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Import of digital products and production fragmentation

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Abstract

Empowering traditional manufacturing through the digital economy can not only enhance the competitiveness of Chinese manufacturing enterprises, but also enhance the degree of specialization of enterprises by optimizing the industrial structure, thus enhancing the embeddedness of Chinese enterprises in the global value chain. Based on this background, on the one hand, this paper extracts and integrates digital product information from China Customs data. On the other hand, this paper constructs the number of production processes of enterprises as a proxy variable for production fragmentation. Finally, by matching these two databases, we get the production segmentation data of Chinese enterprises' digital product import from 2000 to 2014. We found that improving the penetration degree of digital technology by importing digital products can effectively promote the production fragmentation. In order to further clarify the mechanism, we divided the digital products into final and intermediate kinds and found that firms importing digital final goods have a larger marginal impact on their production fragmentation.

Keywords Digital products, Production fragmentation, Digital import, Digital technology

1 Introduction

Digital economy has gradually expanded to many fields such as artificial intelligence, Internet marketing and digital trade at a higher stage (Aghion et al., 2020; Bonfiglioli et al., 2020). With the effective reduction of R&D and production costs, digital technology has gradually covered various areas of economic development from a single production link. (Goldfarb and Tucker, 2019; Acemoglu et al., 2020; Aghion et al., 2020; Jing et al., 2023). The 14th Five-Year Digital Economy Development Plan issued by The State Council in December 2021 clearly states that " To enable transformation and upgrading of traditional industries, foster new industries, new forms and models of business, and make China's digital economy stronger, better and bigger, so as to provide strong support for the building of a digital China."

China is at the juncture of economic structural transformation and the new round of global technological revolution. At the same time, the international industrial division has undergone profound changes. As the main body of the national economy, the manufacturing is not only the foundation of a strong country but also the instrument of national rejuvenation. The transformation and upgrading of the manufacturing have a significant impact on the smooth transformation of China's economic structure. However, there is no denying that China's manufacturing is still characterized by large but not strong, and there is still a big gap in industrial structure, independent innovation capacity, resource allocation efficiency and other aspects compared with developed countries. In fact, empowering the traditional manufacturing through the digital economy can not only enhance the technological competitiveness of Chinese manufacturing enterprises, but also enhance the degree of enterprise specialization by optimizing the industrial structure, so

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as to improve the position of Chinese enterprises in the global value chain.

With the rapid development of digital technology, the types of digital products are increasingly diverse, and gradually become a very important and unique element input in the production process of enterprises (Branstetter et al., 2019).Compared with other types of factor input, although the initial fixed cost of digital factor input is relatively high, it has unique technical attributes such as "low reproduction cost", which can be simply understood as the marginal cost of producing one more unit of the product is almost zero (Goldfarb and Tucker, 2019; Acemoglu and Restrepo, 2020). This attribute makes the spillover effect of technology more direct and simple. Existing theoretical studies show that digital economy can improve the technological level of enterprises through labor force conversion effect or production efficiency improvement effect (Korinek and Stiglitz, 2017; Acemoglu and Restrepo, 2018; Goldfarb and Tucker, 2019), and then affect the production segmentation of enterprises (Bergeaud et al., 2021). Based on the above realistic background and theoretical research, this paper clarified the mechanism of digital technology on the production segmentation of enterprises from the technical attributes of digital products. The specific theoretical mechanism can be summarized as follows: The spillover effect of digital technology is stronger due to its unique technical attributes of high fixed cost and low replication cost, which has a stronger impact on the enterprise's productivity. And enterprises can enhance their own vertical specialization ability by refining the production division and transferring the production processes with comparative disadvantages, so as to promote the advanced process of industrial structure. At the same time, we also use the micro data of Chinese enterprise to test the above mechanism, and finds that the import of digital products is conducive to promoting the production segmentation of enterprises.

The literature related to our research is about the import or use of digital products. However, this kind of literature mainly uses the adoption of industrial robots to study the impact of digital technology on the labor market. Firstly, the existing research of robot import mainly divided into two categories, the first category is based on the data released by the IFR. Based on IFR, scholars believe that the use of industrial robots will have an impact on productivity, wage level and employment, but the effects of industrial robots on the above mentioned effects will be different due to the influence of heterogeneous factors such as industry, age and type of skilled work (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2018). But it is worth noting that there are three prominent shortcomings in IFR data: first, the IFR data has a lot of missing variable data; secondly, there is still ambiguity about how to divide the robot sort; thirdly, IFR data can only be recognized at industry-country level. The above three drawbacks limit the scholars at home and abroad for the further research of digital technology. Therefore, in recent years, more and more scholars have found that the robot import data of each country can well overcome the above determination, and can better explore the impact of digital technology on the real economy from a micro perspective. At the micro level, the import and adoption of robots by enterprises will either directly replace or supplement the existing labor force (Koch et al., 2021; Acemoglu and Restrepo, 2020) or impact existing labor market structures (Bonfiglioli et al., 2020). Throughout this literature, scholars mainly focus on the impact of robot imports on the labor market. Meanwhile, the existing research on digital products is more focused on the narrow level, represented by robots. This paper refers to the latest technical literature, as well as the theoretical definition of digital products in international organizations and domestic policy institutions, and fully combines the definition of generalized digital products, we get the microcosmic conclusion how generalized digital products affect the production division.

The literature related to production segmentation is another focus of our research. Firstly, as to how to measure the production segmentation of enterprises, some scholars measure the production segmentation of enterprises mainly from the perspective of gains form trade and use the method of product value added trade accounting to measure the production segmentation (Hummels et al., 2001; Johnson and Noguera, 2012; Koopman et al., 2014). However, this characterization method can not accurately reflect the complexity of industrial structure. On the other hand, Fally (2012) can accurately measure the number of production processes according to the input–output table, which can accurately reflect the production structure and the production fragmentation of enterprises. In addition, what exactly affects the production fragmentation of enterprises is another issue that scholars pay attention to. According to existing studies, there are many factors affecting the division of production of enterprises, including enterprise innovation and R&D, technological level, factor intensity and etc. (Antras, 2003; Acemoglu et al., 2010; Costinot et al. 2011; Bergeaud et al., 2021). Most relevant to this paper is Bergeaud et al. (2021), who theoretically and empirically verified that technological progress promoted enterprises to outsource non-core technologies by improving production efficiency and the proportion of highly skilled labor. Compared with this literature, this paper uses digital product import data to better capture the characteristics of digital technologies, so as to verify the impact of the use of digital technologies on the production segmentation of enterprises with a more detailed classification.

