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Impact of industrial relatedness on manufacturing structural change: a panel data analysis for Chinese provinces

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ABSTRACT

A large body of literature has explored the determinants of manufacturing structural change, but little has highlighted industrial relatedness. This study probes the impact of technological and vertical relatedness on manufacturing structural rationalisation and advancement by constructing a panel data model with province and year fixed effects using data of 30 Chinese provinces from 2000 to 2019. The empirical results show that manufacturing structural change differs based on industrial relatedness. Specifically, at the national level, technological relatedness can promote both structural rationalisation and advancement within manufacturing. Vertical relatedness holds a negative effect on structural rationalisation and no significant effect on structural advancement. Besides, the effects of industrial relatedness exhibit regional heterogeneity. In coastal China, technological relatedness can still promote structural rationalisation and advancement. Vertical relatedness has no significant effect on structural rationalisation and a negative effect on structural advancement. In inland China, governmental supports help break the dependency of regional manufacturing structural change on industrial relatedness, and the establishment of development zones restrains structural rationalisation within manufacturing. This study offers insights for policymakers to adopt different approaches to support local manufacturing development, depending on the characteristics of regional manufacturing structural evolution.

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1. Introduction

Manufacturing structural change has been one of China's industrial policy priorities. With a manufacturing value added of 3.854 trillion dollars in 2020 (World Bank Data), China has the largest manufacturing sector in the world. However, the traditional scale advantage of China's manufacturing sector is gradually declining, while the technical advantage represented by labour productivity and supply chain

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efficiency has not become prominent. Therefore, optimising and upgrading the manufacturing structure has become a critical task for China. Besides, with the gradual development of new infrastructures (e.g., artificial intelligence, the industrial Internet, and the Internet of things) in China since 2018, machines and devices have more powerful recognition, learning, computation, and collaboration. Due to lower costs of communication and information search, interactions among manufacturing firms have become closer and shared factor resources more efficiently. The growing trend towards closer interactions among manufacturing firms motivates us to ask two questions: Is industrial relatedness a critical determinant of structural change within manufacturing in China? Does the impact of industrial relatedness on manufacturing structural change vary among different regions in China?

Industrial structural change is a multi-layered and multidimensional dynamic process (Zhou et al., 2020). Many studies have focused on determinants of structural change across broad sectors of agriculture, manufacturing, and services (Du et al., 2021; Święcki, 2017; Wang et al., 2019; Zhang et al., 2019). Moreover, some scholars have investigated determinants of structural change within manufacturing (Chen & Qian, 2020; Hu et al., 2019; Samaniego & Sun, 2016; Syrquin & Chenery, 1989). Existing theoretical studies have mainly attributed the driving force of structural change within manufacturing to technological progress (Samaniego & Sun, 2016), arguing that differences in technical efficiency among industries lead to production factors flowing towards high-efficiency industries. Some empirical studies have additionally highlighted the role of foreign direct investment (Hunya, 2002; Zhang, 2014) or industrial policy (particularly environmental regulation) (Chen & Qian, 2020; Hu et al., 2019; Zhou et al., 2020).

Despite the enormous interest of scholars exploring various determinants of structural change within manufacturing, the literature has paid little attention to explaining manufacturing structural change with industrial relatedness. Many studies have discussed the role of industrial relatedness in regional industrial evolution. These studies have associated industrial relatedness with the short-term capacity of a region to respond to an external shock (Cainelli et al., 2019; Diodato & Weterings, 2015) and the long-term entry, expansion, contraction, and exit of local industries (Boschma & Frenken, 2011; Essletzbichler, 2015; Guo & He, 2017; Neffke et al., 2011; Xiao et al., 2018). We argue that structural change within manufacturing is implicit in local industries' ongoing evolutionary process to adapt to changes in the external environment. Industrial relatedness may affect the reallocation of production factors across different manufacturing industries during the evolutionary process, thus influencing structural change within manufacturing.

This study investigates how industrial relatedness affects manufacturing structural change in China and whether this impact differs between China's coastal and inland regions. We focus on two specific types of industrial relatedness: technological and vertical relatedness. As for structural change within manufacturing, we divide it into structural rationalisation and advancement. First, we propose a series of research hypotheses on the impact mechanisms of industrial relatedness on manufacturing structural change. Afterwards, we empirically test the research hypotheses using a panel data model with province and year fixed effects, based on manufacturing data from 30 provinces in China. Considering the potential reverse causality between industrial relatedness and structural change within manufacturing, we construct instrumental variables based on average land slope, land surface relief degree, and medium-and-long-term loan interest rate. We then apply a two-step efficient G.M.M. estimator to obtain coefficient estimates correcting endogeneity bias. Finally, we examine the regional heterogeneity between coastal and inland regions of China.

The contribution of this study is threefold. First, from the perspective of research content, this study advances our knowledge of the role of industrial relatedness in regional industrial evolution by extending the explained variable to multidimensional manufacturing structural change. Second, from the perspective of variable measurement, this study improves the measure of manufacturing structural change and industrial relatedness in terms of accuracy and timeliness. Third, from the perspective of causal identification, this study constructs instrumental variables for industrial relatedness based on strictly exogenous geographical variables and interest rate shocks to deal with the reverse causality issue.

