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Linking production geography and financial performance

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Abstract

Purpose – When is it more profitable for multinational manufacturers to manufacture in high-cost environments and when in low-cost environments? While the literature offers many cues to answer this question, too little empirical research directly addresses this. In this study, we quantitatively and empirically investigate the financial effect of companies' production footprint in low-cost and high-cost environments for different types of production networks.

Design/methodology/approach – Using the data of 770 multinational manufacturing companies, we analyze the relationship between production footprints and profitability during four calendar semesters in 2018 and 2019 ($N = 2{,}940$), investigating the moderating role of companies' production network type.

Findings – We find that companies with networks distinguished by both high levels of product complexity and process sophistication profit the most from producing to a greater extent in high-cost countries. For these companies, shifting production to low-cost countries would be associated with negative performance implications.

Practical implications – Our findings suggest that the production geography of companies should be attuned to their network type, as defined by the companies' process sophistication and product complexity. Manufacturing in low-cost countries is not always the best choice, as doing so can adversely affect profits if the products are highly innovative and the production processes are complex.

Originality/value – We contribute to the scarce empirical literature on managing global production networks and provide a data-driven analysis that contributes to answering some of the enduring questions in this critical area.

Keywords Production networks, Foreign direct investment, Product complexity, Process sophistication, Reshoring

Paper type Research paper

Introduction

In the ongoing debate about production in high-cost versus low-cost environments, several studies (e.g. de Treville *et al.*, 2017; Ketokivi *et al.*, 2017) have proposed that, under certain circumstances, production in high-cost countries can outweigh the benefits of a low-cost environment. While these studies offer rich analyses and insights, they have two limitations.

Erratum: It has come to the attention of the publisher that the article, Oliver von Dzengelevski, Torbjørn H. Netland, Ann Vereecke and Kasra Ferdows "Linking production geography and financial performance", published in *International Journal of Operations & Production Management* was published with the incorrect sentence 'When is manufacturing in high-cost environments and more profitable for multinational manufacturers and when in low-cost environments?' in the Abstract. The correct sentence is 'When is it more profitable for multinational manufacturers to manufacture in high-cost environments and when in low-cost environments?'. The errors were introduced in the editorial process and have now been corrected in the online version. The publisher sincerely apologises for these errors and for any inconvenience caused.

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First, they are based on case studies or small samples. Second, they do not investigate the link between the geography of companies' manufacturing network and their profitability. Therefore, a fundamental question still remains largely unanswered: when is it more profitable for manufacturers to produce in high-cost environments and when in low-cost environments? Our study seeks to contribute to answering this question.

For this purpose, we draw on a panel of 770 manufacturers, covering the pre-pandemic time scope between the first calendar semester of 2018 and the second calendar semester of 2019 ($t = 4$ and $N = 2{,}940$). Based on secondary data on the production geography of companies and their financial statistics, we investigate the relationship between the companies' manufacturing footprint in low-cost and high-cost countries and their financial performance. To structure our investigation, we use the network typology proposed by Ferdows *et al.* (2016) as a conceptual basis. This model presents a useful framework for classifying different types of production networks based on the characteristics of the products they produce and the production processes they use to produce them. Using this typology, Ferdows *et al.* (2016) suggest that different combinations of product complexity and process sophistication are likely to make production in high-cost (low-cost) environments more (less) profitable. Our large-sample empirical study complements, extends and refines the findings of previous studies focused on this topic area (e.g. Barbieri *et al.*, 2018; de Treville *et al.*, 2017; Ferdows, 2020; Hilletofth *et al.*, 2019).

Literature review and hypothesis development

Several research streams contribute to the study of global production networks. A first stream concerns multinational companies, with a focus on diverse inter- and intra-firm relationships. Various theories have been used to explore these relationships, such as network theory (Ghoshal and Bartlett, 1990; Gulati *et al.*, 2000), evolutionary theory (Kogut and Zander, 1993), learning organization (Grant, 2012; Nonaka, 1994) and knowledge transfer (Grant, 1996; Szulanski, 1996). These theories emphasize the benefits of transferring resources and competencies within multinational organizations but rarely delve into plant-level organization and management or focus directly on the effects of low- or high-cost environments on profitability.

A second stream of research examines industrial networks. Relationships with suppliers (Dyer, 1996; Dyer and Nobeoka, 2000), subcontractors and contract manufacturers (Plambeck and Taylor, 2005) are studied extensively. Increased data, information and knowledge transfer in the extended enterprise are seen as beneficial, but concerns exist about excessive outsourcing for core product production and design (Arruñada and Vázquez, 2006; Pisano and Shih, 2009).

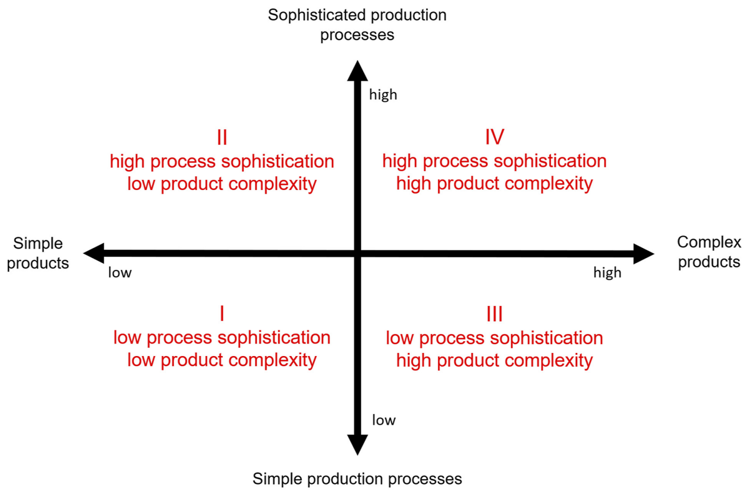
Håkansson (1990) offers a more abstract view of industrial networks as interplay between *actors*, *resources* and *activities* within different firms. Karlsson (2003), Dekkers and Van Luttervelt (2006) and Sköld and Karlsson (2007) suggest that manufacturing strategy is best defined in the context of industrial networks and considering dependencies between various key actors, including suppliers, alliance partners and distributors, among others. This perspective is similar to what Pisano and Shih (2009) call "industrial commons," which can influence companies' options for the locations of their global production sites. The geography of production locations plays a more important role in this line of research, but its relationship with firms' profitability is still not directly investigated.