Our contributions to prior studies can be summarized as follow.

Firstly, by referring to the latest technical literature, the theoretical definition of digital products in international organizations and domestic policy institutions, and fully combining the definition of broad digital products, this paper carefully matches, extracts, identifies and summarizes the tradable products provided by the network. In this way, the import information of digital products of Chinese enterprises is obtained, and further through robust methods such as manual identification, the import categories of digital products involving the dimension of "enterprise-product-time" are defined, identified and sorted out in an all-round way. By matching them with the HS codes of products in the customs database, we finally got the import of digital products data, which covers 280,282 Chinese firms from 2000 to 2016. (Due to the limitation of the enterprise database, the digital import information from 2014 to 2016 is not used in the inspection process of the paper.) On the other hand, according to Fally (2012), we use Chinese input–output table to construct production fragmentation.

Secondly, from the perspective of empirical analysis we found that: First of all, the import of digital products is conducive to the refinement of the production division of the enterprise, so as to improve its specialization level. In order to further clarify the influence mechanism, we divided the digital products into final and intermediate kinds and found that firms importing digital final goods have a larger marginal impact on their production fragmentation. Because the digital technology contained in digital final goods has more direct application.

Finally, in order to avoid endogeneity, we adopted the import of robots in Korean as an instrumental variable. The results of two-stage least squares regression (2SLS) using instrumental variables were found to be consistent with those of the basic regression.At the same time, in order to avoid the influence of extreme values and the sample of large cities on the regression results, we also winsorized the variables and eliminated the sample of enterprises in Beijing, Shanghai, Guangzhou, Shenzhen and other cities, which again verified the robustness of the regression results in this paper.

The remainder of this paper proceeds as follows. Section 2 describes the data. We discuss the empirical strategy and results in Sect. 3. And Sect. 4 is the conclusion.

2 Data and sample

2.1 Data description

In this chapter, we want to verify how the import of digital products influences the firms' production fragmentation. Therefore, we need to use a database containing indicators such as the import index of digital products, the number of production processes and the individual characteristics of enterprises. Specifically, in this chapter, we use China Customs Database from 2000 to 2014, China Industrial Enterprise Database, China input–output table (including 1997, 2002, 2007 and 2012), and digital trade database. By matching the relevant indicators in the above databases, we finally got the information of import and production division of digital products from 2000 to 2014, which lays the data foundation for the subsequent empirical research.

China Customs database contains rich import and export information of firms, such as name, HS code, import and export situation, trade form, total trade volume and total trade quantity, etc., which provides perfect enterprise trade information for subsequent research. Besides, the database of Chinese industrial enterprises contains rich individual characteristics of enterprises, which can provide data basis for empirical research. In this chapter, we first calculate the stage of production process of the firm by using China Customs data and China input–output table, and match the China Customs database with the China Industrial enterprise database by using the company name, address and other relevant information. An then, we merge this data with the digital product import data at year-firm dimension, and finally the unbalanced panel data of the production fragmentation of 71,833 enterprises importing 25 kinds of digital products from 2000 to 2014 is obtained, which is an important material basis for subsequent research.

2.2 The import of digital products

Referring to the existing literature, we use the import data of digital products as the proxy variable of enterprise digital technology penetration (Dixon et al. 2020; Koch et al., 2021; Acemoglu and Restrepo, 2020; Bonfiglioli et al., 2020). However, slightly different from the literature, we extend the range of digital products from a single industrial robot to a wider range. This is because robots are only one of the representative products of digital technology. How to define digital products accurately and classify all kinds of digital products reasonably is one of the key points and difficulties in the construction of import index of digital products. Based on the existing research, we divided digital products into narrow digital products and broad digital products. Narrow digital products refer to the exchange based on information content and digital format or the products delivered by bit stream through the Internet. In addition to digital products in the narrow sense mentioned above, digital products in the broad sense should also include electronic products based on digital technology or transformed into

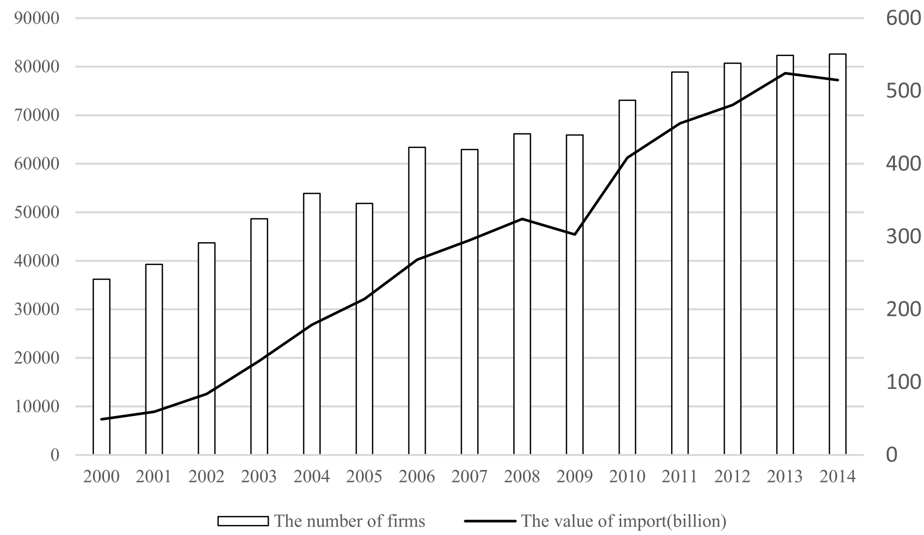

Fig. 1 China's import of digital products from 2000 to 2016

digital forms for transmission and sending and receiving through the network, or products that exist based on certain physical carriers.

