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ORIGINAL ARTICLE

Endogenous rural dynamics: an analysis of labour markets, human resource practices and firm performance

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Abstract
Some rural locations in industrialized countries have experienced considerable employment growth in the last decades, while others suffer from depopulation and decline. The paper aims to contribute to the development of an evolutionary approach that allows for the identification of those often difficult-to-observe evolving factors that explain success and failure of rural locations. It also wants to show how the combined recognition of evolutionary labour market perspectives, the dynamic capability view of the firm, and human resource management (HRM) theories can serve the operationalisation of evolutionary explanations in this context. According to the derived model, apparent locational disadvantages might be compensated for by subtle, potentially self-enforcing labour market dynamics that generate opportunities for certain firms and industries. Empirically, the ideas are substantiated by means of a mediation model. The empirical analysis is based on latent class analysis and discrete choice models using data from an own survey of 200 food-processing firms in urban and rural locations of one German federal state. For these observations, our results support the idea that the exploitation of HRM opportunities may be more important for good performance in rural labour markets than the direct implementation of specific innovation modes. Investment in HRM allows rural firms in our sample to realise those gains in terms of innovation and growth offered by the creation of a stable and experienced workforce. Their focus on internal labour markets potentially generates external effects, which further encourages neighbouring firms to also invest in involved HRM measures.

Keywords Agglomeration advantages · Innovation · Human resource management · Mediation

JEL Classification R1 · J24 · M5

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Introduction

In the last decades, some rural locations in industrialized countries have experienced considerable employment growth (Bryden and Bollman 2000). According to Phillipson et al. (2019), small- and medium-sized rural enterprises in England outperform their urban counterparts on many dimensions. In the UK, economic restructuring has accompanied economic growth in many rural regions at the beginning of the new millennium (Hoyos and Green 2011). Firms in prosperous German rural regions frequently experience modest growth across decades (Massis et al. 2018). Moreover, rural districts in Germany's west have outperformed most of their urban counterparts in terms of employment growth rates in the past decade, even though they typically specialize in low-tech industries (Margarian 2022).

These observations appear to be at odds with the widely held view that growth in developed economies requires innovation and knowledge resources, which are typically concentrated in agglomerated core regions (Hansen and Winther 2011). From this perspective, "the periphery […] is implicitly treated as the laggard in a competition with urban areas that it can never win" (Wirth et al. 2016). Rural locations are thus sites for enterprises of low productivity that cannot afford the high costs of urban "prime" locations, which are attractive for all kinds of firms due to their various agglomeration advantages (Combes and Gobillon 2015; Puga 2010). Many studies have confirmed that agglomeration advantages result in higher productivity (Combes et al. 2012), higher wages (Groot et al. 2014) and more innovation as measured by patents (Moretti 2011).

Given this general deficiency-oriented characterization of rural locations and the positive economic development of some of them, the paper aims to contribute to the development of an evolutionary approach that allows for the theoretical and empirical identification of those often difficult-to-observe evolving factors that may explain the success and failure of rural locations. More specifically, we want to show how evolving differences in firms' exogenous and endogenous labour markets, beyond agglomeration effects, could play an important role in explaining heterogeneous development patterns of rural locations. Therefore we propose that the picture of spatially differentiated development is not complete if we concentrate on the well-documented mechanisms linking agglomeration, rapid innovation and productivity growth alone. Instead, we have to recognize that these mechanisms might be complemented by other, more difficult-to-observe mechanisms. They link employment stability and the endogenous creation of human resources with tacit knowledge, incremental innovation and long-term growth.

Our contribution to the literature emerges from the combined recognition of ideas from the evolutionary labour market perspectives, from the resource-based view of the firm, and from human resource management (HRM) theories. Spatially sensitive, evolutionary labour market models can provide theoretical support for the idea of specific endogenous rural dynamics if they take into account endogenous decisions for the skill acquisition of heterogeneous agents (Moretti 2011). Management approaches, such as the resource-based view, emphasise that firms can generate competitive advantages internally and “integrate, build, and reconfigure internal and external competencies to address rapidly changing environments” (Teece et al. 1997). A variety of authors have discussed that rural firms might have certain advantages in the implementation of practices in endogenous human capital development (Croce et al. 2017; Hoyos and Green 2011; King and Vaiman 2019; Phillipson et al. 2019; Deakins and Bensemann 2019). To the best of our knowledge, however, we are the first to analyse the relationships between rural labour market characteristics, HRM practices, innovation activity and firm growth coherently in a single model.

We employ this model in our empirical analysis, where we seek to qualify HRM and the innovation strategies of firms and relate them to characteristics of local labour markets. Empirically, the paper follows a “detailed micro-level approach” and stresses “the dynamic nature of the relationships between the firm and its environment” (Smallbone et al. 1999). In the empirical analysis, we employ data from an own survey in a single industry (that is, food processing), within one culturally and institutionally homogenous region; that is, the German federal state of Lower Saxony. Measured by employment shares, the food industry is one of the most important manufacturing industries in the European Union, where approximately 95% of companies have fewer than 50 employees (Pilar et al. 2018). Food processing belongs to the low-tech industries (Hansen and Winther 2015) that are characteristically based in rural locations. Accordingly, these firms tend to be concentrated in regions with low population densities and limited local labour resources and are characterized by identifiable employment practices (Findlay and McCollum 2013). The food sector represents a moderately dynamic environment, where organizations have the choice to draw on established knowledge (Eisenhardt and Martin 2000), rather than to constantly reinvent themselves. Due to the resulting relative homogeneity of food-processing firms, the industry focus, which is in line with the argument of Deakins and Bensemann (2019), effectively controls many determinants, which are not the focus of interest here.

According to our results, moderately innovative food-processing firms in rural locations perform well in terms of growth if they exploit their enhanced opportunity for the implementation of involved human resource management (HRM) measures. This investment not only allows rural firms to realise gains in terms of innovation and growth that are offered by the creation of a stable and experienced workforce. The focus on internal labour markets might also further encourage neighbouring firms to also invest in involved HRM measures.

The results imply that certain firms could be better off in thin (rather than thick) labour markets if they adopt appropriate strategies in human resource management (HRM) and innovation. These strategies then allow them to exploit their location-specific opportunities, which from this perspective are not necessarily linked to the exploitation of natural resources (Fieldsend 2011) or low-cost advantages. The proposed perspective thereby questions the idea of the unambiguous urban advantage that could only be attenuated by secondarily derived (congestion) effects as implied by the theory of agglomeration (Wirth et al. 2016; Combes and Gobillon 2015; Puga 2010).

In the next section, we review the literature and derive our model and hypotheses. In Sect. 3, we describe the survey and the data, as well as the composite indicators used for the empirical analysis. Estimation routines and results are presented in "Model" and "Results", respectively, before "Discussion and conclusion" draws conclusions and discusses the results and their limitations.

Literature review and development of hypotheses

Arguments that explain performance differences of firms in urban and rural labour markets are usually based on so-called urbanization externalities that have been discussed ever since at least Marshall (1890). From the perspective of evolutionary labour market models it is crucial that the resulting agglomeration advantages are endogenous to development (Moretti 2011). To capture the specificity of successful rural locations and enterprises, we complement this perspective on externalities with the resource-based view on the firm (Barney 1991) and the dynamic capability perspective. According to the latter, firms are able to develop endogenously those capabilities that are required in order to exploit the specific opportunities in their environment (Teece et al. 1997). We derive our hypotheses from that literature of these fields, which discusses partial or complete relationships between (rural) location, HRM and economic performance. In the literature, economic performance is regularly equated with economic growth. Economic growth, in turn, may be measured in terms of income or in terms of employment. Some authors concentrate more on productivity, which is, however, usually assumed to relate positively to growth (Wirth et al. 2016). Other authors have also defined economic performance more in terms of the resilience of the economy and chosen, for example, firm survival as an indicator (Basile et al. 2017). As a strong link between innovation and general economic growth has been confirmed repeatedly (Coad et al. 2016), innovation is often applied as performance measure itself as well. In many cases, however, innovation is also considered more explicitly as mediating factor that promotes growth, respectively, economic performance.