Section 2 analyses theoretical mechanisms and develops hypotheses. Section 3 explains the research methodology. Section 4 describes the empirical findings, and Section 5 concludes the implications of this study.

2. Theoretical mechanisms and research hypotheses

As previously mentioned, industrial structural change is a multi-layered and multidimensional dynamic process (Zhou et al., 2020). Regarding the structural change across broad sectors of agriculture, manufacturing, and services, most of this literature has concentrated on two classic dimensions: structural rationalisation and advancement (Hartwig, 2012; Peneder, 2003), especially those studies on China (Fan et al., 2003; Wang et al., 2019). In China, structural change within manufacturing is one of the most prominent parts of industrial structural change. Inspired by the existing literature (Fu et al., 2014; Li et al., 2019), we introduce structural rationalisation and advancement to measure manufacturing structural change. Structural rationalisation encourages the dynamic transition towards higher efficiency of resource allocation among manufacturing industries (Zhou et al., 2020). Structural advancement indicates the transition from low-technology-intensive industries (e.g., petrochemical, ferrous and non-ferrous metals) to high-technology-intensive industries (e.g., electrical machinery and equipment, electronic and communication equipment). During the evolution of regional industries, industrial relatedness may influence structural change within manufacturing by altering the reallocation of factor resources. By referring to previous related studies, we focus on two major types of industrial relatedness: technological and vertical relatedness. Technological relatedness exists between local industries with similar knowledge bases (e.g., skills, capabilities, and technologies) (Boschma & Frenken, 2011; Cainelli et al., 2019; Howell et al., 2016). Vertical relatedness exists between local industries linked by input-output relations (Cainelli et al., 2019; Diodato & Weterings, 2015; Essletzbichler, 2015). In the following, we discuss how technological and vertical relatedness influence the structural rationalisation and advancement within manufacturing, respectively, and propose the corresponding research hypotheses.

2.1. Regional heterogeneity between coastal and inland China

Scholars often use technological relatedness to proxy regional historical trajectory and previous production competencies (Boschma et al., 2012; Martin & Sunley, 2006). They have described regional development as a path dependence process. Specifically, regions tend to diversify into new technologically related industries to utilise local relevant skills, capabilities, and technologies (Frenken & Boschma, 2007). Empirical studies on developed economies have confirmed the existence of path dependence. However, in a transitioning economy such as China, path dependence is not sufficient to explain the evolution of regional industries. In the context of China's gradual opening up from east to west, coastal regions participated in the globalisation process earlier than inland regions. With a better environment of market institutions, the coastal regions have a stronger tendency of path dependence in their industrial evolution (Guo & He, 2017). In order to catch up with coastal regions, governments in inland regions have improved local production conditions through a series of favourable policies aimed at attracting or developing advanced industries (Barbieri et al., 2012). Thus, governmental policies have helped inland regions diversify into new industries less related to their previous industrial portfolio and break through the path dependence (Guo & He, 2017). Based on the above discussion, we propose the following hypothesis:

> Hypothesis 1: Technological relatedness is significantly related to manufacturing structural change in coastal regions and shows no significant effect in inland regions.

Vertical relatedness reflects the extent to which manufacturing industries within a region are linked to one another by supplier-customer relationships (Diodato & Weterings, 2015). When the evolution of regional manufacturing structures is path-dependent, diversification into new technologically related industries can utilise the local supplier and customer base (Essletzbichler, 2015; Frenken & Boschma, 2007). Thus, in coastal China, pre-existing networks of supplier-customer relationships suggest which industries the region has already specialised in and which industries the region can develop in the future. However, in inland China, new industries are often introduced by governmental policies rather than the region's previous networks of supplier-customer relationships (Guo & He, 2017). Based on the above discussion, we propose the following hypothesis:

> Hypothesis 2: Vertical relatedness is significantly related to manufacturing structural change in coastal regions and shows no significant effect in inland regions.

2.2. Technological relatedness and manufacturing structural rationalisation

Regions with a higher technological relatedness tend to have better factor mobility across industries (Ji et al., 2016). Technologically related industries benefit from each other's co-occurrence since each of them can draw from a local pool of skills, capabilities, and technologies (Boschma, 2015). Therefore, technological relatedness can contribute to manufacturing structural rationalisation by improving the inter-industry factor allocation efficiency. The above arguments lead to the following hypothesis:

> Hypothesis 3a: Technological relatedness is positively related to manufacturing structural rationalisation at the national level.

Combining Hypothesis 1, we further propose:

> Hypothesis 3b: Technological relatedness is positively related to manufacturing structural rationalisation in coastal regions and shows no significant effect in inland regions.

2.3. Vertical relatedness and manufacturing structural rationalisation

In the early stage of a region's exposure to an external shock, the level of vertical relatedness is crucial for propagating the initial hit to different parts of the economy (Diodato & Weterings, 2015). As manufacturing industries become more embedded in a local productive system, i.e., with more diverse and well-connected local sources of intermediate inputs, they also become more vulnerable to shocks (He & Chen, 2019). If a local productive system is highly vertically connected, even an industry-specific shock can negatively affect the resource allocation efficiency of the entire manufacturing sector through propagation mechanisms (Cainelli et al., 2019). Therefore, higher vertical relatedness is unfavourable for manufacturing structural rationalisation. The above arguments underpin the following hypothesis:

> Hypothesis 4a: Vertical relatedness is negatively related to manufacturing structural rationalisation at the national level.