In order to obtain digital products import data of Chinese enterprises, we need the following four steps. Firstly, according to the relevant contents of Hui and Chau (2002), Mann and Puttmann (2018), OECD (2020) and the White Paper on Digital Economy Development from 2015 to 2019 issued by China Academy of Communications, we distinguish digital products in a broad and narrow sense.[1] In order to ensure the universality of the classification, based on the broad definition, we divided the digital economy into tangible products and intangible products, and extracted 23 keywords[2] belonging to the category of broad digital products. Secondly, we use python to crawl the commodity name containing the above keywords in the new customs clearance network, so as to obtain the commodity name and HS10 containing the above keywords. Thirdly, according to the definition and usage of products obtained by Baidu search and the subitem notes in the Notes on Commodities and Items of Import and Export Tariff (2020 Edition), we manually identify the crawled commodities, eliminate the commodities that contain the above keywords but do not belong to the generalized digital products, and identify the types of commodities (intermediate or final products). Besides, we merged the digital product and codes with ICT products published by OECD (2020), and then we obtain all digital product names and customs code. Finally we uniformly transform the customs codes of the extracted digital products and match them with the customs codes in the customs database, so as to obtain the trade information of 420 kinds (HS6) digital products from 2000 to 2014.

In order to more clearly and intuitively show the situation of digital products imported by Chinese enterprises, first of all, we look at the dynamic changes of digital products imported by Chinese enterprises from the dimension of years, as shown in Fig. 1. As shown in Fig. 1, from 2000 to 2016, the number of enterprises engaged in the import of digital products increased from 36,233 to 87,204, and the scale of enterprises engaged in the import of digital products expanded 2.4 times. Moreover, the import value of digital products rose rapidly from 2000 to 2014, and the import value of digital products increased by more than ten times, indicating that more and more enterprises in our country can achieve a wider penetration of digital technology through the import of digital products, so as to promote the progress of their own technology level. At the same time, we also note that the number of enterprises importing digital products and the total import volume declined in 2009 and 2015, which is related to the global economic background at that time. Affected by the global economic crisis in 2008 and the shock factors of the global trade environment in 2015, the global trade quota declined. The number and import

[1] In the narrow sense, digital products refer to products whose information content is exchanged in digital format or delivered via the Internet in the form of bit streams. In addition to the narrow sense of digital products, digital products also include electronic products based on digital technology or transform them into digital forms through the network to spread and send and receive, or rely on a certain physical carrier and exist.

[2] The keywords are: intelligence, software, long-range, TV, VCD, system, device, robot, radar, mobile, intelligent, electronic, machine, automatic production line, digital, automatic, equipment, artificial intelligence, broadcast, numerical control, communication, computer, data, DVD.

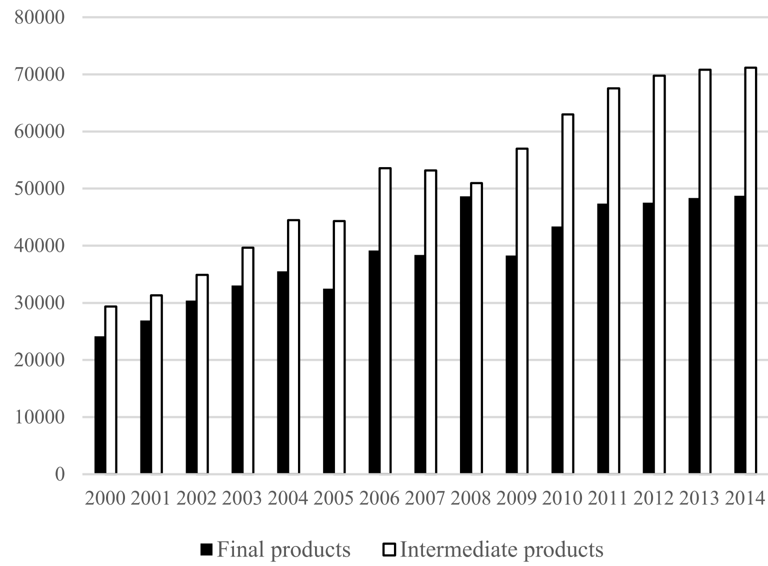

Fig. 2 The number of firms importing two kinds of products in China

quota of Chinese digital product importers also declined slightly. Since then, with the improvement of the economic situation, the trade situation of digital products has gradually turned to an upward trend.

Furthermore, by differentiating the types of digital products imported by enterprises, we divide digital products into digital final products and digital intermediate products. As can be seen from Fig. 2, Although the number of Chinese enterprises engaged in the import of digital final goods and digital intermediate goods showed an overall increasing trend from 2000 to 2016, the number of Chinese enterprises engaged in the import of digital intermediate goods was greater than the number of enterprises engaged in the import of digital final goods. However, the purchase and use of this digital technology is still in a relatively preliminary stage, and the imported digital products contain a low level of technology, so there is still a lot of room for progress.

2.3 Production Fragmentation

Adam Smith mentioned in The Wealth of Nations that "wealth is closely related to the division of labor…, And specialized activities are conducive to promoting economic efficiency ". In recent years, the production process has gradually become fragmented and decentralized. By continuously refining the process of production, the economic subject has promoted the specialization level of enterprises and promoted the improvement of economic efficiency. Based on the above background, how to describe the production fragmentation scientifically and accurately has become the focus of this chapter.

According to Fally (2012), we first construct the position of production stages at industry level using Chinese input–output table in 1997, 2002, 2007 and 2012. The specific index construction formula is as follows:

$$NI_i = 1 \times \frac{V_i}{Y_i} + 2 \times \frac{\sum_{j=1}^{N} \mu_{ij} V_j}{Y_j} + 3 \times \frac{\sum_{j=1}^{N} \sum_{k=1}^{N} \mu_{ij} \mu_{jk} V_k}{Y_k} + \ldots \tag{1}$$

Let us denote by V_i the total value-added of industry i, Y_i the gross output of industry i. μ_{ij} represents the value of inputs from industry j used to produce one dollar of goods in industry i.

