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Total Factor Productivity in Chinese Manufacturing Firms: the Role of E-commerce Adoption

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Abstract

This paper seeks to investigate the relationship between e-commerce and total factor productivity (TFP) at a manufacturing firm level. Using data of 178 A-share listed companies in China during the period from 2015 to 2021, the article empirically tests the questions of whether and how e-commerce used directly by manufacturing firms can boost their productivity growth. The result shows that the penetration of e-commerce in manufacturing has a positive and significant effect on TFP growth. It is also found that the spillovers of intra-firm human capital and the effect of inter-firm market competition both play a crucial role in linking e-commerce to firm-level TFP growth. Specifically, e-commerce is beneficial to driving TFP growth significantly through attracting high- rather than low-quality human capital accumulating in manufacturing firms, as well as through improving appropriately market concentration rather than increasing the intensity of market competition. This article contributes to the existing literature by exploring the productivity-driving force of manufacturing firms which face transformation from a focus on the production to the marketing chain within the context of online business. It also provides policy applications how to improve the TFP of manufacturing firms through the use of digital platforms.

Keywords E-commerce · Manufacturing enterprises · Total factor productivity · Platform economy

1 Introduction

With the development of digital technologies, the internet platform economy is fast emerging as a new economic form changing the trading pattern, value creation as well as the productive system. By the end of 2020, the total value of the global digital platform market reached $12.47 trillion with

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annual growth of 57% [1]. A large number of international competitive companies based on internet platforms can be found in the United States, such as Apple, Google, and Amazon. China, as the biggest emerging economy, is also making significant progress in its online platform economy. By the end of 2020, business activities through e-commerce platforms have increased to $570.28 trillion in China [1]. An increasing number of digital companies have been emerging, such as Alibaba, Tencent, and Baidu. As online business activities are experiencing tremendous increase, manufacturing firms face both opportunities and challenges. On the one hand, digital companies avoid bargaining with wholesalers and other intermediaries allowing them to transact directly with consumers and leading to a decrease in transaction costs and potential increase in productivity. On the other hand, they have to deal with some unfamiliar activities or items because of using online business platforms, such as bargaining with thousands of consumers or dealing with product complaints. The question arises as to whether the manufacturing firms are able to increase their productivity by using e-commerce.

The internet platform, as a new pattern of factor re-allocation and industrial organization, is indeed considered a crucial factor affecting manufacturing productivity. There are two typically controversial viewpoints in the literature. On the one hand, the internet platform brings numerous benefits to manufacturing enterprises, such as increased economic size and positive network externalities, which lead to improving the allocation efficiency of production factors in global networks [2]. In addition, the penetration of the online platform in the entire economic system can reduce the information asymmetry and mismatch between the manufacturing production and consumption sides [3]. Ferguson et al. [4] find that the firms in the market, especially small and medium-sized firms, can improve their efficiencies if they can adapt to the changes successfully caused by the development of e-commerce. On the other hand, the digital platform may have a negative impact on manufacturing productivity because it has a strong market power and factors recombination capability. In fact, it is difficult for current manufacturing enterprises to produce and do business without digital platforms. Particularly in China, the internet platform triggers a lot of competition to deal with business or production, whether for online or offline firms. Furthermore, Kenney et al. [5] suggest that the digital platform turns to use its absolute advantage of intelligent analysis to bargain with the platform-dependent manufacturing enterprises, which, as a result, not only restrains their profit space but also presents a negative effect on technology innovation and efficiency growth. The question of whether e-commerce can indeed boost productivity growth in manufacturing firms remains unanswered in the literature. This is particularly the case in China, where large numbers of manufacturing firms are not only applying the industrial internet platform to organize their production but also using online business platforms to interact directly with consumers, which avoids the bargaining pressures from wholesalers and other intermediaries. Only a few studies attempt to link the development of e-commerce with manufacturing upgrading based on evidence from China.

In response to this situation, we focus on exploring the issue of whether and how the penetration of e-commerce can increase total factor productivity (TFP) at the manufacturing firm level. Based on panel data for 178 A-share listed companies in China during the period from 2015 to 2021, the empirical results show that e-commerce applied by manufacturing firms has a positive and significant effect on their TFP growth. It is also found that e-commerce leads to TFP growth significantly by two mechanisms through: (1) stimulating the spillover effect of high- rather than low-quality human capital in manufacturing firms; and (2) improving manufacturing market concentration appropriately instead of increasing the intensity of market competition. In light of these findings, the paper provides implications for policymakers and managers on how to improve manufacturing firm productivity through the use of digital platforms.

In Section 2, the paper presents a literature review. The influencing mechanism of e-commerce adoption on TFP is analyzed in Section 3. Section 4 describes the data, variables, and econometric models used in the study. The empirical results and discussions are given in Section 5 while the final section presents the conclusions and policy recommendations from the investigation.

2 Literature review

The studies on the relationship between internet usage and productivity are mostly triggered by the "Solow paradox", which can be graphically described as: "You can see the computer age everywhere but in the productivity statistics" [6]. In the 1960s and 1970s, with the development of computers, many countries invested massively in R&D in the field of information technology, however this did not increase their productivity as expected. However, in the 1990s, the "new economy" driven by the development of information technology led to a large increase in productivity and economic growth in the United States [7,8]. In contrast, Acemoglu et al. [9] argue that the rapid growth of the "new economy" is mainly due to an upward economic cycle, nevertheless, the "Solow paradox" still exists. Hence, whether the "Solow paradox" really exists has triggered a wide discussion [10-12].

The debate about the "Solow paradox" resulted in many researchers exploring the relationship between the information and communications technology (ICT) and productivity. This discussion about the productivity effect caused by ICT or internet penetration can be divided into two research branches. One is to treat the internet as a kind of pure information technology innovation, while the other focuses on the role of internet application in the field of business activities, and production or service processes, such as e-commerce and e-delivery. The former branch pays attention mainly to the impact of ICT on the firm's productivity or its performance growth. It is suggested that ICTs can improve the level of informatization and competitiveness of enterprises, which can reshape business processes, increase enterprise resilience and save operational costs, resulting increased corporate performance [13-15]. It is found that investments in ICTs contribute to firm productivity and show a higher return rate than non-ICT investments, especially in manufacturing firms [16]. The convergence of ICTs and other resources in enterprises provides a constant impetus for productivity growth in the long run [17]. Other researchers however find a low productivity growth in ICT-intensive industries and argue that ICTs only have a temporary rather than long-term effects on industrial or regional performance and productivity growth [18].