A third research stream – which we contribute to in this paper – focuses on intra-firm production networks. Within this stream, some scholars focus on the network as the unit of analysis while others focus on plants that compose these networks (Cheng *et al.*, 2015). As important proponents of the latter sub-stream of research, Hayes and Schmenner (1978) explore organizing production networks along products, processes or a combination of both. Other scholars consider the different strategic roles of factories within a network (Ferdows, 1989, 1997; Schmenner, 1982; Vereecke and Van Dierdonck, 2002; Vereecke *et al.*, 2006).

Within the sub-stream of research that considers the network itself as the unit of analysis (Colotla *et al.*, 2003; De Meyer and Vereecke, 2009; Feldmann and Olhager, 2019; Ferdows, 2008; Ferdows *et al.*, 2016; Shi and Gregory, 1998; von Dzengelevski *et al.*, 2020), the strategic capabilities of a network that go beyond individual factories are a central theme of research. In this context, our study engages with the strategic configuration of production networks (Shi and Gregory, 1998), concentrating on their geographic distribution of manufacturing across low-cost and high-cost countries.

A recent strand of growing literature relevant to this study focuses on the "reshoring" phenomenon, i.e. the repatriation of offshore production and offers rich insights into the rationale for production in high-cost countries (Kinkel, 2014; Barbieri *et al.*, 2018). Some authors have argued that reshoring is a correction of earlier mistakes in the calculation of the benefits of production in low-cost countries (Kinkel and Maloca, 2009). Other reasons include regaining access to know-how and qualified workers (e.g. Ellram *et al.*, 2013), markets (e.g. Canham and Hamilton, 2013) or advances in manufacturing technology (Fratocchi, 2018). Echoing key points in this literature, Ketokivi *et al.* (2017) suggest that a main reason for locating factories in high-cost countries is the high intensity of required interaction between production and other functions, such as research and development (R&D), suppliers or market.

This rich literature implies that the profitability of production in high- or low-cost environments depends on a plethora of conditions. We borrow from the model proposed by Ferdows *et al.* (2016), hypothesizing that the complexity and innovativeness of products and sophistication of production processes are among the most critical factors in determining these conditions. Ferdows *et al.* (2016) suggest a framework for assessing the congruency of production networks, business units or entire companies (Ferdows, 2009). It is based on a matrix spanned by the two dimensions of product innovativeness and process sophistication, which are visualized in Figure 1 in adapted form. Although the primary focus of



Note(s): The figure above shows a classification of production networks suggested by Ferdows *et al*. (2016) based on their degree of product complexity and process sophistication. The numbering of the quadrants corresponds to the sequence of the numbering of hypotheses

Source(s): Authors' own creation, content of matrix adapted from Ferdows *et al*. (2016)

Figure 1. Network-type framework

Ferdows *et al.* (2016) is not the issue of production in high- and low-cost locations, the framework provides a helpful structure for our investigation.

Ferdows *et al.* (2016) divide this matrix into four quadrants representing four types of networks: footloose networks (Quadrant I), process innovation networks (Quadrant II), low-investment networks (Quadrant III) and rooted networks (Quadrant IV). They suggest that networks in different quadrants should be composed of plants with different levels of competency to form congruent networks [1].

Ferdows *et al.* (2016) also suggest that the more complex and proprietary both products and processes are compared to the industry standard, the higher the required competency level of the plants in the network would be. In contrast, networks that produce simpler and more standardized products would be best composed of lower-competency plants. We note that the implied notion of network congruence "can also suggest, in broad terms, whether different plants are in right places—for example, which of the plants in high-cost environments are likely to thrive and in the long run which ones are likely to be in vulnerable positions" (Ferdows *et al.*, 2016, p. 67). "Being located in low-cost environments would generally be advantageous" for footloose networks (Ferdows *et al.*, 2016) (Quadrant I) because their mission is to minimize costs while achieving the required quality standards, which can be met by drawing on codified knowledge, thus rendering production easily transferable (for a similar point on the codifiability of knowledge in the context of offshore manufacturing, see Aron and Singh (2005)). We, therefore, hypothesize.

H1. Companies with networks characterized by low product complexity and low process sophistication with a higher ratio of plants in

H1a. high-cost locations are less profitable.

H1b. low-cost locations are more profitable.

Plants in process innovation networks (Quadrant II, referring to networks characterized by low product complexity and higher process sophistication), producing standard products with advanced processes, might close once proprietary production processes leak (Frishammar *et al.*, 2015; Tan *et al.*, 2016) to the rest of the industry. Arguably, this mission is easier to fulfill in high-cost countries with stable institutions than in developing countries. We hypothesize.

H2. The profitability effect of locating a greater share of manufacturing in

H2a. high-cost locations are positively moderated by process sophistication.

H2b. low-cost locations are negatively moderated by process sophistication.

The rooted and footloose network types are described as stable, in contrast to low-investment and process innovation networks. The low-investment network (Quadrant III, referring to networks characterized by high product complexity and lower process sophistication) produces complex products using simple processes, indicating a potential mismatch between product and process. Low-investment networks may be in high-cost environments to fulfill their role of "mitigate[ing] the risk of losing control of its brand image and proprietary information" (Frishammar *et al.*, 2015, p. 66; Tan *et al.*, 2016; also compare Schotter and Teagarden (2014) and Jain (1996)). We hypothesize.

H3. The profitability effect of locating a greater share of manufacturing in

H3a. high-cost locations are positively moderated by product complexity.

H3b. low-cost locations are negatively moderated by product complexity.

Rooted networks (Quadrant IV, referring to networks with higher product complexity and higher process sophistication) producing complex products with sophisticated processes should ideally be long-term *rooted* in industrialized countries as they would require "highly skilled operators and technicians as well as access to expertise and knowledge in their industries" (Schotter and Teagarden, 2014 and Jain, 1996, p. 65). In other words, companies with this type of network should focus on accessing strategic assets (Dunning, 1998), such as skills and knowledge (Nachum *et al.*, 2008; Narula and Santangelo, 2012), rather than seeking out cost-related advantages (also compare Nachum and Zaheer, 2005). We hypothesize.