Secondly, according to Ju and Yu (2015), we take the export share of products as the weight, and weighted the production stage of the industry dimension to the firm, level:

$$NI_{ft} = \sum_i \frac{S_{fit}}{S_{ft}} NI_i \tag{2}$$

where S_{fit} represents the total amount of product i exported by firm f in year t, S_{ft} represents the total export of firm f in year t.

This index can well measure the stage of production processes that a firm has gone through to produce a product. The larger the index is, the longer the production chain for a certain product and the finer the production fragmentation. In order to intuitively see the production fragmentation of Chinese firms, we will conduct simple statistical description analysis according to the production stage indicators calculated in Eq. (2). First of all, as shown in Fig. 3, the average number of production processes in Chinese enterprises showed an

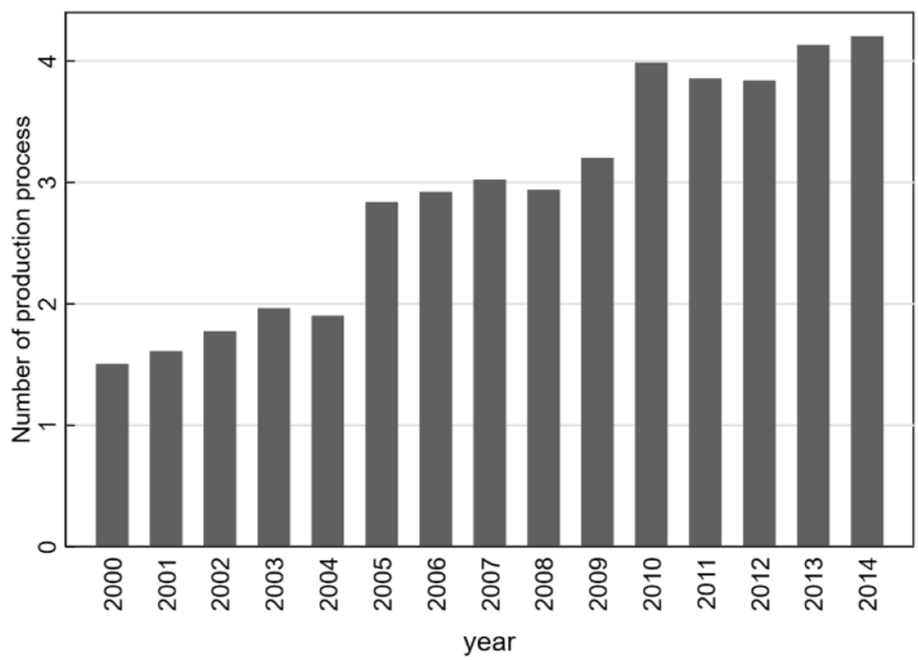

Fig. 3 Average production stages in 2000–2014

overall upward trend from 2000 to 2014, and showed a small jump growth in 2005 and 2010. By 2014, the average number of production processes in Chinese enterprises had increased by 39.92%. This means that with the gradual acceleration of China's opening-up process and the rapid development of China's economy, the industrial division and the complexity of the economic structure has gradually deepened. In order to adapt to the fragmented and specialized global production pattern, Chinese enterprises gradually increase the number of production processes, so as to improve the competitiveness of enterprises by transferring production processes with comparative disadvantages. In addition, there are huge differences in the division of production in different industries. We take the top ten industries with the highest number of production processes as representatives, and the specific situation is shown in Fig. 4. According to Fig. 4, among the top 10 3-digit industries, computer manufacturing industry has the highest number of production processes, while cultural and office machinery manufacturing industry has the lowest number of production processes. This phenomenon is also consistent with the division of production in the real world.

3 Empirical strategy and results

3.1 Empirical strategy

In order to verify whether the import of digital products is conducive to promoting the production fragmentation, we set the following specification:

$$NI_{ft} = \alpha_0 + \alpha_1 Digpro_{ft} + \alpha_3 X_{ft} + d_t + d_f + \varepsilon_{ft} \quad (3)$$

where NI_{ft} is the dependent variable observed for firm f in year t. Our primary dependent variable is log number of production processes, $Digpro_{ft}$ represents the import of firm f in year t. We also include some control variables in X_{ft}: Age is the years since the establishment of the company which is expressed in logarithms. According to Levinsohn and Petrin (2003), we compute TFP to represent the productivity of the firm. Patent is the logarithm of the total number of patents applied for by the firm, which represents the innovation capability of the firm. Since enterprise ownership has an impact on the division of production, we include the dummy variables of state-owned enterprise (SOE) and foreign enterprise (FOE). The term d_t is the year fixed effect and d_f represents the firm fixed effect. We also clustered at firm level. The detailed information of the variables is in the Table 1.

3.2 Baseline results

The digital products imported by enterprises from 2000 to 2014 were matched with the production process indicators, and the regression was conducted according to Eq. (3). The regression results are shown in Table 2.