Agglomeration, innovation and firm performance

Agglomeration advantages have been attributed to thick labour markets, to the proximity to providers of intermediate non-tradable goods and services, to localized knowledge spillovers and to the accessibility of consumer markets or certain (natural) resources. Thick labour markets are considered advantageous because they provide better opportunities for good matches between workers' skills and the job's demands, they offer the possibility to benefit from knowledge externalities (Duranton and Puga 2004) and they reduce risk in relation to the mutual dependence between employers and employees (Moretti 2011).

Thick labour markets and innovation

Many authors have stressed the high relevance of external labour markets and employment strategies for knowledge development and innovation (Roy 2018). The positive relationship between local labour market externalities and innovation has frequently been confirmed (for an overview, see Carlino and Kerr 2015). Given the better availability of workers with a wide range of skills, employers in thick labour markets will be specifically inclined towards attracting talent from external labour markets. This could contribute to a relatively high-labour fluctuation, which implies an outflow of "old" and an inflow of "new" knowledge. Employee mobility has consistently been identified as a crucial determinant of firm performance (Mawdsley and Somaya 2015). From a widespread perspective, frequent "job-to-job quits" reflect opportunities for better skill or job matches (Moscarini 2001) and a better exchange of knowledge and ideas (Vergeer et al. 2015). According to conventional models, there is therefore a direct and positive link between urban labour market characteristics and firm performance in terms of innovation, whereas knowledge creation and innovation are increasingly seen as a precondition for growth in high-wage locations (Maskell and Malmberg 1999).

Firm performance in terms of innovation and growth is not only conditional on local labour market conditions; it might also have an impact on the local labour market itself. This mutual relationship contributes to the positive external effects that define agglomeration advantages (Thisse 2018). Dütsch and Struck (2014), for example, find that "firms that invest in further training or their infrastructure not only improve employment opportunities but also create the conditions for inter-firm mobility processes due to the positive signalling effect ascribed to their employees". Employees would then have a relatively high willingness to invest in the acquisition of general skills that are valuable for many employers (Moretti 2011), which would in turn further increase the attractiveness of the external labour market for local firms.

It has also been shown, however, that the wide-spread conceptualizations of knowledge, innovation and the associated classifications of industries (see specifically Pavitt 1984) might be biased given the relevance of tacit knowledge in the "knowledge economy" (Hansen and Winther 2015). As diversity and worker mobility in urban labour markets is specifically beneficial for the supply and transfer of formal, general knowledge (Eriksson et al. 2008), urban conditions may cause firms to prefer innovation types that rely on "readily available general knowledge" (Vergeer et al. 2015) and fit the locally available commercial and scientific knowledge pools (Tödtling et al. 2009). In line with this, localization and agglomeration effects have been shown to benefit mainly radical and product innovations (Niebuhr et al. 2020). As a result, the advantage of urban firms in terms of innovation is more likely to apply to specific knowledge regimes that support radical innovations of products and services that are completely new to the market (Phillipson et al. 2019). Thereby, we derive a first hypothesis that links urban conditions to innovation:

H1a: Urban firms have an advantage with respect to certain types of innovation.

Agglomeration, innovation and growth

The positive link between innovation and economic growth on an aggregate level is rarely disputed; however, the relationship between innovation and firm growth is less clear (Coad et al. 2016). Moreover, the link between agglomerations and firm performance has been found to be conditional on industry structure, a firm's strategy and performance measures.

As the positive link between performance and agglomeration is conditional on human capital accumulation and the concentration of highly skilled workers in urban regions (Glaeser and Resseger 2010), firms with larger internal knowledge pools tend to benefit less from collocation and knowledge spillovers (Grillitsch and Nilsson 2017). Boschma et al. (2008) find that the skills portfolio of the firm, as well as the type of skill inflow, determine whether or not the effect of workers' inter-firm mobility on firm performance is positive. Higher inter-firm mobility of labour might not only enable a better exchange of knowledge and ideas: it may also reduce firms' incentives to invest into training (Croce et al. 2017) and make firms more inclined to contain innovation activities within the boundaries of the firm rather than to involve external partners (Herstad 2018). In order to benefit from urban conditions, firms need to develop the dynamic capabilities that are required to take advantage of high-labour fluctuation and to adapt to rapid changes of opportunities in agglomerations (Audretsch et al. 2021).

The ambiguous relationship between innovation and employment growth has been discussed frequently due to the possibly labour-saving nature of innovation (Capello and Lenzi 2013). Capello and Lenzi (2013) find in their own analysis that process innovation relates negatively to employment growth, specifically in more urban European locations. The effect of innovation and technological development on employment growth might be ambiguous (Lee and Clarke 2019) because these developments frequently imply an increase in the capital intensity of production (Hansen and Winther 2015). Within this context, sales growth might be the more stable indicator for performance than employment growth.

Given these considerations, we expect that urban firms have advantages in terms of sales growth if they exploit their specific opportunities with appropriate innovation activities.

H1b: The preferred innovation modes of urban firms advance performance in terms of sales growth.

Beyond agglomeration mechanisms

Agglomeration advantages do not seem to apply to all aspects of firm performance (Beaudry and Schiffauerova 2009). They have, for example, not been confirmed with respect to firm survival (Basile et al. 2017) and to innovation performance as measured by indicators other than patenting and licencing (Brodzicki and Golejewska 2019). Generally, the spatial sorting of firms and industries explains, for the most part, performance differences between regions (Niebuhr et al. 2020). Consequently, the effect of observable innovation activity on employment dynamics is conditional on other factors, such as the functional specialization of regions (Capello and Lenzi 2013). Peripheries with sparse labour markets typically specialize in low-tech industries. With sufficient investments in machinery and complementary human capital, however, (rural) medium to low-tech industries continue to contribute significantly to labour market stability, to value added and to export volumes even in high-wage countries (Hansen and Winther 2015; Phillipson et al. 2019). Dauth and Suedekum (2016) find locations that experience "anti-trend growth", despite their specialization in otherwise shrinking industries. Firms in these industries and locations might exploit strategies and advantages that are rarely considered in the analyses of agglomeration effects.

Innovation and growth in rural locations

Innovation is not only crucial for knowledge intensive firms but also for low-tech industries in order to retain competitiveness (Hansen and Winther 2015). Sources, rates and directions in innovation, however, vary across sectors and technologies (Jong and Marsili 2006; Souitaris 2002). Santamaría et al. (2009) show that non-R&D activities, such as design, and the use of advanced machinery and training are of special importance in low- and medium-tech industries. In small firms or in service firms, innovation is also not usually produced by formal R&D activities (Freel 2005) but rather as the result of often unplanned "creative problem solving" that takes place within the working process (Toivonen et al. 2007).

If these firms concentrate within the peripheries, their rural locations will be characterized by specific innovation modes (Whitacre et al. 2019). Studies that rely on widely used quantitative measures, such as patents and licences, and those that mainly capture outcomes from planned, R&D-based innovation processes (Brodzicki and Golejewska 2019; Shearmur 2017), would then be negatively biased against rural firms' innovation performance (Hansen and Winther 2011). We thereby derive a hypothesis for innovation in rural locations that complements H1a for urban locations:

H2a: Rural firms preferably implement specific, frequently unobserved innovation modes.

Implementing these specific innovation modes may help rural firms to perform well in terms of growth. Phillipson et al. (2019) find that rural SMEs are not characterized by a lower performance than their urban counter-parts as long as they implement strategies that are tailored towards the specific challenges and opportunities they face. Thereby, we derive a hypothesis on rural locations' effect on performance via innovation that is an analogue to H1b for urban locations:

H2b: The preferred innovation modes of rural firms advance performance in terms of sales growth.

Endogenous human resource development in rural locations

In order to develop their workforce, urban firms can choose between internal labour development and the acquisition of external skills. These strategies do not exclude each other but a focus on one strategy or the other has been shown to relate to other firm characteristics (see for example Brussig and Leber 2019). Given their sparse external labour markets, rural firms, in contrast, often have no choice but to engage in endogenous human resource development in order to promote innovation and growth. Deakins and Bensemann (2019) find in a qualitative analysis that successful small firms in rural environments do not seek skilled labour as a strategy to enhance their innovative capability but instead rely upon the in-house training of local labour. Employers in their study stress that the quality of jobs and work environments are important factors for worker retention. Smallbone et al. (1999) confirm that rural SMEs respond to their difficulties in attracting skilled workers on the external labour markets by providing on-the-job training that enables them to create a core of specifically trained staff.

