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ORIGINAL ARTICLE

The effects of a large industrial investment on employment in a remote and sparsely populated area using a synthetic control approach

Evans Korang Adjei[1] | Rikard Eriksson[1] | Johan Lundberg[2]

[1]Department of Geography and Centre for Regional Science (CERUM), Umeå University, Umeå, Sweden

[2]Department of Economics and Centre for Regional Science (CERUM), Umeå University, Umeå, Sweden

Correspondence
Johan Lundberg, Umeå School of Business, Economics and Statistics (Department of Economics) and Centre for Regional Science (CERUM), Umeå University, Umeå, Sweden.
Email: johan.lundberg@umu.se

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Abstract

This article examines the impact of establishing a large industrial manufacturing entity on employment and the labor market in a remote, sparsely populated part of Sweden, focusing on how it affects total regional employment because industrial policies aiming to attract investment and reignite employment in stagnating regions have been a central policy tool. The empirical analysis is based on the synthetic control method, which enables the estimation of place-specific causal effects. Using aggregated microdata from 1995 to 2019, the results indicate that employment in the treated region, as compared to synthetic regions, has been negatively affected by the manufacturing establishment. However, the short- and long-term effects differ across different labor market segments (same, related, and unrelated industries) and according to firm size. Overall, the findings suggest that large manufacturing investment does not necessarily have a positive or instantaneous impact on total regional employment. It does, however, provide some potential for long-term diversification because employment in related activities grows in the long run.

KEYWORDS

employment, large industrial investment, remote and sparsely populated areas, synthetic control method

JEL CLASSIFICATION
C12, C54, D22, R11, R12, R58

1 | INTRODUCTION

After decades of disinvestment and population decline, several areas of northern Sweden are now attracting large-scale industrial investments, such as wind farms, battery factories, and underground mines. The Norrbotten and Västerbotten Chambers of Commerce have estimated that the area will receive close to SEK 1000 billion in new investments over the next two decades. If realized, the region will need an estimated 100,000 additional inhabitants in the next ten years to meet the anticipated increased demand for labor, a population growth of about 20% (Larsson, 2022). A large share of these jobs will be created in the manufacturing industry. Such large investment relative to the regional economy is expected to have a long-term positive effect on regional employment, but large investment could also crowd out incumbent activities. Depending on the existing industrial structure, the path-dependent character of investments may hinder rather than facilitate regional development. However, there is scant knowledge of the effects of a relatively large industrial investment on employment, especially in sparsely populated areas, perhaps because such investments are extremely rare and therefore not easily analyzed using standard econometric techniques that require several treated regions.

Although industrial investments of the magnitude described above do not occur very often, it is possible to learn from the effects of previous—though in absolute terms smaller—industrial investments in small and remote labor markets. This article analyzes the effects of a relatively large industrial expansion in the manufacturing industry on employment. This expansion took place in a remote and sparsely populated area of Sweden in 2004 and created approximately 300 new jobs (accounting for roughly 4.9% of regional employment that year). Typically, the regional effects of a labor-demand shock are analyzed using the multipliers an investment may bring to the region in relation to growth and/or decline in other activities (Moretti, 2011). It is fairly well established that the skill content of new jobs typically produces greater regional multipliers (Moretti & Thulin, 2013). However, the literature seldom considers the role of broader regional endowments. In one of the few exceptions, Giroud et al. (2021) showed that large and densely populated regions are more likely to benefit from large investments than are smaller regions due to the diversity of actors and the presence of multilocational firms. Similarly, Greenstone et al. (2010) found that the arrival of a 'million-dollar plant' in large agglomerations increases the total factor productivity of incumbent plants that share workers and use similar technologies. This raises the question of whether small and peripheral regions benefit from large establishments and if they should even compete for large industrial investments.

The article estimates whether and to what extent this investment affected employment in the region. Because an expansion in one part of the local economy could spread unevenly, total employment is classified into same and related industries, building on the premise that local sourcing of skills is dependent on the embeddedness of the entry into skill-related activities (Neffke & Henning, 2013). This also allows us to scrutinize whether or not a large industrial investment can spark a new development path by allowing the region to branch into related activities (cf. Neffke et al., 2018). The focus on investment in the manufacturing industry is motivated by the fact that local policymakers, especially in declining and sparsely populated areas, often aim for these types of investments to increase employment and secure a local tax base. Furthermore, planned investments in the north of Sweden are mainly in the manufacturing industry and, in many cases, target the same type of labor.

To address this, the synthetic control method (SCM), first introduced by Abadie and Gardeazabal (2003) and later elaborated upon by Abadie et al. (2010, 2015), is used to estimate causal place-specific effects. SCM also allows a discussion of both short- and long-term effects, which are relevant when analyzing the regional effects of this type of investment. The analysis is based on aggregated microdata covering Swedish functional labor markets from 1995 to 2019 provided by Statistics Sweden (SCB). The remoteness of the treated area makes it well suited to this type of analysis as potential influences from other regions are unlikely.

The findings suggest that the investment actually had a dampening effect on total regional employment compared to the synthetic control group. This panned out differently in different segments, however, as employment in the same and related activities initially declined and then grew over time. The latter mainly concerns activities related to the focal industry that presumably share similar competencies. This signals the difficulties of managing a large demand shock in economic peripheries due to local poaching but also that there is a potential for (related) diversification in the longer run.

This article contributes not only to the existing literature on the regional effects of industrial investment but also to the policy discussion regarding the effects of large industrial investment on employment. We complement previous studies on multipliers (e.g., Moretti, 2011) by applying SCM to estimate place-specific, rather than average, casual effects, something that has not—to our knowledge—been done within this body of literature before. Moreover, the regional effects of a labor demand shock in small and remote areas are neglected in research but highly relevant from a policy perspective since ways of stimulating growth in peripheral and often 'left behind places' are high on the policy agenda (OECD, 2018; Pike et al., 2023). This is especially the case in the Swedish context, where local governments in the north compete for green industry investments, while the returns on public investment in infrastructure depend on the total and delineated employment effects.

The rest of this article is organized as follows: a brief background and literature review are provided in Section 2, followed by a presentation of the econometric approach in Section 3. The dataset is described in Section 4, followed by the results and concluding remarks in Sections 5 and 6, respectively.

2 | BACKGROUND AND LITERATURE REVIEW

The general long-run equilibrium models developed by Rosen (1979) and Roback (1982), later summarized and elaborated by Moretti (2011), are frequently used as a point of departure when analyzing endogenous adjustments of factor prices and quantities resulting from a labor demand shock. These models rest on the assumptions that (1) each location can be characterized as a competitive economy that produces a single traded good using labor, land, and local amenities with a constant return-to-scale technology; (2) the indirect utility of workers depends on nominal wages, the cost of housing, and local amenities; (3) each worker provides one unit of labor, and labor is homogenous in skills and taste; (4) labor is perfectly mobile, and the labor supply is very elastic; and (5) land is an immobile factor with a fixed supply (see Glaeser, 2008; Glaeser & Gottlieb, 2008). However, the general applicability of these models on specific local labor markets is limited. For instance, small and peripheral regions tend to be characterized as monopsonies (one or a few very large, dominating employers). In the short run, with limited in-migration and low unemployment, greater demand for labor may lead to the poaching of existing labor and higher wages that, in turn, may crowd out existing firms.

More detailed insights into the local effects of large investments can be given following the Canadian regional science tradition, particularly regarding the staple thesis. Innis (1933, 1956), for example, claimed that a staple resource-based development implies an economic injection into the periphery and a possibility to utilize, in that case, a natural resource as a nucleus for the further development of civic society and the diversification of the labor market. However, critics later highlighted that such export-led regional development seldom occurred (Gunton, 2003) and that local control of production remained low (Hayter, 2003), hence, locking in peripheral single-industry towns in a development path that is highly vulnerable to structural change. Similar processes have been identified by (for example) Green et al. (2021), who found that firms in a manufacturing-oriented region, like Birmingham, are confined in a low-wage trap, as their position in the global value chain provides limited scope for upgrading. This, in turn, implies that the path-dependent character of investments may hinder rather than facilitate regional development.

Consequently, it is no surprise that previous empirical studies have shown mixed results regarding the local effects of large investments. Giroud et al. (2021) demonstrated that the opening of a new 'million-dollar plant' raised the productivity of incumbent plants by about 4%, but the benefits were unevenly distributed, with highly populated areas benefitting the most (see also Greenstone et al., 2010). Focusing on Walmart, Neumark et al. (2008) found that an entry resulted in a 2.5% decrease in county-level retail employment and a 1.5% reduction in retail earnings, while Basker (2005) showed that an entry increases employment in the year of entry, but half of these employment gains disappear over the next five years as other retail establishments contract (see also Basker, 2007; Hicks, 2007, 2008; Jia, 2008 for Walmart's additional entry effects). In a Swedish context, Daunfeldt et al. (2017) found that IKEA's entry into some municipalities increased employment by about 17%, while Rudholm et al. (2022) showed mixed regional effects, in which smaller regions generally benefitted more from an IKEA establishment than larger regions (see also Håkansson et al., 2019).