The latter literature attempts to explore the linkage between e-commerce and productivity. E-commerce allows businesses to connect with customers, business partners, and employees from all over the world [19]. Corporations whether in manufacturing or service can adopt e-commerce to reduce transactional and operational costs and respond fast to the needs of their customers and cooperative partners, which helps boost productivity and performance [20-22]. Popa et al. [23]

suggest that e-business has a direct effect on firm performance, while the indirect effect between e-commerce and firm performance is significantly mediated by organizational innovation. Raymond and Bergeron [24] find that e-commerce can positively affect the productivity of SMEs if external environment and organizational context are taken into account. In addition, enterprises using internet platforms, such as e-commerce, e-intelligence and e-delivery, become more productive than other firms. Liu et al. [25] suggest that both e-commerce and R&D have a significant positive effect on firms' productivity growth and find a complementary relationship between e-commerce and R&D on increasing productivity. After analyzing firm-level data from 14 European countries, Falk and Hagsten [26] conclude that e-commerce contributes to the growth in business productivity, particularly with small and medium-sized firms experiencing greater gains in productivity. There are still some scholars holding the opposite view. It is argued that e-commerce applications have a high failure rate and cannot always improve firms' performance [27], even that the procurement of e-commerce may have less impact on the growth of firm efficiency and sales performance [28]. In addition, different types of enterprises and business activities may present different effects. It is shown that e-commerce adoption can generate high productivity for large firms, while it has no significant effect for small firms [29]. Clayton et al. [30] add that online order is found to have a positive impact on productivity, whereas online sale presents a negative effect.

The existing studies have achieved ample and instructive conclusions about the relationship between ICT and productivity growth, but these studies still have some shortcomings. First, previous studies focus mainly on testing the "Solow paradox", leaving the mechanism of why ICTs present a positive or negative effect on productivity still under-explored. Due to this, the relationship between ICT (whether it is treated as a kind of technology innovation or business innovation) and productivity, in the literature, seems to be ambiguous and confusing. Second, several studies have observed the productivity growth effect probably caused by the usage of e-commerce [31], but these studies are still in minority. The majority of studies concentrate on general firms rather than manufacturing firms. As a matter of fact, it is necessary and urgent to detect this issue with evidence from manufacturing firms because global manufacturing is experiencing a transition from a focus on the production chain to the marketing chain in the context of the current popular online platform economy. Third, the majority of related studies pays attention to the developed economies, leading to the situation happening in the developing countries not fully explored. Particularly in China, e-commerce is experiencing enormous increase, at the same time, its manufacturing firms are facing severe pressures of transformation and upgrading. Still, the related exploration is inadequate.

This paper aims at filling in the above research gaps and contributing to the literature in two ways. First, to the best of our knowledge, this article is the first attempt to empirically explore the linkage between e-commerce and TFP growth at the manufacturing firm level in China, where the manufacturing firms are experiencing a transformation from the focus on the production to the marketing side. Second, we construct a systematic framework to identify the mechanism of e-commerce impacting on manufacturing firms' TFP, in which the mechanism is distinguished between intra-firm human capital spillovers and inter-firm market competition. This is not only a step towards providing evidence to test whether the Solow paradox exists in the context of China's manufacturing, but it is also a progress concerning how to improve manufacturing enterprises' TFP through the use of digital platforms.

3 Hypotheses and mechanism analysis

3.1 E-commerce adoption and manufacturing firm-level TFP

The impact of e-commerce adoption on total factor productivity of manufacturing enterprises is reflected in the following three aspects. First, an e-commerce platform broadens the time and scope of transactions, increases the information symmetry between the two sides of transactions, and stimulates more business activities. The change in the business model contributes to increased probability of good match between the supply and demand sides, which is conducive to reducing the manufacturing firm's transaction and search costs and ultimately improving the matching efficiency of transaction [32,33]. Second, the use of e-commerce enables manufacturing enterprises to conduct digital collaborations in the upstream processes of the value chain, such as in designing and technological innovation. Enterprises are able to achieve data aggregation, knowledge reuse and intelligent transformation with the help of industrial internet platforms, which helps to release potential production capability and improve their production efficiency [34]. Third, the digital infrastructure investment in e-commerce is helpful not only for enhancing R&D inputs but also for lowering R&D costs, resulting in increased R&D efficiency. It also helps promoting diversified and multi-body open innovation, drives enterprises to reform their own innovation development mode, and thus accelerates the emergence and transformation of innovation as well as improves the innovation efficiency [35]. Based on the above theoretical analysis, a basic hypothesis is presented as follows.

H1: E-commerce adoption is conducive to TFP growth of manufacturing enterprises.

3.2 Influencing mechanism

As already pointed out, the impact of e-commerce adoption on TFP is embodied in each process of increasing the efficiency of technological innovation, production, and business activities. Overall, such an impacting mechanism can be seen as internal and external. The internal mechanism includes inputs accumulation, knowledge spillovers, and technological change, while the external mechanism incorporates market competition, public policy, and demographic change. Most existing studies pay more attention to the internal mechanisms [36], leaving the external mechanism less explored. It is believed that human capital accumulation, as an important internal factor, is a driving force for the long-term development of enterprises, while proactive adaptation in response to market change is thought to be crucial in increasing enterprise development. In this paper, we comprehensively incorporate both, internal and external factors that may influence the link between e-commerce and firm productivity, with the spillovers of human capital accumulation seen from the perspective of the internal mechanism while market competition as the external mechanism. We propose that e-commerce applied by manufacturing enterprises leads to TFP growth through two types of mechanisms: intra-firm human capital spillover effect and inter-firm market competition effect (see Fig. 1).

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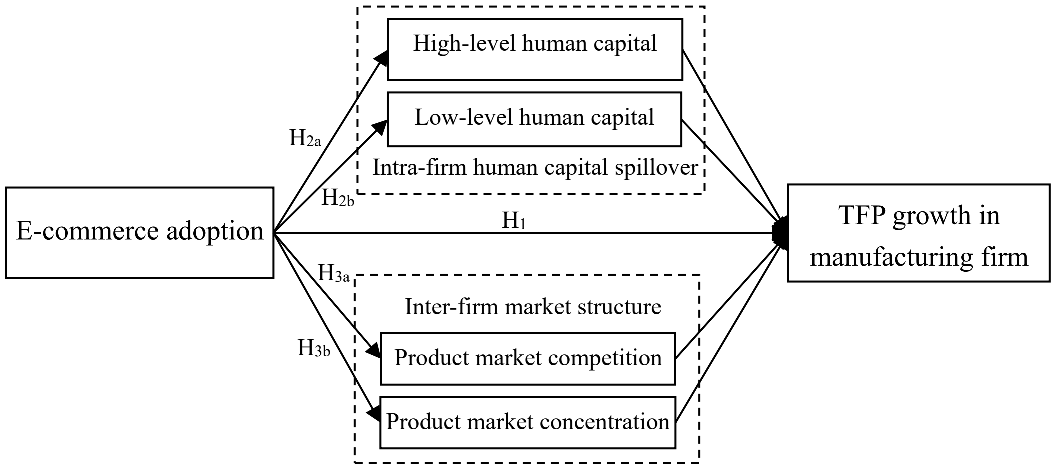