Successful, specialized SMEs have more generally been found to "rely on training to create a skilled workforce" (Eichhorst and Kendzia 2016). "People and place attachment" have been identified as defining characteristics of the German "Mittelstand" (Pahnke and Welter 2019). Díaz-Fernández et al. (2014) confirm that employees develop competencies that are adapted to their firm's strategies and that "human resources management should be aimed at strengthening and promoting" these competencies. However, urban firms tend to under-invest in endogenous human capital development and workplace training due to the danger of labour poaching (Croce et al. 2017).

Rural locations, on the contrary, might simultaneously hamper recruitment but support worker retention as Hoyos and Green (2011) confirm in their case study in the UK. The dependence of rural firms on individual employees then increases their internal labour market focus and their willingness to invest further in their current workforce. If "talent shortage" in a local labour market induces specific talent management practices within companies (King and Vaiman 2019; Phillipson et al. 2019), their specific ability for endogenous knowledge creation could then partially compensate rural firms for the local lack of knowledge spillover. If rural firms prefer to engage and promote employees who they have trained themselves, the reduced risk of labour poaching might further encourage their neighbours to invest into HRM and the internal development of their own workforce (Panagiotakopoulos 2012; Vergeer et al. 2015).

<u>H3</u>: Rural firms are specifically inclined towards the implementation of involved HRM modes.

Endogenous human resource development and firm performance

Successful innovation in German SMEs rests inter alia on "superior employee relations, and community embeddedness" (Massis et al. 2018). Involved HRM modes and long-term employee retention could therefore support the implementation of certain modes of innovation in rural locations (Eder 2019). Vocational training and continuous skill development have been recognised as important conditions for knowledge creation and innovation (Borrás and Edquist 2019). Preenen et al. (2015) identify a positive relationship between flexible work schedules or job rotation and innovation. Others have found that high-involvement work practices relate positively to innovation and firm performance in general (Preenen et al. 2015). Lopez-Cabrales et al. (2009) report a positive relationship between collaborative HRM practices and unique knowledge, between unique knowledge and innovative activity, and finally between innovation and a company's profit.

More generally, measures of HRM promote firm performance by influencing and aligning employee behaviours or because they contribute to employee skills, knowledge and abilities (Seeck and Diehl 2017). It has also been argued that skill enhancement and higher motivation support the attribution of greater discretion to employees, which could in turn contribute positively to firms' productivity and efficiency (Osterman 2018). Specifically small firms seem to benefit from the introduction of formalised HRM practices (Lai et al. 2017). Sheehan (2014) finds positive associations between HRM practices and financial performance, innovation and reduced labour turnover in small firms. According to the author's results, specific effort in training and development, strategic personnel management, and recruitment and selection show a direct positive link to all three performance measures.

Given these differentiated but generally positive results concerning the relationship between HRM and firm performance, we follow Panayotopoulou and Papalexandris (2004) who confirm more generally that HRM has a significant influence on growth and innovation.

H4a: The implementation of involved HRM modes supports performance in terms of innovation.

H4b: The implementation of involved HRM modes supports performance in terms of sales growth.

H2a and H2b both express the expectation that rural conditions might advance growth via certain types of innovation. Specifically, incremental innovation processes that produce well-adapted solutions to local demands rely on firm-specific knowledge, which is embodied and non-tradable (Tavares 2020). Given their specific inclination towards involved HRM modes (H3), and these modes' positive relationships with the relevant modes of innovation (H4a) and sales growth (H4b), firms in rural locations might not only have a comparative but even an absolute advantage in the implementation of certain growth supporting strategies. Rural firms might therefore maintain a similar level of performance to their urban counterparts if they exploit their specific advantage in endogenous human resource development:

H5a: Rural firms can mitigate their location disadvantage in terms of innovation if they exploit their specific opportunities with well-adapted HRM measures.

H5b: Rural firms can mitigate their location disadvantage in terms of sales growth if they exploit their specific opportunities with well-adapted HRM measures.

Survey, data and constructs

Survey setting, data collection and sample

The empirical model uses data from a standardized questionnaire survey that we conducted during Summer 2015, among all firms from the food-processing sector in the federal state of Lower Saxony, Germany. Lower Saxony is situated in Germany's north and has approximately 8 million inhabitants on ca. 48,000 square kilometres (167 inhabitants per square kilometre in the mean). From 1524 food-processing firms in Lower Saxony, 200 firms answered the survey, giving a response rate of 13%. Focusing on one specific industry guarantees a relatively homogenous sample and allowed us to concentrate on survey questions directed specifically towards a deeper understanding of the core topic. Moreover, the food-processing firms are frequently location bound, with 60% of all firms in the survey reporting to have been active at their current location for more than 50 years. One can assume then that firms choose their strategies conditional on location rather than the other way around. This substantially reduces the problem of endogenous selection. Firms in 38 out of the 45 districts (NUTS 3 level) in Lower Saxony responded to the survey. The omnipresence of food-processing firms in the study region allows us to consider many locations and location characteristics.

In Germany, food processing is characterized by a few large and many small- and medium-sized firms that are often located on the peripheries. Our own survey allows for an inclusion of even very-small firms that are often disregarded by other statistics. Conducting an own survey also enables us to combine the survey data with regional information at a district level. This combination of data from secondary sources and the use of various types of questions that demand different patterns of responses (frequencies, yes–no replies, Likert scale selection, ratings and others) also considerably reduces the dangers of common method bias (Podsakoff et al. 2012).

The survey data do not claim representativeness for the whole sector. The study's results are valid for the description of within-sample associations. These can then be related to the theoretically derived specific questions or hypotheses, which in turn support a preliminary theoretical generalization.

Independent variables

External labour market conditions are captured by district-level indicators from secondary statistics. Agglomeration effects are identified by an urban location as identified by district type[1] (Table 1). A second theoretically relevant dimension for the characterization of the local labour market regime is identified by food sector employees' inter-firm mobility.[2] A high mobility value indicates that employees from the industry tend to leave firms frequently or that food-processing firms often recruit employees on the external labour markets. This mobility of skilled and unskilled food sector employees is captured by a measure of excess worker reallocation. Excess worker reallocation can be defined as gross worker reallocation, minus the absolute value of the net employment change (Davis and Haltiwanger 2011), where gross worker reallocation is the sum of all worker entries and exits in a given firm or labour market between two specified points of time. Our corresponding

[1] District types are provided by the German Federal Institute for Research on Building, Urban Affairs and Spatial Development, BBSR.

[2] Provided for 2015 by the German Federal Labour Agency.

Table 1 Independent variables

Firm-level variables from the survey			N	Mean	Std.dev.	Min	Max
Size	Currently, how many employees work in the firm?	(Log.) Number of	199	69.00	131.57	0	1000
Size (Log. scale)		Employees	199	3.08	1.55	− 2.30	6.91
Service	What share of the firm's employees work in customer services like sale, consulting, hospitality?	0–24% vs. 25% or more	193	0.54	0.50	0	1
	Presently, how many of the firm's employees…	Share in all employees at firm-level					
High skilled	… have an academic degree?		198	0.07	0.14	0.00	1.00
Low skilled	… have no formal training?		198	0.33	0.38	0.00	2.67
Training	Does the firm, individually or in cooperation, have a vocational training licence? (no / yes)	Yes (1) vs. No (0)	197	0.82	0.39	0	1
Processed	To which industry would you most probably assign the firm? (Belongs to milk, flavours & sauces, sweets, alcoholic beverages, feed stuff, other activity or industry)	Yes (1) vs. No (0)	199	0.32	0.47	0	1
Market size	Considering sales, how important are the different markets presently for the firm?	Mainly local	197	0.49	0.50	0	1
		Supra-regional	197	0.20	0.40	0	1
		International	197	0.31	0.46	0	1
District-level variables (firm location)							
Urban	City or urban district according to BBSR typology	Yes (1) vs. No (0)	200	0.31	0.46	0	1
Mobility skilled	Aggregate non-growth fluctuation among food sector's skilled and unskilled employees	Share of all job entries or exits (min. function) in all employees	200	0.25	0.10	0.13	0.86
Mobility unskilled			197	0.31	0.19	0.08	1.42
Share food	Share of employees in the food sector	Share in all employees at district-level	200	0.05	0.03	0.01	0.14
Share acad	Share of academically trained employees		200	0.09	0.03	0.05	0.19