According to Table 2, first of all, we can see that in the control of the year and firm fixed effects, regardless of whether add the control variables, the main explanatory variables of regression coefficients under 1% significance level is significantly positive, which mains that

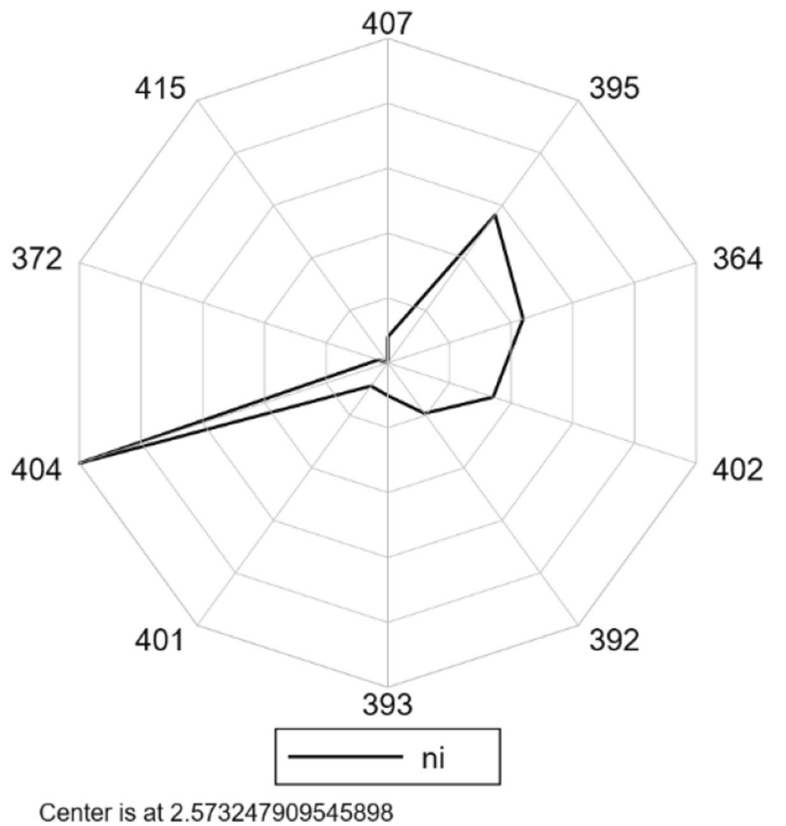

Fig. 4 Top 10 industries (According to GB/T4754-2002, 364 is the printing, pharmaceutical, daily chemical production special equipment manufacturing, 372 is the automobile manufacturing, 392 is the power transmission and distribution and control equipment manufacturing, 393 is the wire, cable, optical cable and electrical equipment manufacturing, 395 is the household electrical appliance manufacturing, 404 is the electronic computer manufacturing, 401 is the telecommunication equipment manufacture, 402 is the radar and supporting equipment manufacturing, 407 is the household audiovisual equipment manufacturing, 415 is the culture, office machinery manufacturing.)

Table 1 Variable Summary

Variable	Observation	Mean	Std	Min	Max
Digpro	391,101	12.04534	3.200703	0	23.5707
Age	391,101	1.993573	0.749452	0	7.601902
Size	391,101	5.848183	1.218804	0	12.37174
TFP	391,101	4.225809	0.973425	0	10.3724
Patent	391,101	11.61298	1.580453	0	19.33697
SOE	391,101	0.056272	0.230446	0	1
FOE	391,101	0.578672	0.493773	0	1

the import of digital products will increase production fragmentation. In addition, we also notice the estimated coefficient of other control variables: the coefficient of firm's age is significantly positive, which suggests that mature enterprises have richer experience in their existing fields and relatively prominent core technologies, and are more inclined to outsource non-core production processes. This situation will motivate enterprises to refine their division structure and promote production segmentation. The coefficient of firm's size is also significantly positive at the significance level of 1%, which is due to the existence of scale effect. Large enterprises tend to concentrate all kinds of factor resources in one or several production processes with comparative advantages, so as to promote the production division of enterprises. The coefficient of TFP of firms is also significantly positive, which shows that the increase of productivity is conducive to promoting the production fragmentation. The coefficient of innovation is also significantly positive, because enterprises with high R&D and innovation intensity are more inclined to allocate internal resources to the production of products with high added value, so as to outsource the production process with low added value, which can promote the specialization of production.The coefficient of state-owned enterprises (SOE) is negative but insignificant, while the estimated coefficient of foreign-funded enterprises (FOE) is positive at the significance level of 1%. This is because the management efficiency of enterprises with different ownership is

Table 2 Baseline results

	(1)	(2)	(3)	(4)
Digpro	0.0430***	0.0399***	0.0332***	0.0332***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Age		0.0796***	0.0541***	0.0482***
		(0.0071)	(0.0072)	(0.0072)
Size		0.0958***	0.0608***	0.0610***
		(0.0043)	(0.0043)	(0.0043)
TFP			0.0337***	0.0341***
			(0.0036)	(0.0036)
Patent			0.1033***	0.1022***
			(0.0045)	(0.0045)
SOE				-0.0022
				(0.0681)
FOE				0.2140***
				(0.0206)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	373,448	373,448	373,448	373,448
R^2	0.851	0.853	0.854	0.855

Note: *, **, *** Represent the significance levels of 10%, 5% and 1%, respectively. Robust standard errors in firms

Table 3 Endogeneity

	(1)	(2)	(3)	(4)
Digpro	0.0982***	0.0367***	0.0157***	0.0149***
	(0.0030)	(0.0035)	(0.0045)	(0.0047)
Age		0.1471***	0.1278***	0.1426***
		(0.0033)	(0.0038)	(0.0035)
Size		0.2987***	0.2587***	0.2652***
		(0.0036)	(0.0026)	(0.0025)
TFP			0.0227***	0.0202***
			(0.0029)	(0.0029)
Patent			0.0678***	0.0705***
			(0.0043)	(0.0046)
SOE				0.3393***
				(0.0111)
FOE				0.0427***
				(0.0073)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM	9842.30	10,857.05	10,178.83	10,209.61
Cragg-Donald Wald F	7169.08	6387.19	5003.79	4814.34
First stage	2.3908***	1.9708***	1.5108***	1.4408***
N	390,892	390,892	390,892	390,892
R^2	0.021	0.098	0.111	0.114

Note: *, **, *** represent the significance levels of 10%, 5% and 1%, respectively. Robust standard errors in firms

different, and foreign-funded enterprises have relatively higher management experience and technical level, so they have a stronger promoting effect on the division of production.