Thus, these accounts all point to the fact that the real effects of investments cannot be assessed through average multipliers as is often assumed in the literature. Instead, the specific geography and region-specific endowments influence the impact of large investments. For example, when a new firm enters a new market, it affects the local market's structure and primarily local firms operating in the same and related industries (Gourio et al., 2016), especially if the entrant is large and part of a conglomerate (and thus relatively resourceful) (Neffke et al., 2018). On the surface, we may assume that new large firms significantly increase employment and wages as well as the sharing of knowledge and skilled labor. This line of thought can be traced to the agglomeration literature and the externalities of sharing, matching, and learning (see Duranton & Puga, 2004). However, new large firms can also introduce challenges, such as increased competition for labor, increased pressure on wages and rent, and endangering a competitive economic landscape. Although a large firm entering a region may initially poach from other local firms, it is expected to increase the supply of labor in the long run, which can negatively affect wages and inversely affect rent.

For successful development, the degree to which workers in existing (or declining) activities can partake in new and developing activities is of central importance (Andersson et al., 2020). This is because structural change in the economy is closely linked to the redistribution of jobs between occupations, industries, and regions, and the ability to attract and retain workers and jobs (Eriksson et al., 2016; Martynovich & Lundquist, 2016). However, as noted at the beginning of this section, the standard models often assume that labor is perfectly mobile and that the supply of labor is very elastic. This is seldom the case in the real economy; both are influenced by both the location (or distance to workers) and the type of firm. The literature discussing the regional impact of different types of entrants provides some insights into the potential labor market channels at play by describing two main types of entrants: firms that locate where industry is relatively underdeveloped or even absent (pioneer firms), and firms that locate where the specific industry is well-represented (cluster firms). Using these typologies, Hausmann and Neffke (2019) showed that, in Germany, pioneers are more likely to hire experienced workers from outside the region and were confined to sourcing local workers without previous industry experience. Pioneer firms are also more likely to hire a greater share of previously unemployed workers. This is an indication of the difficulty associated with hiring more experienced workers in pioneer regions due to the relative shortage of suitable skills but also that the demand shock requires recruitment in new domains among more peripheral labor market segments (see Coad et al., 2014 for similar findings on demand shocks in relation to high-impact firms). On the other hand, the literature on industrial clusters clearly shows that competition for market shares and labor is high in localized clusters (Delgado et al., 2010; Eriksson et al., 2008), implying that there is a risk of skills-poaching in the case of a cluster entry if the new firm can offer higher wages than the existing local firms (Combes & Duranton, 2006). In cases when the entry is more embedded in the region, local firms in similar and related industries employing workers with overlapping skills could be adversely affected by a new entry, especially if they already have problems sourcing skilled labor. In essence, this could hamper a region's long-term development and resilience when the necessary related diversity disappears (Eriksson & Hane-Weijman, 2017). Conversely, the entry could also trigger a related diversification by reinforcing the cohesiveness of the regional capability base (Neffke et al., 2018). Thus, the outstanding question, which the subsequent sections address, is whether a large entry influences employment creation in other local firms or whether it leads to crowding-out effects, and which segments of the regional economies are affected.

3 | ECONOMETRIC APPROACH

The synthetic control method (SCM) has recently grown in popularity. The method was first developed by Abadie and Gardeazabal (2003) and then elaborated upon by Abadie et al. (2010, 2015). SCM has been used for comparative studies in different disciplines, for example, management (Birdsall, 2015), tourism (Belleville & Jolley, 2022), and economic history and economic development (Cavallo et al., 2013; Gilchrist et al., 2022; Hall et al., 2020; Mughan & Propheter, 2017). Like the widely used difference-in-difference (DiD) technique, the basic idea behind SCM is to estimate the treatment effect as the difference in the outcome variable of interest between the treated unit (region) and a counterfactual untreated region. The counterfactual region is created by weighing potential control regions, that is, untreated regions, such that the outcome of the control region and relevant covariates before the treatment have trajectories similar to those of the treated region. The weighted averages of the untreated regions are then used to construct a synthetic counterfactual for the post-treatment period. The observed post-treatment outcome for the treated region is then compared to its synthetic counterfactual. Statistical inference and the robustness of the treatment effect are often based on the placebo testing suggested by Abadie et al. (2010, 2015) and Gilchrist et al. (2022), respectively.

To fix ideas, let y_{it}^{NI} be the outcome of interest that would be observed for region $i=1,\ldots,N$ at time $t=1,\ldots,T$ in the absence of treatment. Region 1 is the only treated region. Let T_0 be the number of pre-treatment periods with $1 \le T_0 < T$ and let y_{1t}^{I} be the observed outcome for region $i=1$ in periods T_0+1 to T after being exposed to some treatment in period T_0. Assume the treatment has no effect on y before the treatment such that $y_{it}^{NI}=y_{it}^{I}$ for $t\in\{1,\ldots T_0\}$ and $i\in\{1,\ldots,N\}$. It is further assumed that the outcome of the non-treated regions (or donors), $i\in\{2,\ldots,N\}$, is unaffected by the outcome of the treated region. Denote by d_{it} an indicator of treatment where $d_{it}=1$ for $i=1$ and $t>T_0$, the observed outcome for region i at time t is

$$y_{it}=y_{it}^{NI}+\left(y_{it}^{I}-y_{it}^{NI}\right)d_{it}=y_{it}^{NI}+\alpha_{it}d_{it} \tag{1}$$

The aim is to estimate the treatment effect, $\widehat{\alpha}_{1t}$, for $t>T_0$. From Equation (1), for $d_{1t}=1$, $\alpha_{1t}=y_{1t}^{I}-y_{1t}^{NI}$, and $y_{1t}=y_{1t}^{I}$. As y_{1t}^{I} is observed, the challenge is to estimate the unknown y_{1t}^{NI}, the untreated outcome for region 1 for $t>T_0$. In principle, the pre-treatment period is used as a training period to assess the predicted power on y_{1t}^{NI} of some covariates using the pre-treatment period as a training period.

If y_{it}^{NI} is given by the factor model

$$y_{it}^{NI}=\delta_t+\boldsymbol{\theta}_t\boldsymbol{z}_i+\boldsymbol{\lambda}_t\boldsymbol{\mu}_i+\varepsilon_{it};\ i\in\{2,\ldots,N\} \tag{2}$$

where δ_t is a common factor, $\boldsymbol{z}_i$ contains observed covariates not affected by the treatment, $\boldsymbol{u}_i$ is a vector of unobserved common factors, ε_{it} is an error term with the usual properties, $\boldsymbol{\theta}_t$, and $\boldsymbol{\lambda}_t$ contains unknown parameters and factor loadings. Then, the challenge is to find weights w such that:

$$\sum\nolimits_{i=2}^{N}w_i y_{it}=\delta_t+\boldsymbol{\theta}_t\sum\nolimits_{i=2}^{N}w_i\boldsymbol{z}_i+\boldsymbol{\lambda}_t\sum\nolimits_{i=2}^{N}w_i\boldsymbol{\mu}_i+\sum\nolimits_{i=2}^{N}w_i\varepsilon_{it} \tag{3}$$

Suppose we find w_j^* such that $\sum\nolimits_{i=2}^{N}w_i^* y_{it}=y_{1t}\ \forall\, t\in\{1,\ldots T_0\}$ and $\sum\nolimits_{i=2}^{N}w_i^*\boldsymbol{z}_i=\boldsymbol{z}_1$, then

$$\widehat{\alpha}_{1t}=y_{1t}-\sum\nolimits_{i=2}^{N}w_i^* y_{it} \tag{4}$$

is a potential estimator of the treatment effect for $t\in\{T_0+1,\ldots,T\}$.

For estimation, denote by $\boldsymbol{x}_1$ a vector of k pre-treatment characteristics of the treated region, and by $\boldsymbol{X}$ a matrix of the same characteristics for the non-treated regions where $\boldsymbol{x}_1$ and $\boldsymbol{X}$ may include pre-treatment values of y.[1] To

[1]Note that $\boldsymbol{X}$ and $\boldsymbol{X}_1$ may include fixed effects, which allow for unobserved time-invariant heteroscedasticity. The factor model employed by SCM generalizes this to allow for the existence of nonparallel trends between the treated and untreated regions after controlling for observables.

construct the synthetic control region, choose a vector $\boldsymbol{w}^* = (w_2^*,\ldots,w_N^*)'$, $\sum_2^N w_i^* = 1$; $w_i^* \geq 0$ to minimize the distance $\boldsymbol{x}_1 - \boldsymbol{X}\boldsymbol{w}$, which can be done using constrained quadratic optimization. Following Abadie and Gardeazabal (2003) and Abadie et al. (2010), let x_{m1} and $x_{m2},\ldots,x_{mN}$ be the value of the m-th variable for the treated (region 1) and non-treated regions (regions 2 to N) respectively, $\boldsymbol{w}^*$ is chosen to minimize

$$\|\boldsymbol{x}_1 - \boldsymbol{X}\boldsymbol{w}\| = \sqrt{\sum\nolimits_1^k v_m (x_{m1} - w_2 x_{m2} \text{-} \ldots \text{-} w_N x_{mN})^2} \tag{5}$$

where v_m reflects the relative importance assigned to the m-th variable in this minimization. Typically, v is selected to weight covariables in accordance with to their predictive power on the outcome. Given $(w_2^*,\ldots,w_N^*)$, the treatment effect is estimated in accordance with Equation (4).