Table 2 Endogenous variables and mediators

Label	Survey question	Categories	N	Shares	Std. dev	Minimum	Maximum
Growth	How did the firm's sales develop in the past five years?	Increased	193	0.53	0.50	0	1
		Stable	193	0.26	0.44	0	1
		Decreased	193	0.20	0.40	0	1
Innovation	Composed indicator (latent classes)	Reactive	200	0.22	0.41	0	1
		Passive	200	0.33	0.47	0	1
		Proactive	200	0.22	0.42	0	1
		None	200	0.24	0.43	0	1
HRM	Composed indicator (latent classes)	Flexible	200	0.21	0.40	0	1
		None	200	0.38	0.49	0	1
		Engaged	200	0.42	0.49	0	1

mobility measure reports the non-growth-related relative share of workers who left or entered a district's firms within 1 year:

$$\text{Mobility}_i = \frac{\min(\text{Entries}_i, \text{Exits}_i)}{\text{Employees}_i}$$

with i indicating different districts.

The share of employees in the food sector and the share of academically trained employees serve as relevant controls for the local labour market conditions.[3]

Among the purely exogenous influencing variables, our analysis focuses exclusively on location-level variables. The firm-level variables among the independent variables in Table 1 serve only as controls for firm-level heterogeneity. They capture the most important structural differences between the food-processing firms in the survey. Firm size, the share of highly skilled employees, the possession of a vocational training licence and market size serve as controls for firms' capacities and capabilities. Because the number of employees among firms in the survey is highly skewed, with only a few very-large and many small firms, the logarithm was used to give differences in employee numbers between small firms more weight in the regression. While the mean number of employees of the firms in the sample is 69, the mean number of employees on a logarithmic scale is 3.08 (respectively, 22) employees.

[3] Variables provided for 2015 by the German Federal Labour Agency. Employment rate, population density and mean firm size in the food industry have been introduced as additional district-level controls in other versions of the estimation. As they did not affect the results significantly, they were excluded from the final estimations for the sake of parsimony.

Dependent variables

Sales growth serves as a performance measure in the analysis (Table 2). The survey distinguishes between three classes of growth: increase, stability and decline. About half (53%) of all firms in the sample experienced sales growth in the past 5 years. Of the remaining firms, roughly half of them each reported stability (26%) and decline (20%). Firms' innovation activities and HRM measures are summarized by composed indicators that are created with latent class analysis (LCA) from multiple survey items.

In contrast to factor analysis, LCA can be based on categorical variables and starts out from multi-way frequency tables. It rests on finite mixture models that identify latent subgroups within a population based on individuals' responses to multiple observed variables (Collins and Lanza 2010). LCA is a mixture model, which posits that a population can be divided into mutually exclusive and exhaustive latent classes with an unobserved categorical variable. The class membership of individuals is unknown but can be inferred from a set of measured items. Estimated parameters represent latent class membership probabilities and item-response probabilities conditional on latent class membership. The latter also expresses the correspondence between the observed items and the latent classes (Lanza et al. 2007). Finite mixture models are usually estimated with maximum likelihood using the expectation–maximization (EM) algorithm (Wurpts and Geiser 2014). Within each latent class, the observed variables are expected to be statistically independent as the association between the observed variables is expected to be explained by the classes of the latent variable. One problem without a unique statistical solution relates to the issues of the assessment of model fit and of how many classes should be admitted into the solution. Relative model fit can be assessed with Akaike's information criterion (AIC) and the Bayesian information criterion (BIC), whereas models with lower AIC and BIC are expected to have a better fit. BIC and the corrected BIC tend to propose underfitting solutions, while the AIC tends towards overfitting (Dziak et al. 2017). An important additional criterion is the interpretability of the obtained classes.[4]

[4] For further information on LCA, see for example Lanza, Bray, and Collins (2012), or Collins and Lanza (2010).

Latent classes on innovation modes

In the survey, owners or executives were asked whether the firm had improved or newly developed products, services, technologies, processes or organizational procedures in the past 5 years. If respondents answered “no”, they were coded as non-innovators and account for 24% of the sample. Using a series of further questions, a common synthetic indicator, which captures firms’ different innovation modes, was developed.

Numerous approaches have been proposed in the literature in order to systematize the different innovation modes observed.[5] Concept and results from our analysis are best reflected by Boly et al. (2014), who differentiate between “proactive”, “preactive”, “reactive” and “passive” modes of innovation. Proactive and preactive innovation both represent managed and structured innovation processes. In the reactive mode, permanent activities to master innovation are not well defined, and in the passive mode, permanent innovation management activities do not exist or are weak. In our low-tech sample, the difference between proactive and preactive innovation is not of relevance.

Table 3 summarizes the survey items that were introduced into the LCA and the parameters that were estimated. The presented three-class solution was selected after its comparison with an alternative two-class solution by means of Akaike’s information criterion and the corrected Bayesian information criterion (AIC and corrected BIC). The class of firms with class membership probability of 41% shows the lowest item-response probabilities for all items. The corresponding innovation mode is subsequently labelled “passive”. The second class has a class membership probability of 28%. Compared to the other two groups, its members are characterized by high item-response probabilities for the realization of organization and marketing innovations and by support from customers and suppliers, as well as by other firm-owned plants or firms from the same industry. This innovation mode is subsequently labelled as the “reactive” mode. The class with a “class membership probability” of 32% differs from the reactive mode specifically by its focus on product and process rather than on organization and marketing innovation. It is also distinguished by a conscious introduction of “green” innovations with positive environmental effects, by a relatively high probability for the presence of specialized R&D personnel, by new employees’ high propensity to contribute to innovations and by their low probability of cooperation with other firms from the same industry. In line with the

[5] Some examples: Berends et al. (2014) apply the concept of effectuation and causation to the explanation of small firms’ product innovation process, wherein causation processes “focus on selecting between means to create that effect” and effectuation processes “take a set of means as given and focus on selecting between possible effects” (Sarasvathy 2001). Rosenberg (1994) differentiates between radical and incremental innovation, where radical innovations are subject to great uncertainty and often consist of a series of subsequent complementary innovations. Incremental innovations “involve endless minor modifications and improvements in existing products, each of which is of small significance but which, cumulatively, are of major significance” (Rosenberg 1994). Jensen et al. (2007) differentiate between the Science, Technology and Innovation (STI) mode of learning and innovation from the experience-based Doing, Using and Interacting (DUI) mode.