Combining Hypothesis 2, we further propose:

> Hypothesis 4b: Vertical relatedness is negatively related to manufacturing structural rationalisation in coastal regions and shows no significant effect in inland regions.

2.4. Technological relatedness and manufacturing structural advancement

Technological relatedness in a region affects the nature and scope of knowledge spillovers (Boschma & Frenken, 2011) since regions with different but technologically related industries can benefit more from knowledge spillovers (Frenken et al., 2007). Either too much or too little cognitive proximity goes against effective knowledge transfers and the emergence of innovation (Nooteboom, 2000). The development of high-tech manufacturing industries is more dependent on technological progress than low-tech manufacturing industries. Therefore, technological relatedness accelerates the development of high-tech manufacturing industries, thereby contributing to the structural advancement within manufacturing. Based on the above arguments, we propose the following hypothesis:

> Hypothesis 5a: Technological relatedness is positively related to manufacturing structural advancement at the national level.

Combining Hypothesis 1, we further propose:

Hypothesis 5b: Technological relatedness is positively related to manufacturing structural advancement in coastal regions and shows no significant effect in inland regions.

2.5. Vertical relatedness and manufacturing structural advancement

Vertical relatedness reflects the extent to which manufacturing industries within a region are linked to one another by supplier-customer relationships (Diodato & Weterings, 2015). As the level of vertical relatedness increases, manufacturing industries can access more diverse and well-connected intermediate inputs locally (He & Chen, 2019). In such a circumstance, incumbent firms are more likely to survive since the co-agglomeration of vertically related industries is conducive to saving transport costs and increasing productivity (Venables, 1996). However, the region also tends to specialise in particular industries and become locked into its previous trajectory (Grabher, 1993), making it more difficult to diversify into new advanced industries. Therefore, higher vertical relatedness is unfavourable for manufacturing structural advancement. The above arguments lead to the following hypothesis:

Hypothesis 6a: Vertical relatedness is negatively related to manufacturing structural advancement at the national level.

Combining Hypothesis 2, we further propose:

Hypothesis 6b: Vertical relatedness is negatively related to manufacturing structural advancement in coastal regions and shows no significant effect in inland regions.

3. Research methodology

3.1. Data collection

This study used the sample of 30 provinces in China (Hong Kong, Macau, Taiwan and Tibet excluded) from 2000 to 2019 for empirical analysis. The output value and employment data of two-digit manufacturing industries at the provincial level were from China Industrial Statistical Yearbooks. Other province-level characteristics were collected from the Statistical Yearbooks of each province. We acquired the direct consumption coefficient information from 2002, 2007, 2012, and 2017 China regional input-output tables. All the monetary values were deflated with 2000 as the base year, and missing values were linearly imputed.

3.2. Variables measurement

3.2.1. Manufacturing structural change

Previous studies (Fu et al., 2014; Li et al., 2019) have typically measured manufacturing structural rationalisation at the provincial level based on the dispersion degree of labour productivity among three categories classified by technology intensity. We improved this measure and based it on two-digit industries rather than the three categories to make it more accurate, as shown in Equation (1):

$$MSR = \sum_{i=1}^{n} \left(\frac{Y_i}{Y}\right) ln\left(\frac{Y_i}{Y} / \frac{L_i}{L}\right) \tag{1}$$

In Equation (1), Y_i/Y and L_i/L respectively denote the output value and employment share of two-digit industry i in the manufacturing sector. Given the total amount of two-digit manufacturing industries n, MSR decreases with the evenness of the distribution of labour productivity. When the manufacturing structure reaches the rationalised state with full factor mobility, it equals zero. In other words, a higher value of MSR implies a lower degree of manufacturing structural rationalisation. By definition, it is also reasonable to measure manufacturing structural rationalisation based on total factor productivity. However, labour productivity is more widely used in evaluating the development of Chinese enterprises (Gao & Yuan, 2020) since it has a stable and positive relationship with total factor productivity over time (Martino, 2015) and is more intuitive and easier to calculate.

By referring to Fu et al. (2014) and Li et al. (2019), we measured manufacturing structural advancement using the ratio of high-tech industries' output value to low-tech industries' output value, as shown in Equation (2). The expansion of high-tech industries and the exit of low-tech industries contribute to a region's more advanced manufacturing structure. High-tech industries include chemicals, pharmaceuticals, general equipment, special equipment, transportation equipment, electrical machinery and equipment, electronic and communication equipment, instruments and meters. Low-tech industries include all other manufacturing industries.

$$MSA = Y_h/Y_l \tag{2}$$

In Equation (2), Y_h and Y_l respectively denote the output value of high-tech and low-tech manufacturing industries. MSA increases with the expansion of high-tech industries and the exit of low-tech industries. A higher MSA implies a higher degree of manufacturing structural advancement.