3.3 Robustness

3.3.1 Endogeneity

After reading the literature and analyzing the data used in this chapter, we find that there are two main reasons that will cause the endogeneity: On the one hand, due to the reverse causality between the import of digital products and the production division of enterprises, that is, not only the technological progress brought by the import of digital products promotes the specialized production of enterprises through the improvement of productivity, but also the scale effect brought by the specialized production can greatly improve the performance level of enterprises. According to Melitz (2003), enterprises with higher productivity tend to preferentially participate in trade competition. On the other hand, there are also cases of missing explanatory variables in this model, such as high-tech labor intensity. Therefore, at this stage, we can only deal with the possible endogeneity problems in this paper by finding appropriate instrumental variables and using the two-stage least squares method (2SLS).

In this subsection, we will test for endogeneity. We select the import of Korean robots as the instrumental variable. To be specific, first of all, China and South Korea have a close geographical relationship and a higher trade correlation. Secondly, according to IFR released statistics about industrial robots, China and South Korea have the similar growth in the industrial robot's trend. And as one of the representative products of digital products, industrial robots have more prominent digital technology characteristics behind them, which is highly correlated with the import data of digital products.Finally, since the number of robots imported by South Korea has little impact on the number of production fragmentation of Chinese firms, the import of robots from South Korea as an instrumental variable also satisfies the exogeneity assumption. In conclusion, the selection of this instrumental variable is feasible to a certain extent.

The regression results of the 2SLS method are shown in Table 3. The estimated coefficient of the main explanatory variable is positive at the significance level of 1%, which is highly consistent with the basic regression results. At the same time, the test results of Kleibergen-Paap RK. LM statistic and Cragg-Donald Wald F statistic in Table 3 show that this instrumental variable does not have the phenomenon of insufficient and weak

Table 4 Sample selection

	(1)	(2)	(3)	(4)
	Winsor		Drop 4 cities	
Digpro	0.0470***	0.0359***	0.0399***	0.0300***
	(0.0016)	(0.0015)	(0.0016)	(0.0015)
Age		0.0476***		0.0484***
		(0.0072)		(0.0088)
Size		0.0617***		0.0701***
		(0.0043)		(0.0054)
TFP		0.0349***		0.0413***
		(0.0037)		(0.0045)
Patent		0.1039***		0.1026***
		(0.0045)		(0.0056)
SOE		-0.0010		0.1352
		(0.0680)		(0.0959)
FOE		0.2139***		0.2277***
		(0.0206)		(0.0264)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	373,448	373,448	249,748	249,748
R^2	0.873	0.876	0.878	0.882

Note: *, **, *** represent the significance levels of 10%, 5% and 1%, respectively. Robust standard errors in firms

identification, which confirms the reasonable validity of this instrumental variable.

3.3.2 Sample selection

This section is mainly to test the robustness of sample selection problems in the regression. First of all, there are great differences in the import of digital products by Chinese firms. For example, most firms only imported certain kinds of digital products, while a few firms imported almost all the categories of digital products. In order to avoid the impact of the extreme value on the estimation results, we winsorize the index of imports of digital goods. The results are shown in columns (1)—(2) of Table 4. It can be seen from columns (1)—(2) that the regression coefficients of digital product import are significantly positive regardless of whether control variables are added, which verifies the robustness of the regression results. Second, the city's development scale will also affect the regression results, such as Beijing, Shanghai, Guangzhou, Shenzhen and other cities in China's first-tier cities, their economic structure complexity is higher, these factors will affect the enterprise division of labor structure, so we dropped China's first-tier cities.The regression results are shown in columns (3)—(4) in Table 4. The estimated coefficients of the main explanatory variables are consistent with the basic regression, which again verifies the robustness of the regression results in this paper.

3.4 Further analysis

In fact, the differences in the types of digital products to a certain extent also reflect the technical differences, which will directly affect the spillover effect, thus have different effects on the production process of enterprises. In this subsection, according to the detailed description in the Notes on Commodities and Items of Import and Export Tariff (2020) Edition, the generalized digital products are finally divided into two categories: digital final goods and digital intermediate goods.

According to the above classification criteria, we perform group regression on the data, and the results are shown in Table 5.Columns (1)—(2) of Table 5 show the regression results for digital final goods, and columns (3)—(4) show the regression results for digital intermediate goods. It can be seen that although the regression coefficient of the main explanatory variable for both groups are positive at 1% significance level. However, the absolute value of the regression coefficient of the main explanatory variable in the digital final goods group is higher, because the digital final goods contain richer digital technology and have stronger spillover effect, which will accelerate the stage of production process.

3.5 Heterogeneity analysis

The above regression results once again verify the transmission mechanism of digital technology on the production division of enterprises from the perspective of the technical attributes behind digital products. But in addition, industry characteristics and enterprises' own attributes will also affect the effect of digital technology on enterprises' production specialization. Therefore, in this section, we select the industrial automation index represented by automation degree, and the enterprise heterogeneity index represented by enterprise management performance level to analyze the regression of this paper.

Firstly, the level of industrial automation has a great impact on the absorption of technology spillover by enterprises. Considering that the industry with a high degree of automation can provide a rich material basis for the introduction of advanced technology, and then promote the absorption and spillover of this digital technology. This argument has been demonstrated in the existing literature (Graetz and Michaels, 2018). Therefore, in this section, we take the degree of occupational computerization in the United States measured by Frey and Osborne (2017) as an important proxy variable to measure the degree of industrial automation, and match them one by one according to the industry codes of China and the United States, so as to obtain the degree of automation of the quartile industries in which Chinese enterprises importing digital products are located.

