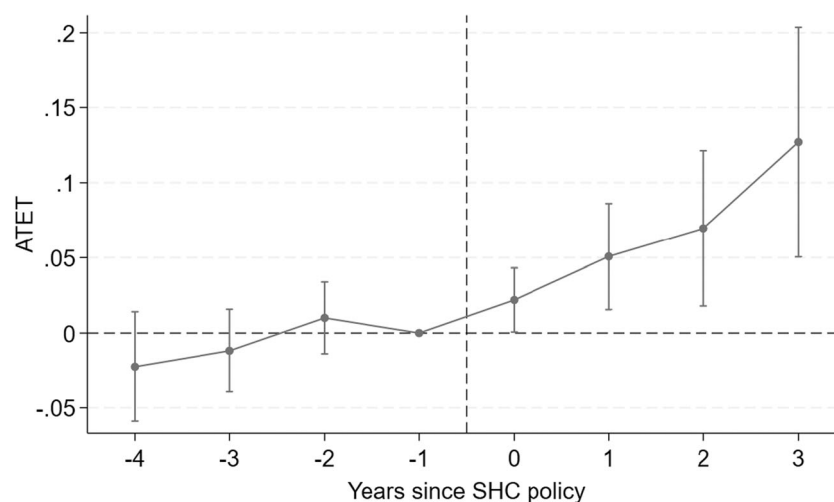


FIGURE 6 | Schmidheiny and Siegloch (2023) event study model estimates with 95% CI, LPS 2-NN matching.

TABLE 7 | Schmidheiny and Siegloch (2023) event study model estimates, LPS 2-NN matching.

Exposure to treatment	Coefficient	Standard errors
−4	−0.022	0.019
−3	−0.012	0.014
−2	0.010	0.012
−1	0	
0	0.022**	0.011
1	0.051***	0.018
2	0.070***	0.026
3	0.127***	0.039
Average total effect	0.051***	0.017
Controls		Yes
Observations		6920
Number of firms		755

Note: Standard errors clustered at firm level.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

enterprises 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 pretreatment period and a significant positive dynamic effect in the posttreatment period. The ATET averaged across all treatment years is 4.3% for the SME subsample, and 4.2% for the large firms subsample, but 95% confidence intervals mostly overlap. Consequently, the effect heterogeneity driven by firm size appears negligible.

5.5.2 | Mechanism Analysis

To test whether spillover effects could be the channel that lead to productivity gains, we hypothesize that spillovers traditionally reduce as the distance between firms increases. We have therefore retrieved geographical coordinates (longitude, latitude) from firm addresses, then computed the aerial distance

in kilometers between each firm within the same cluster group. The average of distances weighted by number of firms within the same cluster is used as measure of geographical proximity. The average distances among the cluster members vary considerably. The most central firm is a member of the logistics cluster and has an average distance to its other cluster members of 33.2 km. The most “isolated” firm is also in the logistics cluster with an average distance of 118.7 km to its other cluster members. The differences among the clusters is relatively small though. The minimum distances among members range between 33.2 km (logistics cluster) and 46.7 km (materials cluster) and the maximum ranges between 107 km (materials cluster) and 118.7 km (logistics cluster).

Given that the treatment effect heterogeneity across units and periods turned out to be not relevant, we employ a basic DiD regression model where we add the interaction term of the treatment with the average distances (AvgDist) to assess whether geographical clustering affects the impact of the program. We do find that proximity boosts SHC policy effectiveness at the 5% significance level: the TFP increases by 0.2% for each km the firm is closer on average to its other cluster members (Table 9). We also calculated the marginal effects over the range of the distances. The “breakeven point” is at 67.1 km which conforms to the 72th percentile of the distance distribution. Any distance above completely offsets the beneficial policy effects at the 5% significance level. In other words, the most “isolated” 28% of cluster members do not gain from the policy. This suggests the presence of spillover effects that reduce with increasing distance.

In our final robustness test, we control for other public support that firms have received from the Flemish government. The other subsidies are R&D grants that are distributed as a result of a competitive peer review process of submitted R&D project proposals by firms (see Czarnitzki and Lopes-Bento 2013, for a detailed analysis of the subsidies treatment effects on R&D in Flanders). This analysis is conducted to rule out that the cluster benefits are confounded with the presence of financial support from the government. We add a dummy variable “Other subsidies” to the regression that takes the value 1 when a firm got an R&D grant in the corresponding year and is zero otherwise. 318 out of 4826 firms in our sample received such an R&D grant.