Fig. 1 Research framework and hypotheses

The term human capital refers to the sum of knowledge, skills and physical strength embodied in people that helps them to be more productive. Its accumulation and spillover effects, whether within a firm or region, can boost the TFP growth. E-commerce is often used by both, capital and technology-intensive industries. The penetration of e-commerce in manufacturing firms not only attracts talents or skilled workers but also needs a large number of medium- and low-skilled labor force. Notwithstanding previous classifications of e-commerce, it can be generally be seen as two basic categories, i.e. transaction type and innovation type [37]. The transaction-targeted e-commerce, such as Amazon, Airbnb and Uber, applied by manufacturing enterprises helps expand their production and market scale, which in turns increases the demand for ordinary workers, including blue-collar and online salespeople. Innovation-targeted e-commerce, such as industrial internet platforms and cloud computing, can not only improve manufacturing's efficiency but also help create new products, new process and new services. Therefore, it needs a large number of talented people working in the manufacturing firms to achieve the goal of technological innovation.

The relationship between high-level human capital and productivity growth is commonly suggested to be positive. It is found that a firm with more skilled workers or occupations exhibits a relatively larger increase in TFP [38], or a city with a higher level of human is more likely to trigger knowledge spillovers [39]. In particular, the penetration and development of e-commerce platforms in manufacturing is conducive to knowledge sharing, spillovers and organizational learning across firms in a much larger market space than in the off-line economy, resulting in attracting external knowledge-based and skilled people working in this sector, as well as accelerating their inter-industry mobility. Cerver-Romero et al. [40] confirm that knowledge spillover is more likely to be encouraged by the mobility of specialized personnel. However, the question of whether low-level human capital has a positive or negative effect on productivity is unclear. Some studies empirically support it. For example, Rodríguez-Moreno and Rochina-Barrachina [41] find that investing in ordinary workers' training sessions integrated with ICT use can positively drive firms' productivity growth and increased capacity which can set higher markups. However, others hold the opposite view. For example, Wang et al. [42] argue that human capital measured by primary-level education has an inhibiting effect on productivity, while this is not significantly shown in the study by Zhang and Zhuang [43]. A third point argues that both, low-level and high-level human capital can boost productivity growth only if they systematically match the industrial structure [44,45]. Therefore, two alternative hypotheses are introduced as follows.

H2a: E-commerce adoption improves the TFP of manufacturing firms by stimulating high-level human capital spillovers.

H2b: E-commerce adoption improves the TFP of manufacturing firms by stimulating low-level human capital spillovers.

The rise of digital platforms changes the manufacturing competition pattern. On the one hand, e-commerce applied by manufacturing firms may intensify their product market competition. It is argued that an e-commerce platform can not only expand the manufacturing's upstream procurement market, but also attract its downstream consumers to purchase goods online directly from manufacturers instead of wholesalers [46,47]. Such integration between the producing and marketing chain in a digital platform is quite different from the traditional pipeline competition. First, the transaction cost of manufacturing firms can be largely decreased as information and price transparency increase due to the use of e-commerce platforms. However, it is unambiguously beneficial to consumer welfare. The use of e-commerce increases the intensity of product market competition because manufacturers not only have to compete with online rivals through dynamic pricing and product diversity strategies, but also need to deal directly with consumer demand. Second, e-commerce, as a typical two-side market, can not only attract consumers clustering online for goods purchasing but also encourage thousands of enterprises, especially SMEs, to do business online [48]. In this case, the entry barriers into the type of manufacturing are significantly reduced, while the market competition is increased.

However, on the other hand, an e-commerce platform may increase the market concentration of manufacturing firms. As a start, based on the digital platform, manufacturers can take advantage of big data and cloud computing to effectively analyze consumer information, such as consumer characteristics and purchasing behaviors, and even forecast potential and/or existing competitor information. In this process, large-scale manufacturers always have more advantages and higher competitiveness than small and medium-sized enterprises. Furthermore, consumers can directly bargain with manufacturers via the online platforms, causing numerous channel intermediaries and wholesalers to go bankrupt or switch to other business activities. Under the pressure, whether from inner-enterprises or from the external consumers and competitors, the Matthew effect inevitably occurs, which means that a large-sized firm increases its market share while a small-sized firm decreases its market share.

The relationship between the pattern of market structure (whether dominated by perfect or monopolistic competition) and productivity is a classical topic, however, the conclusion seems to be inconclusive in the literature. The supporting evidence shows that the market structure triggered by a fierce competition can positively affect productivity growth [49-52], while others point out that market concentration instead of competition is more likely to increase productivity, particularly at low-level competition [53]. Recently, Sekkat [54] concludes that the increase of market competition in Egypt seems to promote productivity, whereas market concentration has a positive effect on productivity growth in Jordan and Morocco. In fact, the effect of market concentration on the growth in productivity can be traced back to Schumpeter's creative destruction. In this paper, we intend to test the relationship between market structure and productivity growth, as well as identify which mechanisms may play a more important role in linking e-commerce with TFP growth. Therefore, market structure, as one such mechanism, is analysed. Accordingly, two alternative hypotheses are presented as following:

H3a: E-commerce adoption boosts the TFP growth of manufacturing firms by enhancing market competition.

H3b: E-commerce adoption boosts the TFP growth of manufacturing firms by increasing market concentration.

4 Empirical model and variables

4.1 Empirical model

To test the impact of e-commerce adoption on total factor productivity at the manufacturing firm level, the following econometric model is constructed:

$$TFP_{it} = \alpha + \beta \times Eplatform_{it} + \varphi \times Controls_{it} + \sigma_i + \mu_t + \xi_{it} \quad (1)$$

where *i* and *t* denote firm and time, respectively; TFP_{it}, the explained variable, measures total factor productivity of firm *i* and period *t* ; $Eplatform_{it}$, the explanatory variable, represents e-commerce adoption of firm *i* and period *t* ; $Controls_{it}$ denotes a series of control variables; σ_i denotes firm-fixed effect, μ_t denotes year-fixed effect, and ξ_{it} denotes random error terms and is assumed to satisfy an independent identical distribution.