To evaluate the post-treatment relative to the pre-treatment fit, the root mean squared prediction error (RMSPE) developed by Abadie et al. (2010) is used. For $0 \leq t_1 \leq t_2 \leq T$ and $i \in \{1,\ldots,N\}$, let

$$R_i(t_1,t_2) = \sqrt{\left(\frac{1}{t_2 - t_1 + 1}\sum\nolimits_{t_1}^{t_2}\left(y_{it} - \hat{y}_{it}^{NI}\right)^2\right)} \tag{6}$$

where $\hat{y}_{it}^{NI}$ is the predicted outcome on period t produced by the synthetic control. Then,

$$r_i = \frac{R_i(T_0+1,T)}{R_i(1,T_0)} \tag{7}$$

measures the quality of the fit of a synthetic control for region i in the post-treatment period relative to the quality of the fit in the pre-treatment period. For inference, the permutation distribution of r_i is used.

Some of the assumptions underlying the validity of SCM in providing a plausible causal inference and interpretation of the impacts of the treatment merit special attention. First, as pointed out by Xu (2017), the treatment at the time of its implementation must be independent of the outcome of interest in the pre-treatment period. In other words, the treatment should have no prior impact on the outcome of interest because if it does, it is unlikely to produce a plausible representation of the impact of the treatment. Second, the donor pool of regions must not be exposed to the same treatment as the treated region, at least during the same study period. As recommended by Cao and Dowd (2019), regions in the donor pool exposed to the same or similar treatment are excluded to isolate the impact of the treatment on the treated region. Third, the spatial correlation between the treated region and the regions within the donor pool should be zero. This holds for both the outcome variable and the covariates.

When these assumptions are satisfied, SCM offers several advantages. First, SCM does not rely on the parallel trend assumption necessary for DiD estimation, an assumption not easily verified. Second, SCM requires only one treated unit, making it possible to estimate region-specific causal effects in contrast to average effects. Third, as pointed out by Birdsall (2015), SCM offers an intuitive and transparent way to construct the counterfactual outcome and, based on this, to estimate the treatment effect. Fourth, SCM enables a discussion of both short- and long-term effects. Finally, one important key advantage of SCM is in dealing with the problem of endogeneity from omitted variable bias due to the presence of unobserved time-invariant and time-varying factors that may affect the outcome variable (Abadie et al., 2010, 2015). According to Abadie et al. (2015), unlike fixed effects and DiD, SCM helps control for both observed and unobserved time-varying and time-invariant factors affecting the outcome variable by matching pre-treatment outcomes.

Unlike most regression methods, the traditional inferential techniques for assessing statistical significance are not possible in SCM. Furthermore, because the inference in SCM is based on a single treated region and in the absence of randomization (or because the treatment in question is not randomly assigned per se), statistical inference becomes a challenge. To test the statistical significance of the outcome gap, Abadie et al. (2010, 2015) suggest a series of 'in-space placebo tests'. The tests iteratively reassign the treatment to different regions in the donor pool to create a distribution of placebo effects to determine whether the effect of the treatment is specific to the treated region or likely observable in the control sample. The placebo tests are significant if the results produce smaller gaps in the non-treated regions than the effects observed in the treated region. In effect, if the placebo tests produce gaps similar to that of the treated region, then there is no significant evidence of a causal treatment effect.

For SCM, the robustness or strength of the post-treatment gap of the treated region is obviously dependent on the composition of the donor pool. As argued by Gilchrist et al. (2022), the composition of the donor pool, by default, is an implication for statistical significance. To check the robustness of the results, Abadie et al. (2015) suggest conducting 'leave-one-out' (LOO) analysis. LOO is where the baseline model is iteratively re-estimated to construct a synthetic region by omitting from each iteration one of the regions with non-zero weights defining the synthetic region for the treated region. While this approach sacrifices some goodness of fit, the sensitivity check allows an evaluation of the extent to which the results are driven by any specific control region. Following Gilchrist et al. (2022), the LOO estimation is extended by excluding the entire synthetic control group from the donor pool to check whether the size and significance of the effect are stable.

4 | DATA

The empirical analysis is based on matched employer–employee data on all firms and workers in Sweden between 1995 and 2019 obtained from Statistics Sweden (SCB). Based on these data, we can make spatial aggregates and also break down employment into different segments. The main spatial unit of analysis is functional labor markets as classified by SCB, based on the degree of urbanization and inter-municipal commuting patterns. The treated region in focus here has two functionally integrated municipalities and is a relatively isolated regional labor market, with a population density of approximately nine inhabitants per square kilometer during the period for which we have data. Over this period, the population decreased from almost 17,000 in 1995 to roughly 14,000 in 2019, a decline of about 15%. For the same period, employment declined by roughly 22%. The region is characterized by labor expertise in forestry, wood, paper and pulp, and the construction industries, with a growing tourism industry. About 5% of the workforce have three or more years of university education.[2]

The donor pool consists of 28 other local labor markets defined as small and remote regions, with similar development and urbanization trajectories to the treated region, to improve the estimation of the counterfactual. Over the period of analysis, the donor pool population declined by approximately 19% and employment declined by about 8%.

In 2004, a manufacturer of household and sanitary goods started operating in the treated region. During the first year, 308 workers were employed by this manufacturer.[3] Of these workers, 46% were males, about 5% had post-secondary education of three to five years, and about 88% had compulsory and secondary school education. About 72% of those employed had been previously engaged in work related to construction, manufacturing, machine operating, and transport. The majority (94%) of workers were recruited from the region, with 64% receiving a higher annual wage than from their previous work.

As 2004 is the year of treatment our dataset span nine years of pre-treatment and 15 years of post-treatment. The main outcome variable, y_{it}^{TE}, is defined as total regional employment based on the registered number of employees at each workplace in November of each year. This variable is relevant not only because it gives the overall development of the region but also because there are regions where unemployment coexists with labor shortages. For this reason, it is important to assess how a treated region generally responds to the entry of a large firm. Apart from the main variable of employment, we also make use of the detailed NACE sector codes to classify employment. Based on the three-digit level, we define employment in the same three-digit sector as the entry, employment in skill-related sectors, and finally, in all unrelated sectors. When defining skill-related sectors, we resort

[2]We cannot reveal details about the region nor the entry described for confidentiality reasons related to data-access.

[3]For comparison, the European Commission defines a large firm as any organization with more than 249 employees and/or a turnover of more than 50 million euros.

to the definition offered by Neffke et al. (2017), who define related sectors as those industries with more than expected labor flows at the national level (relative risk). Because our data contain all workers and their respective work industries for each year, a national flow matrix can be computed for each year of the data. While this measurement on revealed relatedness is a good proxy for shared capabilities (industries with more than expected labor flows share similar human capital resources), it may also be related to the outcome variable in relation to a demand shock. To mitigate that the entry (treatment) influences the definition of relatedness, we define relatedness over a five-year period prior to the entry (1998 to 2003) and then, based on this definition, select the 25% most skill-related sectors to the focal industry, and follow how employment develops in both the treated region and in the control regions.[4] All remaining industries are defined as unrelated. Given the few observations, we could not fit a model on same-industry employment change and therefore merged the same and related industries into one category. As seen in Table 3, including same-industry employment among the related industries (Column 3) produces a worse fit compared to only the related industries (Column 2). In essence, this would not change the potential mechanisms at play, as we expect that sourcing experienced personnel into a new industry would predominantly originate from the same and related activities due to the interindustry matching that skill-relatedness implies (cf. Boschma et al., 2014).

To construct the counterfactual, the predictors are divided into three categories that are likely to affect employment. The first category is internal firm factors, which are included to reflect the demand for labor. For many firms, hiring personnel or creating jobs depends on the firm's financial position and productivity (Papanikos, 2004). Here, average firm profitability and productivity, respectively, in the region are used as indicators for the local demand for labor, together with income levels. These indicators were retrieved from our database. Productivity is defined as the value added per employee, while profitability is defined as the final results after costs are deducted. Income is based on the average income from work for all those employed in the region. The second category is local socioeconomic and demographic factors because recruitment and localization strategies are influenced by local demographic factors in many ways (e.g., Smith et al., 2001; Urwin & Di Pietro, 2005). Hence, this category of covariates reflects the labor supply but may also affect firms' decisions to expand and/or invest in a region. For this reason, we controlled for total population, population density, the share of the population aged between 20 and 64 years (working age), the proportion of men, average age, and the share of people with three or more years of university education. The third category is related to competition and matching in the labor market (e.g., Dauth, 2013; Duranton, 2013; Duranton & Puga, 2004). Here, the share of manufacturing, the share of knowledge-intensive business services (KIBS), the share of other services, the share of public sector firms, and the degree of specialization and diversity are used to reflect both the degree of competition within the labor market and matching. To measure regional specialization and diversity, the location quotient and the entropy measure, respectively, are used.[5]

Table 1 presents the descriptive statistics of the treated region and the donor pool.