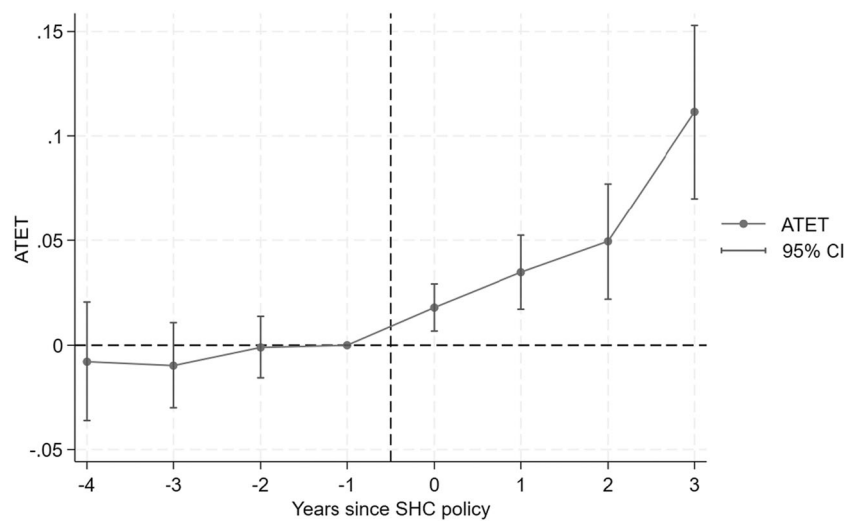


FIGURE 7 | De Chaisemartin and D'Haultfœuille (2020) DiD estimates.

TABLE 8 | De Chaisemartin and D'Haultfœuille (2020) DiD estimates.

Exposure to treatment	Coefficient	Standard errors	Observations
−4	−0.008	0.014	9,168
−3	−0.010	0.010	13,753
−2	−0.001	0.008	13,981
1	0		
0	0.018***	0.006	13,981
1	0.035***	0.009	13,753
2	0.049***	0.014	9,168
3	0.111***	0.021	4,598
Average total effect	0.043***	0.009	41,500
Controls	Yes		

Note: Standard errors clustered at firm level.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

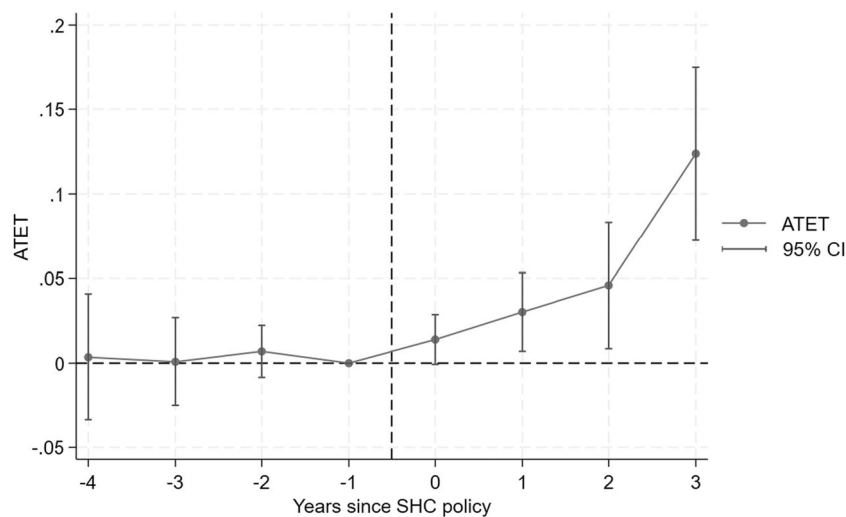


FIGURE 8 | De Chaisemartin and D'Haultfœuille (2020) DiD estimates, LPS 2-NN matching.