3.2.2. Industrial relatedness

Previous studies on China (Guo & He, 2017; Howell et al., 2016) have typically measured industrial relatedness using the Annual Survey of Industrial Firms (A.S.I.F.) data set. However, the data set is only publicly available until 2013, limiting the timeliness of the measured industrial relatedness indicators. To overcome this deficiency, we used the data of two-digit manufacturing industries by province to measure industrial relatedness at the provincial level from 2000 to 2019.

Following Cainelli et al. (2019), we measured technological relatedness based on the technological similarity between every pair of product sectors and the number of employees in each product sector. The intensity of technological spillovers between two product sectors was assumed to depend on the technological similarity and the number of employees in each sector.

Following Fan and Lang (2000), we first estimated technological similarity (ω_{ij}) using the cosine similarity measure applied to the intermediate input structure in two manufacturing product sectors.

$$\omega_{ij} = \frac{\sum_{k=1}^{m} a_{ik} \cdot a_{jk}}{\sqrt{\left[\sum_{k=1}^{m} (a_{ik})^2 \cdot \sum_{k=1}^{m} (a_{jk})^2\right]}} \tag{3}$$

In Equation (3), a_{ik} and a_{jk} are direct consumption coefficients from input-output tables reflecting the likelihood of firms in product sectors i and j acquiring inputs from product sector k, and m denotes the total number of manufacturing product sectors in input-output tables. The more similar the intermediate input structure in product sectors i and j, the closer ω_{ij} is to 1.

We then computed technological relatedness (TR) as in Equation (4):

$$TR = \frac{\sum_{i=1}^{m}\sum_{j=1}^{m}(L_i \cdot L_j \cdot \omega_{ij})}{\sum_{i=1}^{m}\sum_{j=1}^{m}(L_i \cdot L_j)} \tag{4}$$

L_i and L_j denote the respective employment of product sectors i and j, and ω_{ij} denotes the technological similarity between product sectors i and j. TR increases with the similarity in the composition of manufacturing product sectors' inputs. A higher TR implies a higher level of technological relatedness.

Following Cainelli et al. (2019), we measured vertical relatedness (VR) by assuming that the likelihood of each product sector acquiring inputs from the same sector or another sector is correlated linearly with the number of employees in the supply-side sector.

$$VR = \frac{\sum_{i=1}^{m}\left[(L_i \cdot a_{ii}) + \sum_{j=1, j\neq i}^{m} (L_j \cdot a_{ij})\right]}{\sum_{i=1}^{m}\left(L_i + \sum_{j=1, j\neq i}^{m} L_j\right)} \tag{5}$$

In Equation (5), L_i and L_j denote the respective employment of product sectors i and j, and a_{ii} and a_{ij} denote the share of inputs acquired by product sector i from the same sector or sector j ($j \neq i$). VR increases with the local accessibility of intermediate inputs for manufacturing product sectors. A higher VR implies a higher level of vertical relatedness.

3.2.3. Control variables

To examine the impact of industrial relatedness on manufacturing structural change, we followed prior studies to control province-level characteristics. The control variables include development zone (*ZONE*), financial development (*FD*), urbanisation (*URBAN*), R&D expenditure (*RD*), infrastructure construction (*INFRASTR*), globalisation participation (*GLOBAL*), population density (*POPDEN*). These control variables are expected to affect manufacturing structural change significantly. For example, infrastructure construction may positively affect manufacturing structural change as infrastructure is a generic localised capability generally required in regional industrial evolution. Table 1 shows the description and measurement of control variables.

Table 1. Description and measurement of control variables.

Variables	Symbol	Measure
Development zone	*ZONE*	Number of development zones
Financial development	*FD*	Loan balance from financial institutions/Regional GDP
Urbanisation	*URBAN*	Urban population/Total registered population
R&D expenditure	*RD*	Governmental expenditure on R&D/Regional GDP
Infrastructure construction	*INFRASTR*	Highway density + Railway density
Globalisation participation	*GLOBAL*	Actually utilised foreign capitals
Population density	*POPDEN*	Urban population density

Source: The authors.

Table 2. Descriptive statistics.

Variables		Obs.	Mean	Std. Dev.	Min.	Max.
Explained variables	*MSR*	600	0.201	0.172	0.032	1.602
	MSA	600	0.865	0.654	0.105	3.480
Core explanatory variables	*TR*	600	0.337	0.070	0.178	0.604
	VR	600	0.038	0.008	0.020	0.082
Control variables	*ZONE*	600	0.492	0.442	0.000	1.860
	FD	600	1.197	0.441	0.545	3.848
	URBAN	600	0.506	0.154	0.139	0.896
	RD	600	0.014	0.011	0.002	0.070
	INFRASTR	600	1.128	0.904	0.072	5.623
	GLOBAL	600	2.711	2.958	0.001	14.884
	POPDEN	600	2.353	1.362	0.026	6.307

Source: The authors.

Table 2 presents the descriptive statistics for all variables. The mean value of all variables except *GLOBAL* is larger than the standard deviation, indicating that the data does not include extreme values and the overall dispersion is not high.