5 | RESULTS

Table 2 shows the estimated weights, w_i, assigned to each region in the donor pool based on SCM. The low RMSPE for all models except the one including same-industry employment should be noted (between 2.6% and 6.4%, while Model 2 has 18.1%), as it indicates a good fit for the pre-treatment period. Note also that only five regions from the donor pool on total employment contribute to the counterfactual treated region and that $\sum_{i=2} w_i = 1$, which prevents extrapolation. In subsequent models, the number of regions included in the

[4]The final relatedness variable ranges along a continuum from 0 to 1 for all industries with observed labor flows, and there is no predefined threshold. As a robustness check we have used different thresholds including more sectors with similar, although slightly more moderate, effects.

[5]LQ is a relative measure of the regional share of workers relative to the national share of workers in a specific industry (Feldman & Audretsch, 1999). LQ > 1 shows that the region is more specialized on average in that industry. The entropy measure captures diversity through the large size of employment base in all other industries (Wixe, 2015). The entropy measure ranges from zero (no diversity) to $\ln(n)$ (maximum diversity) where n is the maximum number of employed in an industry.

TABLE 1 Descriptive statistics of the treated region and donor pool. Annual averages for the period 1995 to 2019. All monetary values in Swedish Kronor (SEK).

	Treated region				Donor pool			
Variable	Mean	Std. dev.	Min.	Max.	Mean	Std. dev.	Min.	Max.
Total regional employment	8.74	0.07	8.67	8.89	8.17	0.69	6.86	9.48
Similar & top 25% related total employment	6.82	0.16	6.60	7.17	6.56	0.80	4.68	8.25
Unrelated total employment	8.52	0.11	8.38	8.69	7.90	0.69	6.51	9.29
Top 25% related total employment	6.82	0.16	6.10	7.17	6.56	0.69	6.86	9.48
Profitability (100s)	418	159	241	894	358	149	−245	1089
Productivity (100s)	464	40	398	557	483	66	346	1087
Average wages (100s)	1614	254	1179	2111	1771	365	997	2886
Proportion male	0.74	0.03	0.67	0.79	0.72	0.03	0.61	0.80
Average age	47	3	40	52	46	3	38	53
Share of highly educated	0.05	0.03	0.00	0.09	0.05	0.03	0.00	0.13
Total population	15,154	791	14,253	16,787	10,909	6974	2489	32,858
Population density	7.99	0.42	7.52	8.85	4.12	4.22	0.19	16.91
Share of potential labor	0.54	0.01	0.51	0.55	0.53	0.02	0.46	0.60
Share of manufacturing	0.13	0.05	0.08	0.22	0.12	0.04	0.03	0.27
Share of KIBS	0.04	0.01	0.03	0.07	0.04	0.02	0.00	0.10
Share of other services	0.37	0.06	0.29	0.49	0.41	0.06	0.27	0.60
Share of public	0.03	0.01	0.01	0.06	0.03	0.01	0.00	0.06
Degree of specialization	0.34	0.04	0.27	0.45	0.32	0.24	0.00	0.98
Degree of diversity	59	16	27	81	525	1411	8	9598

TABLE 2 Composition of the synthetic group.

Region	(1) Total regional employment Weight	(2) Same and top 25% related industry employment Weight	(3) Unrelated regional employment Weight	(4) Top 25% related industry employment Weight
Arjeplog	0	0	0	0
Arvidsjaur	0	0	0	0
Dorotea	0	0	0	0
Eda	0	0	0	0.217
Fagersta	0	0.120	0	0
Filipstad	0	0	0	0
Gällivare	0	0	0	0
Hagfors	0	0	0.038	0
Haparanda	0	0.003	0.010	0
Hällefors	0	0	0	0
Härjedale	0	0.081	0.177	0
Jokkmokk	0	0	0	0
Kramfors	0.277	0	0.113	0.375
Ljusdal	0	0	0	0
Lycksele	0	0	0	0
Malung	0	0.019	0	0
Pajala	0.139	0.121	0.086	0
Sollefteå	0.260	0.402	0.008	0.104
Sorsele	0	0	0	0
Storuman	0	0	0	0
Torsby	0	0	0	0
Vansbro	0.129	0.180	0.123	0.067
Vilhelmina	0	0	0	0
Vimmerby	0.195	0	0.442	0.034
Årjäng	0	0.073	0	0
Åsele	0	0	0	0
Överkalix	0	0	0	0
Övertorneå	0	0	0.002	0.203
RMSPE	**0.026**	**0.181**	**0.042**	**0.064**

Note: An RMSPE below 0.05 relates to the conventional 95% level of significance.

counterfactual range from six to nine. All regions from the donor pool with $w_i > 0$ are located far from the treated region, making correlation between those regions and the treated region unlikely. Due to the relatively poorer pre-treatment fit for same (three-digit) industry employment, we decided to also include related employment separately in the analysis (Column 4).

Table 3 compares the pre-entry characteristics of the predictors for the outcome variables for the treated and the synthetic regions. The predictive balance for the treated region is shown in Column 1, while Columns 2 to 5 show the synthetic regions for each of the outcome variables. In most cases, the synthetic controls provide good proxies

TABLE 3 Predictor balance.

	(1) Real region	(2) Total regional employment Synthetic	(3) Same and top 25% related employment Synthetic	(4) Unrelated total regional employment Synthetic	(5) Top 25% related employment Synthetic
Profitability (100s)	372	309	300	324	303
Productivity (100s)	477	484	476	477	489
Average wages (100s)	1330	1354	1355	1366	1338
Proportion male	0.71	0.71	0.71	0.70	0.71
Average age	43	43	43	43	43
Share of highly educated	0.03	0.03	0.03	0.02	0.02
Total population	16,078	20,030	16,042	20,772	15,177
Population density	8.48	7.62	4.98	8.32	8.31
Share of potential labor	0.54	0.53	0.54	0.54	0.53
Share of manufacturing	0.18	0.17	0.15	0.18	0.15
Share of KIBS	0.03	0.03	0.03	0.03	0.03
Share of other services	0.43	0.44	0.46	0.42	0.46
Share of public	0.04	0.02	0.02	0.03	0.03
Degree of specialization	0.34	0.32	0.46	0.33	0.23
Degree of urbanization	41	207	58	208	247

for the treated region. For instance, for the local socioeconomic and demographic factors, the synthetic regions have similar population densities and share of potential labor force as the treated region. For the internal firm factors, the proportion of men, average wages, and age are well matched with the synthetic regions. Again, for both the industry-specific and agglomeration-related attributes, the treated region and the synthetic control groups are synthetically well matched for shares of manufacturing, KIBS, services, public sectors, and the degree of specialization with an overall low RMSPE. This indicates a low risk of pre-existing trends obscuring an employment gap associated with the entry of a large new manufacturing plant (e.g., Abadie et al., 2010, 2015). Notwithstanding these clear similarities, there are a few notable discrepancies, such as profitability and the degree of urbanization, that are evident in all the SCM analyses.

Figure 1 shows the entry's impact on total employment by comparing the counterfactual impact of the entry (treatment). Apart from creating the counterfactuals with similar employment trends in the pre-tretmant periods, Figure 1 shows the employment trajectories for the treated and synthetic regions in the post-treatment periods. In general, for total regional employment, the results indicate that after 2004 the employment trajectories in the treated region and the synthetic ones diverge considerably. This is particularly true during the first five years after entry, only to slowly converge again. This implies that the entry negatively affects total regional employment. Suffice

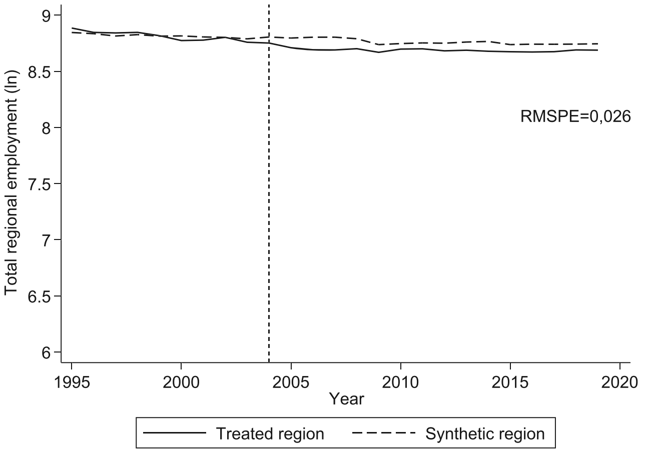

FIGURE 1 Comparative analysis of the impact of a large new manufacturing plant on total regional employment.

it to say that though there is a general decreasing trend in employment in the treated region (as in the synthetic regions), the entry itself did not spark a new employment trajectory, which in turn points towards a demand shock that did not automatically trigger employment-inducing externalities.