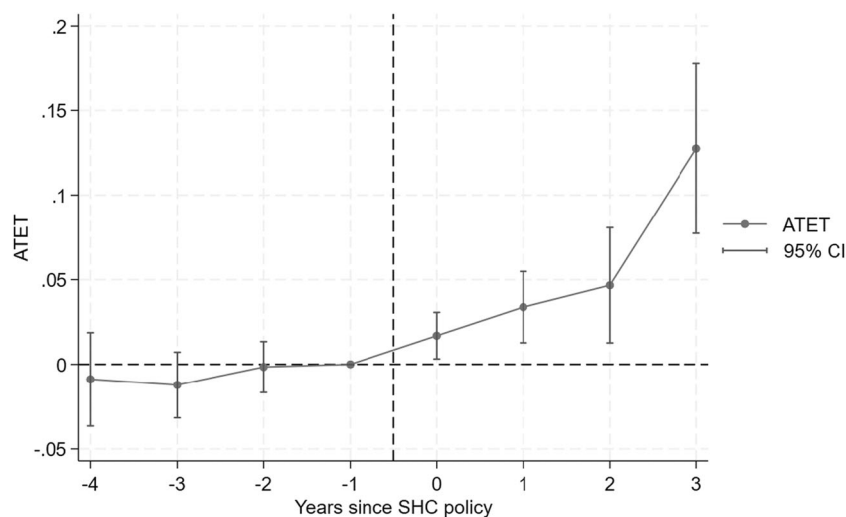


FIGURE 9 | De Chaisemartin and D'Haultfœuille (2020) DiD estimates, SMEs.

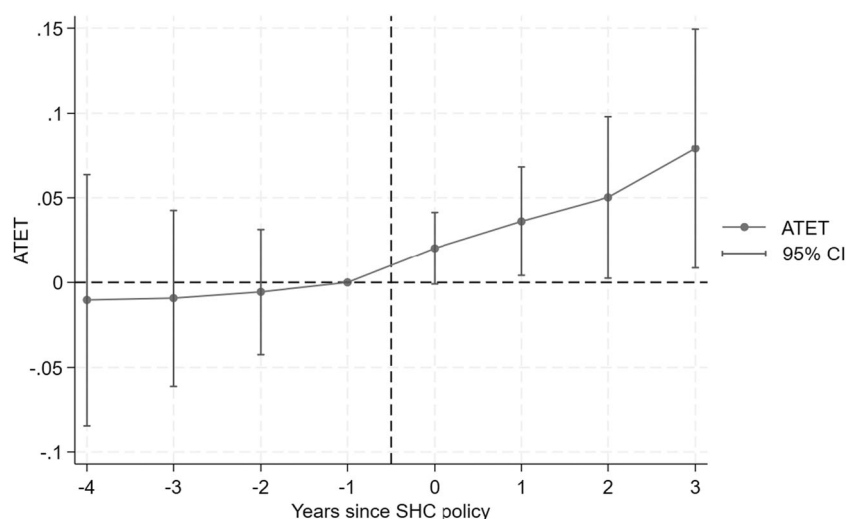


FIGURE 10 | De Chaisemartin and D'Haultfœuille (2020) DiD estimates, Large firms.

TABLE 9 | Spearhead cluster policy and geographical proximity, basic DiD regression.

treatSHC	0.133*** (0.043)
treatSHC × AvgDist	−0.002** (0.001)
Controls	Yes
Firm FE	Yes
Year FE	Yes
Observations	38,424
Number of firms	4803

Note: Standard errors clustered at firm level in parentheses.

** $p < 0.05$; *** $p < 0.01$

TABLE 10 | Spearhead cluster policy and other subsidies, basic DiD regression.

treatSHC	0.046*** (0.011)
Other Subsidies	0.007 (0.008)
Controls	Yes
Firm FE	Yes
Year FE	Yes
Observations	38,608
Number of firms	4826

Note: Standard errors clustered at firm level in parentheses.

*** $p < 0.01$.

As can be seen in Table 10, our results regarding the cluster policy remain robust with an estimated treatment effect of a 4.6% productivity increase. The subsidy dummy is not statistically significant.

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 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 database on cluster membership and (iii) we apply state-of-the-art econometrics to calculate the TFP which to the best of our knowledge has not been applied to Belgian data before.