Based on the mediation model developed by Baron and Kenny [55], a group of econometric models is constructed to verify the mechanism of e-commerce adoption impacting on the TFP growth of manufacturing firms as follows. Models (2) to (3) are used to test the mechanism of human capital spillovers, while Models (4) to (5) are applied to test the market competition mechanism.

$$HCS_{it} = \partial_1 + \eta_1 \times Eplatform_{it} + \lambda_1 \times Controls_{it} + \sigma_i + \mu_t + \xi_{it} \quad (2)$$

$$TFP_{it} = \partial_2 + \eta_2 \times Eplatform_{it} + \omega_2 \times HCS_{it} + \lambda_2 \times Controls_{it} + \sigma_i + \mu_t + \xi_{it} \quad (3)$$

$$MSE_{it} = \partial_3 + \eta_3 \times Eplatform_{it} + \lambda_3 \times Controls_{it} + \sigma_i + \mu_t + \xi_{it} \quad (4)$$

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$$TFP_{it} = \partial_4 + \eta_4 \times Eplatform_{it} + \omega_4 \times MSE_{it} + \lambda_4 \times Controls_{it} + \sigma_i + \mu_t + \xi_{it} \quad (5)$$

where HCS_{it} denotes the spillovers of human capital, while MSE_{it} denotes the market structure effect. The representation of the remaining variables is the same as shown in Model (1). All regressions incorporate industry-fixed effects.

4.2 Variable definitions

Table 1 Names, definitions and symbols of variables

Variable name	Variable description (unit)	Symbol
Total factor	Total factor productivity measured by the LP method	*TFP_LP*
productivity	Total factor productivity measured by the OP method	*TFP_OP*
E-commerce adoption	Online sales of enterprises (10 thousand yuan)	*Eplatform*
Human capital	The number of technicians in enterprises (people)	*HHCS*
spillover	The number workers in the enterprise with a bachelor's degree or above (people)	*SubHHCS*
	The number of ordinary workers in the enterprise (people)	*LHCS*
	The number of workers in the enterprise with a degree below bachelor's (people)	*SubLHCS*
Market structure	The ratio of firms' selling expenses to main business revenue (%)	*MCompetition*
	The share of operating revenue in the total operating revenue of all A-listed companies in the industry (%)	*MConcentration*
	The ratio of depreciation and earnings before interest and taxes to main business income (%)	*PCM*
Enterprise age	Extrapolation based on the number of years since establishment (years)	*Age*
Profit margin	The ratio of total profit to operating revenue (%)	*PM*
Gearing ratio	The ratio of liabilities to assets (%)	*Lev*
Enterprise nature	A dummy variable of whether an A-listed company is a state-owned enterprise or not	*Soe*
Enterprise size	Fixed assets of enterprises (10 thousand yuan)	*Size*

Explained variables – many researchers use OP [56] or LP [57] methods to measure total factor productivity at the manufacturing firm level because these methods can overcome a potential endogeneity problem and control the loss of effective information [58]. In this paper, we use the TFP index measured by LP method (*TFP_LP*) for baseline regressions, while the same index measured by the OP method (*TFP_OP*) is applied for the robustness test.

Explanatory variables – we use the online sales (*Eplatform*) of the flagship stores and directly-managed stores run by manufacturing listed companies in the two biggest e-commerce platforms in China, Tmall.com and JD.com, to measure the degree of e-commerce adoption at the firm level.

Mechanism variables – based on our theoretical model, the HCS mechanism is distinguished

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between high-level human capital spillovers (*HHCS*) and low-level human capital spillovers (*LHCS*). The former is represented by the number of technicians, while the latter is measured by the number of ordinary workers. In terms of market structure mechanism, it is classified as two types, i.e. market competition (*MCompetition*) and market concentration (*MConcentration*). The former is represented by the ratio of a firm's selling expenses to main business revenue, while the latter is measured by the percentage of operating revenue in the total operating revenue of all A-share listed companies in the industry to which they belong.

Control variables – according to the existing studies [16,17], a series of control variables are chosen. The age of the firm (*Age*) is measured by the data about firm establishment. Profit margin (*PM*) of a firm is measured by the ratio of its total profit to the operating income, which can reflect the firm's profitability level. A firm's gearing ratio (*Lev*) defined by the ratio of its liabilities to its assets is introduced to describe the degree of the firm's ability to use liabilities for business activities. The nature of firm ownership (*Soe*) is a dummy variable that measures whether a listed company is a state-owned enterprise or not, while the size of the firm (*Size*) is measured by the fixed assets of enterprises. Table 1 shows the name, description and symbol of all variables.

4.3 Data

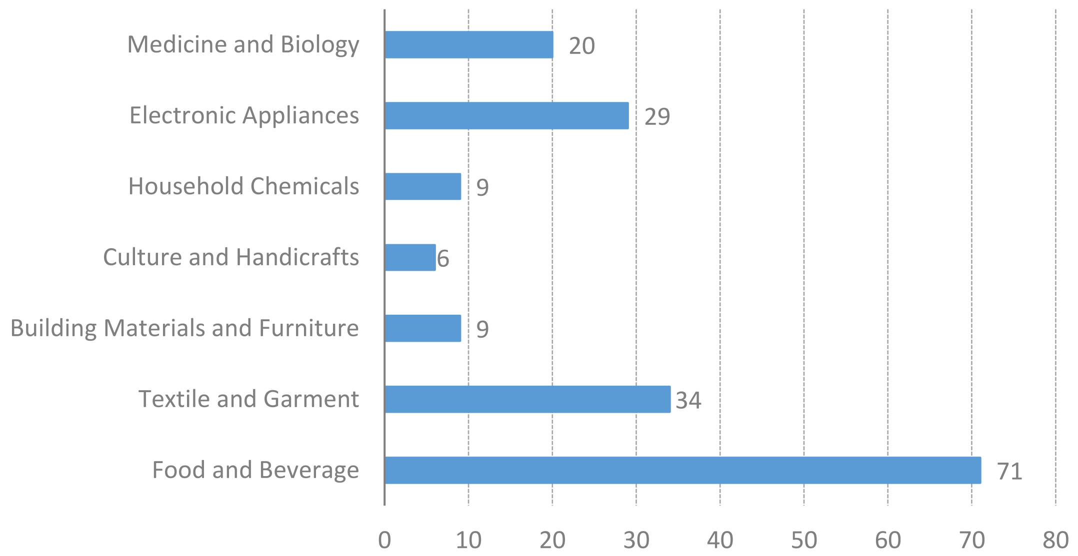

Fig. 2 Number of sample firms by manufacturing sectors

In this study, we use two widely accepted databases to obtain data for each variable. One is the China Stock Market and Accounting Research (CSMAR) database (www.gtarsc.com), while the other is the Wind Economic (Wind) database (www.wind.com.cn). These two databases are regarded as the most authoritative data sources about listed firms in China [59]. The Wind database computes and reports monthly sales data of directly-managed stores and flagship stores of 208 listed manufacturing companies on the platforms of Tmall.com and JD.com. In this context, we obtained annual data about e-commerce trading volume for each manufacturing company by accumulating the monthly data. During the process of data collection, we found that some listed firms were missing while some firms had been delisted during the period of 2015-2021. As a consequence, we deleted the samples with missing data and ultimately obtained the panel data for 178 listed manufacturing firms from 2015 to 2021. These firms are publicly traded on China's A-share markets of the Shanghai and Shenzhen Stock Exchanges. The reason why 2015 was chosen as the beginning year is because manufacturing firms began to report their e-commerce data from that year. As shown in Fig. 2, the 178 companies selected in this study can be classified in 7 sub-sectors, i.e. food and beverage, textiles and garments, building materials and furniture, cultural handicrafts, household chemicals, electronic appliances, medical and biological items.

