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Analysing evolutionary growth regimes of regional economies and transformative shocks: Proposal for a regression-based counterfactual simulation approach to local inter-industry structural change

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ABSTRACT

Inter-industry relationships constitute growth regimes in regional evolutionary developments. The paper proposes a regression-based counterfactual simulation approach with location-level industry data in order to analyse systematically how the relationships between different industries and the growth regimes these relationships constitute differ across regions, and how these differences affect the response of regional development to interventions. At the core of the approach are complete descriptive panel regression models that decompose agglomeration effects into industry, spillover, and structure effects. With the identified coefficients simulations are carried out. To demonstrate its advantages, we apply the approach to the analysis of path-dependent employment growth in a livestock-intensive German location facing capacity constraints. In some of the scenarios, where individual industries are affected by exogenous shocks, we observe compensatory growth in other industries. This confirms the occurrence of evolutionary dynamics and the relevance of approaches that recognise and reproduce them.

Economic growth is largely determined by industry structures and processes of structural change (Saviotti et al., 2020). Because growth depends on industry composition and industry composition depends on growth (Matsuyama, 2017), locally observed patterns of structural change are in principle much more complex than its global dynamics. Given the resulting evolutionary dynamics, literally all sites may differ systematically from each other in their production regimes (Scott and Storper, 2015), i.e., in their modes of organizing production processes (Bianchi and Labory, 2019). Descriptive empirical analyses for example in shift-share approaches have repeatedly confirmed that industry dynamics differ between locations and between periods of time (Margarian and Hundt, 2023; Möller and Tassinopoulos, 2000). However, we have little systematic knowledge of the patterns of evolutionary development in different environments, nor do we have a comprehensive perspective on how economic growth, supported by interlinked industries and subject to capacity constraints, responds to exogenous shocks (Diodato and Weterings, 2015). In this paper, we develop an approach to investigate systematically, how the relationships between different industries and the growth regimes these relationships constitute differ across regions, and how these differences affect the response of regional development to interventions.

Shrinking, mature industries with low skill requirements and low wages, for example, can remain competitive in high-wage locations and experience "anti-trend growth" (Dauth and Suedekum, 2016) if they benefit from industry specific positive production externalities. If this growth takes place at the expense of other industries in locations with capacity constraints, path-dependencies and lock-ins might result (Martin and Sunley, 2010). If a lock-in favours mature industries, the resulting concentration of low-skill jobs can then lead to "occupational disadvantage" (Markusen, 2004) and the consolidation of a low-skill, low-wage growth regime (Dawley et al., 2014). With such path-dependence, exogenous shocks can initialize transformation processes "that reflect initial conditions, local characteristics and particular dynamics" (Scazzieri, 2018, p. 53). Path-breaking through an exogenous shock (Martin and Sunley, 2010) could lead to economic downturns (Hassink, 2010) and cause a permanent decline in the economic performance of a location (Hundt and Grün, 2022) given the low diversity of the local economy. Considering the suppressed dynamic of other industries, however, the shock could also "activate compensating adjustments" (Martin, 2012, p. 4) and induce compensatory growth or "catch-up effects" (Hundt and Grün, 2022) of other industries. Compensatory growth means that one industry responds to the decline of another with increased growth. If the system was previously trapped in a lock-in, this accelerated growth may even overcompensate for the

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initial loss (Li et al., 2021). Phenomena of compensatory growth provide clear evidence for the prevalence of evolutionary dynamics.

Under such conditions of evolutionary industry development, analytical approaches or models have to dispense with the assumption of perfect factor mobility and ubiquitous factor availability (Kilkenny and Partridge, 2009) and to distinguish between economic growth as "more of the same" and economic development as a transformation of structures (Radzicki and Sterman, 1994). In contrast to neoclassical growth models, Input-Output (IO) analysis explicitly focuses on differences between commodities and between inputs required for their production (Los, 2001). Simple IO models, however, are static and reversible, i.e. non-evolutionary in character. They assume fixed prices and perfectly elastic supply (Irwin et al., 2010). IO models therefore cannot estimate "supply-induced displacement of other economic activity" (Partridge and Rickman, 2010, p. 1312). Positive scale effects and especially forward linkages, i.e. potential advantages resulting from the good availability of certain goods in one location, are usually not considered in simple input-output models either (Hamilton et al., 1991, see however Norbu et al., 2021). Discrete dynamic IO-models assume full capital utilization and reversible investments and do not fit the characteristics of evolutionary developments as well (Johnson, 1985). Non-equilibrium IO-models demand micro-consistent extensions (see for example Los, 2001). They and micro-consistent computable general equilibrium (CGE) models would in principle be able to meet the formulated expectations on evolutionary models and could principally capture both, positive multiplier and negative crowding-out, effects of exogenous stimuli (Partridge and Rickman, 2010). However, sufficiently detailed micro-consistent models are not applicable in many relevant research contexts (Saviotti et al., 2020) due to their excessive data requirements (see for example Partridge and Rickman, 2010, p. 1313).

Against this background, and because there are no viable alternatives to these models that would allow the systematic analysis of evolutionary pathways, this paper develops a reduced form modelling approach that relies on industry data alone. Therein, meso-level industry dynamics are seen as "a crucial link between changes in individual industries, the primary locus of innovation, diffusion and competition, and broader aggregates" (Dosi and Nelson, 2010, Footnote 73). Such "reduced form models" may be used, when "the data needed to identify structure and estimate parameters for a highly disaggregated model may not be available" (Sterman, 2018, p. 20). They do not work from the level of behavioural equations, but from the level of "emergent phenomena". At the core of the proposed approach are descriptive regression models that identify the mean relationship between the absolute cumulative development of an industry and the absolute size and development of all other industries, as well as the size of the endogenous industry itself. The estimation ultimately decomposes the agglomeration effects at a location into its different mechanisms at the industry level that have been described in the literature.

The use of absolute growth variables makes the model quasi complete. Since the model is descriptive and generalisation to a larger population is not intended, it is only advantageous that the results are so perfectly adapted to the case at hand. However, working with absolute values makes it difficult to interpret the estimation results. For example, the strength of an industry's economies of scale is now not only reflected in the estimation coefficient, but also depends on the initial size of the industry at a particular location. Therefore, the evaluation and presentation forms developed for the interpretation of the results are an indispensable part of the proposed analytical approach. The identified coefficients for inter-industry relations characterise evolutionary growth regimes; the effect sizes show where individual sites stand in the development. In the simulation, the resulting complex and non-linear industry developments and the effects of exogenous shocks on them can then be examined in a counterfactual design.

The added value of the proposed approach becomes all the more evident the more the economic development of a location is characterised by positive externalities on the one side and by path dependencies and limits to growth, i.e. congestion and competition effects, on the other side. In order to demonstrate the potential importance of evolutionary developments and thus of the regression-based simulation approach at the industry level, we demonstrate its application in the case of a special site in north-west Germany. This site is characterised by a fast-growing livestock sector but is confronted with severe limits of growth and awaits an economic transformation. With the regression-based simulation, we analyse possible effects of an anticipated political intervention that drastically reduces the extend of livestock production and thereby of initial agricultural employment within the region. We also interpret this case as a test-case: As the counterfactual analysis of simulation results identifies phenomena of compensatory growth, it provides a clear indication of evolutionary dynamics and against the employment of simple IO models for the identification of intervention effects at least in this case.

Chapter 1 describes the approach and the rationale behind it. Chapter 2 describes its application. Chapter 3 presents the results and chapter 4 concludes.

1. The regression-based simulation approach

The regression-based simulation approach at the industry level combines a number of different analytical steps (Fig. 1). First, we use quasi-complete panel regression models to identify the correlations between the growth of industries on the one hand and their initial size as well as the growth and initial size of other industries on the other. The estimated coefficients describe mean relationships across observations (regions). A second step applies Monte Carlo simulation in order to identify those values from a reasonable range of values around the estimated coefficients that in total provide the best fit between observed and simulated data for each region. We then apply these best-fit coefficients as well as the estimated (mean) coefficients to a simulation of industry dynamics that starts from the initial industry structures in the regions. A last step evaluates intervention effects in a counterfactual comparison of the outcomes of different simulation scenarios, with and without intervention and with different coefficients.

1.1. *The distinguished industry relationships and their theoretical foundations*

At the core of the proposed approach are panel regression models that identify the complex relationships between industries in the growth process. These inter-industry relationships characterize a growth regime. Since the times of Marshall and Jacobs we know that the local industry composition and the local concentration of specific industries affect further industry dynamics (Demidova et al., 2020). The estimated coefficients illuminate, for example, with regard to a well-known antagonism (Fujita and Thisse, 2013), which industries are dominated by negative congestion effects and which industries benefit more from positive spillover effects under which structural conditions. More specifically, the model enables us to distinguish between the following effects: the growth inherent in an industry itself (innate effects), positive or negative scale effects respectively self-reinforcing or -inhibiting growth of an industry (own-size effects), the impact of all other industries' size on an industry's growth (structure effects), and the influence of other industries' growth on the growth of an industry (spillover effects).

Innate effects reflect that industries in structural change are characterised by specific growth rates during an observation period, which can, however, differ between growth regimes and be subject to some variation between locations. Measured in terms of the number of employees, the agricultural sector, for example, has consistently shrunk in recent years and decades in the high-income countries, independent of the location conditions; but the rate of shrinkage was influenced by general labour market regimes as well as by industry-specific conditions (Margarian, 2012).