As indicated above, presumably the entry could affect various parts of the economy differently. One reason for entry can be traced to agglomeration externalities that facilitate sharing, matching, and learning. Hence, investments are likely to be made where similar and related activities already exist, which in turn facilitates hiring skilled personnel. We could therefore expect that in small and peripheral regions with limited in-migration, poaching employees from incumbent firms with similar skills may explain this overall negative effect. Figure 2, therefore, distinguishes between the same and related, unrelated, and related employment.

According to Figure 2, the overall worse employment in the treated region compared to the synthetic regions originates from a short-term decline in same-industry employment in particular but also in related employment. Thus, some initial poaching is evident in the sense that incumbent firms employing similar and related skills are subject to employment losses connected to a large demand shock. While the pre-treatment fit of the same industries is poor, we do not discuss this further and instead focus on related and unrelated employment. In the former, we can observe that, after an initial decline (presumably caused by poaching), related employment in the treated region is higher than in the synthetic regions. Hence, the entry may induce externalities that benefit related activities and thereby also trigger (related) diversification long term. Unrelated activities are less affected but do perform slightly worse in the treated region than in the synthetic regions.

The evidence thus far indicates that the entry of a large manufacturing plant in a small, relatively peripheral region negatively impacts total employment, though employment in related industries seems to benefit in the longer run. The question here is how can we evaluate the statistical significance of this effect over time. We follow Abadie et al.'s (2010) inferential technique to evaluate whether our results occurred purely by chance. We do so by relying on the in-space placebo analyses by performing a series of placebo simulations in which the synthetic control estimator is iteratively applied to all the regions in the donor pool that did not experience entry of a large new manufacturing plant during the studied period. The placebo tests are statistically significant if the results produce gaps that are smaller in the non-treated units than the effects observed in the treated unit. In effect, if the placebo tests produce gaps similar to those of the treated unit, then there is no significant difference in the graphs produced above. Figure 3 shows the results from the placebo analyses. The light grey solid lines show the gaps observed for the control regions that were not treated and the black solid lines show the gaps observed for the treated region. To prevent any artificially created gaps in the post-entry periods, we omitted control regions with an RMSPE two times more

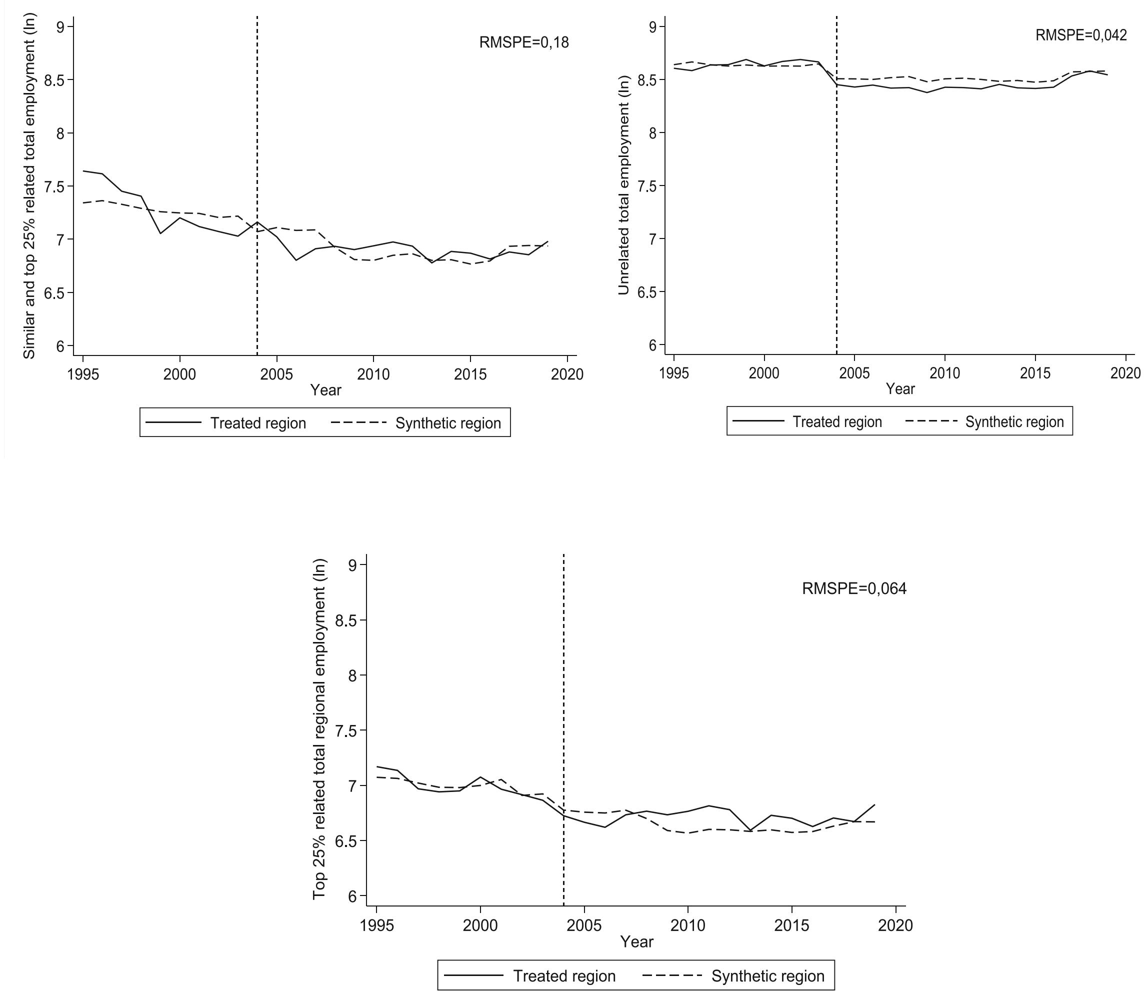

FIGURE 2 Comparative analysis of the impact of a large new manufacturing plant on same and related (upper left), unrelated (upper right), and related activities (below).