In order to measure the TFP by the OP and LP methods, we obtain total output, capital input, labour input, and intermediate goods input data from the CSMAR and Wind databases. The mechanism variables concerning the numbers of technicians and ordinary workers, the ratio of firms' selling expenses to main business revenue, the share of operating revenue in the total operating revenue of all A-share listed companies in the related industry, and the control variables related to Enterprise age, Profit margin, Gearing ratio, Enterprise nature, Enterprise size all are captured from the CSMAR and Wind databases. In order to decrease the influence probably caused by data heterogeneity, all continuous variables, in this paper, have been subjected to a 1% tail shrinkage as well as have been taken the logarithm. Table 2 presents the descriptive statistics of all variables.

Table 2 Descriptive statistics of the variables

Variables	Obs	Min	Max	Mean	SD
TFP_LP	1,246	8.141	14.876	11.439	1.090
TFP_OP	1,246	3.881	8.953	6.809	0.732
Eplatform	1,246	2.156	19.523	9.964	2.278
HHCS	1,246	2.565	10.006	5.860	1.224
SubHHCS	1,246	2.565	10.389	6.408	1.218
LHCS	1,246	2.197	11.808	7.300	1.409
SubLHCS	1,246	0.000	11.800	7.950	1.664
MCompetition	1,246	0.706	91.325	18.786	11.982
MConcentration	1,246	0.002	29.589	1.531	2.817
PCM	1,246	-113.726	71.704	14.459	13.417
Age	1,246	3.000	43.000	20.073	6.076
PM	1,246	-194.288	243.708	11.654	21.523
Lev	1,246	3.113	212.348	38.774	18.306
Soe	1,246	0.000	1.000	0.236	0.425
Size	1,246	5.711	16.245	11.313	1.312

5 Empirical results and analysis

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5.1 Baseline regression

Table 3 presents the empirical results related to the impact of e-commerce adoption on TFP of manufacturing firms. Column (1) shows the core explanatory variable (*Eplatform*). It shows that the coefficient of e-commerce adoption is positive at the significance of 1 percent. Columns (2)-(6) add the controls of *Age*, *PM*, *Lev*, *Soe*, and *Size* step by step. It is found that the sign and significance of *Eplatform* are similar to the result in Columns (1), indicating that e-commerce applied by manufacturing firms is indeed beneficial to the TFP growth. This finding lends strong support to hypothesis 1.

In terms of control variables, the item of *Age* presents a positive and significant effect on TFP. Firms with a longer period of living time generally can gain more experience and resources, develop more maturely in all aspects, and therefore have higher productivity. The items of *PM* and *Lev* both turn out to be significantly correlated with TFP. A possible reason is that enterprises with higher gearing ratio tend to have stronger financing capacity and face lower financing constraints. Generally speaking, firms with lower financing constraints usually have higher TFP [60]. The control of *Soe* appears to be insignificant, indicating that there is no significant difference in TFP between state-owned and non-state-owned enterprises. The last control of *Size* is found to have a positive and significant impact on TFP.

Table 3 Baseline estimates on the effects of e-commerce adoption on TFP

Variables	(1) *TFP_LP*	(2) *TFP_LP*	(3) *TFP_LP*	(4) *TFP_LP*	(5) *TFP_LP*	(6) *TFP_LP*
Eplatform	0.035***	0.035***	0.032***	0.032***	0.032***	0.027***
	(3.354)	(3.354)	(3.080)	(3.069)	(3.067)	(2.629)
Age		0.026***	0.029***	0.025***	0.025***	0.021**
		(2.748)	(3.040)	(2.637)	(2.638)	(2.192)
PM			0.002***	0.003***	0.003***	0.003***
			(3.305)	(4.146)	(4.142)	(4.825)
Lev				0.003***	0.003***	0.003***
				(3.979)	(3.978)	(4.147)
Soe					0.006	-0.005
					(0.113)	(-0.083)
Size						0.100***
						(5.338)
Constant	10.918***	10.467***	10.413***	10.371***	10.368***	9.363***
	(96.635)	(46.302)	(46.168)	(46.262)	(45.892)	(32.088)
Firm fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.323	0.323	0.330	0.340	0.340	0.358

Observations	1,246	1,246	1,246	1,246	1,246	1,246

Note: *** *p < 0.01,* ** *p< 0.05,* * *p <0.1*

5.2 Mediator effect test

Table 4 lists the mediator regression results concerning the issue of how e-commerce adoption affects firms' TFP through human capital spillovers. The results in columns (1) and (2) show that the coefficient of *Eplatform* is significantly positive. When the items of *Eplatform* and *HHCS* are added into the model, their coefficients are still significantly positive. It can be inferred that the spillover effect triggered by high-level human capital plays a significant mediating role in the relationship between e-commerce adoption and the TFP growth of manufacturing firms. The result further indicates that the adoption of e-commerce in manufacturing firms is conducive to attracting knowledge-based and skilled worker clustering in these firms, as a result, it triggers human capital spillovers and an increase in TFP. It means that hypothesis 2a can be supported. In contract, the coefficient of *Eplatform* in column (3) seems to be not significant, indicating that e-commerce adoption in manufacturing firms cannot increase their TFP significantly through low-level human capital spillover. It also means that hypothesis 2b cannot be supported.