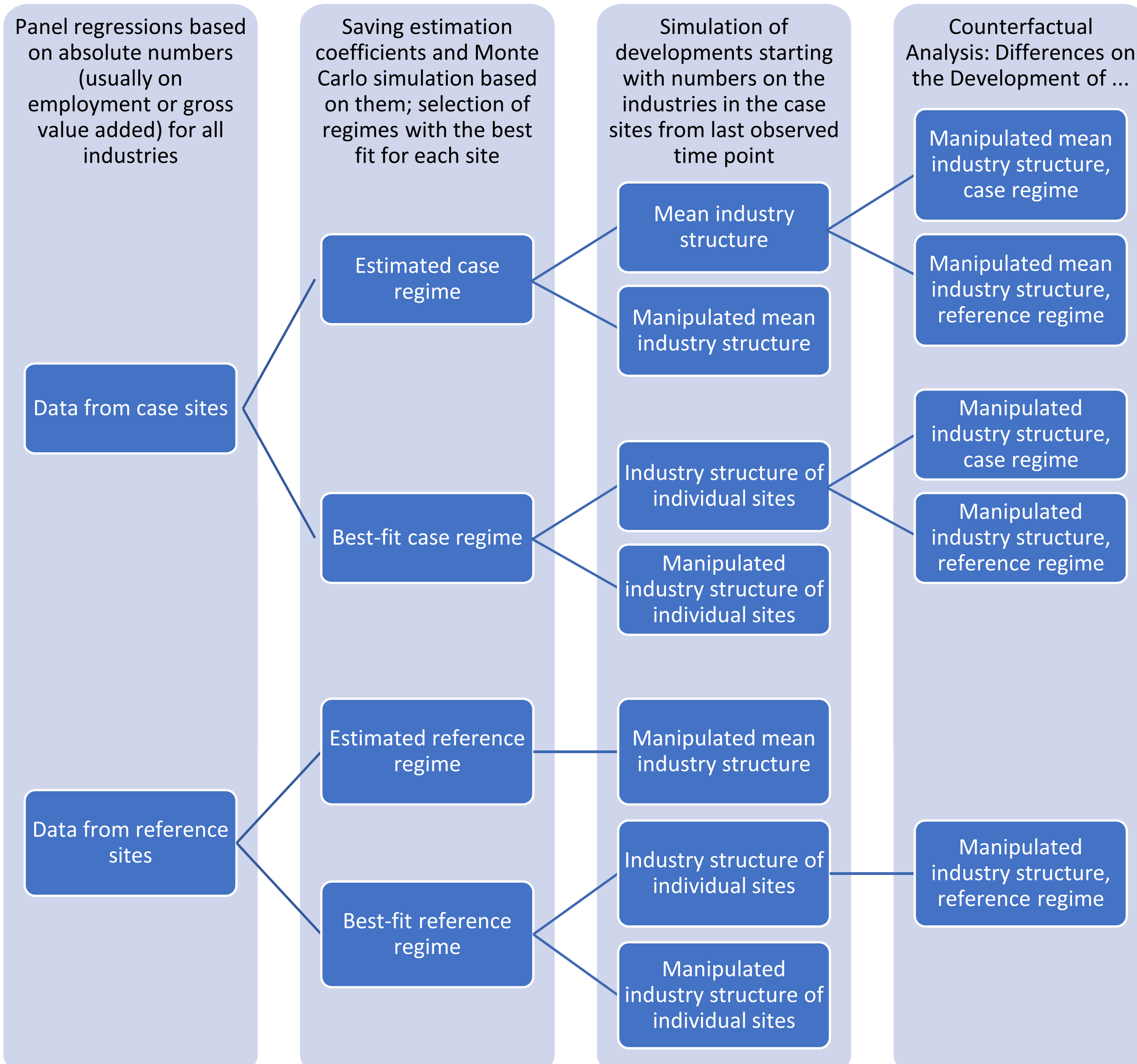

Fig. 1. The regression-based simulation approach in a process flow diagram.

Own-size effects reflect the fact that industry growth can be affected by positive or negative scale effects within or beyond the boundaries of firms. External effects and increasing returns induce self-enforcing growth (Martin and Sunley, 2006), path-dependent development and "competitive success" (Martin and Sunley, 2010). If an industry at a specific location is dominated by one large enterprise that benefits from positive scale effects, its self-enforcing growth might determine the growth of the whole industry at that location. From the discussion of clusters, however, it is well-known that firms can also benefit from a neighbourhood of other firms from the same industry (Gilbert et al., 2008). Specialized resources in turn are more likely to support further growth of related firms and industries. These effects of industry concentration are known as localization or Marshallian effects from a regional perspective (Beaudry and Schiffauerova, 2009). They might be of specific importance in economic downturns (Demidova et al., 2020) or at locations with small labour markets, where local industrial specialization might help firms in the creation of specifically knowledgeable work-forces (Margarian, 2022b). Negative own-size effects can be due to saturation or overcrowding effects (Cai and Hu, 2022) that evolve, for example, if industries serve mainly local demand, or if industries rely on specific scarce local resources (Staber, 2001).

The other two effects refer to externalities from other industries. Discussions of these agglomeration effects usually do not clearly distinguish between the externalities of co-location itself and the externalities of the growth of the co-located firms and industries. We introduce this clear distinction between what we call structure and spillover effects for the sake of the following analysis. Among the many classifications that have been proposed for agglomeration effects (Duranton and Puga, 2004), the differentiation between (static) efficiency externalities and (dynamic) development externalities (Johansson, 2005) seems to align best with this differentiation.

Structure effects describe how the size of other industries affect the growth of an industry. Many industries benefit from a high local industry diversity and simultaneously experience positive structure effects from a variety of other industries. The positive effects resulting from the co-location of various industries are referred to as urbanization effects (Beaudry and Schiffauerova, 2009) or Jacobs externalities (Demidova et al., 2020). In agglomerations, local enterprises have been found to benefit from a large and diverse pool of resources and at the same time contribute to its further growth (Beaudry and Schiffauerova, 2009), to new firm creation, innovation and diversification (Corradini and Vanino, 2022). If, however, factor availability is restricted, negative competition or congestion effects might dominate the relationship between industries. Effective constraints can result, for example, from restricted availability of labour, capital and specifically land (Grossmann, 2013), or arise from environmental considerations such as on air and water quality (Dixon and Parmenter, 1996). Young industries, knowledge-intensive industries and services benefit more from Jacobs externalities than mature and land-intensive industries (Desmet and Henderson, 2015). The latter cannot compete for the scarce resources in the agglomeration centres and settle in the periphery, where the economy is less concentrated and diverse (Desmet and Henderson, 2015). For these industries, the negative structure effects may outweigh the positive structure effects across all industries. Even then, industries may still respond positively to the presence of *specific* other industries that provide certain services or inputs, or have prepared the labour market, or indicate the presence of favourable resources.

Spillover effects capture how the *growth* of other industries affects the growth of an industry. Growth in certain industries may come at the expense of growth in other activities (Hamilton et al., 1991). Such negative spillover effects can be observed, for example, when industries in rural locations with inelastic labour supply (Irwin et al., 2010) require specific skills for their growth that are otherwise mainly used in other industries. Positive spillover effects result from multiplier and demand effects via forward- and backward linkages between industries (Norbu et al., 2021). The growth of one industry may also have positive spillover effects on other industries if, for example, this growth leads to innovation in other industries.

If both industries compete mostly for the same local resources, the growth or spillover effect of one industry on another may have the opposite sign to its co-location or structure effect. The distinction therefore proves quite helpful for the comprehensive analysis of evolutionary dynamics. Significant positive own-size effects together with negative spillover effects, for example, might result in the crowding out of other industries and in lock-ins that hinder a region's adaptation to changing circumstances and thus impede its long-term growth prospects (Martin and Sunley, 2010).

1.2. Estimation

The analysis begins with a series of descriptive panel regressions that identify the mean relationship between industries and industry developments in the observations (sub-regions) of the case region and, potentially, of a reference region. The estimation relies on absolute numbers describing for example the number of employees[1] per industry i ($Empl_{jti}$) for each sub-region j and each year t in the observation period and the absolute cumulative difference of this number from the initial number in the base year ($DiffEmpl_{jti}$). The "trick" is to work with absolute changes, accepting that the coefficients themselves are difficult to interpret. Then, a fixed effects panel regression that explains the cumulative differences in total employment as an endogenous variable by the absolute employment numbers per industry as exogenous variables has zero degrees of freedom if it includes all industries. The estimated coefficients take the value of one and simply indicate that the sum of employment changes per industry in each year is equal to the difference in total employment.

However, if an industry k is removed from the estimation, the coefficients for all other industries i deviate from one, provided they are not completely independent of the development of the missing industry and the growth contribution of the missing industry is not zero. A coefficient's deviation from one then indicates the direction and the extent of the correlation of the development of an industry i with that of the missing industry k. The estimated coefficients are equal to the differences between these coefficients and one if the cumulative difference in employment for the missing industry k ($DiffEmpl_{tk}$) rather than for total employment is used as the endogenous variable. It should be noted that, given the objective of identifying the relationship between the development of the one missing industry and the economy as a whole, this model is complete, i.e. there are no missing variables. Due to the resulting model specificity, the identified mean correlations cannot be extrapolated to other observations outside the region, but this is not the aim of this essentially descriptive analysis.