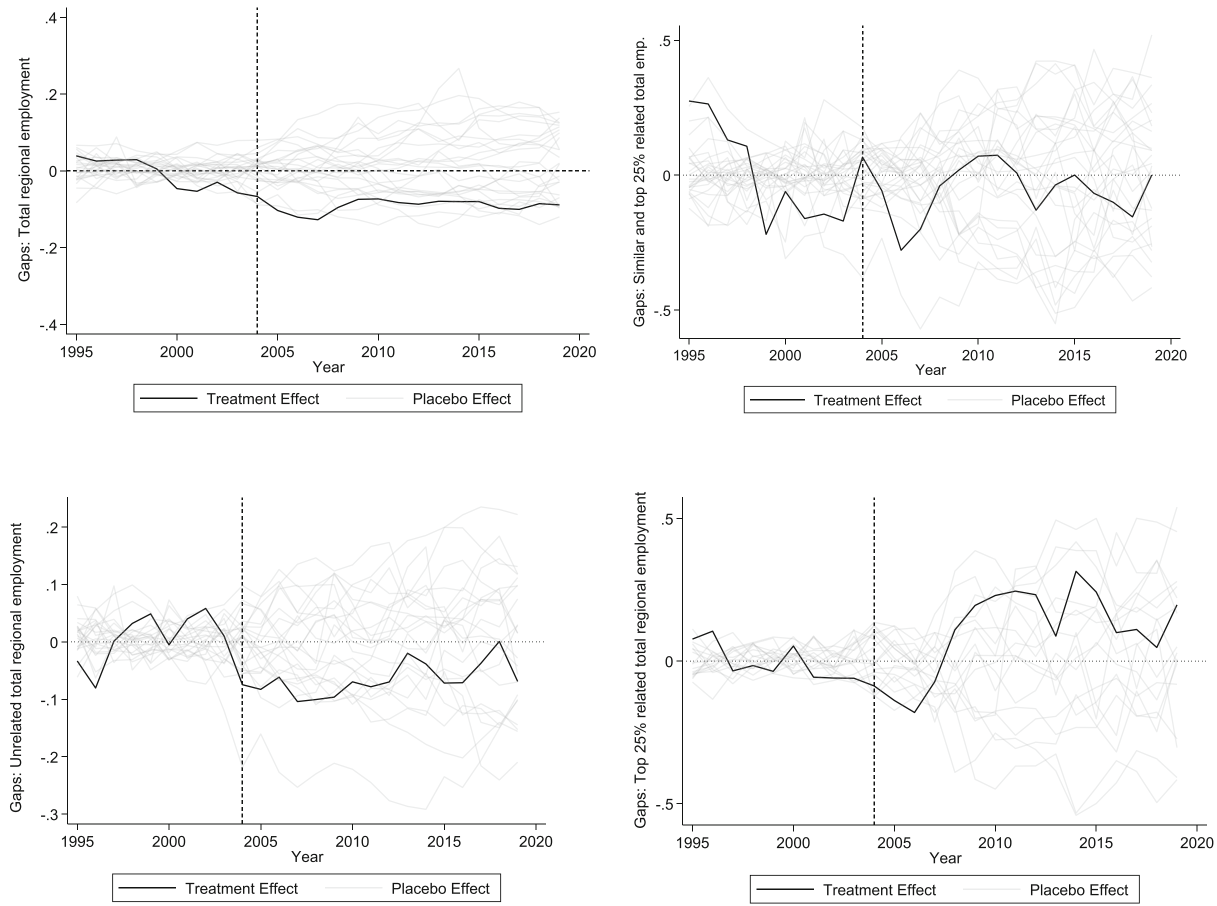

FIGURE 3 Employment gaps (placebo test) for the treated region for total employment (upper left), total employment in the same and related industries (upper right), unrelated industries (lower left), and related activities (lower right).

than the treated region from the placebo analyses. Consequently, three regions were omitted from the analysis for total employment, one for same and related industries, five for unrelated industries, and 11 for related industries only. Comparatively, the gaps for the treated region are very low, with few regions outperforming the treated one in the post-entry period. The probability of estimating a gap of the magnitude found for the treated region under a random permutation is 1 in 25 (0.04) for total regional employment, 1 in 27 (0.04) for same and related industries, 1 in 23 (0.04) for unrelated, and 1 in 17 (0.05) for related industries, signaling that these findings are statistically significant.

5.1 | Robustness checks

Several robustness checks were conducted. First, to determine that the entry's impacts were not influenced by some control regions, LOO analysis was performed as recommended by Abadie et al. (2015), where we iteratively re-estimated the synthetic regions by omitting from each iteration one of the regions with non-zero weights defining the synthetic regions for the treated region. The intuition is that the result is robust when the post-intervention employment gap between the treated region and synthetic regions remains in each of the LOO estimates. If any of the LOO synthetic regions passed the treatment region, then it would be enough to argue that good performance in one or two of the control regions is responsible for the divergent outcome but not necessarily the entry of the large new manufacturing firm. Figure 4 shows the LOO analyses for the treated region. The black solid lines show the trajectory of the treated region's outcome, the black dashed lines show the trajectory of the original synthetic control region's outcome, and the light grey solid lines show the trajectories of the synthetic LOO estimates. The results are robust even when any of the original control regions in the synthetic counterpart are excluded, as the gap between the treated and synthetic regions remains in each of the LOO estimates.

Second, to further test the results' robustness, a more rigorous LOO analysis was performed, where all the control regions that defined the synthetic region (13 in total) were excluded from the donor pool. The results in Figure 5 are comparable with those in Figures 1 and 2, showing that there is a general negative employment trajectory in the treated region resulting from the entry.

Third, while breaking down the effect for different parts of the regional economy, additional heterogeneity may explain the results. For example, a small incumbent firm may face greater difficulties retaining skilled workers than a larger employer. In this sense, the local ecosystem of small and medium-sized firms (SMEs) may be affected differently than larger incumbents. Figure 6, therefore, depicts the employment trajectories in SMEs only (defined as enterprises with fewer than 250 employees). These types of firms play a crucial role in Sweden's economic landscape, accounting for 99% of firms and employing more than 65% of the Swedish workforce (SCB, 2021). As for total employment, the pre-treatment fit in all these models is generally low (albeit slightly higher than total employment), except for same and related industries, for which the RMSPE is 21.5%. Here, we also find that employment in smaller firms on average in the treated region was worse than in the synthetic regions. This is, however, primarily driven by unrelated employment, as both same and related and related activities approximately follow the synthetic regions' trends after the treatment. The latter, however, should be interpreted with some caution due to the poorer pre-treatment fit. While this pattern in turn could be driven by compositional changes (smaller firms grow over time and are therefore no longer defined as SMEs), the number of SMEs pre- and post-entry was examined. These analyses (which are not reported but can be retrieved upon request, see Figure A1) revealed that the number of SMEs increased in the treated region compared with the synthetic ones. This is particularly driven by a continuous increase in SMEs in related industries, again indicating the potential for related diversification.

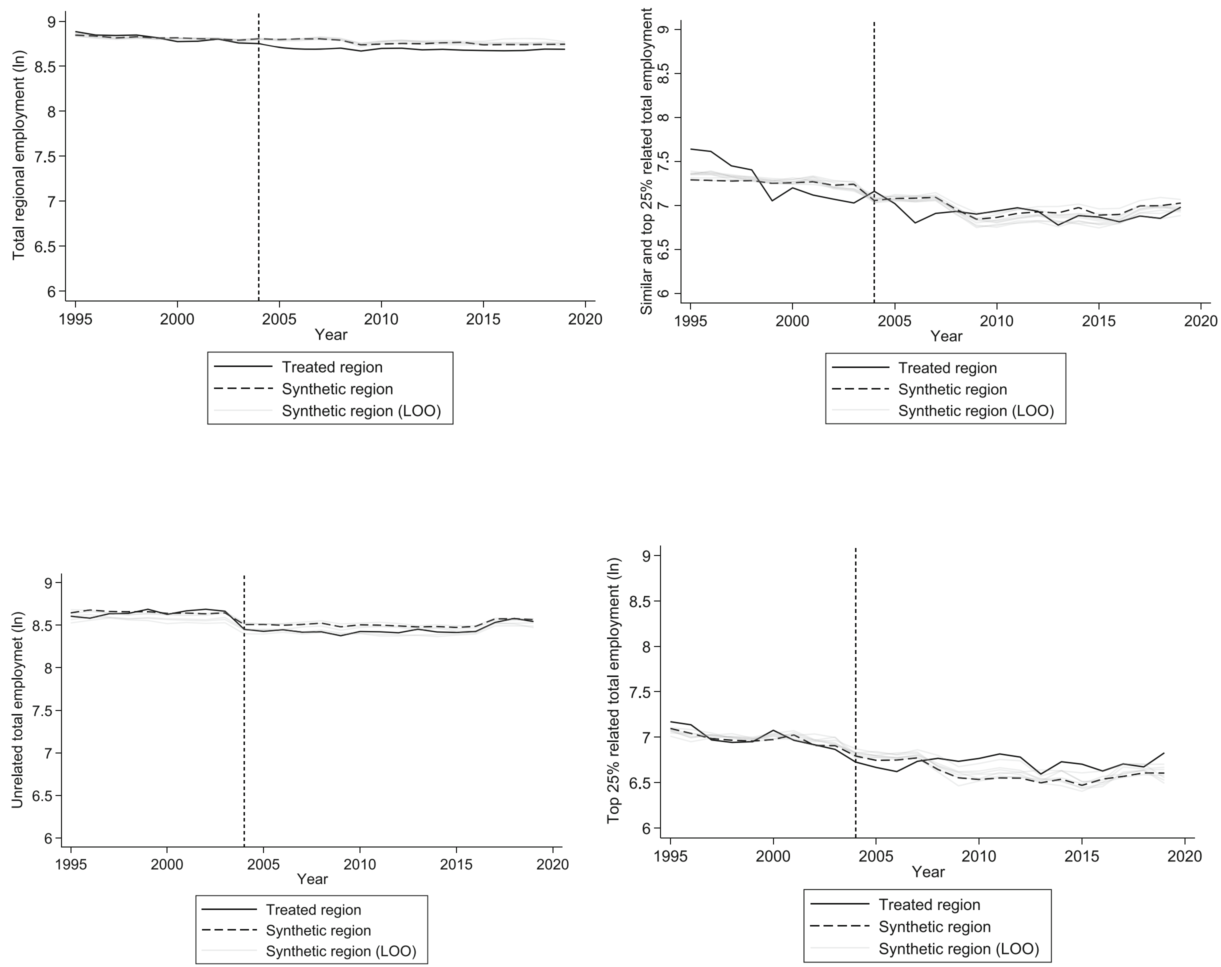

FIGURE 4 LOO distribution for the synthetic regions on total employment (upper left), and total employment in the same and related industries (upper right), unrelated industries (lower left,) and related activities (lower right).