For this study, we could rely on 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 TFP estimated in line with the latest insights of Gandhi et al. (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 between 3.1% and 5.1% depending on the method used. When taking into account the staggered treatment in the way proposed by De Chaisemartin and D'Haultfœuille (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 is around 4.3% and there is no significant impact heterogeneity driven by size. A mechanism analysis suggests that the beneficial cluster effects are not driven by monetary public support (R&D grants). Instead we find evidence for knowledge spillovers because the positive treatment effects are negatively moderated by an increasing aerial distance of the focal firm to its other cluster members.

The evidence of a 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% respectively after 4 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 in our sample cover the year 2020. In addition, some cluster initiatives already had a predecessor as some sectoral R&D associations already existed under a previous policy instrument. Unfortunately we do not have information on the membership in these prior structures, and can therefore not account for these. 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 and so on. In our analysis we also do not account for spill-over effects of member firms to non-member firms within the same sector.

Endnotes

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

²Inconsistencies can include: typos in the VAT numbers, duplicates, changes in VAT numbers due to M&A activities, and so on.

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

⁴The 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.

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

⁶Lopez and Gutman (2017) reports that matching on logit propensity score provides smaller balancing biases.

⁷These 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 nontreated firm is a match. Higher values are given if the same firm is matched more with multiple treated firms.

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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 five 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:

$$S\left(\frac{\partial}{\partial m_{it}}f(l_{it}, k_{it}, m_{it})\right) = \sum_{0 \leq \tau_k + \tau_l + \tau_m \leq 2} \gamma'_{\tau_k, \tau_l, \tau_m} k_{it}^{\tau_k} l_{it}^{\tau_l} m_{it}^{\tau_m} \quad (A1)$$

$$C(l_{it}, k_{it}) = \sum_{0 \leq \tau_k + \tau_l \leq 2} \alpha_{\tau_k, \tau_l} k_{it}^{\tau_k} l_{it}^{\tau_l} \quad (A2)$$

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:

$$\ln TFP_{it} = \sum_{0 < a_{\omega} + a_{SHC} \leq 2} \delta_{a_{\omega}, a_{SPC}} \ln TFP_{it-1}^{a_{\omega}} treatSHC_{it}^{a_{SHC}} + \xi_{it} \quad (A3)$$

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

$$\begin{aligned} \hat{y}_{it} = & \sum_{0 < a_{\omega} + a_{SHC} \leq 2} \delta_{a_{\omega}, a_{SPC}} \left(\hat{y}_{it-1} + \sum_{0 < \tau_k + \tau_l \leq 2} \alpha_{\tau_k, \tau_l} k_{it-1}^{\tau_k} l_{it-1}^{\tau_l} \right)^{a_{\omega}} treatSHC_{it}^{a_{SHC}} \\ & - \sum_{0 < \tau_k + \tau_l \leq 2} \alpha_{\tau_k, \tau_l} k_{it}^{\tau_k} l_{it}^{\tau_l} + \xi_{it} \end{aligned} \quad (A4)$$

The moments employed for GMM estimation stay the same:

$$\begin{aligned} E\left[\xi_{it} k_{it}^{\tau_k} l_{it}^{\tau_l}\right] &= 0 \\ E\left[\xi_{it} \hat{y}_{it-1}^a\right] &= 0 \end{aligned} \quad (A5)$$

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

$$\ln TFPfe_{it} = \delta_{\omega} \ln TFPfe_{it-1} + \delta_{SPC} treatSHC_{it} + \xi_{it} \quad (A6)$$

It is worth reminding that the Markov process must be linear 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:

$$\begin{aligned} \hat{y}_{it} - \hat{y}_{it-1} = & - \sum_{0 < \tau_k + \tau_l \leq 2} \alpha_{\tau_k, \tau_l} k_{it}^{\tau_k} l_{it}^{\tau_l} + \delta(y_{it-1} - y_{it-2}) \\ & + (\delta_{\omega} + 1) \left(\sum_{0 < \tau_k + \tau_l \leq 2} \alpha_{\tau_k, \tau_l} k_{it-1}^{\tau_k} l_{it-1}^{\tau_l} \right) \\ & - \delta_{\omega} \left(\sum_{0 < \tau_k + \tau_l \leq 2} \alpha_{\tau_k, \tau_l} k_{it-2}^{\tau_k} l_{it-2}^{\tau_l} \right) \\ & + \delta_{SPC} (treatSHC_{it} - treatSHC_{it-1}) + (\xi_{it} - \xi_{it-1}) \end{aligned} \quad (A7)$$