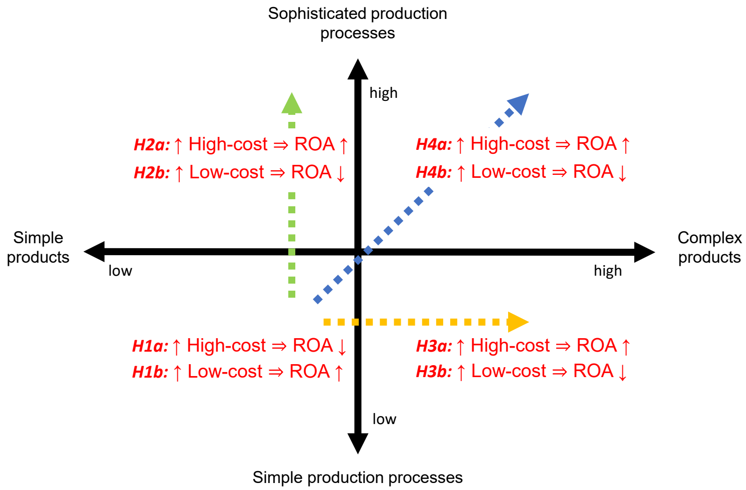
H4. The profitability effect of locating a greater share of manufacturing in

H4a. high-cost locations are moderated by product complexity and process sophistication in such a way that when both variables are high, the relationship becomes stronger.

H4b. low-cost locations are moderated by product complexity and process sophistication in such a way that when both variables are high, the relationship becomes weaker.

To summarize, the model conceptually implies that plants in Quadrants II, III and IV can benefit from being located in high-cost locations. In contrast, plants in Quadrant I would be best located in low-cost locations. Note that our above-formulated hypotheses do not focus on the locations of individual plants. Instead, they address the aggregate production footprints of companies in relation to high-cost and low-cost locations. Figure 2 illustrates our hypotheses based on the above-discussed network classification adapted from Ferdows *et al.* (2016).

The figure above sets our hypotheses into the context of the network matrix derived from Ferdows *et al.* (2016). As shown, the different sets of hypotheses correspond to the different quadrants of the matrix. The use of arrows signifies that our interaction hypotheses concern continuous variables (process sophistication and product innovation), not discrete categories. (1) The first set of hypotheses (H1a + H1b) corresponds to networks of the lower left quadrant, which are low in product complexity and process sophistication, suggesting that they would not profit (profit) from a greater extent of high-cost (low-cost) locations. (2) The second set (H2a + H2b) of hypotheses corresponds to the upper left quadrant.



Source(s): Authors' own creation, based on additions to Figure 1

Figure 2.
Hypotheses illustrated in the network type matrix

We hypothesize that companies low in product complexity profit (not profit) from a greater extent of high-cost (low-cost) locations the higher their process sophistication is (i.e. as they verge from the lower left into the upper left quadrant, signified by the green arrow). (3) The third set of hypotheses (H3a + H3b) corresponds to the lower right quadrant. We hypothesize that companies that are low in process sophistication profit (not profit) from a greater extent of high-cost (low-cost) locations the higher their product complexity is (i.e. as they verge from the lower left into the lower right quadrant, signified by the yellow arrow). (4) The fourth set of hypotheses (H4a + H4b) corresponds to the upper right quadrant. We hypothesize that companies profit (not profit) from a greater extent of high-cost (low-cost) locations the higher their process sophistication and product complexity are (i.e. as they verge from the lower left into the upper right quadrant, signified by the blue arrow).

Data and measures

We investigate the link between production geography and financial performance in a pre-coronavirus disease 2019 (COVID-19) panel sample of manufacturers, covering the time scope between the first calendar semester of 2018 and the second calendar semester of 2019. For this, we curated a purpose-fit set of secondary data, combining information about the location of companies' production sites from secondary sources with financial statistics. Based on the raw data available to us, we formed a semester-based panel data set beginning in the first semester of 2018 and ending in the second semester of 2019. By constructing a panel data set, we can tackle the issue of omitted variable bias – which needs to be considered particularly in the context of topics relating to global operations strategy (Ferdows, 2018) – by including random intercepts for the companies in our sample (Wooldridge, 2010). Our full sample covers 770 companies and four calendar semesters ($t = 4$), resulting in a total of 2,940 observations.

We obtained information about the global production networks of the companies in our sample from the Uniworld directory. The directory was first published in 1955 as the *Directory of American Firms Operating in Foreign Countries*. Its earlier versions were issued in print (see Young, 1989) and have been available as a searchable online database since 2015, covering the subsidiary addresses of both USA and global companies [2]. All information contained in the subscription-based data directory is researched and reviewed by the editorial staff in the United States of America and undergoes additional software-based checks. New, revised and deleted entries all require editorial approval. Primary sources of information for the database include the annual reports and press releases of companies. The editorial staff contacts companies directly via phone or email to verify and clarify details if necessary. Hence, we are confident in the validity of the secondary data used in our study. The primary users of the database are global corporations extending their network of business-to-business contacts (see the data set review by Gee, 2019).

We used data published by Thomson Reuters to obtain financial data about these companies. We used the data for the same periods and matched the two databases for each company in the sample. Table A1 in the Appendix provides the details.

The typical company in our sample is a large multinational company with an average sales volume of about US$5bn. Table A2 in the Appendix provides an overview of the regional distribution of companies by headquarters country. The distribution of companies in our sample approximately reflects the global gross domestic product (GDP) distribution. Among the top 10 countries in our sample, the majority are also represented in the global top 10 economic output as measured by GDP. A notable difference between the distribution of company headquarters in our sample and the global GDP distribution is the relative under-representation of China and India and possible over-representation of Switzerland, likely related to its attraction as the site for corporate headquarters.

Dependent and independent variables

We measure our dependent variable, *profitability*, by the logarithm of the companies' return on assets (ROA). ROA is a widely used measure of profitability regarded to be a good indicator of a firm's financial performance (e.g. Hunton *et al.*, 2003; Lampel and Giachetti, 2013).