Table 3 Latent classes on innovation modes

Class		Reactive	Passive	Proactive
Class membership probability		0.28	0.41	0.32
Were improvements in the following fields important for the firm's development in the past 5 years?				
Product innovation	Yes	0.81	0.71	_0.85_
Process innovation	Yes	_0.98_	0.59	0.89
Organization innovation	Yes	_0.92_	0.25	0.55
Marketing innovation	Yes	_0.82_	0.26	0.51
Has the firm in the last 5 years introduced improvements in order to trigger positive environmental effects in production or consumption?	Yes	0.24	0.10	_0.58_
In your firm, are there employees specifically for the field of Research and Development?	Yes	0.10	0.00	_0.57_
Did new employees of the firm in the past 5 years contribute to the implementation of improvements in the firm?	Yes	0.35	0.20	_0.76_
Does the firm stand out from its competitors on the market in the field of originality/innovativeness?	Yes	_0.61_	0.29	0.49
Were the following partners important for the support or stimulation of improvements in the firm?				
Customers, suppliers, own plants	Yes	_1.00_	0.72	0.78
Other firms from the same industry	Yes	_0.67_	0.45	0.14
Consultants, universities, other public offices	Yes	0.44	0.00	_0.51_
Does product development take place in other locations or in other firms?	Yes	0.07	0.04	0.07

Underlined are the highest coefficients per line

Table 4 Latent classes on HRM modes

Class		Flexible	None	Engaging
Class membership probability		0.23	0.37	0.40
Currently, are there people employed in fixed term jobs in the firm?	Yes	0.80	0.19	0.38
Currently, are there employees from temporary staffing working in the firm?	Yes	0.83	0.02	0.02
Do the firm's executives usually consult their staff if decisions concerning alterations are pending?	Yes	0.52	0.41	0.82
In the last 5 years, has the firm supported further training measures for employees?	Yes	0.90	0.24	0.80
Are there written plans for personnel development and further training in the firm?	Yes	0.37	0.00	0.25
Are there idea generating routines like forms, letterboxes, meetings in the firm?	Yes	0.45	0.01	0.55
Is job rotation prevalent among skilled employees in the firm?	Yes	0.93	0.73	0.90
Would the firm primarily adapt to negative business developments by job cuts (rather than by reduced hours or wages)?	Yes	0.57	0.44	0.39
Can employees receive bonus payments or other material recognitions for particular achievements?	Yes	0.85	0.18	0.67
Are wage levels in the firm affected by the requirement	Definite	0.14	0.09	0.20
to keep or attract employees?	Rather	0.61	0.33	0.56

Underlined are the highest coefficients per line

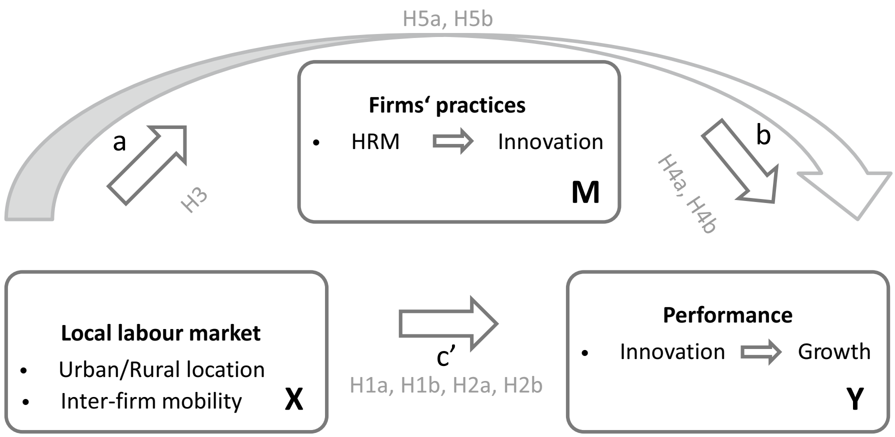

Fig. 1 The empirical mediation model with hypotheses

selected classification scheme for innovation processes, this mode will subsequently be labelled the "proactive" mode.

Latent classes on HRM modes

Another synthetic indicator constructed with LCA captures firms' different HRM practices. The practices that have been considered (Table 4) reflect the main areas of HRM described by Sheehan (2014): recruitment and selection, performance appraisal, performance-based compensation pay, training and development, employee voice, consultation, participation and information sharing, strategic people management. In order to systemize the different HRM practices, the competing value framework (Quinn and Rohrbaugh 1983) differentiates four HRM models by the two dimensions of "external focus" and "control orientation", while Arthur (1994) differentiates between the two HRM systems "control" vs. "commitment". High-commitment work practices allow for large internal, functional flexibility but require high employment security; that is, low numerical flexibility (Appelbaum and Berg 2001). Based on our data, we differentiate between firms in an "engaging" HRM mode that concentrate on the long-term retention of employees and apply high-commitment work practices, firms in a "flexible" HRM mode that concentrate on external labour markets for staffing and skill-acquisition, and firms that minimize their investments in HRM.

As in the LCA for innovation, the AIC and the corrected BIC both prefer the three-class solution (see Table 4). The class of firms with "class membership probability" of 37% shows the lowest item-response probabilities for all items but one. The corresponding HRM mode is subsequently labelled "None". The class of firms with "class membership probability" of 23% is specifically characterized by high item-response probabilities for the existence of employees in fixed term jobs and from the employment of temporary staff. Firms in this HRM mode also have a higher propensity than other firms to adapt to negative business developments by job cuts and to offer bonuses for achievements. Their HRM mode is consequently labelled “Flexible”. Firms in the class with “class membership probability” of 40% have a much lower propensity for fixed term jobs and temporary staffing than firms in the flexible mode, but their executives have a much higher probability for a regular consultation of subordinates in decision-making situations. This high-commitment HRM mode receives the label “Engaging”.

Model

Figure 1 translates the ideas and hypotheses derived in “Literature review and development of hypotheses” into a mediation model (see for example Iacobucci 2012), where location conditions X are considered as exogenous variables, firms’ practices serve as mediators M, and innovation and sales growth serve as endogenous variables Y (see for example Weigl et al. 2014). In Fig. 1, c’ represents the direct or net effect given that the mediator M is controlled for. The coefficient c, in contrast, represents the gross effect, that is, the estimated relationship between X and Y if M is not controlled for, which equates the sum of direct and indirect effects.

Our econometric approach allows for an explorative substantiation of the empirical mediation model but not for a formal test of its general validity. In a first step, HRM, innovation and growth are explained in separate regression models that include X- and M-, as well as control variables, before indirect or mediated effects are calculated from the coefficients in a second step. In the first step, multinomial models with a generalised logit link function are estimated for the explanation of HRM and innovation modes, and ordered logit models (see for example Agresti 2006) explain firm growth. The proportional odds assumption is not violated in our ordered logistic model for the explanation of growth; that is, the coefficients remain constant across stages (see for example Williams 2016).

To allow for a comparison of coefficients across models, and thereby to enable mediation analysis, coefficients are normalized. As the estimated variance of the outcome variable depends on the type and number of coefficients included in the logistic regression model, coefficients are therein divided by standard deviations of the latent outcome variable that is assumed to underlie the binary outcome variable (Mackinnon and Dwyer 1993). To make coefficients comparable not only across models but also across variables, they are also multiplied with the exogenous variables’ standard deviation. Effect size is accordingly measured in terms of normalized standard deviations. Categorical variables were coded as dummy variables, and their coefficients were only normalized but not multiplied by the dummies’ standard deviations. The estimated and standardized effects from the multinomial and ordered logistic models are presented in Table 5.

As the sample is not generated randomly and as the analysed effects do not result from controlled experiments, the lack of knowledge about the true data generation process and the (possibly) resulting biases in the statistical model are of higher concern than random errors. Therefore, formal “hypotheses tests” would be misleading in our context (see for example Ludwig 2005). We consequently