Table 4 Results of human capital spillover effect

Variables	(1) *HHCS*	(2) *TFP_LP*	(3) *LHCS*	(4) *TFP_LP*
Eplatform	0.024*	0.024**	0.016	0.025**
	(1.655)	(2.395)	(1.477)	(2.455)
HHCS		0.134***		
		(6.424)		
LHCS				0.123***
				(4.186)
Age	0.009	0.019**	-0.025**	0.024**
	(1.279)	(2.085)	(-2.457)	(2.524)
PM	0.007***	0.002***	0.000	0.003***
	(7.964)	(3.267)	(0.418)	(4.809)
Lev	0.001	0.003***	0.002**	0.003***
	(0.481)	(4.258)	(2.023)	(3.908)
Soe	-0.063	0.003	0.169***	-0.026
	(-0.780)	(0.054)	(2.890)	(-0.461)
Size	0.330***	0.057***	0.342***	0.058***
	(12.209)	(2.932)	(17.275)	(2.743)
Constant	1.643***	9.124***	3.675***	8.911***
	(5.617)	(31.616)	(11.933)	(28.839)
Firm fixed	Yes	Yes	Yes	Yes

Year fixed	Yes	Yes	Yes	Yes
Industry fixed	Yes	Yes	Yes	Yes
R^2	0.203	0.383	0.292	0.369
Observations	1,246	1,246	1,246	1,246

Note: *** $p < 0.01$, ** $p< 0.05$, * $p <0.1$

Why does e-commerce adoption drive the TFP growth of manufacturing firms through high-level spillovers rather than low-level human capital spillovers? A possible reason is that the penetration of e-commerce in manufacturing enterprises promotes human capital flows across sectors and regions, with more skilled workers having greater ability to flow than less skilled workers. Another possible reason is that the portfolio of talent demand caused by e-commerce is quite different between manufacturing enterprises. The rise of e-commerce, as one of the information technology-intensive sectors, needs a large number of skilled or professionally educated workers and talents but its need for low-skilled workers is relatively constant. As fact, it is difficult for the low-level human capital to keep up with the changes in information technology in the manufacturing enterprises [42]. In this case, it can be inferred that the development of e-commerce in manufacturing firms can significantly drive TFP growth through spillover effects caused by high quality instead of low quality human capital.

Table 5 Results about market structure effect

Variables	(1) *MCompetition*	(2) *TFP_LP*	(3) *MConcentration*	(4) *TFP_LP*
Eplatform	0.086	0.027**	0.048**	0.019**
	(0.365)	(2.025)	(2.136)	(1.988)
MCompetition		-0.003		
		(-1.089)		
MConcentration				0.165***
				(12.352)
Age	-0.774***	0.019***	-0.054***	0.030***
	(-3.522)	(2.669)	(-2.581)	(3.336)
PM	-0.028**	0.003**	0.003**	0.002***
	(-1.993)	(2.489)	(2.065)	(4.364)
Lev	0.014	0.003**	0.007***	0.002***
	(0.772)	(2.412)	(3.779)	(2.963)
Soe	-2.049	-0.010	0.199	-0.037
	(-1.599)	(-0.292)	(1.636)	(-0.721)
Size	-1.631***	0.096*	0.046	0.092***
	(-3.775)	(1.806)	(1.117)	(5.286)
Constant	53.173***	9.509***	1.377**	9.136***
	(7.902)	(18.261)	(2.155)	(33.479)

Firm fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
Industry fixed	Yes	Yes	Yes	Yes
R^2	0.109	0.360	0.155	0.441
Observations	1,246	1,246	1,246	1,246

Note: *** $p < 0.01$, ** $p< 0.05$, * $p <0.1$

Table 5 presents the mediator regression results to test whether Hypothesis 3a and/or 3b can be supported. The results in Columns (1) and (2) show that the effect of e-commerce adoption on market competition is not significant, while the impact of market competition on TFP is also found to be insignificant, indicating that e-commerce adoption cannot drive the TFP growth of manufacturing firms by enhancing market competition. It also means that Hypothesis 3a cannot be supported. On the other hand, the coefficient of *Eplatform* is significantly positive in columns (3) and (4), indicating that e-commerce adoption can drive the manufacturing firm's TFP growth by increasing market concentration. It also means that Hypothesis 3b is empirically supported.

Why does e-commerce adoption drive the TFP growth by increasing market concentration rather than enhancing competition? Compared with developed countries, manufacturing in China is less concentrated [61], and the market competition is still at a low level, so the market competition effect does not present a significant contribution to the TFP growth in our sample. It is similarly supported by Aghion et al. [53] who argue that market concentration is more likely to increase productivity, particularly at the low-level of competition. In contrast, increased market concentration in manufacturing as a result of e-commerce is beneficial to promoting productivity. Therefore, if the objective is to increase the manufacturing productivity in China, it is essential to increase market concentration instead of competition.

5.3 Robustness test

Table 6 Robustness test results of replacing the explanatory variables

Variables	(1) *TFP_OP*	(2) *TFP_OP*	(3) *TFP_OP*	(4) *TFP_OP*	(5) *TFP_OP*	(6) *TFP_OP*
Eplatform	0.023**	0.023**	0.020**	0.019**	0.019**	0.021**
	(2.381)	(2.381)	(2.009)	(1.991)	(1.994)	(2.102)
Age		0.025***	0.028***	0.025***	0.025***	0.026***
		(2.721)	(3.139)	(2.806)	(2.773)	(2.880)
PM			0.003***	0.003***	0.003***	0.003***
			(4.594)	(5.226)	(5.227)	(5.026)
Lev				0.002***	0.002***	0.002***
				(3.223)	(3.218)	(3.189)
Soe					-0.020	-0.018
					(-0.384)	(-0.334)

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Size						-0.024
						(-1.320)
Constant	6.419***	5.998***	5.928***	5.896***	5.906***	6.142***
	(60.316)	(28.169)	(28.041)	(27.986)	(27.818)	(22.114)
Firm fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.269	0.269	0.284	0.291	0.291	0.292
Observations	1,246	1,246	1,246	1,246	1,246	1,246

Note: *** *p < 0.01,* ** *p< 0.05,* * *p <0.1*

Table 7 Robustness test results of replacing the mechanism variables

Variables	human capital spillover effect				market structure effect	
	(1)	(2)	(3)	(4)	(5)	(6)
	SubHHCS	*TFP_LP*	*SubLHCS*	*TFP_LP*	*PCM*	*TFP_LP*
Eplatform	0.057***	0.025**	0.008	0.027***	0.409*	0.031***
	(3.695)	(2.443)	(0.237)	(2.618)	(1.777)	(3.106)
SubHHCS		0.096***				
		(6.007)				
SubLHCS				0.037***		
				(3.670)		
PCM						0.002*
						(1.775)
Age	0.017***	0.020**	-0.025	0.022**	-0.345***	0.018***
	(2.781)	(2.152)	(-0.838)	(2.301)	(-3.224)	(3.988)
PM	0.005***	0.002***	0.002	0.003***	0.301***	0.003***
	(4.581)	(3.934)	(1.214)	(4.712)	(21.719)	(3.620)
Lev	0.003**	0.003***	-0.001	0.003***	-0.025	0.004***
	(1.960)	(3.962)	(-0.533)	(4.233)	(-1.375)	(4.559)
Soe	-0.032	0.007	0.146	-0.010	1.006	-0.006
	(-0.353)	(0.135)	(0.854)	(-0.182)	(0.780)	(-0.107)
Size	0.347***	0.074***	0.517***	0.081***	2.275***	0.107***
	(11.393)	(3.884)	(8.944)	(4.183)	(5.306)	(5.723)
Constant	1.407***	9.089***	2.640***	9.265***	-11.437**	9.261***
	(4.325)	(31.285)	(2.934)	(31.813)	(-2.464)	(46.218)
Firm fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed	Yes	Yes	Yes	Yes	Yes	Yes