In line with the original definition of Ferdows *et al.* (2016), we define the independent variable *Product complexity* as the degree to which the product design of companies embeds knowledge that is proprietary and exceeds the simple industry standard. As proprietary knowledge is gained by means of R&D, we draw on the R&D investment of companies to proxy this variable. Given that the magnitude and importance of R&D investment is dependent on the industry in which a company operates, we operationalize the variable using the industry-centered R&D to sales ratio. This ratio reflects the degree to which a company spends more or less of its revenue on R&D activities to gain proprietary product knowledge relative to its industry competitors. In its uncentered form, the R&D to sales ratio has been used to proxy "firm innovative effort" in economics (Cohen and Klepper, 1992, p. 773). It is also referred to as a measure of R&D intensity in operations management research (e.g. Ehie and Olibe, 2010; Swink and Jacobs, 2012; Woo and Suresh, 2022) and is also commonly used to proxy a "firm's innovation intensity" (Kim and Zhu, 2018, p. 11). Following a similar rationale, our industry-centered measure additionally accounts for managerially meaningful differences between industries.

To proxy *Process sophistication*, the second key independent variable in our model, we use the industry-centered ratio of capital expenditure to sales, which reflects the degree to which a company uses its resources to acquire and upgrade physical assets, such as production machinery, equipment and facilities, relative to its competitors in its industry. The variable is industry-centered, because the level of investment required to upgrade production processes differs across industries. In its uncentered form, capital-to-sales ratio is used as a measure of capital intensity of firm technology in statistical research in economics (e.g. Himmelberg *et al.*, 1999). In similar capacity, this ratio was also used by prior studies in operations management (e.g. Steven and Britto, 2016). Our adapted measure follows a related rationale; however, the undertaken industry-centering of the variable provides a refinement, rendering it more suitable for the managerial context of our study.

Specifically, both the independent variables that act as moderators in our models are centered at the 25th percentile of the company's industry [3]. This means that the value 0 designates a company's *Product complexity* (*Process sophistication*) to be equal to the 25th percentile within the respective industry and, therefore, at a low level. Both variables remain continuous variables, the values of which reflect the relative distance above or below 0 (i.e. the 25th percentile in the respective industry). As the simple effect of a variable in the presence of interaction terms in a model can be interpreted as the effect of the variable when all interaction terms are 0, centering both variables at a low level allows us to interpret the simple effect of *Production in high-cost countries* (*Production in low-cost countries*) in the full model (corresponding to the first row in Table 2 and, respectively, Table 3) as the effect when both *product complexity* and *process sophistication* are low. Low levels of both variables correspond to companies in quadrant I of the framework (Figure 1). Furthermore, both variables are normalized by their respective standard deviations to facilitate the interpretation of the coefficients in our regression analysis.

A limitation of both above-discussed proxies for our independent variables is that they measure the concepts of interest on the input side, not the output side, which, in the context of our study, is unfeasible as we are drawing on secondary data. In other words, both proxies assume that the respective investments (in R&D and physical assets, including production machinery and equipment) are generally successful (e.g. R&D investments translate into proprietary knowledge) so that input and output are correlated. Although case-by-case exceptions that add "noise" to the statistical model certainly exist, we hold this assumption to be tenable in a large sample of companies as the one we study.

We define *Production in high-cost countries* as the company's share of production subsidiaries in high-cost countries, i.e. the ratio between the number of a company's production sites in high-cost countries over its total number of production sites. This way the individual plant locations of each company are aggregated into a variable that captures the production footprint of the company in high-cost countries. To define *high-cost countries*, we draw on GDP per capita, a measure of a country's standard of living that is highly correlated to its production cost level (Ketokivi *et al.*, 2017), with the exception of the non-representative cases of tax havens. For the time scope under investigation, we define countries with a GDP per capita of more than US$40,000 as high-cost countries. For *Production in low-cost countries,* we define the share of production facilities in countries with a GDP per capita of less than US$10,000 over all production facilities of the company. Specifically, we follow the same logic of aggregating individual plant locations into a production footprint variable as for our above-defined variable *Production in high-cost countries*. This matches approximately the cut-off rate used by the World Bank threshold for "upper middle-income" countries. This category covers a wide range of countries from China and India to Vietnam, Mexico and Turkey, as well as most African countries. As implied by our definition of high- and low-cost countries, the countries not included under either definition are mid-cost countries.

Control variables

We control for company size because firm size and profitability could arguably be correlated (e.g. Hall and Weiss, 1967; Whittington, 1980). We measure size by the logarithm of sales volume in US$ in the relevant calendar semester in question. As economies of scale are key variable in the management of production networks (Shi and Gregory, 1998), we also control for the average plant size of companies, proxied by a company's number of employees divided by the number of plants. As a count variable, it is included in logarithmic form.

We also control for the companies' scope of business to account for alternative explanations of profitability involving economics of scope (e.g. Gimeno and Woo, 1999). We do this by using a count variable representing the number of six-digit North American Industry Classification System (NAICS) codes listed by a company as a description of the scope of its activities reported in the location database. This count variable is log transformed as well.

Additionally, we include a set of fixed effects to account for the country context of the companies' headquarters and their industry membership (Nielsen and Raswant, 2018). A set of fixed effects for time periods is also included (Wooldridge, 2010).

To counteract potential omitted variable bias, we fit our models with company-level random effects. We choose company-level random effects over company-level fixed effects on theoretical grounds because our study is primarily focused on between effects rather than within effects (i.e. the performance differences between companies in our panel rather than differences within companies in our panel across time) (Ketokivi *et al.*, 2021).

Descriptive statistics

Table 1 provides an overview of the descriptive statistics of key variables used in our analysis and the pairwise correlations between the continuous variables. The low correlations between our variables suggest that our models do not suffer from multicollinearity induced by highly correlated explanatory variables. An additional investigation of individual variables also suggests the stability and robustness of our presented results.