Table 5 Coefficients from the ordered and multinomial logistic regression models

Exogenous variables X	Mediating variables M							Endogenous variable Y	
	HRM vs. None		Innovation vs. None[a]		Innovation vs. Proactive			Growth	
	Flexible	Engaging	Reactive	Passive	Reactive	Passive	None	Model 1	Model 2
Size (log. scale)	0.62 (0.14)	0.53 (0.11)	0.23 (0.14)	− 0.03 (0.13)	-0.06 (0.14)	− 0.23 (0.13)	− 0.19 (0.12)	0.26 (0.10)	0.24 (0.11)
Service (0–1)	− 0.29 (0.19)	0.19 (0.19)	0.13 (0.23)	− 0.25 (0.25)	0.64 (0.21)	0.31 (0.19)	0.43 (0.20)	0.18 (0.23)	0.19 (0.23)
High skilled (%)	0.06 (0.10)	0.22 (0.11)	0.46 (0.22)	0.37 (0.24)	− 0.05 (0.12)	− 0.13 (0.11)	− 0.32 (0.16)	0.10 (0.10)	0.07 (0.10)
Low skilled (%)	− 0.19 (0.09)	0.04 (0.08)	− 0.21 (0.09)	− 0.12 (0.09)	− 0.02 (0.10)	0.05 (0.09)	0.11 (0.09)	0.05 (0.08)	0.07 (0.09)
Training (0–1)	− 0.08 (0.30)	0.18 (0.20)	0.06 (0.25)	0.79 (0.29)	− 0.63 (0.54)	− 0.11 (0.48)	− 0.54 (0.43)	0.17 (0.24)	0.14 (0.25)
Highly processed (0–1)	0.05 (0.18)	0.26 (0.19)	0.13 (0.20)	0.27 (0.22)	− 0.14 (0.19)	− 0.04 (0.15)	− 0.19 (0.15)	0.24 (0.18)	0.21 (0.18)
Market (suprareg. vs. local)	− 0.11 (0.11)	− 0.12 (0.14)	0.29 (0.18)	0.28 (0.20)	− 0.01 (0.14)	− 0.03 (0.12)	− 0.18 (0.14)	− 0.13 (0.13)	− 0.16 (0.14)
Market (internat. vs. local)	0.36 (0.13)	0.21 (0.14)	− 0.15 (0.16)	− 0.36 (0.19)	− 0.12 (0.14)	− 0.21 (0.12)	0.00 (0.12)	0.38 (0.17)	0.39 (0.16)
Mobility skilled (%)	0.00 (0.08)	− 0.01 (0.11)	− 0.18 (0.12)	− 0.29 (0.12)	− 0.17 (0.12)	− 0.21 (0.10)	− 0.03 (0.10)	− 0.02 (0.10)	0.00 (0.10)
Mobility unskilled (%)	− 0.08 (0.09)	− 0.12 (0.10)	0.32 (0.13)	0.18 (0.13)	0.11 (0.11)	− 0.01 (0.09)	− 0.11 (0.10)	− 0.10 (0.11)	− 0.13 (0.11)
Urban location (0–1)	− 0.48 (0.18)	− 0.67 (0.22)	0.46 (0.24)	− 0.04 (0.28)	− 0.34 (0.23)	− 0.62 (0.22)	− 0.55 (0.20)	0.23 (0.22)	0.15 (0.23)
Share food employees (%)	− 0.32 (0.09)	− 0.20 (0.11)	0.13 (0.16)	0.13 (0.14)	− 0.36 (0.12)	− 0.32 (0.10)	− 0.37 (0.12)	− 0.05 (0.11)	− 0.09 (0.11)
Share academic employees (%)	0.12 (0.09)	0.03 (0.10)	0.08 (0.12)	0.11 (0.11)	0.04 (0.12)	0.05 (0.10)	− 0.02 (0.10)	− 0.13 (0.10)	− 0.15 (0.10)
HRM (flexible vs. none)			− 0.28 (0.18)	− 0.46 (0.25)	− 0.27 (0.21)	− 0.32 (0.20)	− 0.04 (0.16)	− 0.23 (0.17)	− 0.21 (0.18)

Table 5 (continued)

Exogenous variables X	Mediating variables M							Endogenous variable Y	
	HRM vs. None		Innovation vs. None[a]		Innovation vs. Proactive			Growth	
	Flexible	Engaging	Reactive	Passive	Reactive	Passive	None	Model 1	Model 2
HRM (engaging vs. none)			0.39 (0.14)	0.35 (0.16)	− 0.13 (0.18)	− 0.16 (0.16)	− 0.34 (0.15)	0.37 (0.13)	0.33 (0.13)
Inno (reactive vs. proactive)									0.12 (0.16)
Inno (passive vs. proactive)									− 0.01 (0.15)
Inno (none vs. proactive)									− 0.27 (0.16)
Adjusted Pseudo-R-square[b] (Cox-Snell)		0.59		0.60			0.60		0.30

Note: Standard errors in brackets. For a graphically enhanced version of the table see Table A0 in supplementary material.

[a]The "Proactive vs. None" case is not reported as it mirrors exactly the "None vs. Proactive" case in column 7 with opposite signs

[b]The Cox-Snell R-squared depends on the change in terms of log-likelihood from the intercept-only model to the current model. As its upper bound may be below 1, we report the value after the Nagelkerke adjustment, which can reach a maximum of 1

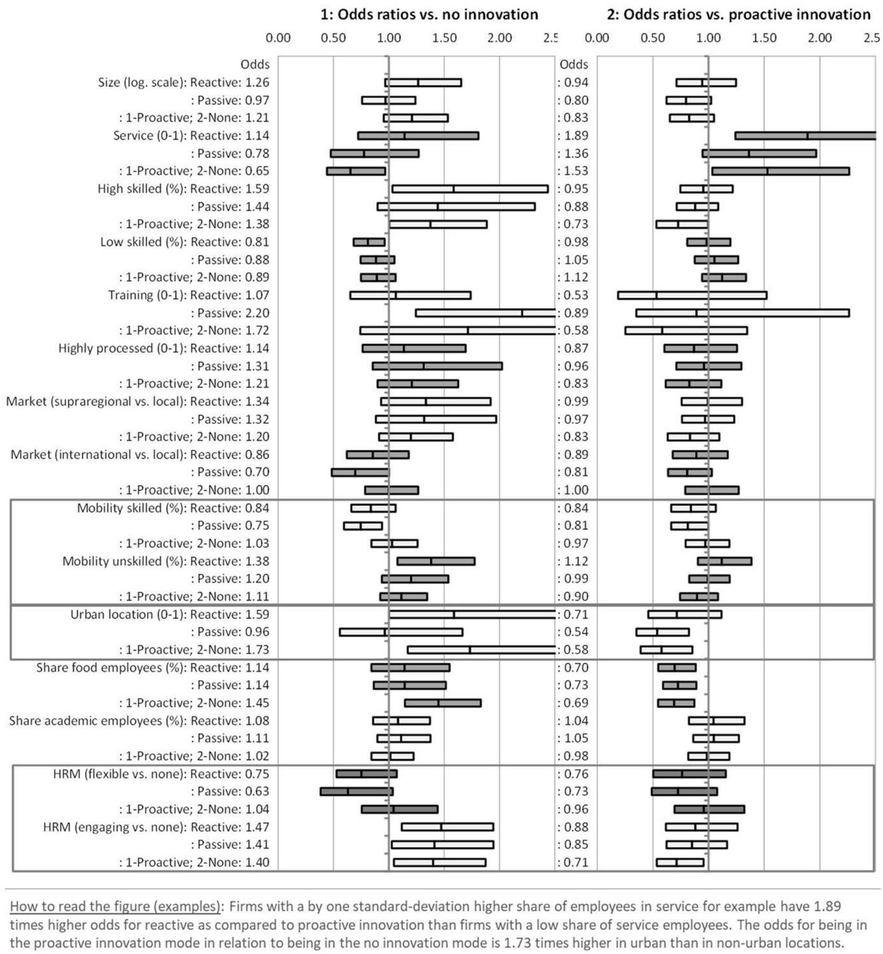

Fig. 2 Odds for innovation modes

refrain from a presentation of p-values and significance levels in order to avoid widespread misinterpretations (see also Wasserstein and Lazar 2016).

It is important to recognize that all further calculations are based on these initial regressions. Mediated or indirect effects are calculated as follows:

- Explanation models for mediators M yield exogenous variables' (X's) effects *a* on M (Fig. 1);
- Explanation models for endogenous variables Y yield mediators' effects *b* as well as X's direct effects *c'* on Y;

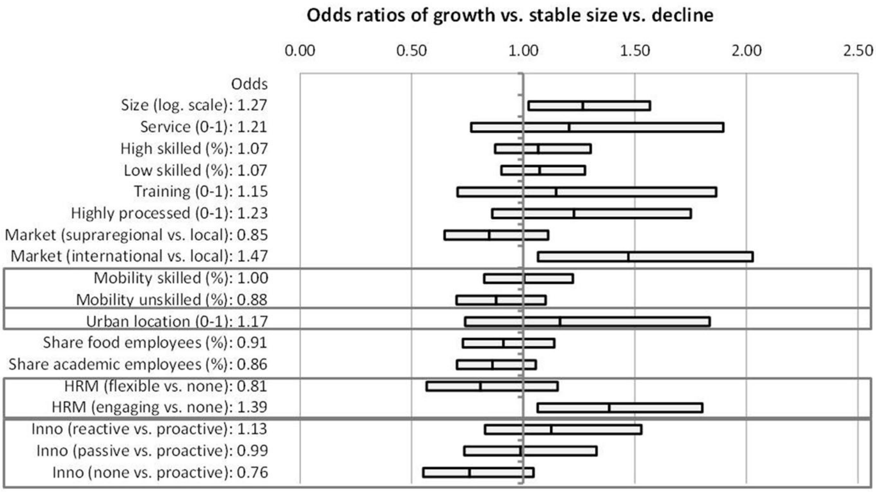

Fig. 3 Odds for growth

- According to the "product of coefficients" method, multiplication of $a * b$ yields X's indirect effects on Y (Breen et al. 2013);
- The total effect c of X on Y could be estimated in an explanation model for Y that includes only exogenous, but no mediation variables (see Table A1 in supplementary material). The total effect c equals the sum of X's direct (c') and indirect ($a * b$) effects on Y only for linear but not for logistic models (Breen et al. 2013).