3.3. Model specification and estimation strategy

Our regression models are shown in Equations (6) and (7). We included province and year fixed effects to control for unobservable provincial heterogeneity and shocks that simultaneously affect all provinces' manufacturing structures. We also included all control variables as lagged values (t-1) to deal with the potential reverse causality between the explained and control variables. According to the results of Frees (1995) Q test, the error term structure has cross-sectional dependence. Therefore, we estimated the models using Driscoll and Kraay (1998) robust standard errors.

$$MSR_{pt} = \alpha_0 + \alpha_1 TR_{pt} + \alpha_2 VR_{pt} + \alpha_3 Control_{p,t-1} + \sum Province,\ \ Year \tag{6}$$

$$MSA_{pt} = \beta_0 + \beta_1 TR_{pt} + \beta_2 VR_{pt} + \beta_3 Control_{p,t-1} + \sum Province,\ \ Year \tag{7}$$

The reverse causality between manufacturing structural change and industrial relatedness might create a systematic distortion in our estimation. For example, regions with high manufacturing structural rationalisation and advancement are more likely to follow their previous industrial trajectory (Boschma et al., 2012). The entry of technologically related industries and the exit of unrelated industries will lead to a greater concentration of the technology base and the supplier-customer relationship network (Essletzbichler, 2015), thus a higher technological and vertical relatedness. We employed the instrumental variable (I.V.) regression to address this concern. The two-step efficient G.M.M. estimator is preferred over the traditional 2SLS estimator since it is more efficient in such an over-identified model with cross-sectional dependence. By referring to Han et al. (2018) and Chen and Qiu (2020), we constructed a set of instrumental variables, including one-year lagged technological and vertical relatedness values and the interaction of interest rates with two geographical variables.

The two geographical variables, i.e., average land slope and land surface relief degree, capture a region's topographic characteristics. They are negatively related to the closeness of interactions among manufacturing firms by altering the cost of communication and transportation (Burchfield et al., 2006) but cannot directly determine manufacturing structural change. Thus, the two geographical variables can nicely meet the two conditions of valid instrumental variables: closely correlated with industrial relatedness and strongly exogenous. However, our sample was in the form of panel data, while the average land slope and the land surface relief degree did not vary much over the sample period. Therefore, we had to combine the geographical variables with an exogenous time-varying variable. We selected the benchmark interest rates for medium and long term loans (including 1–3 years, 3–5 years, and more than five years), published by People's Bank of China. When interest rates decrease, firms have lower financing costs and are more willing to make relocation decisions. The relocation of firms optimises the spatial allocation of resources and tends to increase industrial relatedness in the regions involved. Since the two geographical variables and the interest rates are all negatively related to industrial relatedness, we multiplied the average land slope and the land surface relief degree by interest rates of different maturities. For now, the number of instrumental variables equalled the number of endogenous variables. We could not test the exogeneity of all instrumental variables using Hansen's (1982) J test for such an exactly-identified model. Thus, we referred to Han et al. (2018) and further included one-year lagged values of industrial relatedness in the set of instrumental variables.

4. Empirical results

4.1. National full-sample results

Table 3 shows the national full-sample results for the impact of technological and vertical relatedness on manufacturing structural rationalisation. It is noteworthy that a higher value of *MSR* indicates a lower degree of structural rationalisation. Thus, a negative coefficient of an explanatory variable implies that it favours the rationalisation of manufacturing structures and vice versa. According to the proposed hypotheses H3a and H4a, manufacturing structural rationalisation is positively affected by technological relatedness and negatively affected by vertical relatedness at the national level. We first conducted O.L.S. regression to test the two hypotheses, as shown in Model (1). The coefficient of technological relatedness is negative and significant, indicating that technological relatedness is beneficial to the structural rationalisation within manufacturing. The coefficient of vertical relatedness is positive but not

Table 3. Full-sample results: the explained variable is structural rationalisation.

Model	(1)	(2)	(3)	(4)
TR_t	−0.345**	−0.532***	−0.524***	−0.523***
	(0.139)	(0.146)	(0.146)	(0.146)
VR_t	0.250	2.162**	2.196**	2.134**
	(0.991)	(0.893)	(0.914)	(0.924)
$ZONE_{t-1}$	−0.012	−0.021	−0.019	−0.021
	(0.027)	(0.022)	(0.022)	(0.022)
FD_{t-1}	−0.065***	−0.084***	−0.083***	−0.082***
	(0.022)	(0.019)	(0.018)	(0.018)
$URBAN_{t-1}$	0.169**	0.212***	0.208***	0.208***
	(0.069)	(0.059)	(0.058)	(0.058)
RD_{t-1}	1.562**	2.050***	1.980***	2.033***
	(0.724)	(0.648)	(0.633)	(0.636)
$INFRASTR_{t-1}$	−0.021	−0.026*	−0.025	−0.025
	(0.019)	(0.016)	(0.016)	(0.016)
$GLOBAL_{t-1}$	−0.006***	−0.005***	−0.005***	−0.005***
	(0.002)	(0.001)	(0.001)	(0.001)
$POPDEN_{t-1}$	−0.027***	−0.030***	−0.030***	−0.030***
	(0.008)	(0.007)	(0.007)	(0.007)
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Observations	570	570	570	570
R^2	0.201	0.081	0.081	0.081
Kleibergen-Paap rk LM statistic		7.893	7.855	7.864
p-value		[0.048]	[0.049]	[0.049]
Kleibergen-Paap rk Wald F statistic		12.251	12.314	11.994
Stock-Yogo critical value		9.93	9.93	9.93
Hansen J statistic		2.090	2.528	2.256
p-value		[0.352]	[0.283]	[0.324]