Table 5 Mechanism analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	Final			Intermediate		
Digpro	0.0260***	0.0221***	0.0197***	0.0094***	0.0081***	0.0070***
	(0.0019)	(0.0019)	(0.0018)	(0.0006)	(0.0006)	(0.0006)
Age		0.0446***	0.0281**		0.0690***	0.0537***
		(0.0122)	(0.0124)		(0.0083)	(0.0083)
Size		0.1136***	0.0704***		0.0926***	0.0553***
		(0.0074)	(0.0074)		(0.0049)	(0.0049)
TFP		0.0791***	0.0370***		0.0716***	0.0379***
		(0.0065)	(0.0068)		(0.0041)	(0.0041)
Patent			0.1034***			0.1028***
			(0.0084)			(0.0046)
SOE			0.1580			0.0297
			(0.1229)			(0.0805)
FOE			0.2483***			0.1628***
			(0.0337)			(0.0268)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	145,700	145,700	145,700	224,001	224,001	224,001
R^2	0.863	0.866	0.867	0.863	0.865	0.867

Note: *, **, *** Represent the significance levels of 10%, 5% and 1%, respectively. Robust standard errors in firms

We put the interaction of product of the import of digital products and the degree of automation (*Digpro* × *Auto*) into Eq. (3), and the regression results are shown in Table 6. From this we can see, for digital final goods, the estimated coefficients of the interaction terms (*Digpro* × *Auto*) are significantly positive. In addition, because the digital technology contained in the digital final product is more abundant, the absolute value of the coefficient of the interaction term in the digital final product group is larger than that in the digital intermediate product group.

Considering that enterprise management efficiency, as one of the important manifestations of enterprise heterogeneity, reflects the operation ability of enterprise operators to a certain extent. When an enterprise has high management efficiency, it can timely adjust its own operation and management mode according to the changes of the external business environment, thus changing the decision of the most intermediate product input (Lev and Radhakrishnan, 2005). In addition, the refinement of the production division of enterprises also requires operators to coordinate in various aspects, so a higher level of management efficiency affects the action mechanism of digital technology on the production division of enterprises through a lower coordination cost. Therefore, in this section, we refer to the description method of management efficiency by Qi and Yu (2015) and construct the following equation from the perspective of management expenses.

Table 6 Industrial Automation

	(1)	(2)	(3)	(4)
	Final		Intermediate	
Digpro	0.0243***	0.0179***	0.0101***	0.0077***
	(0.0021)	(0.0021)	(0.0008)	(0.0008)
Digpro× Auto	0.0058*	0.0060*	0.0015	0.0014
	(0.0034)	(0.0035)	(0.0012)	(0.0012)
Auto	-0.0489	-0.0587	0.0149	0.0102
	(0.0443)	(0.0430)	(0.0183)	(0.0180)
Age		0.0282**		0.0537***
		(0.0124)		(0.0083)
Size		0.0702***		0.0553***
		(0.0074)		(0.0049)
TFP		0.0369***		0.0379***
		(0.0068)		(0.0041)
Patent		0.1035***		0.1028***
		(0.0084)		(0.0046)
SOE		0.1597		0.0297
		(0.1228)		(0.0805)
FOE		0.2483***		0.1628***
		(0.0337)		(0.0268)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	145,700	145,700	224,001	224,001
R^2	0.863	0.867	0.863	0.867

Note: *, **, *** Represent the significance levels of 10%, 5% and 1%, respectively. Robust standard errors in firms

Table 7 Management efficiency

	(1)	(2)	(3)	(4)
	Final		Intermediate	
Digpro	0.0226***	0.0165***	0.0085***	0.0060***
	(0.0021)	(0.0020)	(0.0007)	(0.0007)
Digpro× Management	-0.0013***	-0.0014***	-0.0004***	-0.0005***
	(0.0004)	(0.0004)	(0.0002)	(0.0002)
Management	-0.0106**	-0.0138***	-0.0012	-0.0014
	(0.0047)	(0.0045)	(0.0024)	(0.0024)
Age		0.0281**		0.0543***
		(0.0124)		(0.0083)
Size		0.0709***		0.0550***
		(0.0074)		(0.0049)
TFP		0.0363***		0.0371***
		(0.0068)		(0.0041)
Patent		0.1027***		0.1025***
		(0.0084)		(0.0046)
SOE		0.1605		0.0327
		(0.1226)		(0.0804)
FOE		0.2482***		0.1626***
		(0.0337)		(0.0268)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	145,633	145,633	223,916	223,916
R^2	0.863	0.867	0.863	0.867

*, **, *** Represent the significance levels of 10%, 5% and 1%, respectively. Robust standard errors in firms

$$lnG\&A_{ft} = \alpha_1 l_{ft} + \alpha_2 exp_{ft} + \alpha_3 markup_{ft} + \varepsilon_f + \varepsilon_t + \mu_{ft} \tag{4}$$

In Eq. (4), $lnG\&A_{ft}$ is the log of management expense of firm f in year t, l_{ft} represents the log of employment, exp_{ft} is the log value of export, $markup_{ft}$ is defined by the ratio of corporate earnings to the difference between corporate earnings and profits. At the same time, we control year and firm FE. Then the residual (μ_{ft}) is the indicator of management efficiency, and the smaller the index value is, the higher the management efficiency of the enterprise is.

We put the interaction of management efficiency index and the import of digital products into Eq. (3), and the results are shown in Table 7.

From Table 7, we can see that, first of all, the coefficient of digital product import is still significantly positive, which once again verifies that digital product import is conducive to promoting the production division of enterprises. And then, the coefficient of the interaction is negative at the significance level of 1%, indicating that the marginal contribution of digital technology to the production division of enterprises is more obvious in enterprises with higher management efficiency. This is because when the management efficiency of enterprises is high, the adjustment cost of production and operation decision-making of enterprises is lower, so when enterprises face strong technology spillover, it is beneficial to lengthen its production chain and promote the enterprise's own production specialization level. Finally, by comparing the absolute value of the coefficient of the interaction term in different digital product categories, it is found that the absolute value of the coefficient of the interaction term in the digital final product group is larger, which means that the marginal impact of management performance on the division of production by digital technology is greater in the digital final product group.

At the same time, regional heterogeneity can affect the transmission mechanism. Donaldson and Hornbeck (2016) and Baum-Snow et al. (2017, 2020) argued that market access has a positive role in promoting economic growth, population increase and employment by reducing inter-regional trade costs. Further, from the perspective of micro enterprises, changes in market access will also have differentiated impacts on enterprise productivity and intermediate product input (Huang and Xiong, 2017; Gibbons et al., 2019), and the improvement of market access plays a role in redistributing the market share of incumbent enterprises through the competition effect. The changes in production efficiency and market share of enterprises caused by the expansion of regional market access are bound to have an impact on the transmission mechanism between digital technology and the production division of enterprises, so we must introduce market access indicators to analyze the regression.