We use a random effects model instead of a fixed effects model to also identify the effects of the time constant initial industry structure (Allison, 2005).[2] It is estimated in a restricted maximum likelihood approach. The initial industry structure is represented by the total number of employees ($AllEmpl\_t1_j$) and the number of employees per industry i in the base year ($Empl\_t1_{ji}$). We estimate structurally identical panel models for each industry k and region type [case or reference] ν. Annual common fixed effects ($Year_t$) control the general business dynamic of each industry. The estimated coefficients from all industry models per region type then describe a case and a reference regime. Coefficients that are estimated at hand of case sites describe the case regime, those estimated at hand of the reference sites describe the reference regime:

$$DiffEmpl_{jtk\nu} = \beta_{00k\nu} + \beta_{1k\nu} AllEmpl\_t1_j + \sum_{i \neq k} \beta_{2k\nu i} Empl\_t1_{ji} + \sum_{i \neq k} \beta_{3k\nu i} Empl_{jti} + \sum_{t} \beta_{4tk\nu} Year_t + u_{j0k\nu} + \varepsilon_{jtk\nu}$$

The first right-hand-side term is the intercept $\beta_{00k\nu}$. $u_{j0k\nu}$ controls the variance τ_{00} between site level means with $u_{i0k\nu} \sim iid\ N(0,\tau_{00})$. $\varepsilon_{jtk\nu}$ controls the variance between years within sites with $\varepsilon_{itk\nu} \sim iid\ N(0,\sigma^2)$. We impose a first order autoregressive variance structure on σ^2. The regression coefficients obtained are meaningful when interpreted in the context of the variable values (see beginning of section 2.2.1). They can then show how innate effects (β_{00}), own-size effects (β_1), structure effects (β_2), and spillover effects (β_3; see introduction) contribute to the growth of the different industries in different locations and regimes. We sometimes summarize innate and own-size effect as *industry effect*.

1.3. Measure of fit, Monte Carlo simulation, and best fit variants

The estimated coefficients also serve as input of subsequent simulations. For the simulation, we additionally identify site-specific "best fit" regimes that better fit the individual sites than the estimated regimes. Therefore, we initially run Monte Carlo simulations using the estimated coefficients from the two regimes as baseline values. We run one random simulation over all coefficients of the estimated case and reference regime, each with 10,000 draws from a normal distribution where the mean is equal to the estimated starting value. We also set the absolute size of this mean as one standard deviation. This ensures that within the range of two standard deviations, there is a non-negligible probability of a change in sign.

In order to assess the fit of the coefficients with respect to individual sites and industries, we calculate the following "absolute relative residuals" (ARR) as measure of fit:

[1] Gross Value Added would be an obvious alternative choice.

[2] As before, all coefficients in this random effect model now correspond to the deviation from "one" exhibited by the coefficients of an otherwise identical model in which, however, the cumulative difference in total employment rather than the cumulative difference in employment of the omitted industry serves as the endogenous variable. This now applies both to the effects of time-varying industry employment numbers and to the effects of the (constant) industry employment number from the base year.

$$AbsRelRes_{ij} = \sum_{t=1}^{12} abs\left(PredDiffEmpl_{ijt} - DiffEmpl_{ijt}\right) \Bigg/ \sum_{t=1}^{12} abs\left(DiffEmpl_{ijt}\right)$$

where *PredDiffEmpl* is the absolute cumulative growth in employment number by industry that is predicted by the estimated coefficients for specific sites. In order to additionally assess the fit across industries we calculate the sum across industries:

$$GesRelRes_j = \sum_i AbsRelRes_{ij}$$

The average variable values of the case sites and the reference sites characterise the mean case site and the mean reference site. The estimated coefficients reflect the corresponding mean reference and mean case regimes that are optimally adapted to these mean sites: With them, the deviations of the predicted values from the observed values add up to zero if they are not included in the calculation as absolute values but with their respective sign. The ARR of the estimated regimes for the mean sites can therefore serve as a reference point to assess the magnitude of the ARR for individual sites. The ARR is used to compare the fit of the reference regime predictions with those of the case regime, to select the best-fit sets of coefficients from the Monte Carlo simulation and to compare their fit with the fit of the estimated regimes. The sets with the best fit are used in the simulation.

1.4. Simulation and counterfactual analysis

The simulations are carried out with the coefficients from the estimated and from the best-fit regimes. A first simulation may be run starting with the industry structure from the first time point of the observation period. This simulation can be used to sort out those regimes or coefficient sets that generate non-feasible results like negative employment numbers. The simulation proper for analysing possible further developments then begins with the data from the last time point of the observation period.

The simulation is based on the equation used for the estimation, only without the random deviations and without the controls for the years. It runs recursively. Here, the position in time $t(n,m)$ is given by two dimensions: n denotes the iteration phase, m the iteration stages within a phase. A phase comprises as many iteration stages $\overline{m}$ as the panel estimation covers observation periods (often years). The variables $AllEmpl\_t_j$ and $Empl\_t_{ji}$ that represent the initial structure in estimation and simulation for the determination of the own-size and the structure effects are thus kept constant over multiple iteration stages before being redetermined at the beginning of the next phase from the last iteration stage $\overline{m}$ of the previous phase [n-1]. The current size of the industries, on the other hand, is updated at each iteration stage within and across phases by adding the growth $DiffEmpl_{jt(n,m-1)kv}$ calculated in the previous stage to the number of employees from the previous stage $Empl_{jt(n,m-1)i}$:

$$\begin{aligned} DiffEmpl_{jt(n,m)kv} &= \beta_{00kv} + \beta_{1kv} AllEmpl\_t(n-1,\overline{m})_j \\ &\quad + \sum_{i \neq k} \beta_{2kvi} Empl\_t(n-1,\overline{m})_{ji} + \sum_{i \neq k} \beta_{3kvi} Empl_{jt(n,m)i} \end{aligned}$$

with $Empl_{jt(n,m)i} = Empl_{jt(n,m-1)i} + DiffEmpl_{jt(n,m-1)i}$where, in the special case of the transition between two simulation phases, the index $(n, m-1)$ must be replaced by $(n-1, \overline{m})$.

To identify intervention effects in the counterfactual analysis, two simulations are carried out on the basis of the case regime coefficients: One starting from the original values of the variables of the last year of observation and with the coefficients previously identified, and one with manipulated conditions reflecting the consequences of an exogenous shock or an expected intervention. The shocks considered can be of different types: they can change the size of industries (manipulation of the initial values of variables), affect the growth dynamics of individual industries (manipulation of innate effects) or change economies of scale (manipulation of own-size or structure effects). In addition, the simulations can be repeated with the reference regime coefficients to determine the possible effects of a regime switch. The industry and growth dynamics derived from the non-manipulated scenarios are then compared with the industry and growth dynamics derived from the manipulated scenarios in the case and in the reference regime in a counterfactual design (see Fig. 1).

2. Application

We illustrate the approach by analysing development scenarios for a rather peripheral German region characterised by intensive pig and poultry production with strong scale effects and capacity limits to growth. The region consists of 16 districts[3], all of which belong to the group of 18 German districts with the highest number of pigs per square kilometre in 2016.[4] All 16 districts form a coherent region in the northwest of Germany; eight of them belong to the federal state of Lower Saxony (LS) and eight to North Rhine-Westphalia (NW). We compare the development in the 16 case districts to "reference districts". These are the 219 non-city districts of the western federal states that do not belong to the 16 case districts. For seven of them the employment data are not available at the level of our industry aggregates, which leaves us with 212 reference districts.

2.1. Description of the case

Between 2007 and 2019, the number of employed persons in the reference districts grew by 12.3 percent, whereas in the LS and NW case districts it grew by 24.4 and 14.8 percent, respectively.

Pig density is highest in the two adjacent districts of Cloppenburg and Vechta in LS. In the district of Cloppenburg (LS), 19 percent of all employees worked in the agricultural and food industry in 2019, compared to a total of seven percent in the 16 case districts and only 3.7 percent in the reference districts. Other than the districts in NW, those in LS are not only characterised by a strong agricultural and food economy, but also by a relatively small service sector.[5] In Cloppenburg, not only services but also manufacturing beyond the food industry are relatively weak. In Warendorf and Emsland, on the other hand, "complex" manufacturing (Table 1) and services contribute most to employment growth.

An important explanatory factor for the still persistent spatial concentration of pig and poultry production even among our case sites is the competitive advantage of having livestock and slaughterhouses spatially close to each other in the face of high livestock transport costs. Concentration dynamics are further driven by technological and organisational advances that enable the realisation of ever-increasing economies of scale in both sectors. Growing local availability of specialised services, for example from veterinarians, and increasingly specialised labour markets additionally generate positive externalities of concentrated production (Roe et al., 2002). We thereby analyse a location that is characterised by a concentrated agri-food industry, which experiences considerable positive scale effects within and beyond individual enterprises, and may be closely interlinked with some other local industries.

Simultaneously, the location experiences considerable capacity constraints. The factor markets for land and labour in the case districts in LS are heavily strained by the rapid growth within and outside the agrifood sector. The purchase price for farmland in the districts of Vechta

[3] NUTS 3-level according to the European Nomenclature of Territorial Units for Statistics.

[4] Among the 18 districts with the highest pig densities in 2016, only two districts were not adjacent to the core region: Schwäbisch-Hall and Landshut in the federal states of Baden-Württemberg and Bavaria.

[5] See years 2007 and 2019 (t0), in Figure 8 in the results section.

Table 1
Differentiation between"complex" and "other" manufacturing (two-digit NACE).