Econometric model

Equation (1) shows the model for testing our hypotheses pertaining to the high-cost production footprint of companies (i.e. H1a, H2a, H3a and H4a). To test H1b, H2b, H3b and

Variable	Mean	Std	(1)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) ROA	4.4558	0.05	1.00							
(2) Sales (in billions)	0.4619	1.62	0.14	1.00						
(3) Scope of business	1.4378	0.79	−0.01	0.37	1.00					
(4) Employees per plant	2.8019	1.69	0.05	0.58	0.20	1.00				
(5) Process sophistication	0.6166	1.00	−0.05	0.07	−0.11	0.04	1.00			
(6) Product complexity	0.2115	1.00	−0.09	−0.04	−0.07	0.00	0.11	1.00		
(7) Production in high-cost countries	36.9961	36.72	−0.01	−0.02	0.07	−0.07	0.04	0.02	1.00	
(8) Production in low-cost countries	31.3410	33.92	0.01	0.02	−0.09	0.17	0.06	−0.03	−0.20	1.00

Note(s): The table above shows the mean and standard deviation of the continuous variable included in our analysis in the full sample of our regression study as well as the pairwise correlation between them. Pairwise correlations between our variables are generally relatively low, indicating that our analysis is unlikely to suffer from the issue of multicollinearity. Re-estimating our models without variable (4), which features a correlation greater than 0.5 with variable (3), leads to consistent estimates of coefficients, further evidencing the stability of our results. The unit of variables (1), (5), (6), (7) and (8) is percentage points (compare section *Measures* for the underlying ratios), which aids the interpretability of our models. Log-transformed variables: *ROA, Sales, Scope of business* and *Employees per plant*

Source(s): Authors' own creation

Table 1. Descriptive statistics and pairwise correlations

H4b, we substitute *"Production in high-cost countries"* with *"Production in low-cost countries"* in the equation below.

$$\begin{aligned}
\log \backslash(\mathrm{ROA})_{\mathrm{itmn}} = {} & \alpha_0 + \beta_1 \text{Process sophistication}_{\mathrm{itmn}} + \beta_2 \text{Product complexity}_{\mathrm{itmn}} \\
& + \beta_3 \text{Process sophistication}_{\mathrm{itmn}} \times \text{Product complexity}_{\mathrm{itmn}} \\
& + \beta_4 \text{Production in high} - \text{cost countries}_{\mathrm{itmn}} \\
& + \beta_5 \text{Process sophistication}_{\mathrm{itmn}} \times \text{Production in high} - \text{cost countries}_{\mathrm{itmn}} \\
& + \beta_6 \text{Product complexity}_{\mathrm{itmn}} \times \text{Production in high} - \text{cost countries}_{\mathrm{itmn}} \\
& + \beta_7 \text{Process sophistication}_{\mathrm{itmn}} \times \text{Product complexity}_{\mathrm{itmn}} \\
& \times \text{Production in high} - \text{cost countries}_{\mathrm{itmn}} \\
& + \gamma \mathrm{X}_{\mathrm{it}} + \mathrm{I}_{\mathrm{i}} + \mathrm{J}_{\mathrm{m}} + \mathrm{K}_{\mathrm{n}} + \mathrm{L}_{\mathrm{t}} + \varepsilon_{\mathrm{itmn}}
\end{aligned} \tag{1}$$

$\mathrm{Log(ROA)}_{\mathrm{it}}$ indicates profitability as measured by the logarithm of the ROA of company *i,* industry *m*, in country *n* at time *t*. The regression constant is represented by α_0. The coefficients of the included explanatory variables and their interaction terms are given by β_1 to β_7. X_{it} is a vector of control variables with the associated vector of coefficients γ. A vector of company random effects is given by I_{i}. Industry-level fixed effects are accounted for by a vector of industry dummies J_{m}. Likewise, company headquarters country effects are accounted for by vector K_{n}. A vector of time fixed effects, L_{t}, is also included. $\varepsilon_{\mathrm{itmn}}$ is the error term in the regression. The standard errors used to judge the level of significance of the results presented in our regression tables are robust standard errors, which account for potential heteroskedastic residuals as well as cross-sectional and temporal dependence (Driscoll and Kraay, 1998).

Results

Our results concerning H1a, H2a, H3a and H4a are presented in Table 2 and those concerning H1b, H2b, H3b and H4b are in Table 3. We test our hypotheses based on the full models (i.e. Model 3 in Table 2 and Model 6 in Table 3).

	Model 1 (main effects only)	Model 2 (one-way interactions)	Model 3 (full model)
(1) Production in high-cost countries (H1a)	−0.00004**	−0.00007***	−0.00003**
(2) Process sophistication × Production in high-cost countries (H2a)		0.00004**	−0.00002
(3) Product complexity × Production in high-cost countries (H3a)		0.00004	−0.0001**
(4) Process sophistication × Product complexity × Production in high-cost countries (H4a)			0.0002**
(5) Process sophistication	−0.0010**	−0.0114**	−0.0061***
(6) Product complexity	−0.0106*	−0.0149**	−0.0069
(7) Process sophistication × Product complexity			0.0205***
(8) Sales (in billions)	0.0153***	0.0153***	0.1534***
(9) Scope of business	−0.0092**	−0.0092**	−0.0093***
(10) Employees per plant	−0.0047**	−0.0047**	−0.0046***
(11) Constant	0.0000	4.4416***	4.4963***
Controls for industry membership	Yes	Yes	Yes
Controls for headquarters location	Yes	Yes	Yes
Controls for calendar semesters	Yes	Yes	Yes
Random effects for companies	Yes	Yes	Yes
Sample size (*N*)	2,940	2,940	2,940
R^2	0.1560	0.1560	0.1641

Note(s): ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels of significance, respectively. Statistical significances are reported based on estimation with robust standard errors. The results pertain to a panel regression with fixed effects (i.e. dummies included for time [calendar semester 2018–2019] and companies) on return on assets. Log-transformed variables: *ROA, Sales, Scope of business* and *Employees per plant*
Source(s): Authors' own creation

Table 2. Regression results (high-cost production footprint)

We test H1a based on the coefficient of variable 1, which, in the presence of the interaction effects (Table 2, rows 2–4), gives the correlation between *Production in high-cost countries* and *ROA* when both *Process sophistication* and *Product complexity* are at low levels (i.e. when they are both 0, which corresponds to the 25th percentile in their respective industries). We find the coefficient to carry the hypothesized sign and to be significant at the 5% level. Therefore, we retain H1a. It is also interesting to note that the average treatment effect, given by the main effect in Model 1 (Table 2, row 1), is negative, which implies that *overall* production in high-cost countries is negatively associated with company *ROA*.

We do not find the coefficient of the interaction term *Process sophistication* × *Production in high-cost countries* (Table 2, row 2) to be significantly correlated with company profitability. Therefore, we reject H2a. The first interaction term corresponds to the association between *Production in high-cost countries* for companies with higher *Process sophistication* but low *Product complexity* (i.e. when *Product complexity* equals 0, which represents a low level of the variable relative to other companies in the respective industry).