R^2	0.347	0.380	0.127	0.366	0.348	0.324
Observations	1,246	1,246	1,246	1,246	1,246	1,246

Note: *** *p < 0.01*, ** *p< 0.05*, * *p <0.1*

To further verify the reliability of the research findings, we use the substitution variable method and instrumental variable method to improve the robustness of the results. First, we use another method, i.e. the OP method, to re-measure the TFP index and re-calculate the regressions. It shows that the coefficient of *Eplatform* in Table 6 is quite consistent with the basic regression result. Second, we use the number of personnel with a bachelor's degree and above (*SubHHCS*) and the number of personnel with educational level below a bachelor's degree (*SubLHCS*) as substitution variables for the mechanism variables of human capital spillovers. In addition, we use the price cost margin (*PCM*) as a substitution variable for market structure effect, where a higher degree of *PCM* means a more concentrated market. The regression result (see Table 7) shows that the effect of higher educated human capital spillovers still remains significant, while the lower educated human capital spillovers are insignificant. Furthermore, the effect of market concentration still remains positively significant. In fact, the regression results, whether the mechanism variables are replaced or not, are extremely consistent.

Table 8 Robustness test results for the instrumental variables

Variables	First stage		Second stage	
	(1)	(2)	(3)	(4)
	Eplatform	*Eplatform*	*TFP_LP*	*TFP_LP*
Eplatform			0.222**	0.143***
			(2.386)	(14.311)
phone	0.001***			
	(3.456)			
LagEplatform		0.944***		
		(97.524)		
Age	-0.056***	-0.001	-0.009	-0.014***
	(-5.598)	(-0.302)	(-1.445)	(-4.154)
PM	0.022***	0.004***	0.008***	0.009***
	(6.296)	(3.436)	(3.333)	(7.985)
Lev	0.018***	0.000	0.013***	0.014***
	(4.727)	(0.132)	(6.361)	(11.137)
Soe	0.272*	-0.039	0.108**	0.127***
	(1.906)	(-0.813)	(1.984)	(2.688)
Size	0.452***	0.074***	0.487***	0.529***
	(8.969)	(4.250)	(10.763)	(30.658)
Constant	5.361***	-0.233	3.414***	3.746***
	(8.338)	(-1.011)	(6.155)	(16.741)

Underidentification test	12.375***	964.556***		
Weak identification test	11.947***	9510.893***		
Firm fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
Industry fixed	Yes	Yes	Yes	Yes
R^2	0.337	0.933	0.699	0.729
Observations	1,246	1,068	1,246	1,068

Note: *** *p < 0.01,* ** *p< 0.05,* * *p <0.1.* The statistic used for the underidentification test in the table is Anderson LM statistic and the statistic used for weak identification test is Cragg-Donald Wald F statistic. As the number of endogenous explanatory variables and the number of instrumental variables are exactly the same in this paper, no over identification tests are required.

In addition, based on a previous study [62], we used the 2021 number of fixed-line telephone subscribers (unit: million, *phone*) in the cities where each listed company in the sample is located as an instrumental variable for e-commerce adoption. The number of fixed-line telephone subscribers can also reflect the development level of the city's telecommunications infrastructure, which can affect the level of e-commerce adoption by firms. As in 2001 the development of e-commerce in China was still in its infancy, this instrumental variable is unlikely to correlate with TFP growth at the firm level in subsequent years. As shown in Table 8, the result of the Anderson LM statistic test is 12.375 and significant at the 1% level, indicating that we can statistically reject the possible problem of underidentification. The result of the Cragg-Donald Wald F statistic test is 11.947 and significant at the 1% level, indicating that we can reject statistically the possible problem of weak identification. Columns (1) present the first stage regression results of the 2SLS (Two Stage Least Square) approach, verifying that the instrumental variable is correlated with the endogenous explanatory variables. The coefficients of the explanatory variables in Columns (3) are positive and significant at the 5% level, denoting that our empirical results are indeed robust. We also choose e-commerce application with a one-period lag (*LagEplatform*) as another instrumental variable and the results are also robust, as presented in Columns (2) and (4).

5.4 Heterogeneity analysis

Two types of heterogeneity tests are used to examine how the sample heterogeneity may affect the relationship between e-commerce and TFP. All manufacturing enterprises belong to two groups, i.e. in the labor-intensive or technology-intensive sector. Based on the National Economic Classification of Industries in China, the labor-intensive manufacturing sector includes food and beverage, textile and clothing, building materials and furniture, and culture and handicrafts, whereas household chemicals, electronic appliances and medicine and biology can be classified as belonging to the technology-intensive sector. According to our sample, the labor-intensive sector contains 120 firms, while the technology-intensive sector contains the remaining 58 firms. The regression result shows the development of e-commerce whether in the labor-intensive or technology-intensive sector indeed presents a positive and significant impact on the firm's TFP growth (see Table 9).

Furthermore, the coefficient of *Eplatform* in the labor-intensive sector is greater than that in the technology-intensive sector, implying that the productivity increase effect occurring in the former sector is higher than the latter. We also divide the manufacturing firms into two groups based on the location of the company's registration address in the country, i.e. coastal location and inner location enterprises. According to the sample, there are 125 firms in the coastal region and 53 firms in the inner region. It shows that e-commerce applied by manufacturing firms whether in the coastal or inner regions has a positive and significant effect on TFP. Moreover, the growth effect of TFP in the inner region is found to be greater than that in the coastal area.

Also, we use Fisher's Permutation test method [63] to test whether or not differences exist between the two groups of sectors and two groups of regions. The test result shows that the P-value concerning the coefficient of the two types of sectors is 0.492, while the P-value in testing the different region groups is 0.054. This means that the former cannot reject the null hypothesis, indicating that the difference in coefficients between the two sector groups is not statistically significant. In other words, the impact of e-commerce adoption on TFP growth does not differ significantly between labor-intensive and technology-intensive sectors. The latter can reject the null hypothesis at the 10% significance level, suggesting that the difference of the coefficients between the two groups of regions is statistically significant. This implies that the impact of e-commerce used by manufacturing firms on TFP growth in the inner region is greater than in the coastal region.