Complex manufacturing	Other manufacturing
19 Manufacture of coke and refined petroleum products	13 Textile production
20 Manufacture of chemicals and chemical products	14 Manufacture of wearing apparel
21 Manufacture of pharmaceuticals, medicinal chemicals	15 Manufacture of leather and related products
and botanical products	16 Manufacture of wood and of products of wood
22 Manufacture of rubber and plastic products	and cork, except furniture
23 Manufacture of glass and glass products, ceramics	17 Manufacture of paper and paper products
and related products	18 Manufacture of printed matter and reproduction
26 Manufacture of computers, electronic and optical products	of recorded media
27 Manufacture of electrical equipment	24 Manufacture of basic metals and fabricated metal products
28 Manufacture of machinery and equipment	25 Manufacture of fabricated metal products
29 Manufacture of motor vehicles, trailers and semi-trailers	31 Manufacture of furniture
30 Other transport equipment	32 Manufacture of other products
33 Repair and installation of machinery and equipment	

and Cloppenburg was more than twice the LS average in 2019. Four from the eight case districts in LS are among the six regions in Germany where the most non-residential building land per employee was designated between 1995 and 2018. At the same time, there is no "excess capacity" of labour (Haggblade et al., 1991) in the two labour market regions that make up the largest part of our case region. In 2020, across all occupations, there were 2.3 unemployed people with matching occupations for every vacancy reported to the employment agency in LS.[6] In the two relevant labour market regions of our region, the figures were only 1.8 and 1.7. There were even only 0.6 unemployed registered skilled workers for every vacancy reported by the meat processing industry in the districts in NW. These capacity constraints can lead to competition effects in the relationships between industries in the region.

Intensive livestock and meat production also creates major challenges in terms of working conditions, animal welfare and environmental protection (Dumont et al., 2013). Observers expect stronger regulation of livestock density and other aspects of production to reduce environmental damage (e.g. Anker et al., 2018).

2.2. Data, regression, and simulation

For the panel regression we use annual absolute employment numbers by industry for each site, i.e., district. Our data cover the years between 2007 and 2019. Due to the formation of the cumulative differences, the first year is lost, so that the regression is based on observations on 12 years. This gives 192 observations for the 16 case districts and 2544 for the 212 reference districts.

We use data on all employed persons from the German Federal Statistical Office and data for more differentiated industries on employees that are subject to social security contributions (ssc employees) from the German Federal Employment Agency. Because *agriculture* in western Germany is characterised by family farms, its structure is not well represented by the Federal Employment Agency's figures on ssc employees. For *food manufacturing* (two-digit NACE[7] codes 10-12), on the other hand, only data on ssc employees are available. With the data on ssc employees we also represent "*complex manufacturing*" with manufacturing industries characterised by large units or relatively high innovation intensity (Table 1). The number of ssc employees in food and complex manufacturing is subtracted from the number of all employees in total manufacturing (NACE level 1, class C) in order to calculate the number of all employees in the remaining "*other manufacturing*".

Corporate headquarters in the food industry (as in other industries) are often not listed under the industry of their subsidiary's main product, but are assigned to NACE classes M ("Professional, scientific and technical activities") and N ("Other business activities") according to their own main activity. In the absence of more differentiated data, we assign the ssc employees from industries M and N to "*corporate services*" and all other employees from these industries as well as all employees from industries K ("financial and insurance activities") and L ("real estate, renting and business activities") to "*other business services*". Finally, we group sectors B ("mining and quarrying"), D ("Electricity, gas, steam and air conditioning supply") and E ("sewerage, waste management and remediation activities") as "*other production*", G ("Wholesale and retail trade; repair of motor vehicles and motorcycles"), H ("Transport and storage"), I ("Hotels and restaurants") and J ("Information and communication") as "*private services*" and O, P, Q, R, S, and T as "*public services*"[8] (see also Table A1 in the appendix).

With the number of employees per year and industry groups by district we run the estimations as described in chapter 1.2. Tables A2a and A2b in the appendix presents the estimated coefficients.[9] The coefficients are not very meaningful on their own because of the interrelation between them and because of the absolute reference values. For the discussion of results, they are therefore first multiplied by the observed values before the resulting effect sizes for specific sites are interpreted. The fit of the development predicted by the estimated coefficients from the case and the reference regime to the observed development is determined at hand of the measure of fit described in section 2.2. Observed developments in four out of the 16 case districts seem to be better replicated by coefficients from the reference regime than by those from the case regime (first vs. second column in Table 2).[10]

The Monte-Carlo simulation with 10.000 random draws of coefficients per coefficient set provides us with 1.6 Million sets of coefficients for the 16 district and 10 industries. The selection of all regimes that generate a better fit than the estimated regime leaves us with 17,605 coefficient sets. We repeat the same procedure with the coefficients from the reference regimes as initial values for the random draws. For each industry in each district, we keep the initially estimated coefficients and the one per cent coefficient sets with the best fit for the reference and the case regime. The product of the number of these coefficient sets by industry per regime type and district provides the

[6] Statistics of the Federal Employment Agency: Skilled Labour Radar, May 2019 to April 2020.

[7] Statistical Classification of Economic Activities in the European Community, https://nacev2.com/en.

[8] Public administration and defence; social security; education and training; Health and social work; Arts, entertainment and recreation; Other service activities; Activities of households as employers of domestic staff; Manufacture of goods and provision of services by private households for own use with no particular focus.

[9] The estimated standard errors are reported in brackets beyond coefficients. However, the estimated coefficients are descriptive and simply express the true mean relationships within the population. We do not have to deal with random errors that are due to between-sample variation since we use observations on the complete populations of interest (the case and reference districts) (Ludwig, 2005; Margarian, 2022a). The estimated standard errors are influenced by "sample" size and do not tell us much about the size of the non-observable true standard deviations of the coefficients. We account for the fact that the coefficients can vary between the individual observations of the samples by determining best-fit coefficients with our Monte Carlo simulation approach.

[10] A summary of these measures of fit differentiated by industry is presented in Table A3 in the appendix.

Table 2
Fit for case districts with original coefficients and with best fit coefficients.

District		fit of regime with estimated coefficients		fit of district-specific best fit regime variants	
		smallest test values across years			
		Case regime	Reference regime	Case regime	Reference regime
3251	Diepholz	55.3	80.6	34.8	**29.1**
3453	Cloppenburg	58.7	85.0	36.6	**36.3**
3454	Emsland	35.2	73.9	28.1	32.9
3456	Grafschaft Bentheim	91.6	**87.4**	68.4	**37.1**
3458	Oldenburg	155.8	**97.2**	79.6	*
3459	Osnabrück	38.5	90.1	25.8	43.0
3460	Vechta	62.7	83.5	32.4	**30.9**
5154	Kleve	91.2	219.8	57.8	96.5
5554	Borken	48.3	81.1	29.9	34.0
5558	Coesfeld	133.3	**105.0**	64.3	**52.1**
5566	Steinfurt	55.9	82.3	37.9	58.2
5570	Warendorf	117.1	135.4	60.4	70.4
5754	Gütersloh	60.7	120.4	44.8	**43.8**
5770	Minden-Lübbecke	79.2	102.2	45.5	61.2
5774	Paderborn	132.0	**71.2**	48.1	**35.4**
5974	Soest	80.5	92.9	53.7	**41.9**

* Simulations with the feasible solutions for the reference regime have been omitted for Oldenburg due to hardware capacity restrictions. As Oldenburg is a fringe district this restriction seems acceptable.

Bold numbers mark reference regime cases with smaller test values than in the corresponding case regime.

number of regimes to be further analysed (see Table A4 in the appendix).[11] We keep as feasible variants those that do not lead to negative employment figures in any industry after two simulation runs starting from 2007 (t0; see section 2.3). From these feasible variants we select the one case regime and the one reference regime that generate the best fit with the observed development. Compared to the estimated coefficients, our measure of fit shows a clear improvement with the best-fit variants for most districts (first vs. third and second vs. fourth column in Table 2). With the best-fit variants, half of the case districts show a better fit with the reference than with the case regime (third vs. fourth column in Table 2). For the peripheral district Grafschaft Bentheim that lies on the edge of our case region and on the border between Germany and the Netherlands, this improvement seems specifically substantial.

Then, starting from the employment numbers from the end of the observation period 2019 (t0), simulation runs over two phases follow, corresponding to a total period of 24 years. Given the environmental pressure imposed by livestock farming, a second simulation experiment examines the local labour market effects of policies that would force a drastic reduction in livestock density in the region. Research indicates that implementing such measures might lead to a fall in earnings by up to 55 percent for livestock production (Haß et al., 2020). In the simulation, the scenario is implemented by initially and permanently halving the number of people employed in the agricultural sector at simulation time t0. Permanent here means that the number of employed people in agriculture is persistently kept at a maximum of 50 per cent of the initial value from t0 in all simulation stages. Since some districts seem to be better described by the reference regime than by the case regime (see Table 2), and since we cannot know whether the districts will maintain their old regime after an exogenous shock, both scenarios, the one with full employment and the one with half employment in the agricultural sector, are simulated again with the (best-fit) coefficients of the reference regime.

The different scenarios are then compared according to the scheme depicted in Fig. 1. In the simulation, we are only interested in the case districts. For each of them, we compare the development in the original scenario of full agricultural employment with that in the manipulated scenario of halved agricultural employment. For this second scenario, we additionally compare the development under the case regime with the alternative development under the reference regime. While we analyse the estimated regimes for the mean case district, we focus on the best-fit regimes for the individual districts.