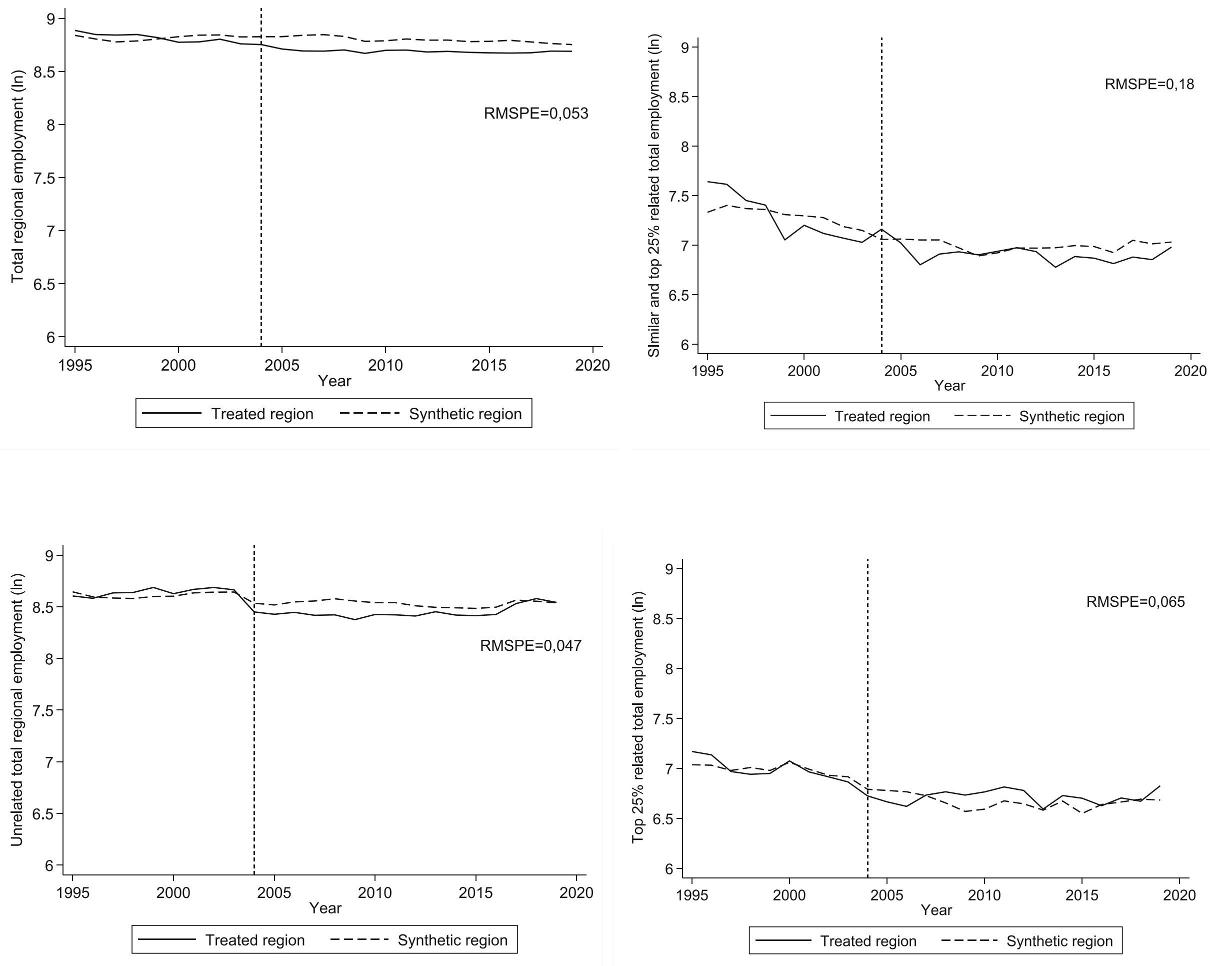

FIGURE 5 Regressive LOO analysis on total employment (upper left), and total employment in the same and related industries (upper right), unrelated industries (lower left), and related activities (lower right).

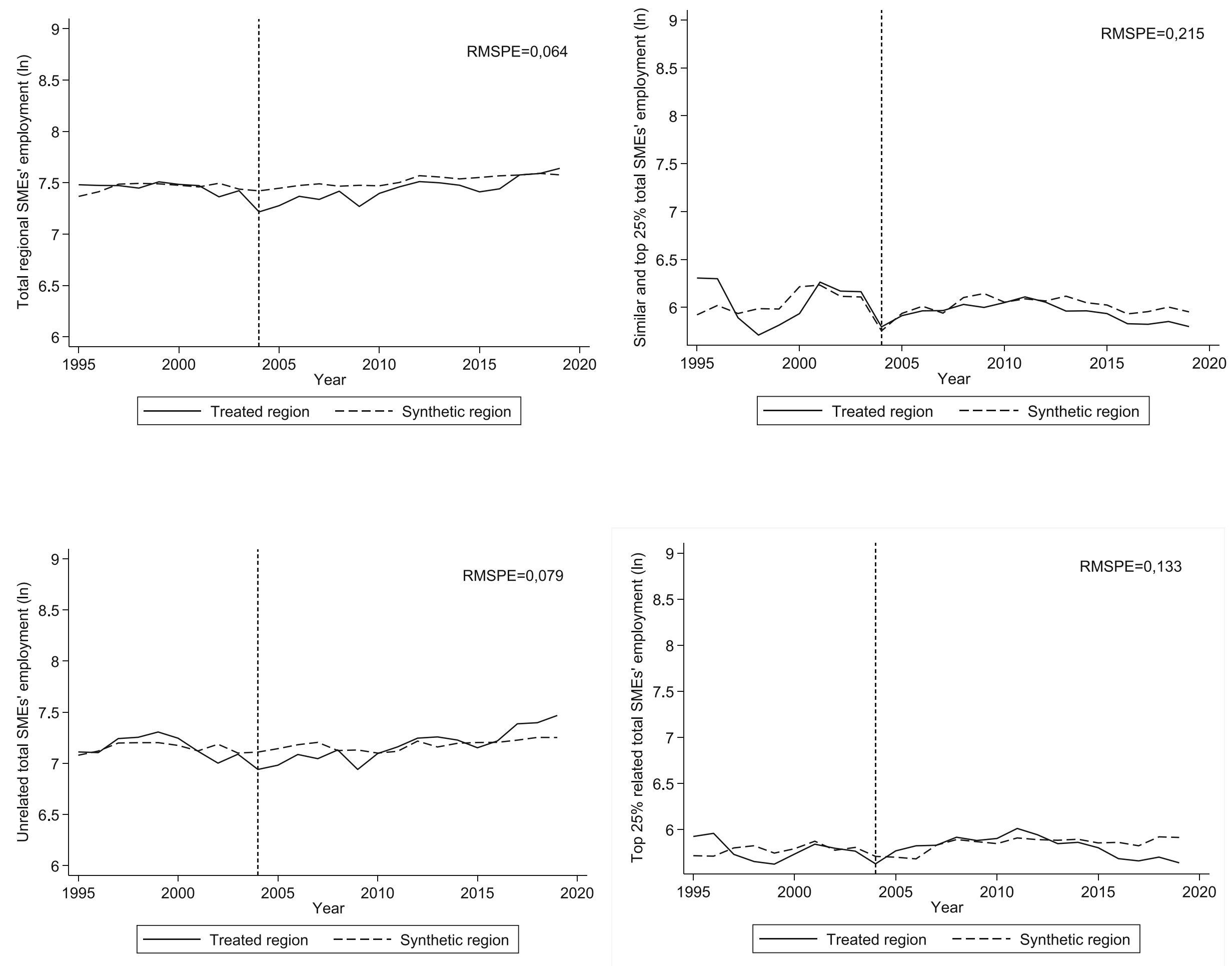

FIGURE 6 Comparative analysis of the impact of a large new manufacturing plant on total SME employment (upper left), and SME employment in the same and related industries (upper right), unrelated industries (lower left), and related activities (lower right).

6 | CONCLUDING REMARKS

This article analyzes the effect of a relatively large industrial expansion in the manufacturing industry on regional employment. This expansion took place in a remote and sparsely populated area of Sweden in 2004 and initially accounted for approximately 300 new jobs. Our focus on investment in the manufacturing industry in a peripheral region is motivated by the fact that local policymakers, especially in declining and sparsely populated areas, often aim for this type of investment in an effort to increase employment and secure a local tax base. However, standard econometric tools are usually confined to average effects associated with the problems of few treated cases and poorly matched regions. To address this, the current study applied the synthetic control method (SCM) to estimate causal place-specific effects. The analysis is based on aggregated microdata covering Swedish functional labor markets from 1995 to 2019 provided by Statistics Sweden (SCB).

The empirical findings suggest that a relatively large investment in a small and peripheral region may actually dampen regional employment. Due to the relative remoteness of the region and its low rates of in-migration and/or commuting, we might expect this to be driven by poaching from incumbent employers. In other words, a large demand shock could, in a case of inelastic supply, impede rather than stimulate employment. This general negative effect, however, panned out differently in different segments of the regional economy. Our findings suggest that same and related industries, presumably employing workers with skills similar to the entry activity, initially performed worse in the treated region than in the synthetic regions, hence supporting the poaching argument. However, in the longer term, this part of the economy grew. Unrelated activities, however, never recovered from the initial negative effect. When assessing the development of employment among smaller firms, this conclusion is supported, as the population of firms in related activities increased despite the fact that employment in SMEs is relatively stable. Hence, initial SMEs in related activities grew (to not be defined as SMEs) at the same time as the ecosystem of related firms also grew. Overall, the findings signal the difficulties of managing a large demand shock in economic peripheries due to local poaching but also that there is potential for (related) diversification in the longer run.