Notes: ***, ** and * represent significance at 1%, 5% and 10% level, respectively. All specifications include a constant term. The Driscoll-Kraay robust standard error in () and the *p*-value in []. Kleibergen-Paap rk LM statistic for the under-identification test, Kleibergen-Paap rk Wald F statistic for weak identification test, and Hansen J statistic for over-identification test.
Source: The authors.

significant, indicating that the negative effect of vertical relatedness on manufacturing structural rationalisation fails the significance test. The results of Model (1) align with H3a but not with H4a.

Given that reverse causality may bias the coefficient estimates, we employed I.V. regression to re-estimate the relationship between industrial relatedness and manufacturing structural rationalisation, as shown in Model (2)–(4). Model (2), (3) and (4) use instrumental variables based on interest rates of three different maturities, respectively. Regardless of which set of instrumental variables, technological relatedness shows significantly positive effects, and vertical relatedness shows significantly adverse effects. After dealing with endogeneity issues, the results of Model (2)–(4) are in line with H3a and H4a. At the national level, technological relatedness contributes to manufacturing structural rationalisation by improving the inter-industry factor allocation efficiency. Vertical relatedness increases the region's vulnerability to shocks, which is unfavourable for manufacturing structural rationalisation.

Besides, we tested the validity of instrumental variables used in Model (2)–(4). Kleibergen and Paap (2006) rank L.M. tests reject the null hypothesis that the matrix of reduced form coefficients is under-identified, thus supporting the relevance of our instrumental variables. Kleibergen and Paap (2006) rank Wald F tests present higher values than Stock and Yogo (2005) critical values, suggesting that our instrumental variables are not weak. Hansen's (1982) J tests fail to reject the null hypothesis that all instrumental variables are exogenous. The above tests demonstrate the validity of instrumental variables and suggest that the I.V. regression results are more reasonable and rigorous than the O.L.S. regression results. We will only report the I.V. regression results in the next section to save space.

According to the I.V. regression results in Model (2)–(4), various control variables, including *FD*, *URBAN*, *RD*, *GLOBAL* and *POPDEN*, show various effects on manufacturing structural rationalisation. In detail, the positive effects of *FD* show that financial development contributes to manufacturing structural rationalisation by mitigating the capital mismatch caused by financial frictions (Wu, 2018). The effects of *URBAN* are adverse, suggesting that the increased labour supply from urbanisation is relatively less educated and flows more into labour-intensive industries (Liu et al., 2019), hindering the rational allocation of factors. The adverse effects of *RD* indicate that the increased R&D intensity may strengthen the specialisation of human capital and discourage factor mobility, hampering manufacturing structural rationalisation. The positive effects of *GLOBAL* imply that globalisation participation brings about a more competitive market environment and higher resource allocation efficiency among industries (Lu & Yu, 2015). The effects of *POPDEN* are also positive, indicating that higher population density may correspond to better labour mobility and thus more rational manufacturing structures.

Table 4 presents the national full-sample results for the impact of technological and vertical relatedness on manufacturing structural advancement. According to the proposed hypotheses H5a and H6a, manufacturing structural advancement is affected positively by technological relatedness and negatively by vertical relatedness at the national level. Model (5) shows that the technological and vertical relatedness coefficients are not significant in the O.L.S. regression, which is not in line with the expectations of H5a and H6a. After addressing the endogeneity bias, technological relatedness shows significantly positive effects, and vertical relatedness shows adverse but insignificant effects in the I.V. regressions in Model (6)–(8). The findings of technological relatedness are in line with H5a, implying that technological relatedness contributes to manufacturing structural advancement by accelerating the development of high-tech industries at the national level. However, the findings of vertical relatedness are inconsistent with H6a. This inconsistency may be because active governmental policies have intervened in the evolution of manufacturing structures at the national level to a large extent, especially in inland regions. Overall, the pattern of regional manufacturing specialisation implied behind the network of supplier-customer relationships have not fully conditioned the emergence of new advanced industries. Moreover, several tests have confirmed the instrumental variables' validity in Model (6)–(8).

According to the I.V. regression results in Model (6)–(8), various control variables, including *ZONE*, *URBAN*, *RD*, *INFRASTR* and *POPDEN*, present various effects on manufacturing structural advancement. Specifically, the positive effects of *ZONE* show that establishing development zones has promoted manufacturing structural advancement at the national level by selecting advanced industries for priority development following the principle of comparative advantage (Li & Shen, 2015). The

Table 4. Full-sample results: the explained variable is structural advancement.