However, we find the interaction term *Product complexity* × *Production in high-cost countries* (Table 2, row 3) to be negatively and statistically significant at the 5% level, evidencing negative moderation. In other words, for companies with higher *Product complexity* and low *Process sophistication*, we find a negative link between *Production in high-cost countries* and *ROA*. Therefore, our data do not support H3a.

Moreover, our findings show support for H4a, as indicated by the positive coefficient of the three-way interaction *Process sophistication* × *Product complexity* × *Production in high-cost countries* (Table 2, row 4), which is significant at the 5% level. In other words, at higher levels of both *Process sophistication* and *Product complexity*, *Production in high-cost countries* becomes more profitable for companies.

	Model 4 (main effects only)	Model 5 (one-way interactions)	Model 6 (full model)
(1) Production in low-cost countries (H1b)	0.0000	0.0001	0.0001
(2) Process sophistication × Production in low-cost countries (H2b)		−0.0001**	−0.00004*
(3) Product complexity × Production in low-cost countries (H3b)		−0.0002**	0.00004
(4) Process sophistication × Product complexity × Production in low-cost countries (H4b)			−0.0001**
(5) Process sophistication	−0.0100**	−0.0071**	−0.0078***
(6) Product complexity	−0.0107*	−0.0107*	−0.0153**
(7) Process sophistication × Product complexity			0.0009**
(8) Sales (in billions)	0.0153***	0.0138***	0.0154***
(9) Scope of business	−0.0094**	−0.0098**	−0.0100***
(10) Employees per plant	−0.0046**	−0.0048**	−0.0046***
(11) Constant	0.000	4.4602***	4.478***
Controls for industry membership	Yes	Yes	Yes
Controls for headquarters location	Yes	Yes	Yes
Controls for calendar semesters	Yes	Yes	Yes
Random effects for companies	Yes	Yes	Yes
Sample size (*N*)	2,940	2,940	2,940
R^2	0.1558	0.1569	0.1603

Note(s): ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels of significance, respectively. Statistical significances are reported based on estimation with robust standard errors. The results pertain to a panel regression with fixed effects (i.e. dummies included for time [calendar semester 2018–2019] and companies) on return on assets. Log-transformed variables: *ROA, Sales, Scope of business* and *Employees per plant*
Source(s): Authors' own creation

Table 3.
Regression results (low-cost production footprint)

Table 3 provides an overview of our findings concerning network location in low-cost countries.

As hypothesized, we find a negative sign for the conditional simple effect for *Production in low-cost countries*, but the coefficient is not significant (Row 1, Table 3). Therefore, we reject H1b.

We find the coefficient of the interaction term *Process sophistication* × *Production in low-cost countries* (Table 3, row 2) to be negatively associated with *ROA*, which is significant at the 10% level. This interaction pertains to the effect of *Production in low-cost countries* at higher levels of *Process sophistication* (i.e. >0 for our variable centered at the 25th percentile) and low levels of *Product complexity* (i.e. = 0, i.e. at the 25th percentile). In line with this, we retain H2b.

We also find the interaction term *Product complexity* × *Production in low-cost countries* (Table 3, row 3) to be uncorrelated with company profitability, which means that we do not find support for H3b.

Lastly, we find the coefficient of the interaction *Process sophistication* × *Product complexity* × *Production in low-cost countries* to be significantly and negatively associated with company profitability (Table 3, row 4), which aligns with H4b. This result implies that *Production in low-cost countries* becomes less profitable for companies with higher levels of both *Process sophistication* and *Product complexity*.

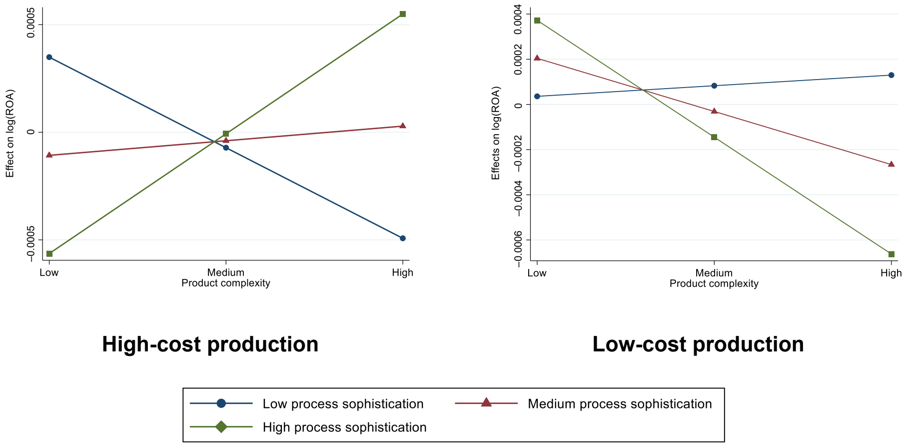
Table 4 provides a summary of our results.

Figure 3 below illustrates the marginal effects (calculated using the delta method) of production in high-cost countries, which aid the interpretation of the relationships implied in the above-presented interaction model. The mapped marginal effects provide an indication of

Table 4. Hypotheses and empirical evidence

Network type	Performance effects concerning additional production in high-cost countries (sub-hypotheses a)		Performance effects concerning additional production in low-cost countries (sub-hypotheses b)	
	Hypothesized effect/moderation	Observed effect/ moderation	Hypothesized effect/moderation	Observed effect/ moderation
H1. Networks characterized by low product complexity and low process sophistication	Negative (–)	Negative (–)	Positive (+)	None (0)
H2. Moderation of profitability effect by process sophistication	Positive (+)	None (0)	Negative (–)	Negative (–)
H3. Moderation of profitability effect by product complexity	Positive (+)	Negative (–)	Negative (–)	None (0)
H4. Moderation of profitability effect by product complexity and process sophistication	Positive (+)	Positive (+)	Negative (–)	Negative (–)

Source(s): Authors' own creation



Note(s): The figure above plots the marginal effects of an increase in companies' extent of production in high-cost (low-cost) countries on ROA, conditional on their degrees of process sophistication and product complexity. The y-axis gives the expected effect of a one-unit increase (i.e., 1 percentage point) in the ratio of high-cost production on companies' ROA (measured in percentage points). Companies' degree of product complexity is given by the x-axis and varies for the three curves depicted: the blue line (circle symbol) corresponds to companies with low product complexity, the red line (triangle symbol) to companies with medium product complexity, and the green line (diamond symbol) to companies with high product complexity. The label "medium" corresponds to the average value. The labels "low" and "high" correspond to values that are 1.5 standard deviations from the average
Source(s): Authors' own creation

Figure 3. Marginal effects of production in high-cost countries (low-cost countries)

the effect an expansion of companies' production footprints in high-cost (low-cost) countries would have, conditional on different levels of *Process sophistication* and *Product complexity*. The level of *Product complexity* is represented by the x-axis of the graph. The level of *Process sophistication* corresponds to one of the three differently colored lines, blue (with circle symbols) representing a low level (μ-1.5σ), red (with triangle symbols) a medium level (μ) and green (with square symbols) a high level ($\mu+1.5\sigma$).