3. Results

In discussing the results, we focus on five sites. From the data of the case and reference districts we calculate their mean values, which characterize the *mean case district* and the *mean reference district*.[12] As selected case districts, we focus on *Emsland* (EL), which has the best fit to the case regime of all case districts (see Tables 2 and A3); *Cloppenburg* (CG), which is characterised by extremely high livestock density and has a reasonable fit to the case regime, but whose best-fit regime is based on the reference regime (see Table 2); and *Grafschaft Bentheim* (GB), for which both the estimated reference regime and the reference-based best-fit regime each have a better fit than the corresponding case-based regimes.

3.1. Regression results: Effect sizes

We multiply the estimated coefficients by the values of the associated variable values of the last observation year (2019) for the mean district to derive and discuss effect sizes. For the mean reference and case district we calculate effects sizes at hand of estimated coefficients. For individual districts, we calculate effects sizes with estimated as well as best fit case and reference regime coefficients. For better comparability, effect sizes are expressed as a percentage of the sum of all effect sizes calculated for each observation or district.

The innate effects represented by the intercepts are small compared to all other growth effects (Fig. 2). However, seemingly small positive innate effects can make a huge difference because innate effects can set in motion self-reinforcing development in new locations. Agriculture exhibits neither innate nor own-size effects in the case regime. In the reference regime, on the other hand, agriculture experiences a small innate decline and noticeable negative own-size effects, i.e. it contributes to a decreasing extent negatively to local employment growth.

Food manufacturing shows a (slightly) negative innate growth in the case regime, but a slightly positive innate growth in the reference regime. However, it consistently shows a positive own-size effect. Accordingly, it grows in the case regime especially where there are already many employees in the food sector. This is consistent with the still persistent spatial concentration of the meat processing industry, which dominates food manufacturing in the case region. This clear concentration process of food manufacturing in the case region is quite unique. Normally, positive own-size effects are accompanied by positive innate effects. In the case regime, we observe such autonomous, self-sustaining growth for complex manufacturing, construction and public services, in the reference regime additionally for private and especially for corporate services.

Particularly striking is the strong negative own-size effect of corporate services in the case districts. Large corporate services here often conceal the headquarters of large companies in the meat industry (compare section 2.2). The negative own-size effect could be

[11] We create these sets of coefficients only for the one percent of the coefficients per industry with the best fit, because otherwise the number of combinations and thus the computational effort in the next step would be excessive.

[12] Our model is adapted to district level observations. As it considers scale effects, we cannot simply work with the sums of employees across all districts in order to generate results for the whole case region. However, if that is desired, results for the mean case district can simply be multiplied by 16 for the 16 case districts.

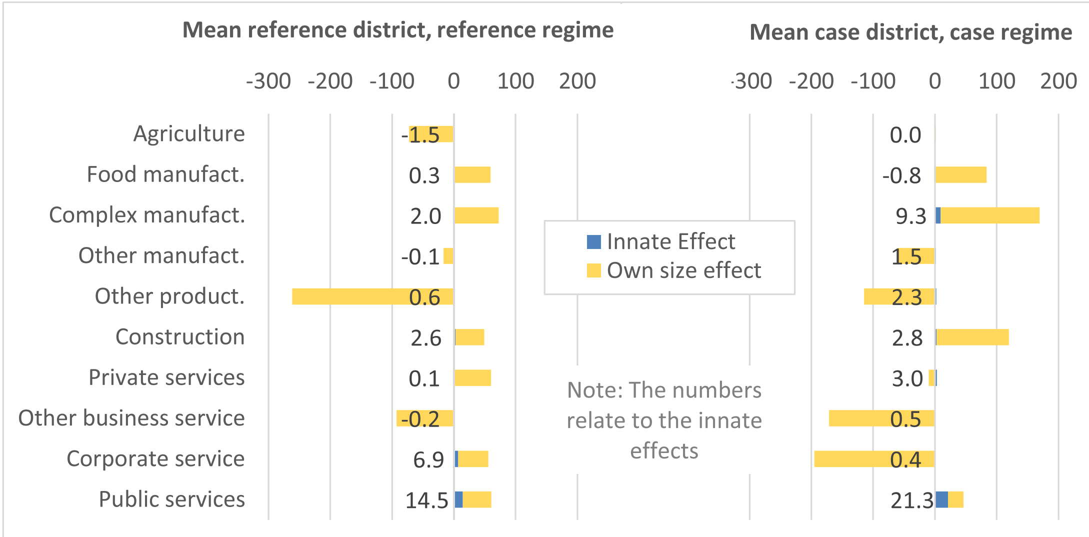

Fig. 2. Relative innate growth and own size effect by industry in the mean case and reference districts.

attributable to a low growth of the respective company headquarters as well as to a low tendency of comparable headquarters to locate in their immediate neighbourhood.

Fig. 3 also considers all other effects that determine industry growth in the model. Here, innate and own-size effects are combined into "industry effects". The sum per industry shows the contribution of the intrinsic growth of the individual industries to the overall growth. The category "Total" sums up the effects across industries and indicates the extent to which total growth in the different locations and regimes is determined by the different effect types. These total effects across industries add up to one hundred, as we report relative contributions to growth. The effects as they are reported in this Figure define what we call "growth regimes". A comparison of the mean case district and the mean reference district in this respect shows that the case regime is characterised by the high positive net contribution of spillover effects to growth in the case districts.

Structure and industry effects are antagonistic in all regimes and industries. Agriculture is an exception in the case regime only insofar as its industry effect is zero (see also Fig. 4). The antagonism can be explained by the fact that (mature) industries without positive own

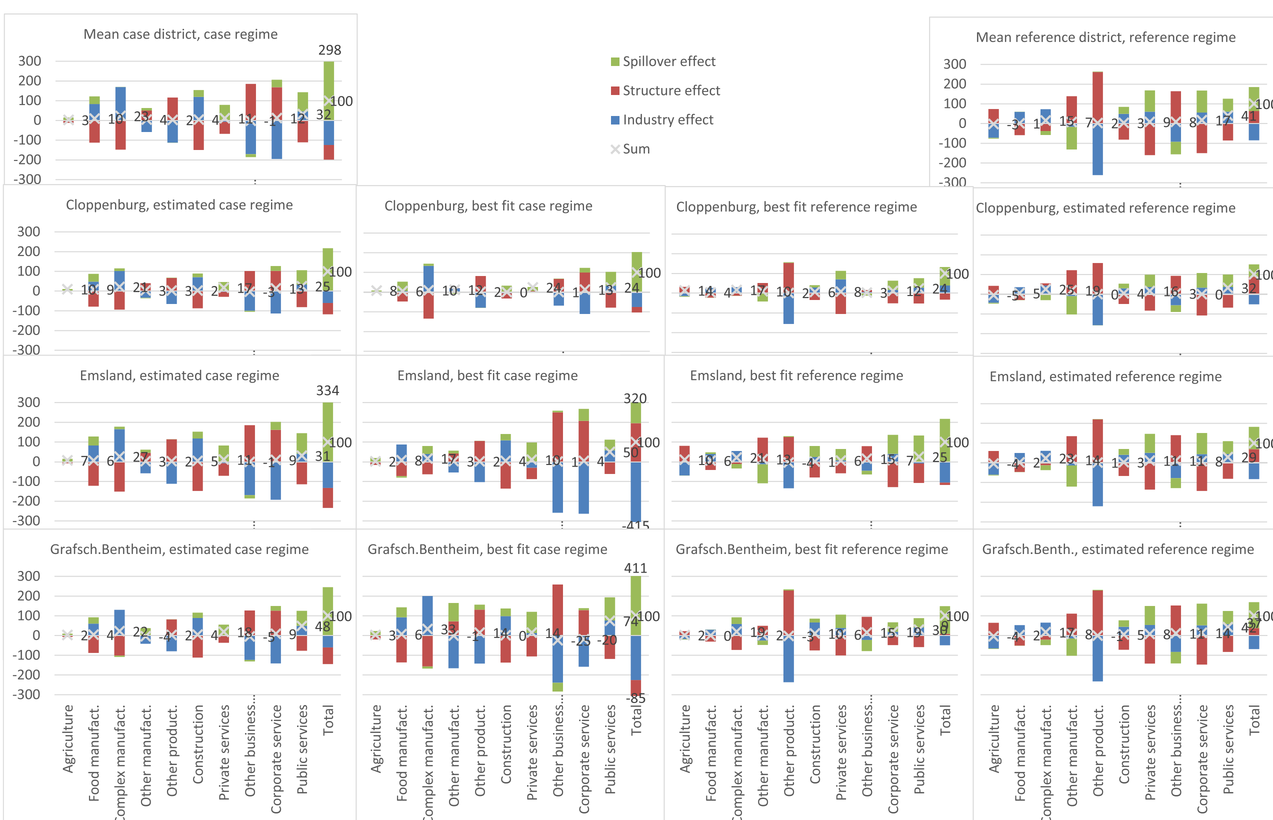

Fig. 3. Effect types that determine industry growth in different locations, regimes and industries.