Model	(5)	(6)	(7)	(8)
TR_t	0.002	0.361*	0.366*	0.366*
	(0.198)	(0.209)	(0.209)	(0.209)
VR_t	−1.566	−1.813	−1.686	−1.653
	(1.978)	(1.379)	(1.396)	(1.393)
$ZONE_{t-1}$	0.031	0.064**	0.063**	0.065**
	(0.054)	(0.031)	(0.031)	(0.031)
FD_{t-1}	0.039	0.033	0.037	0.039
	(0.065)	(0.039)	(0.040)	(0.039)
$URBAN_{t-1}$	0.594***	0.671***	0.672***	0.675***
	(0.162)	(0.114)	(0.114)	(0.114)
RD_{t-1}	−7.189**	−6.025***	−5.887***	−5.831***
	(2.812)	(2.114)	(2.080)	(2.069)
$INFRASTR_{t-1}$	0.077***	0.069***	0.069***	0.070***
	(0.010)	(0.012)	(0.012)	(0.012)
$GLOBAL_{t-1}$	0.022*	0.009	0.009	0.009
	(0.011)	(0.008)	(0.007)	(0.007)
$POPDEN_{t-1}$	−0.039**	−0.043***	−0.042***	−0.042***
	(0.015)	(0.011)	(0.011)	(0.011)
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Observations	570	570	570	570
R^2	0.180	0.076	0.076	0.075
Kleibergen-Paap rk LM statistic		7.893	7.855	7.864
p-value		[0.048]	[0.049]	[0.049]
Kleibergen-Paap rk Wald F statistic		12.251	12.314	11.994
Stock-Yogo critical value		9.93	9.93	9.93
Hansen J statistic		3.110	2.964	2.793
p-value		[0.211]	[0.227]	[0.247]

Notes: ***, ** and * represent significance at 1%, 5% and 10% level, respectively. All specifications include a constant term. The Driscoll-Kraay robust standard error in () and the P-value in []. Kleibergen-Paap rk LM statistic for the under-identification test, Kleibergen-Paap rk Wald F statistic for weak identification test, and Hansen J statistic for overidentification test.
Source: The authors.

positive effects of *URBAN* suggest that urbanisation contributes to manufacturing structural advancement by improving resource utilisation and providing a better environment for technological innovation (Chen et al., 2020). The effects of *RD* are adverse, indicating that high-tech manufacturing industries may have lower efficiency to transform governmental expenditures on R&D into output expansion. The positive effects of *INFRASTR* imply that a well-developed transport infrastructure facilitates the improvement of innovation networks, leading to more advanced manufacturing structures (Fritsch & Slavtchev, 2011). The adverse effects of *POPDEN* indicate that population density is more of a disincentive than a facilitator of regional innovation, i.e., higher population density generates labour-intensive industries and inhibits capital- and technology-substituting innovation (Zhu et al., 2019).

4.2. Regional sub-sample results

As discussed in Section 2.1, there is apparent heterogeneity in the manufacturing evolutionary patterns between China's coastal and inland regions. Hence, we divided the entire sample of 30 provinces into two sub-samples: coastal and inland regions. Coastal regions include Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan and inland regions include the rest of

Table 5. Regional sub-sample results.

Explained variables	Structural rationalisation		Structural advancement	
Sub-sample	Coastal	Inland	Coastal	Inland
Model	(9)	(10)	(11)	(12)
TR_t	−1.237***	−0.009	1.408***	−0.084
	(0.245)	(0.076)	(0.286)	(0.342)
VR_t	2.408	0.222	−30.071***	1.801
	(1.946)	(1.029)	(4.815)	(1.407)
$ZONE_{t-1}$	−0.065	0.048***	0.077	−0.063
	(0.054)	(0.017)	(0.052)	(0.048)
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Observations	209	361	209	361
R^2	0.193	0.156	0.461	0.163
Kleibergen-Paap rk LM statistic	8.207	7.278	8.207	7.278
p-value	[0.042]	[0.064]	[0.042]	[0.064]
Kleibergen-Paap rk Wald F statistic	56.766	13.197	56.766	13.197
Stock-Yogo critical value	9.93	9.93	9.93	9.93
Hansen J statistic	1.879	0.055	2.063	4.056
p-value	[0.391]	[0.973]	[0.356]	[0.132]

Notes: ***, ** and * represent significance at 1%, 5% and 10% level, respectively. All specifications include a constant term. The Driscoll-Kraay robust standard error in () and the p-value in []. Kleibergen-Paap rk LM statistic for the under-identification test, Kleibergen-Paap rk Wald F statistic for weak identification test, and Hansen J statistic for overidentification test. All control variables included but not shown to save space.
Source: The authors.

provincial administrative regions. As shown in Table 5, we estimated Model (9)–(12) to examine whether the impact of industrial relatedness on manufacturing structural change varies with the location. To save space, we only reported the regression results using instrumental variables based on interest rates with the term of 1–3 years. A series of tests have demonstrated the validity of instrumental variables.