As Figure 3 shows, for companies with a high level of *Process sophistication* (left subgraph, green line), the marginal effect of an increase in *Production in high-cost countries* increases with the *Product complexity* of the companies. In other words, the more "rooted" its network is (i.e. the higher its *Product complexity* and *Process sophistication*), the more profitable it would be for the companies to produce to a greater degree in high-cost countries. This dynamic, which concerns the main diagonal in our research model, is in line with our conceptual thought. The point estimator of the effect of *Production in high-cost countries* for companies with high levels of *Process sophistication* and *Product complexity* ($\mu+1.5\sigma$) is 0.006 ($p = 0.000$). The right subgraph, which shows the marginal effects of *Production in low-cost countries,* evidences that the more "rooted" a production network is (see green line at high levels of *Product complexity*), the less profitable it would be for a company to manufacture to a greater extent in low-cost countries.

For companies with high levels of both *Process sophistication* and *Product complexity*, we find a significantly negative effect of additional production in low-cost countries ($p = 0.000$). For several other combinations of the two variables, we find positive effects of low-cost production. For example, for low levels of *Process sophistication* and medium levels of *Product complexity*, i.e. companies with networks that to some extent resemble footloose networks, we find a positive and significant ($p = 0.016$) effect. To some degree, contrary to our expectations, we find a positive and significant marginal effect of *Production in high-cost countries* ($p = 0.007$) for companies with low levels of both moderators. However, the point estimator (0.004) is smaller than for companies with high levels of *Process sophistication* and *Product complexity*. For companies with low levels of *Process sophistication* and medium levels of *Product complexity*, the effect is significantly negative ($p = 0.000$). The same outcome holds true for companies with medium levels of *Process sophistication* and low levels of *Product complexity*.

Robustness checks

Although the data we used for this analysis are from the two years predating the COVID-19 pandemic (which was declared by the World Health Organization on March 11, 2020), we still checked for the potential early impact of COVID-19, especially since the financial performance of some companies, especially in China, might have been affected by local measures in the winter of 2019. To check the robustness of our findings, we added a control variable for data about Chinese companies in the second half of 2019 and found that the inclusion of this additional control variable did not change our findings.

Furthermore, we included an additional control variable that measures companies' size not by their sales volume but by the size of their production network, which might, for instance, affect the extent to which economies of scale can be realized. For this, we used the total number of production sites of a company. Moreover, including this additional control variable did not change the pattern of statistical significance in our findings.

Using company-wide measures for *Process sophistication* and *Product complexity* gives rise to limitations as it assumes a certain degree of homogeneity across plants within the production networks of companies. In other words, the underlying assumption is that plants within a company's network have comparable levels of the two moderating variables *Process* *sophistication* and *Product complexity*. This assumption of homogeneity is arguably less likely to hold for large production networks than for small ones. Hence, we re-estimate our models in a subsample of companies that has less than the median number of plants (6), finding consistent and comparable results concerning the moderation hypotheses we tested. Taking a step further to assure that our results were not adversely affected by this assumption, we used the subsample of 165 companies in our sample with only one manufacturing facility for an additional test. Despite the drastically reduced sample size and the associated loss of statistical power, our key results from our moderation analysis concerning *Production in high-cost countries* remained consistent and quantitatively comparable for this subsample. We conclude that our findings were not driven by the assumption of homogeneity of product and process characteristics of the companies' factories.

This additional analysis also provides supplementary evidence that our aggregation of plant locations in production footprint measures at the network level (i.e. ratios reflecting the degree to which a company's factories are located in high-cost or low-cost countries) did not introduce a major bias into our findings. The analysis of 165 companies with only one plant is de facto an analysis at the plant level. Although our study was conceptualized and carried out at the network level and made conclusions about production footprints and not individual plant locations, our additional robustness check implies that the insights we generated would also have some applicability when considering our research question at the plant level.

Finally, in addition to using ROA, a widely accepted measure of profitability, as a dependent variable, we rerun our models using an alternative measure of the companies' financial performance: the logarithm of *earnings before interest and taxes (EBIT)*. We observe quantitatively and practically similar results concerning the key findings of our moderation analysis, which supports the generalizability of our findings. Furthermore, our key moderation result concerning production in low-cost countries can be replicated using the log-transformed gross profit margins of companies.

Discussion and conclusion

Our findings show that production in both high-cost and low-cost environments can be profitable depending on the specific circumstances. We find the framework presented by Ferdows *et al.* (2016) – which distinguishes production networks based on the complexity and proprietary nature of the product and sophistication of the production processes – to be useful to determine these circumstances. Generally, our results suggest that the locational configuration of production networks needs to be congruent with the type of network that companies operate.

More specifically, our results suggest that companies with rooted networks profit the most from a higher level of production in high-cost countries. Considering widely held cost-centric views on the issue of manufacturing location, the notion that production in high-cost countries *can* be profitable might appear counterintuitive to some. Conceptually, this finding shows that the cost-disadvantage associated with these locations can be compensated for by other locational factors. Potential driving factors are well articulated in the literature, ranging from access to highly skilled labor and technicians and high-quality infrastructure to adequate protection of intellectual property and presence of advanced developed business ecosystems (Dunning, 1998; Shi and Gregory, 1998).