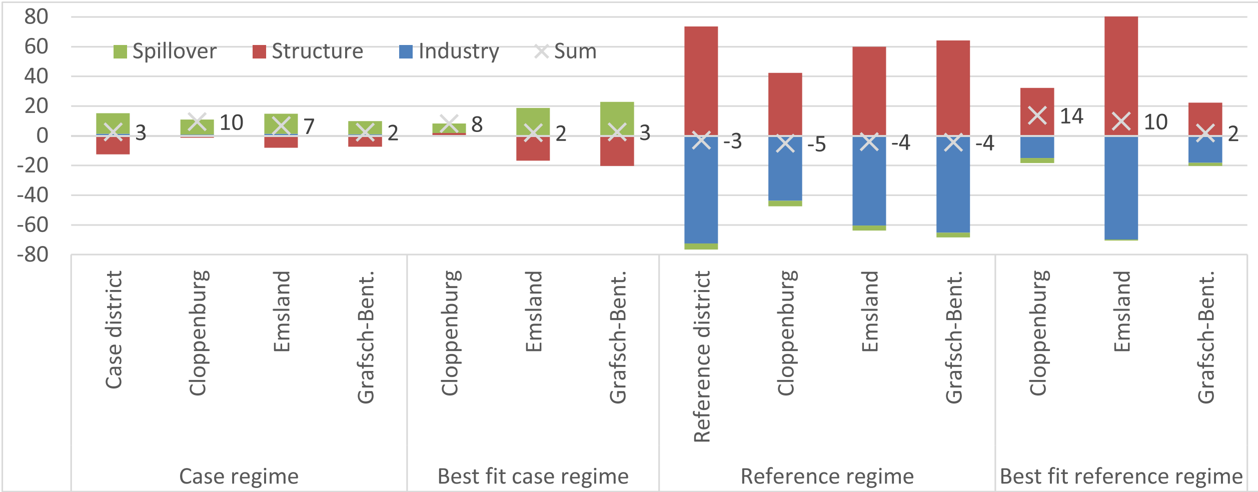

Fig. 4. Effect types that determine agricultural growth in different locations and regimes (relative effect sizes).

growth dynamics are competitive primarily in low-cost locations, where competition from other industries is weak and positive structure effects dominate. Innovative, growth-intensive industries, on the other hand, settle primarily in competitive locations where negative structure effects dominate. In these locations, the corresponding industries benefit from positive agglomeration respectively spillover effects (see in particular construction as well as private, corporate and public services in the reference regimes in Fig. 3).

The relatively strong growth of food processing in the case regime is driven by positive industry and spillover effects. According to Fig. 3, in the best fit case regime, spillover effects alone drive food industry growth in Cloppenburg (CG), while positive industry effects alone drive food processing growth in Emsland (EL). However, in the case districts, growth of food processing as of complex manufacturing is hindered by local industry structures in the case regime. This is not observable for the reference regime.

Fig. 4 focuses on agriculture alone and illustrates, why agriculture grows in the case districts despite of a nil industry effect. In the case regimes, agricultural growth is due to positive spillover effects from other industries. Under the best-fit reference regimes, on the other hand, the positive net total structure effect of all other industries explains the growth of agriculture in the case regions.

Fig. 5 breaks down for the case regime in the mean case district and for the reference regime in the mean reference district which other industries generate the structure and spillover effects on agriculture summarised in Fig. 4. In the case regime, positive structure effects from construction and positive spillover effects from public services dominate. They are, however, more than compensated by negative structure effects from public services. Possibly this can be explained by the fact that the growth of agriculture, given its many externalities and its subsidy intensity, is often accompanied by a growth of public administration, but that a strong public sector is then a sign of already high competition for local resources. This would also be supported by the fact that in the reference districts, with their usually less intensive agriculture, both effects of public services are positive. The considerable positive structure effect on agriculture in the reference regime is caused by all industries outside agriculture. Agricultural employment development seems to benefit from a strong and diversified economic structure in the reference regime.

Agriculture and food manufacturing influence the growth of other industries as well (Fig. 6). Due to strong positive structure effects, the overall effect of agriculture on other industries is more positive in the mean reference district than in the mean case district. The positive structure effect indicates that a strong agricultural sector outside the case region usually goes along with good availability for example of land and low competition on factor markets among other industries. In the mean case district, on the other hand, agriculture has considerable positive spillover effects specifically on food manufacturing, which are

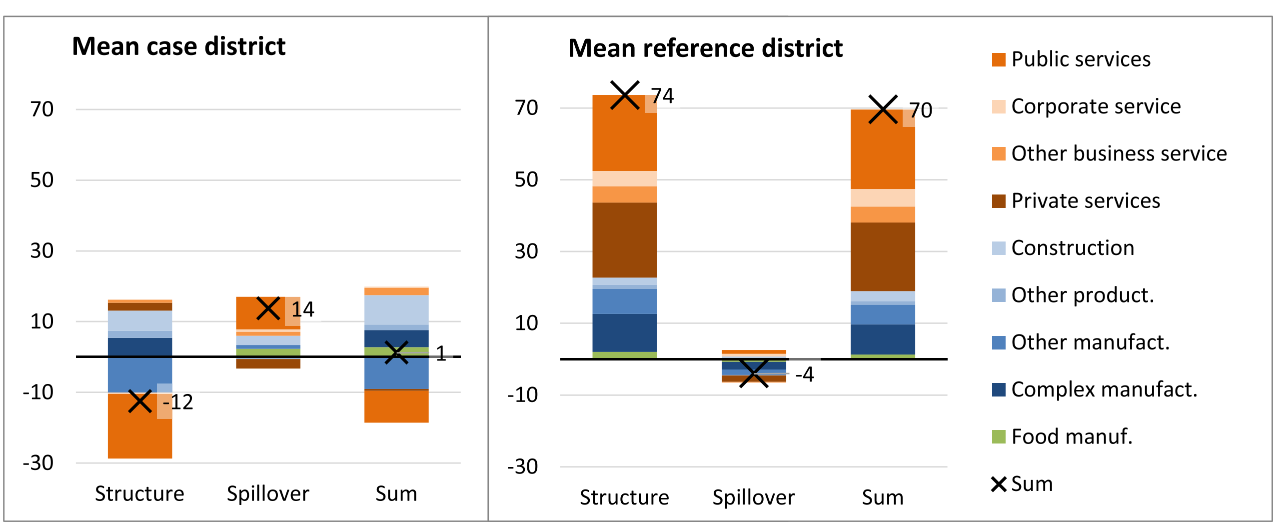

Fig. 5. Industry contributions to structure and spillover effects on agricultural growth in the case and reference regime.

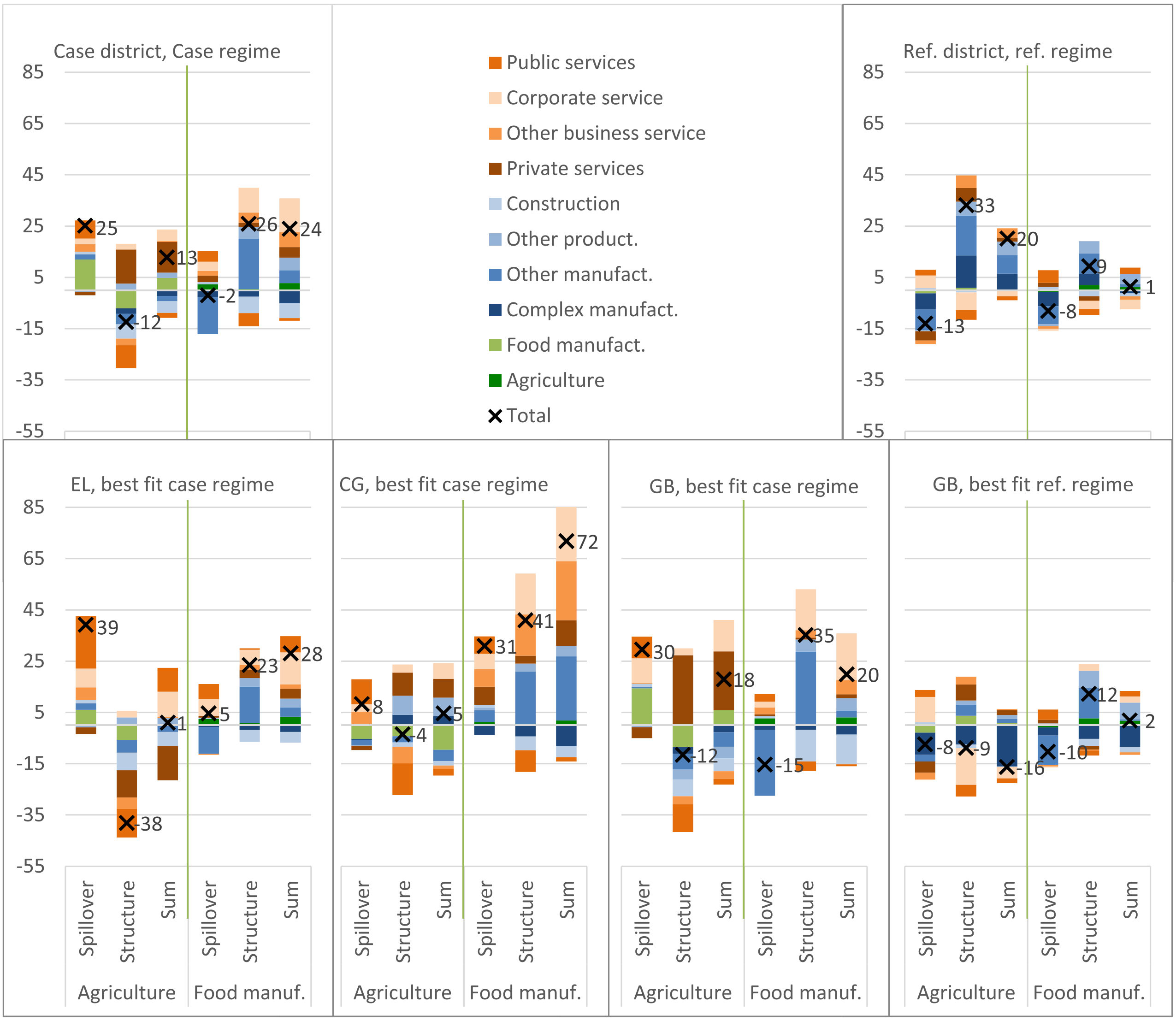

Fig. 6. Growth effect of agriculture & food manufacturing on other industries by location & regime.

partly compensated by negative structure effects. Food manufacturing again tends to have positive spillover effects on agriculture in the case, but not in the reference regime. This suggests a mutually reinforcing growth of the two industries in the case districts, which could be an important driver of the ongoing scale-dependent concentration of livestock and meat production (see introduction to chapter 2). According to the best-fit regimes, the spillover effect from agriculture on the food industry is relatively small in Emsland (EL) and even negative in Cloppenburg (CG), but relatively strong in Grafschaft Bentheim (GB). GB, however, is better described by the best-fit reference regime, where there are no positive spillover effects from agriculture to food manufacturing.