We applied a bootstrapping approach for the calculation of standard errors of direct and indirect effects (Hayes 2009). As the estimated coefficients refer to log odds, they are difficult to interpret; thus, the discussion of results will be based on odds and their "confidence intervals".[6] We interpret confidence intervals as a measure of dispersion and calculate them by subtracting (respectively, adding) 1.96 times the coefficients' standard error to them. Exponentiation yields asymmetric intervals for the odds.

Results

Direct determinants of innovation modes (H1a, H2a, H4a)

According to the regression model, the proportion of highly skilled employees in a firm, the existence of a training licence as indicator for the degree of

[6] In this rather complex setting, odds are preferred over marginal effects as they remain constant across variable values.

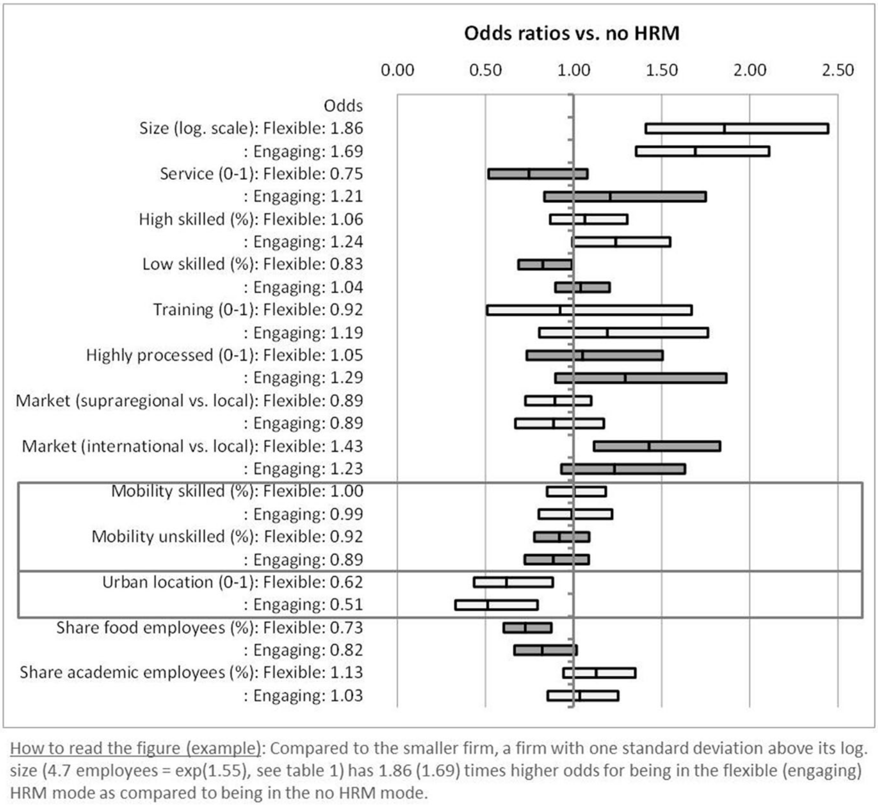

Fig. 4 Odds for HRM modes

professionalisation, an urban location and HRM modes show the strongest relationship with innovation (Fig. 2). The results are partly in line with the expectations concerning the direct effect c' in Fig. 1: urban location, in line with H1a, has a negative effect on the propensity for being in the none-innovation mode and has a specifically positive effect on a firm's propensity for being in the reactive or in the proactive innovation mode. Only passive innovation seems to be relatively unaffected by agglomeration effects. This implies a relative but not an absolute (direct) advantage of rural firms in passive innovation, in line with H2a.

Also in line with H1a, the higher inter-firm mobility of skilled employees negatively affects the odds of being in the reactive or in the passive innovation mode against being in the "none" or in the proactive innovation mode. Higher inter-firm mobility of unskilled employees, in contrast, relates positively to the odds of being in the reactive innovation mode.

With respect to effect b in Fig. 1, we find in line with H4a that engaging HRM advances all types of innovation processes. The flexible HRM mode, however, does not advance any type of innovation. It decreases the odds for being in the reactive or passive innovation mode against both others; that is, the none and the proactive innovation modes.

Direct determinants of sales growth (H1b, H2b, H4b)

In accordance with the inconclusive discussion in the literature, the results do not identify a significant direct link between location and firm growth. According to the regression results, firm size, activity on international markets and, in line with H4b, engaging HRM show the most positive direct relationship to sales growth (Fig. 3). As there is no positive relationship between flexible HRM and growth, the best practice character of engaging HRM is further confirmed (compare Fig. 2).

According to the results, non-innovators have a lower propensity for growth than firms in the proactive innovation mode, while differences in the positive effects of reactive, passive and proactive innovation modes on sales growth are small to negligible. This implies that firms can advance their growth with different innovation strategies and that firms in different locations might choose different innovation modes to enhance their performance in line with H1b and H2b.

Direct determinants of HRM modes (H3)

Figure 4 presents the odds for being in the flexible or in the engaging HRM mode compared to being in a no HRM mode. Firm size has the most positive relationship to the implementation of HRM modes, while urban (rural) location in line with H3 has the most negative (positive) relationship.[7]

In an urban location, the odds of being in the engaging (flexible) mode compared to being in the no HRM mode is only about half (two-thirds) that of being in a non-urban location. The results imply that urban firms generally have a lower propensity to invest in any HRM measures than rural firms. The negative effect of a high share of employees in food-processing firms could indicate that not only urbanization but also localization effects (Beaudry and Schiffauerova 2009) increase the risks of, or decrease the demand for, investment into internal labour markets.

Local inter-firm mobility of skilled labour does not relate to firms' adoption of flexible (or engaging) HRM in the sample, and the mobility of unskilled labour is only mildly negatively linked with flexible and engaging HRM.

[7] Figure 4 additionally shows more generally that most explanatory variables affect the flexible HRM mode in a similar way to the engaging HRM mode. Accordingly, firms with and firms without HRM differ more than firms with different HRM modes. Nevertheless, firms with a strong focus on service have lower odds for flexible and higher odds for engaging HRM compared to firms with low service orientation. Similarly, a high share of low skilled employees has a negative effect on the odds for flexible but not for engaging HRM, while firms with highly processed products have higher odds for engaging but not for flexible HRM. The two HRM modes therefore differ qualitatively from each other.