Future research could investigate the trade-off between various locational advantages in the form of case studies, with focus on a specific company or country. In this context, our findings also tie in with the growing literature on reshoring, which has been concerned with the identification of driving factors that lead companies to return to production in high-cost countries (e.g. Johansson *et al.*, 2019; Wiesmann *et al.*, 2017). Future research could investigate the role of network type and the strategic roles of plants within them in managers' decision to retain production in high-cost countries or return production back to a high-cost country. For this, qualitative studies (e.g. Blomqvist and Turkulainen, 2019) are likely to be able to add most value owing to the required depth of detail that needs to be considered. Additional research could also focus on the networks in quadrants II and IV of Figure 1, as for both we found moderation results that were not fully aligned with the hypotheses we formulated.

Our findings also show that for rooted networks, additional production in low-cost countries is, on average, not a profitable choice. To the contrary, we find that greater reliance on production in low-cost countries is associated with reduced profitability for companies with this type of network. For other combinations of product complexity and process sophistication and the resulting network types, we find that production in low-cost countries has positive implications for financial performance. This finding is in line with the to-be-expected cost advantage associated with locating manufacturing in these countries and the global spread of manufacturing in the past decades. Our findings that greater production in low-cost countries is performance-neutral for companies with networks distinguished by low product complexity and product sophistication and that some profitability benefit could be captured by producing in high-cost countries are to some extent unexpected. These findings might suggest that companies with these networks have overemphasized production in low-cost countries and would benefit from, to some extent, rebalancing their footprint and thereby diversifying their production geography. This result elaborates prior thinking about this type of network and illustrates the complexity involved in the management of global production networks (Ferdows, 2018). While the present research has taken a dedicated network-level perspective, future research could supplement our findings by considering locational questions and the moderating roles of product complexity and process sophistication at lower levels of aggregation, such as the plant level (Cheng *et al.*, 2015) or the level of product groups within a multinational manufacturing company.

Limitations

Although we are able to draw on panel data econometrics, which makes managing the omitted variable bias particularly problematic in the context of global operations (Ferdows, 2018), our research remains subject to several limitations. For instance, the production networks of the companies in our sample remain relatively steady in the studied time frame, such that changes in their production footprint (e.g. concerning locations in high-cost or low-cost countries) could only be studied at the expense of representativeness and sample size. Moreover, given the limitations of relevant available data on the manufacturing networks of multinational companies and to make the analysis manageable, we have used relatively simple measures to operationalize the variables *Product complexity* and *Process sophistication*.

Another limitation of our study is that we have not been able to take into account the sizes and production volumes of the different factories in our analysis. More refined measures may provide deeper insights.

Our robustness checks suggest that no systematic bias was introduced in our model estimations. Nonetheless, a limitation of our study is the implied assumption of approximate homogeneity in product complexity and process sophistication across the plants in a companies' production network. Given the quantitative nature of our work in this study, simplifying assumptions need to be made to render the analyses manageable and should be taken into account when interpreting our findings. Another limitation of our study is that we were unable to take into account regional heterogeneities within production locations, which future research might consider.

Practical implications

Our results inform the production footprint strategy of manufacturing companies. The general message of our paper for managers of global production networks is that "cost optimization" by means of network configuration should be exercised with a view toward product complexity and process sophistication. Different types of networks can afford different degrees of production in high-cost countries and lend themselves to varying degrees of rationalization measures. We suggest that rooted networks (high in process sophistication and product innovation) could even profit from a greater extent of production in high-cost countries because they benefit to a greater degree from their characteristic locational advantages. Overall, our findings suggest that the production geography of companies should be attuned to their network type, which is defined by their process sophistication and product complexity.

Notes

1. Competency level is one of the defining variables in the plant role model of Ferdows (1989).
2. The database we used only allows for the widespread identification of manufacturing subsidiaries since 2018, which means that earlier data cannot be considered. The panel does not consider data after 2019 to avoid distortion due to the effects of COVID-19.
3. We used the 10th and 33rd percentiles as alternatives to gauge the robustness of using the 25th percentile as a centering point. Likewise, we assured the robustness of our presented results by centering our variables at higher levels of industry aggregation, which yields comparable results.

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Appendix

Rank	Industry	Frequency	Percent
1	Industrial machinery	76	9.99
2	Auto parts and equipment	53	6.96
= 3	Commodity chemicals	39	5.12
= 3	Packaged foods and meats	39	5.12
= 5	Construction machinery and heavy trucks	32	4.20
= 5	Electronic components	32	4.20
7	Pharmaceuticals	28	3.68
= 8	Electrical components and equipment	27	3.55
= 8	Specialty chemicals	27	3.55
= 8	Steel	27	3.55
11	Aerospace and defense	22	2.89
12	Building products	20	2.63
13	Technology hardware, storage, and peripherals	19	2.50
= 14	Electronic equipment and instruments	18	2.37
= 14	Health care equipment	18	2.37
Sum (Top 15)		477	62.68
Sum (Total)		761	100.00

Note(s): This table shows the industry composition of our panel sample of companies in the second half of 2019. Shown are the top 15 industries. The industry composition of our sample remains relatively stable, which is why the panel composition is only reported for the second half of 2019 for reasons of parsimony and brevity
Source(s): Authors' own creation

Table A1. Industry distribution of the sample

Rank	Headquarters country	Frequency	Percent
1	The United States of America	230	30.22
2	Japan	213	27.99
= 3	France	29	3.81
= 3	Taiwan	29	3.81
5	Germany	25	3.29
= 6	South Korea	24	3.15
= 6	The United Kingdom	24	3.15
8	Canada	23	3.02
9	Switzerland	22	2.89
10	China	19	2.50
11	Italy	13	1.71
12	Sweden	11	1.45
13	Mexico	10	1.31
= 14	Finland	8	1.05
= 14	The Netherlands	8	1.05
Sum (Top 15)		688	90.40
Sum (Total)		761	100.00

Note(s): This table shows the geographic composition of our panel sample of companies in the second half of 2019. Shown are the top 15 locations. The distribution of headquarters locations of the companies in our sample is notably correlated with the global gross domestic product (GDP) distribution. Within the top 10 countries in our sample, most are also represented in the global top 10 of economic output, as measured by GDP, warranting a degree of representativeness for the global economy with respect to economic output. The geographic composition of our sample remains relatively stable, which is why the panel composition is only reported for the second half of 2019 for reasons of parsimony and brevity
Source(s): Authors' own creation

Table A2. Geographic distribution of the sample