In the reversed perspective, Figure A1 in the appendix gives an overview of the aggregate growth effects of all industries. According to that, private services, construction and - in the case regime - public services exert strong positive spillover effects. The strongest negative spillover effects in both regimes come from complex and other manufacturing. Because private services exert strong positive spillover effects and also tend to benefit from a strong agricultural sector (see Fig. 6), a strong decline in agriculture could have significant secondary effects. Certain industries like corporate and public services are simultaneously associated with positive structure effects and positive spillover effects under some conditions (see Figure A1). Sometimes this applies to food manufacturing as well (see Figure A1 and Fig. 6). This could indicate that it is a "pioneer" industry. Pioneer industries benefit from abundant simple resources in structurally underdeveloped regions and then contribute to the development of advanced capacities and capabilities there (Margarian and Hundt, 2023). In doing so, they increase the attractiveness of the location for other industries as well. This could explain the strong positive relationship between the food industry and rural employment growth that has been repeatedly observed in Germany (Margarian et al., 2022; Margarian, 2013).

3.2. Simulation results

All these effects together are responsible for employment development. Fig. 7 shows the different absolute employment trends in different districts and regimes as observed between 2007 (t0) and 2019 and as simulated for the first phase from 2019 (t1) and for the second phase (t2).

The first column of the figures in Fig. 7 shows the growth in total employment and the growth in agriculture without intervention. The second and third columns show the changes that would occur relative to the "normal" development in the first column if the number of people employed in the agricultural sector was permanently halved beginning in 2019 (t1). Without intervention, the absolute employment figures

Fig. 7. Employment growth between periods (t0 observed, t1 & t2 simulated) in thousands and effects of agricultural decline on growth in thousands by regimes.

increase at increasing scale in the mean case district, in Cloppenburg, and in Emsland, which is the natural result with constant relative growth rates. For the Graftschaft Bentheim, on the other hand, we observe a decline in growth in the second simulation phase in the best-fit case regime. This indicates that the best-fit case regime leads to the development of an unfavourable industry structure in this district. The best-fit reference regime not only shows a better match with the observed development of this district (see Table A3 and Table 2); according to the simulation results, it would also constitute a better growth performance and a higher resilience to the decline of agriculture.

Grafschaft Bentheim would experience significant losses in employment growth with declining agriculture in the best-fit case regime.[13] In t2, this structurally disadvantaged district, which already experienced relatively low employment growth between 2007 and 2019, would then actually experience a loss in total employment, even though the loss in agricultural employment itself is small. In the best-fit reference regime, on the other hand, the district would experience strong compensatory growth.

In Cloppenburg, in Emsland, and in the mean case district, considerable, albeit reduced, employment growth would still be expected with a decline in agriculture in the case regime and, albeit to a lesser extent, with a change to the reference regime. The negative growth effect of a change from the best-fit case regime to the best-fit reference regime would be particularly strong for Cloppenburg. In the best-fit case regime, on the other hand, we even find a positive growth effect of the agricultural decline for Cloppenburg in t2, which more than compensates for the loss in agriculture.[14]

Fig. 8 shows the relative growth in the three selected case districts in their best-fit regimes and how each sector contributes to this relative growth. In addition, the change in relative growth with a decline in agriculture is shown in percentage points. Without intervention, the simulated growth is not fundamentally different in its industry composition from the observed growth in t0. In Emsland, according to the best-fit case regime, non-food manufacturing and other production as well as corporate services contribute decreasingly to growth from phase to phase while other business services contribute increasingly. In Cloppenburg in its best-fit case regime and in Grafschaft Bentheim in its best-fit reference regime, private services as well as complex and other manufacturing industries contribute increasingly to growth. Corporate and other business services, on the other hand, contribute decreasingly to growth in Cloppenburg, but increasingly in Grafschaft Bentheim.

The industries contribute very differently to the changes resulting from the halving of the agricultural sector. In the best-fit reference regime of Grafschaft Bentheim, the reduction of the agricultural sector hardly leads to additional reductions in other industries, but rather to significant compensatory growth in other production and especially in complex manufacturing. In the best-fit case regimes of Cloppenburg and Emsland, on the other hand, we observe the strongest compensatory growth in other manufacturing and the strongest additional reduction in complex manufacturing (Cloppenburg) and in food manufacturing (Emsland).

Owing to the differentiated growth processes in the various industries, the industrial structures in the districts change. As Fig. 9 shows for the case regime in the mean case district, these changes are rather slow and gradual, in line with the general inertia of industry structures. Figure A2 in the appendix shows the same for the three individual districts.[15] In the mean case district in the "normal" scenario, especially the employment shares of food manufacturing, complex manufacturing and corporate services are increasing, while the employment shares of other manufacturing and other business services are decreasing significantly. In summary, the share of the production sector would increase relative to the service sector.

If the agricultural sector is halved, the industrial structure shows a similar development as without intervention. However, if the case region switches to the reference regime after the shock, the employment share of the service sector would now increase in relation to the production sector. This would not remain without further economic consequences, since in rural regions a higher prominence of the service sector, which is usually not very knowledge-intensive here, tends to come along with lower incomes.

4. Conclusions

The regression-based simulation approach presented in this paper makes it possible to examine industry developments and economic growth at a specific location in detail. The approach has also been used to simulate and evaluate the possible effects of an expected external shock on the development. At its core is an estimation models that identifies inter-industry relationships, which characterize evolutionary growth regimes. The approach identifies which industries contribute to growth independently (innate effect), where this industry growth is self-reinforcing (own-size effect), whether certain industries influence the attractiveness of a location for certain other industries (structure effect) and which industries support or hinder each other in their growth (spillover effects). The identified coefficients are then applied in simulations of different scenarios that are evaluated in a contrafactual design.

We applied the approach to the analysis of industry dynamics in a region that has benefited from the scale-driven growth of a mature industry (livestock intensive agriculture), which is now reaching the limits of what the region can sustain economically, ecologically and socially. The results show that the case region's growth regime is characterized by a dominance of positive spillover effects if compared to the growth regime in the reference region. The marked spatial concentration process of the agri-food sector observed in the case districts seems to be specific to the case regime, as in other industries and regions positive own-size effects are usually accompanied by positive innate effects, which allow an industry to establish itself in new locations as well. The results also indicate that the case region, or parts of it, could experience a negative lock-in because for some sites, we observe substantial compensatory growth when agriculture declines. The existence of compensatory growth confirms the evolutionary nature of growth in this case and the inappropriateness of approaches such as simple IO models that do not take this into account.

We also find that negative spillovers, i.e. competition effects, rarely outweigh positive spillovers. This mainly occurs with the manufacturing sector. Structure effects and industry (innate plus own size) effects are found to be antagonistic, as mature industries with low growth potentials locate in low-cost production locations, while fast-growing industries locate where many industries compete for local resources. This leads to negative structure effects, but in return the industries benefit from positive spillover effects at the locations concerned. The approach thus proves its ability to identify patterns of evolutionary regional developments and to contribute significantly to their systematic study at the industry level.

The approach has additional advantages of relatively low data requirements and simplicity over CGEs. The downside to this is that its

[13] In Figure 7, this loss is also expressed in relation to the "normal" growth in the reference regime as well (shaded field), but only for illustrative reasons. In reality, while a switch from the case- to the reference regime seems to be plausible after an exogenous shock, the reversed switch from the reference to the case regime, seems much less plausible.

[14] Using the estimated mean case regime instead of the best-fit case regimes, we obtain development patterns for all case districts that are quite similar to those of the mean case district in Figure 7. In particular, there would be no over-compensation of employment losses in agriculture.

[15] There, for GB, the halved agricultural sector is only depicted for the reference regime but the full agriculture case is presented for both, the case and reference regime in deviation from the other three presentations.