Typically, the regional effects of a shock in the demand for labor are analyzed through the multipliers an investment may bring to the region in relation to the growth and/or decline of other activities (Moretti, 2011). It is fairly well established that the skill content of new jobs typically produces greater regional multipliers (Moretti & Thulin, 2013). These canonical insights, however, mainly build on national averages based on global analyses, thereby finding that the general regional welfare effects are greater in larger regions (e.g., Giroud et al., 2021). Combined with the assumption that labor is perfectly mobile (which tends to make more sense in large urban regions than in peripheral and declining regions), previous accounts may mainly reflect the different growth trajectories of large regions compared to small and remote regions, rather than the entry effect per se. The present article contributes to this body of literature by applying SCM to estimate place-specific, rather than average, casual effects, thereby comparing one case with a synthetic version of similar but arguably unaffected regions. In so doing, we first reveal the predominantly local sourcing of labor and thereafter tease out both total effects and more delineated effects in different parts of the regional economy. This allows us to extend our analysis of regional effects beyond more structural regional endowments to find a local effect, concluding that an investment does not necessarily contribute to employment growth, even when compared with similar regions.

Moreover, the local effects of investments are highly relevant from a policy perspective, not least given the challenges of stimulating development in all regions and not just the economic cores (e.g., Martin, 2021; OECD, 2018). The findings presented here, in combination with the limited previous literature using similar methods, indeed reveal the need to consider the specific regional context (e.g., peripherality and labor supply) and the short- and longer-term effects. With increasing awareness that not only core regions have been privileged over the last decades of policy (e.g., Rodríguez-Pose, 2018) but also that the remaining 'left behind places' consist of a plethora of regions with different endowments (Pike et al., 2023), this calls for a much more place-sensitive assessment of how to stimulate more inclusive regional development. This is relevant in the Swedish context, where local governments (especially in remote and sparsely populated areas with decreasing local tax bases and declining populations) currently compete for private investments and new establishments associated with green investments. Based on the present empirical case, it is difficult to provide any general suggestions regarding such a reindustrialization policy. This is because while the overall negative employment trajectory does not change, there still seems to be potential for related diversification as well as growth in the number of (related) SMEs. Both aspects are crucial to sustaining a resilient regional ecosystem and are in line with the European Union's current smart specialization agenda. Nevertheless, based on our findings, it is important to stress the temporal horizon of these effects, because the short-term effects are negative while diversification necessarily is a long-term process. Thus, policies need to extend beyond the typical mandate of local governments (four years in Sweden's case).

Finally, this study is not without its limitations that warrant further analysis. SCM offers one plausible solution for assessing treatment effects and also creates scope for more case-sensitive analyses compared to, for example, traditional DiD approaches. While we mainly focused on employment effects, there are of course other treatments than an entry that could be assessed as well as other outcomes. As important as employment is in income development, diversity of employees in terms of sex or foreign background, for example, could also be explored, depending on the specific local policy aim. We also use a relatively broad definition of SMEs (companies with fewer than 250 employees); hence, further studies could examine ownership (private versus public, domestic versus international), look in more detail into the effects on micro-enterprises and small firms, and take a population-based approach to assessing human capital formation. For instance, Andersson et al.'s findings (2022) suggest that human capital from a large multinational circulates in the regional economy via labor flows, thereby increasing the potential for knowledge diffusion. Together with the well-established notion that experienced compared to inexperienced startups are more competitive (Klepper, 2011), this could explain the long-term growth of related activities identified in the current study. Moreover, other types of regions could be assessed to further address whether large labor markets do indeed benefit more from large investments, as highlighted by Giroud et al. (2021). If this is the case, then policy tools other than attracting investment are needed for 'left behind places'. We believe, however, that the growth of related industries identified here shows some potential for diversification that, in turn, could generate important development that enhances spillovers in the longer run. Further analyses are required to assess whether such diversification can actually take place, which direction the diversification takes, and also to what extent it could lead to more sustainable and inclusive regional development.

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ORCID

Evans Korang Adjei https://orcid.org/0000-0002-7179-347X
Rikard Eriksson https://orcid.org/0000-0003-3570-7690
Johan Lundberg https://orcid.org/0000-0002-7905-1825

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APPENDIX A

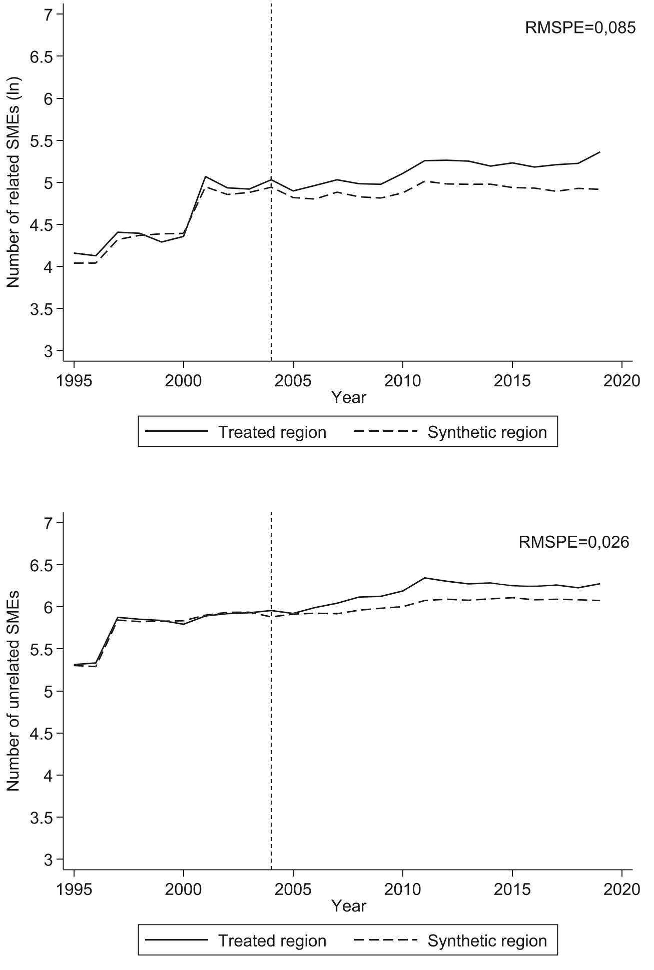

FIGURE A1 Number of related and unrelated SMEs upon the entry of large manufacturing plant.

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Resumen. Este artículo examina el impacto del establecimiento de una gran entidad industrial manufacturera en el empleo y el mercado laboral de una zona remota y escasamente poblada de Suecia, para lo cuál se centra en cómo afecta al empleo regional total, ya que las políticas industriales destinadas a atraer inversiones y reactivar el empleo en regiones estancadas han sido una herramienta política esencial. El análisis empírico se basa en el método de control sintético, que permite estimar los efectos causales específicos de cada lugar. Se utilizaron microdatos agregados de 1995 a 2019, y los resultados indican que el empleo en la región de estudio, en comparación con las regiones sintéticas, se ha visto afectado negativamente por la entidad manufacturera. Sin embargo, los efectos a corto y largo plazo difieren entre los distintos segmentos del mercado laboral (mismo sector, sectores relacionados y no relacionados) y según el tamaño de la empresa. En general, los resultados sugieren que las grandes inversiones manufactureras no tienen necesariamente un impacto positivo o instantáneo en el empleo regional total. Sin embargo, ofrece cierto potencial para la diversificación a largo plazo porque el empleo en actividades relacionadas crece a la larga.

抄録: 景気の低迷が続く地域に投資を呼び込み、雇用の再活性化を目的とした産業政策が政策手段の中心となってきたことから、本稿ではスウェーデンの辺境の人口の少ない地域における大規模な工業生産施設の設立が雇用と労働市場に与える影響を、地域全体の雇用にどのような影響を与えるかに焦点を当てて検証する。実証分析は合成コントロール法に基づいており、場所固有の因果効果の推定が可能である。1995~2019年までの集計されたマイクロデータを使用したところ、結果から、合成した他の地域と比較して、当該地域の雇用が生産施設の設立によって悪影響を受けることが示される。しかし、短期的・長期的な影響は、労働市場の部門(同業種、関連業種、非関連業種)や企業の規模によって異なる。概して、この結果から、生産施設への大型投資は、地域全体の雇用に必ずしもプラスまたは即効性のある影響を与えないことが示唆される。しかし、長期的には関連活動での雇用が増加するため、長期的な多角化の可能性はある程度与えられる。