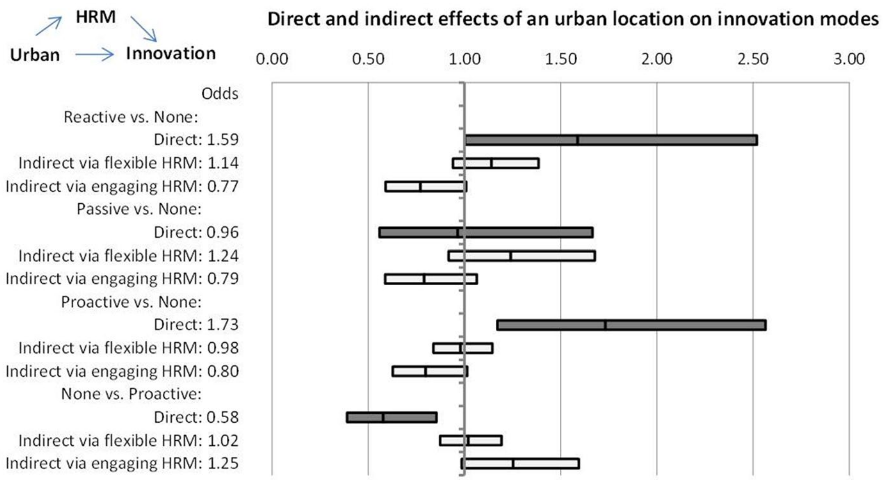

Fig. 5 Odds for indirect effects on innovation

Indirect effects on innovation and growth (H5a, H5b)

The generally positive relationship between urban location and reactive or proactive innovation (see Figs. 2 and 5) is counteracted by the negative relationship between urban location and engaging HRM (see Fig. 4). This means that in terms of innovation, the urban advantage can be partially compensated for in line with H5b if rural firms exploit their specific opportunity for the implementation of an engaging HRM mode. From the gross perspective, however, this indirect link via HRM does not make up for the direct innovation advantage of urban firms. According to the results that are presented in Fig. 5, rural firms will only have an absolute gross advantage in terms of passive innovation.

The rather positive indirect relationship between urban location and reactive and passive innovation via flexible HRM in Fig. 5 is not due to a positive contribution of the flexible HRM mode. Instead, it is due to its negative relationship to reactive and passive innovation (see Fig. 2), in combination with the reduced demand of urban firms for the flexible HRM mode (see Fig. 4). Due to the different counteracting forces, the still positive total effects (direct effect plus indirect effect) of an urban location on innovation (Table A1 in supplementary material) are smaller than its direct effects (Table 5).

The direct positive effect from an urban location on growth is non-significant (see Fig. 3 and Fig. 6). However, the indirect effects via less demand for flexible HRM (see Fig. 4) and via more reactive and proactive innovation (see Fig. 2) add to the direct effect (Fig. 6). Consequently, the general expectation that urban firms have a growth advantage if they successfully exploit their agglomeration advantages by the implementation of adapted innovation measures is weakly supported.

Nevertheless, due to urban firms' reduced propensity for the engaging HRM mode, there is also a significant negative indirect relationship between urban location

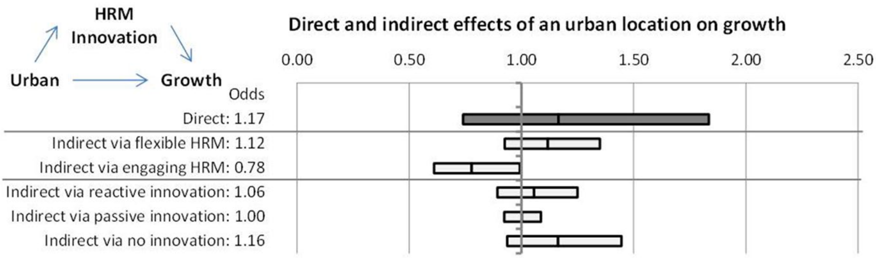

Fig. 6 Odds for indirect effects on growth

and sales growth. The (unstable) positive direct relationship between urban location and sales growth is more than compensated for by the (stable) negative indirect relationship via engaging HRM. This result further supports hypothesis H5b: in terms of growth, even more than in terms of innovation, rural firms can compensate for their disadvantages if they exploit their specific opportunity for the implementation of the engaging HRM mode. Rural firms cannot, however, effectively counterbalance their disadvantage by the direct implementation of specific innovation modes (H5a), according to the evidence presented in Fig. 6.

Discussion and conclusion

The paper has proposed that rural labour market conditions offer specific advantages to certain firms and industries. If firms can exploit these conditions, their resulting concentration on the internal labour development may not only advance their own performance in terms of innovation and growth but may also exert positive external effects. Positive external effects could be due, for example, to a reduced risk of labour poaching or to vocational training beyond the firms' own immediate demands. They may set in force a self-enforcing dynamic between neighbouring firms. Firms at a given location are then increasingly willing to invest in HRM measures that strengthen their internal labour markets. These specific labour market effects could be understood as a rural analogue to those labour market effects that are conventionally expected to contribute to the agglomeration advantages of urban locations.

A simplified, non-recursive version of these ideas has been transferred into an empirical mediation model and substantiated by means of data from a survey among German food-processing firms in rural and urban locations.

Empirical results

The results confirm that urban firms have advantages in certain innovation types (Phillipson et al. 2019), while rural firms are more inclined towards the implementation of involved HRM modes than urban firms (Croce et al. 2017).

However, by considering the different relationships simultaneously, we can additionally show, beyond what is known so far, that among the companies in our survey, the exploitation of HRM opportunities might be more important for good performance in rural labour markets than the implementation of specific innovation modes. Despite a remaining disadvantage in terms of innovation, rural firms perform absolutely and relatively well in terms of growth if they implement "engaging" HRM measures. In contrast, the direct implementation of specific innovation modes that are well-adapted to local labour market conditions does not help the firms in our sample to overcome their disadvantage in terms of growth.

Managerial implications

Rural enterprises in sparsely populated labour markets should therefore particularly invest in engaging HRM measures for the benefit of a long-term stabilisation of their workforce and the utilisation of their special competences. According to the corresponding latent class in our sample, engaging HRM measures are particularly characterised by the consultation of employees in important management decisions and by the potential participation of all employees in idea generation and innovation activities (see Table 4).

Urban firms, on the other hand, must exploit their specific opportunities for reactive or proactive innovation in order to realise the full potential of their location. Given firms' restricted resources and the best practice character of engaging HRM, urban firms might face a trade-off: they can maximize the universally positive effects that stem from the effective accumulation and exploitation of the experience of their own staff; or they can invest all of their free resources into the realization of reactive and proactive innovation to make full use of their location's specific advantages.

Theoretical and policy implications

By complementarily considering internal labour markets in the firm-based perspective, our results contribute to a more complete explanation of the development of local labour markets, which has so far been based almost exclusively on agglomeration mechanisms. Our results support the idea that endogenous development dynamics also exist in rural locations. However, they also suggest that different mechanisms underlie these dynamics in rural regions than in urban agglomerations. Our findings might explain the ambiguous results on agglomeration effects and SME performance reported in the literature. We have found that differences in firm performance are conditional on performance measurement in terms of innovation or sales growth, that location effects are mediated by firms' strategies, and that urban firms face a trade-off between the exploitation of agglomeration advantages and the exploitation of within-firm knowledge resources. Firm-level characteristics then need to be considered in order to explain not only the between-firm but also the between-region performance variations.

These insights add to those arguments that caution against a one-sided support of increased agglomeration dynamics (Thissen and van Oort 2010) and of those knowledge or R&D intensive industries that benefit most from them (Hansen and Winther 2011). The neglect of specific advantages of sparse but stable labour markets could be harmful, even from a purely economic perspective, and may contribute to the loss of valuable production capacities in the peripheries.

Future research directions

Our empirical analysis has focused on one specific industry within the specific environment of one large German federal state. This focus provides the advantage of controlling unwarranted excessive variance, spurious correlation and related biases: it also implies, however, that empirical generalizations of our results are not possible. Whether our empirical results hold true over variations in persons, settings, treatment variables and measurement variables (Shadish 2010, p. 4), and thereby generalize beyond the sample of firms from the food sector as expected by the theory and its auxiliary assumptions (Fariss and Jones 2018), will have to be reappraised with samples of other firms, industries and regions.

As the associations we have found largely substantiate our hypotheses, they may serve as a reference for further analyses in other regions and industries. Our broader idea that investments into internal labour markets could set in force a self-enforcing labour market dynamic, however, has not been explored in the empirical analysis. Its substantiation remains for future research and poses similar challenges to those experienced in the empirical substantiation of mechanisms that are expected to explain agglomeration advantages.

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Author contributions AM conceptualised the study and collected the data; AM, CD-D, AB, CT contributed to design and material preparation and writing—review and editing; AM, CD-D helped in formal analysis and investigation and writing—original draft preparation; C-D, A acquired the funding.

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Availability of data and materials The data that support the findings of this study are not openly available due to legally binding data protection reasons. In anonymised form they can be made available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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