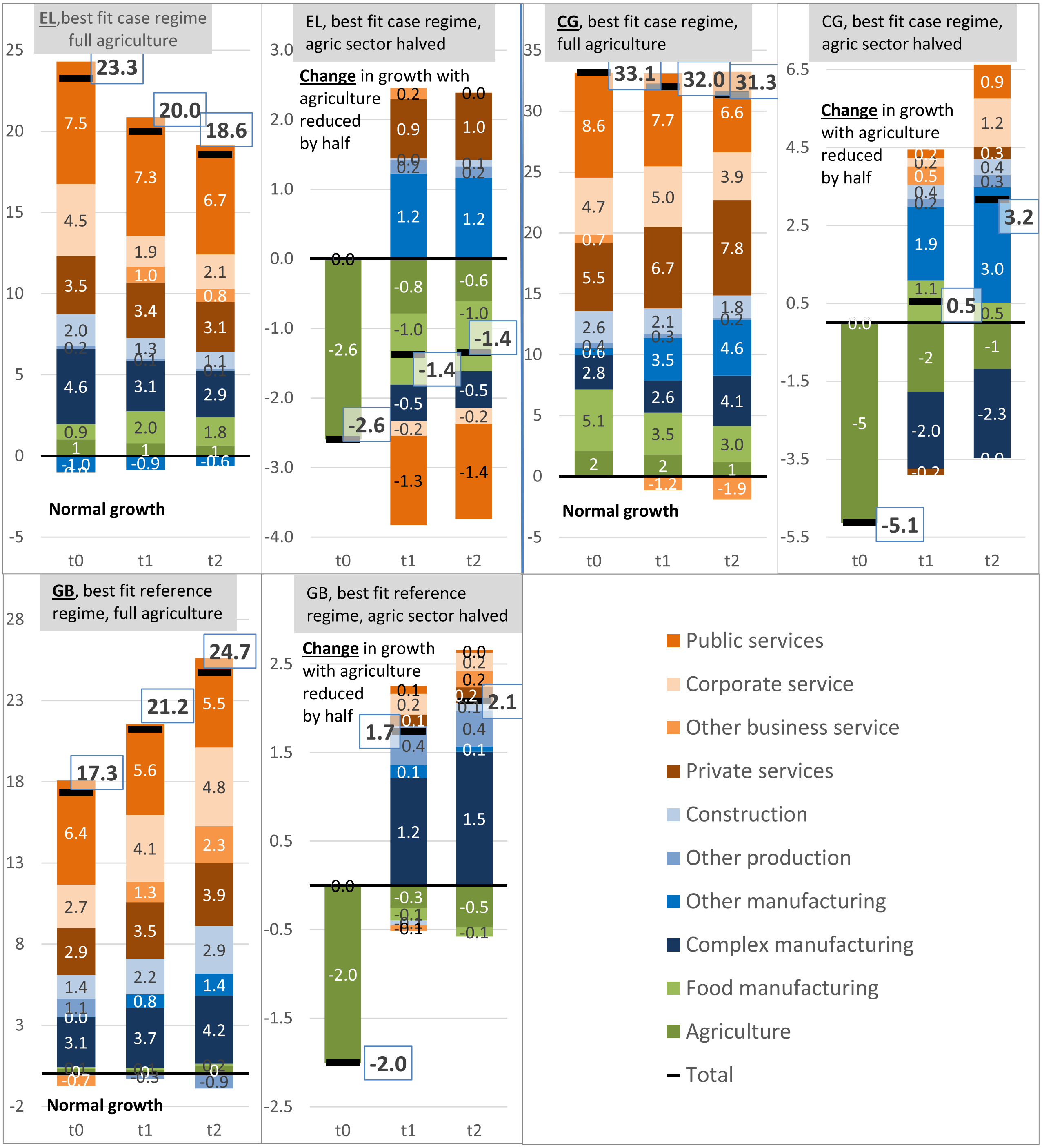

Fig. 8. Observed (t0) and simulated (t1, t2) relative growth with industry contributions in percentage points and change in growth if agriculture is halved (selected case districts in best fit regimes).

models are empirically derived and provide no insights into the deeper causes of observed patterns. The lack of anchoring in economic behavioural equations as well as the use of quasi complete models prevents universally valid relationships or coefficients from being identified and restricts the external validity of the results. Nevertheless, the lack of external validity reflects the specificity of sites in the evolutionary context. And the simplicity and low data requirements of the approach allow for systematic large-scale analyses and comparisons. We also partially compensate for the limited external validity of the estimated coefficients by identifying best-fit regimes through Monte Carlo simulations and by regime switching experiments. It becomes clear that the effects of exogenous shocks on evolutionary processes cannot be unambiguously identified on the basis of historical data alone, owing, for example, to indeterminate bifurcation points. This paper therefore does not provide a tool for forecasting. It provides an approach for carrying out simulation experiments. The proposed approach thereby helps to systematise the empirical analysis of evolutionary phenomena at the meso or industry level.

Our operationalisation of the analytical framework still has some weaknesses. In the estimation, we have used a series of multiple models by industry and region type. This is not only computationally and econometrically inefficient. It also prevents us from identifying inter-

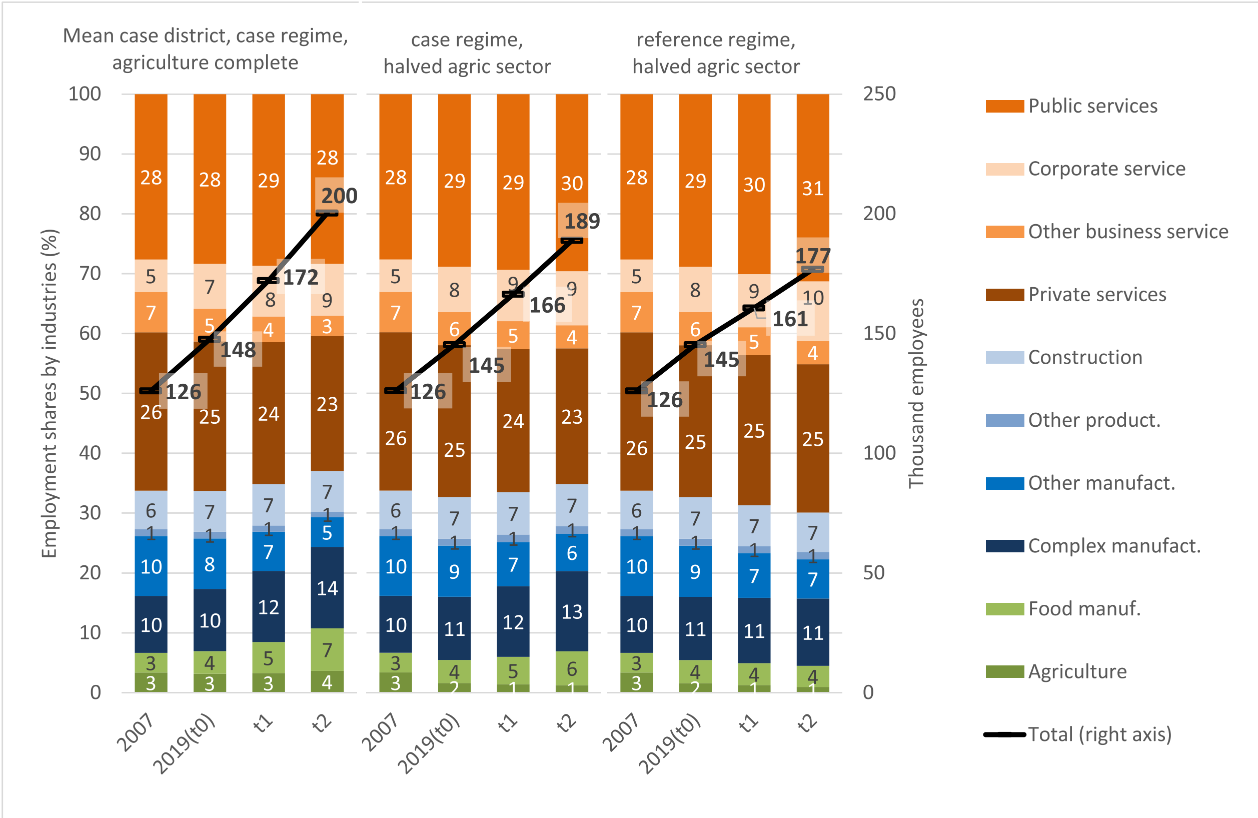

Fig. 9. Industry shares and employment growth in mean case district in different szenarios.

model covariances of endogenous industry growth and its determinants. Future development of a more comprehensive modelling approach that allows the simultaneous estimation of relationships across industries and regions potentially contribute significantly to more robust results and simulations. This is particularly true because our Monte Carlo simulation-based method for determining site-specific growth regimes is computationally inefficient. The identification of best-fit regimes could become more efficient and accurate if the covariance matrices from the estimation were used to guide the generation of "random" coefficient sets (see for example Mangino and Finch, 2021). In this context, it might also be worthwhile to replace the inefficient Monte Carlo approach with, for example, a random forest approach, which is better suited to the clustered nature of the coefficients. This brings us to a final weakness: We relied on ad-hoc decisions to assign sites to the case region and thus to a specific regime. However, our own analyses have shown that some of the sites at the edge of the region may be better described by the other regime. In the future, approaches for data-driven classification of sites into different classes of regions and regimes could be applied (Mangino and Finch, 2021).

There are also many opportunities to extend the application of the approach to a wider range of open questions. To gain more insight into the stability of evolutionary regimes and their robustness to perturbations, panel data covering longer time periods would be extremely valuable. With a finer differentiation between regions and regimes, or with a cross-sectional extension of the data, the spatial extent of growth regimes could be analysed. Other scenarios could also be simulated. For example, if the macroeconomic environment of an industry changes, it might be worth manipulating the industry's innate effect to analyse how its local dynamics or adjustment to exogenous shocks is affected. If the macroeconomic environment cools down, we might for instance expect weaker compensating effects. If the approach is carefully handled and developed in this sense, it may contribute to a systematisation of the analysis of evolutionary regional economic processes and thus to a cumulative broadening of our knowledge of the intricate patterns of structural change.

Declaration of competing interest

The author reports there are no competing interests to declare.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.strueco.2024.01.003.

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