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

$$\begin{aligned} E\left[(\xi_{it} - \xi_{it-1}) k_{it-1}^{\tau_k} l_{it-1}^{\tau_l}\right] &= 0, \text{ for } t \geq 1 \\ E\left[(\xi_{it} - \xi_{it-1}) \hat{y}_{it-1}^a\right] &= 0, \text{ for } t \geq 2 \end{aligned} \quad (A8)$$

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

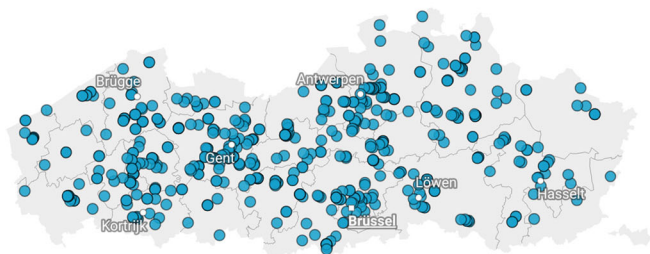
TABLE A2 | Cluster grouping.

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

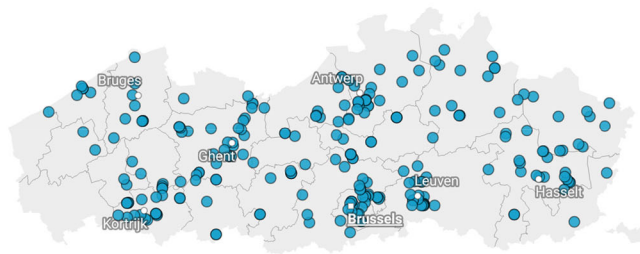
Location of Cluster Members

Food cluster



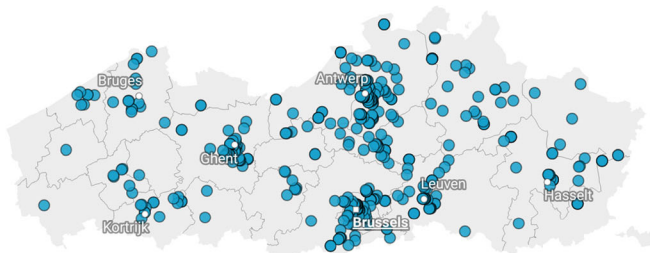
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Materials cluster



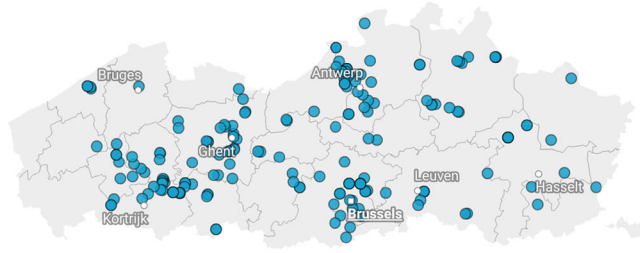
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Energy cluster



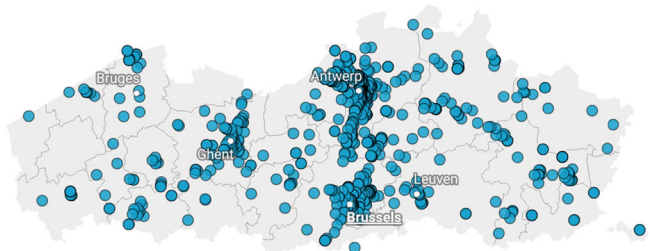
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Chemicals/plastics cluster



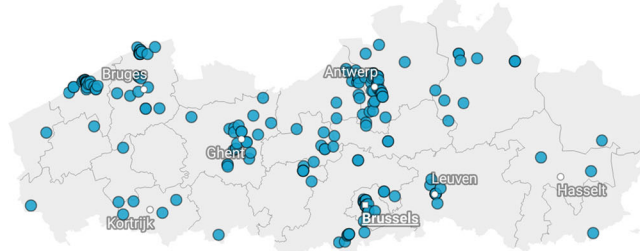
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Logistics cluster



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Blue economy cluster



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