Firstly, with reference to Donaldson and Hornbeck (2016), the calculation formula of Market Access (MA) index is derived according to the E-K framework:

$$MA_i = \sum\nolimits_j \tau_{ij}^{-\theta} Y_j \tag{5}$$

where i and j represent two different cities respectively, Y is the GDP of the city j, and τ_{ij} represents the trade cost between any two cities. The formula for calculating the trade cost from city i to inland city j is as below.

$$\tau_{ij} = 1 + 0.004\rho(hoursoftraveltime_{ij})^{\lambda} \tag{6}$$

where ρ and λ reflect the transformation relationship between transportation time and transportation cost. Referring to Baum-Snow et al. (2020), we set $\rho = 1$,$\lambda = 0.8$. This indicator measures the ease of entry and exit of products in a region through trade costs. The larger the index is, the lower the trade cost of goods

Table 8 Market Access

	(1)	(2)	(3)	(4)
	Final		Intermediate	
Digpro	0.0193***	0.0120***	0.0057***	0.0035***
	(0.0032)	(0.0031)	(0.0011)	(0.0011)
Digpro× MA	0.0174***	0.0196***	0.0100***	0.0093***
	(0.0063)	(0.0061)	(0.0025)	(0.0025)
MA	0.0015	0.00004	0.0001	-0.0003
	(0.0009)	(0.0009)	(0.0005)	(0.0005)
Age		0.0276**		0.0535***
		(0.0125)		(0.0083)
Size		0.0719***		0.0567***
		(0.0075)		(0.0049)
TFP		0.0387***		0.0379***
		(0.0068)		(0.0042)
Patent		0.1018***		0.1023***
		(0.0085)		(0.0046)
SOE		0.2912***		0.0430
		(0.1068)		(0.0735)
FOE		0.2497***		0.1612***
		(0.0337)		(0.0269)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	143,968	143,968	221,238	221,238
R^2	0.863	0.868	0.863	0.867

moving in and out of the region is, and it is easier to move in and out.

The market access indicator (MA) is substituted into the measurement Eq. (3) as an interaction term, and the regression results are shown in Table 8. From Table 8, we can see that the estimated coefficient of the interaction term ($Digpro \times MA$) between digital product import and market access is significantly positive both for digital final goods and digital intermediate goods. However, the absolute value of the estimated coefficient of the interaction term of digital final goods is larger, which means that in the regions with higher market access, the import of digital products has a stronger promotion effect on the production division of enterprises. This is because the expansion of market access reduces the threshold for the cross-regional flow of intermediate goods, weakens the influence of geographical agglomeration on the division of labor of enterprises, and is more conducive to the formation of scale effect of enterprises, thus strengthening the marginal contribution of digital technology to the specialized production of enterprises.

4 Conclusion

Starting from the technical attributes of digital products, this paper uses firm level digital product import data as an important index to measure the penetration degree of firms' digital technology, and uses the production stages as a proxy variable of production fragmentation. After matching and regression of the above two indicators, we found that improving the penetration degree of digital technology by importing digital products can effectively promote the production fragmentation. In order to further clarify the mechanism, we divided the digital products into final and intermediate kinds and found that firms importing digital final goods have a larger marginal impact on their production fragmentation. Because the digital technology contained in digital final goods has more direct application. Finally, in order to avoid endogeneity, we adopted the import of robots in Korean as an instrumental variable. The results of two-stage least squares regression (2SLS) using instrumental variables were found to be consistent with those of the basic regression.

This paper makes an in-depth analysis of digital technology and production division empirically, which provides academic support for the development of digital economy in our country and the specialized production of enterprises. Combined with the conclusions of this paper, on the one hand, the arrival of the digital era marks that digital technologies represented by artificial intelligence and cloud computing will be widely used in various fields of production and life. The inherent cost attribute of digital technology will make the popularization and innovation of this technology greatly improve the production efficiency and innovation ability of enterprises, which is conducive to promoting the transformation and upgrading of industrial structure. Therefore, how to correctly encourage, guide and support industries related to digital technology, focus on cultivating "specialized and innovative" enterprises, promote the deep integration of digital technology and the real economy, guide the manufacturing industry should take digitalization, intelligence and networking as an important starting point, create "digital + manufacturing" business form, and accelerate the digital transformation of traditional manufacturing enterprises. On the other hand, enterprises should strengthen their production specialization ability, strengthen the writing ability of division of labor with upstream and downstream enterprises, actively participate in the global production value chain, and take the development of digital economy as an important opportunity to improve the level of independent innovation of enterprises, improve the construction of digital infrastructure, introduce high-tech talents, and improve the level of core technology of enterprises. At the same time, through the application of digital technology, the management and service level can be improved to help the digital transformation of manufacturing enterprises. In the field of digital technology enabling services, the change of consumer demand, the choice of enterprises themselves and the development of digital technology determine that the digital transformation of the service industry is an inevitable choice. The development of big data, artificial intelligence and other digital technologies makes the service industry transform from " thousand of people, one policy" to " thousands of people, thousands of faces".

In addition, this paper still has shortcomings in the construction of indicators related to digital products. We use a simple text recognition and manual screening to conduct computer retrieval of relevant field information including keywords in China Customs database, and then conduct manual screening of the obtained samples based on the definition of related products or technologies. However, this method may have certain biases in the case of large samples, and the manual identification process needs to consume a lot of manpower and material resources. In further research in the future, we will extract relevant information by using keyword recognition and naive Bayes algorithm. The use of naive Bayes algorithm has two prominent advantages: one is that it will not over-fit due to relatively few estimated parameters, the other is that the independence of the occurrence probability of markers makes this classification method more robust in concept transfer compared with other methods (such as the nearest neighbor algorithm). Bayesian estimation is used through the keyword identification method to ensure the accuracy of the index construction.

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Availability of data and materials
Data will be available for reasonable request.

Declarations

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