According to the proposed hypotheses H3b and H4b, manufacturing structural rationalisation is significantly affected positively by technological relatedness and negatively by vertical relatedness only in coastal regions. Technological and vertical relatedness is assumed to have no significant effect on manufacturing structural rationalisation in inland regions. We also suppose that governmental intervention plays a much more essential role than industrial relatedness in the evolution of manufacturing structures in inland regions. Establishing development zones has been one of the most critical policies conducted by local governments to promote manufacturing development. Furthermore, many detailed policies such as low-priced land and income tax break have targeted the firms in development zones. Therefore, we took the establishment of development zones as a proxy of governmental supports and paid particular attention to its estimated coefficient.

As presented in Model (9) and (10), the findings of technological relatedness are in line with H3b, implying that technological relatedness contributes to manufacturing structural rationalisation only in coastal regions by improving factor allocation efficiency. However, the findings of vertical relatedness are inconsistent with H4b. We suppose that vertical relatedness significantly dampens manufacturing structural rationalisation in coastal regions, but the estimate shows an insignificant effect. The reason may be that coastal regions are more mature in developing manufacturing and their institutional environments are more capable of withstanding external shocks. Even when the productive system is highly vertically connected, the local government can minimise the negative impact of external shocks on manufacturing structural rationalisation through measures such as tax incentives, information dissemination, and social security. The findings of establishing development zones are in line with our expectations. Establishing development zones does not significantly affect manufacturing structural rationalisation in coastal regions where industrial relatedness typically characterises manufacturing structures' evolution. In inland regions where governmental policies strongly intervene in regional industrial evolution, establishing development zones inhibits manufacturing structural rationalisation while industrial relatedness has no significant effect. Establishing development zones in inland regions has intended to accelerate industrial agglomeration. However, the limited local supply of high-quality human capital has reduced the efficiency of resource allocation and restricted manufacturing structural rationalisation (Yuan & Zhu, 2018).

According to the proposed hypotheses H5b and H6b, manufacturing structural advancement is significantly influenced positively by technological relatedness and negatively by vertical relatedness only in coastal regions. Technological and vertical relatedness is supposed to have no significant effect on manufacturing structural advancement in inland regions. As shown in Model (11) and (12), the findings of technological relatedness align with H5b, implying that technological relatedness contributes to manufacturing structural advancement only in coastal regions by accelerating the development of high-tech industries. The findings of vertical relatedness are also in line with our proposed hypothesis H6b, indicating that vertical relatedness hinders manufacturing structural advancement only in coastal regions by decreasing the region's potential to diversify into new advanced industries. As to the impacts of establishing development zones, we suppose it significantly promotes manufacturing structural advancement in inland regions as it does at the national level, but the estimate shows an insignificant effect. The reason may be that the limited independent innovation capacity in inland regions and the imitated industrial policies due to inter-regional competition have weakened the facilitating role of establishing development zones on manufacturing structural advancement (Guo & He, 2017).

5. Conclusions and implications

Based on the analysis of impact mechanisms of industrial relatedness on manufacturing structural change, we empirically examine the effects of technological and vertical relatedness on the structural rationalisation and advancement within manufacturing using panel data of 30 provinces in China from 2000 to 2019. We also explore whether the impact of industrial relatedness on manufacturing structural change differs between coastal and inland regions. The main conclusions are as follows. At the national level, technological relatedness can promote both structural rationalisation and advancement within manufacturing. Vertical relatedness holds a negative effect on structural rationalisation and no significant effect on structural advancement. Besides, the effects of industrial relatedness exhibit regional heterogeneity. In coastal regions, technological relatedness can still promote manufacturing structural rationalisation and advancement. Vertical relatedness has no significant effect on structural rationalisation and a negative effect on structural advancement. In inland regions, governmental supports help break the dependency of regional manufacturing structural change on industrial relatedness, and the establishment of development zones restrains manufacturing structural rationalisation.

Our findings can help policymakers answer how regional manufacturing should develop and what they can do to promote a rationalised and advanced manufacturing structure. Our study highlights the role of industrial relatedness. The impact of industrial relatedness on manufacturing structural change shows substantial regional differences between China's coastal and inland regions. For coastal regions, there is strong path dependence in the evolution of regional manufacturing structure. Therefore, local governments in coastal regions should have a comprehensive understanding of historical production capability in local manufacturing when undertaking industrial planning. Policymakers should focus on attracting and supporting industries that are technologically related to existing local industries. The introduction of technologically related industries can reduce the uncertainty in developing new industries by taking advantage of existing relevant skills, capabilities, and technologies. It can also rapidly embed itself into the local productive system by utilising the local network of supplier-customer relationships. In inland regions, governmental supports have played an essential role in breaking the path-dependent trajectory. Governments have improved the local production conditions by adopting favourable policies to attract or develop new industries unrelated to their previous industrial portfolio. However, empirical results show that governmental support, represented by the establishment of development zones, has not promoted structural rationalisation and advancement within manufacturing. This finding implies that the facilitating role of preferential policies in inland regions on manufacturing structural rationalisation and advancement has been constrained by the supply of high-quality human capital and the capacity for independent innovation and further weakened as they became more widely used. In order to practically promote manufacturing structural rationalisation and advancement, local governments should do more than build supporting upstream and downstream industrial chains for introduced industries. More importantly, policymakers should make efforts to improve the region's capacity for independent innovation, provide a more abundant supply of human capital and build a more stable institutional environment to develop local core competitiveness.

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