Table 9 Heterogeneity analysis regression results

Variables	Labor intensive	Technology intensive	Coastal region	Inner region
	(1)	(2)	(3)	(4)
	TFP_LP	*TFP_LP*	*TFP_LP*	*TFP_LP*
Eplatform	0.035***	0.029*	0.022*	0.060***
	(2.940)	(1.726)	(1.895)	(2.612)
Age	0.013**	0.024***	0.022**	0.003
	(2.236)	(2.938)	(2.066)	(0.116)
PM	0.000	0.004***	0.004***	0.002**
	(0.532)	(4.135)	(5.016)	(2.367)
Lev	0.002**	0.005***	0.004***	0.006***
	(2.250)	(3.018)	(3.797)	(4.231)
Soe	-0.025	0.001	-0.057	0.048
	(-0.261)	(0.018)	(-0.742)	(0.592)
Size	0.130***	0.076**	0.109***	-0.005
	(5.688)	(2.142)	(4.758)	(-0.155)
Constant	9.048***	9.815***	9.342***	10.394***
	(37.508)	(25.653)	(28.146)	(13.642)
Firm fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
Industry fixed	Yes	Yes	Yes	Yes

R^2	0.328	0.301	0.358	0.454
Observations	840	406	875	371

Note: *** $p < 0.01$, ** $p< 0.05$, * $p <0.1$

6 Conclusion and implication

The rapid growth of e-commerce activities, such as online shopping, online booking, and online banking, is not only affecting the efficiency of goods transportation and marketing, but it is also having a revolutionary effect on the process of goods' design and manufacturing. In this paper, we analyzed whether and how e-commerce applied by manufacturing firms affects TFP growth at the firm level. We put forward five hypotheses in which the impacting mechanism is distinguished based on intra-firm human capital spillovers and inter-firm competition effect. The analysis of panel data for 178 A-share listed manufacturing companies during the period of 2015 to 2021 in China shows that the development of e-commerce whether in the labor-intensive or technology-intensive sector as well as whether in the coastal or inner region has a positive and significant effect on TFP growth at the manufacturing firm level. This also means that the Solow paradox does not exist in the context of China's manufacturing. The mechanism test shows that e-commerce adoption in manufacturing can significantly drive the firm's TFP growth through high-level human capital rather than low-level human capital spillovers. In addition, the market structure dominated by industrial concentration instead of fierce market competition triggered by e-commerce is in favor of increasing the TFP growth of manufacturing firms.

The empirical findings in the study have implications for policymakers and business managers. First, company executives should focus on promoting collaboration or integration between the internet platform and manufacturing upgrading by encouraging each company module to use various types of digital platforms, such as online business platform, industrial internet platform, and intelligent decision platform based on big data. Manufacturing firms should provide more resources for such upgrades, including attracting and retaining more skilled and talented workers, R&D investment and so on. Second, policy makers should increase investment in high-level human capital accumulation projects, particularly in ICT, big data, digital production and digital trading. More professional training and in-service education programmers are required to assist the low-level human capital in gaining higher professional capability and entering the group of skilled workers. If these two policies can be effectively and complementarily implemented, particularly in manufacturing, firm productivity will increase. Third, if the policy goal is to increase firm productivity by developing the digital economy, governments and the general public should be more tolerant of industrial concentration caused by e-commerce. The study confirmed that industrial concentration, rather than competition, can significantly boost TFP growth at the manufacturing firm level. This does not mean that competition is of no use. On the contrary, we contend that a certain increase in industrial concentration as a result of market competition in manufacturing can drive firms' TFP growth in the context of e-commerce. Policy makers should take measures to balance the increase in productivity and industrial concentration.

This paper contributes to the literature by testing whether e-commerce can drive firms' productivity growth and by shedding light on why this is the case. Previous studies have focused on how to increase the productivity of manufacturing firms from the perspective of product innovation, process innovation, and/or service innovation, with little attention paid to business formation innovation in the e-commerce context. To our knowledge, this article is the first step in empirically investigating why manufacturing firms drive their TFP growth by directly interacting with the end consumers via e-commerce platforms. We hope that this exploration attract more attention to the relationship between the type of digital economy and manufacturing productivity growth.

Notwithstanding this, the paper has some limitations which need to be explored in the future. On the one hand, the focus was on the productivity growth effect caused by digital transaction platforms alone; a future study can investigate the same effect caused by digital production platform or discuss the interaction effect of two types of platforms on productivity. On the other hand, analysis systematically distinguished between intra-firm human capital spillovers and inter-firm competition; however, there may be other mechanisms hiding in the channel of e-commerce impacting on the firms' productivity, such as the collaboration effect between production and marketing or the digitalization governance mechanism. These novel mechanisms can further to be explored and verified.

Appendix A. Estimating details concerning the LP and OP estimators

The Olley-Pakes (OP) method and Levinsohn-Petrin (LP) method, as two classical methods to measure the total factor productivity of enterprises, can overcome the potential endogeneity problem and control the loss of effective information quantity [58]. Therefore, this paper measures the TFP of 178 manufacturing A-share listed companies in China from 2015 to 2021 using the OP method and LP method. The OP or LP method is basically the same and the LP method is improved on the basis of the OP method. The measurement process is as follows.

First, the equation between the firm's current capital stock and investment is constructed:

$$K_{it+1} = (1-\delta)K_{it} + I_{it} \tag{1}$$

where K is the capital stock of the enterprise and I represents the current investment.

Second, the basic equation, Ln Y=Ln A+α Ln K+β Ln L, is transformed into an econometric model:

$$\ln Y_{it} = \alpha \ln K_{it} + \beta \ln L_{it} + \omega_{it} + e_{it} \tag{2}$$

Where ω_{it} is the part of the residual term that can be observed by the firm and affects the factor selection in the current period. e_{it} is the part of the residual term that contains unobservable technology shocks and measurement errors. After that, an optimal investment function is generated as follows:

$$i_{it} = i_t\left(\varpi, \ln K_{it}\right) \tag{3}$$

We can find the inverse function of this optimal investment function. Assuming that $h(\cdot) = i^{-1}(\cdot)$, ω

can be written as

$$\varpi_{it} = h_t\left(i_{it}, \ln K_{it}\right) \tag{4}$$

Substituting equation (4) into equation (2), we obtain the following equation:

$$\ln Y_{it} = \alpha \ln K_{it} + h_t\left(i_{it}, \ln K_{it}\right) + \beta \ln L_{it} + e_{it} \tag{5}$$

It is defined that $\phi_{it} = \alpha \ln K_{it} + h_t\left(i_{it}, \ln K_{it}\right)$, i.e. ϕ_{it} is a polynomial containing the logarithmic values of the investment and the capital stock, and define its estimate as $\tilde{\phi}_{it}$, so that the following equation can be obtained as:

$$\ln Y_{it} = \phi_t + \beta \ln L_{it} + e_{it} \tag{6}$$

By estimating equation (6), we can obtain a consistent unbiased estimation coefficient of the labor term $\hat{\beta}$. Afterwards, the estimated coefficients are used to fit the value of the polynomial $\tilde{\phi}_{it}$ consisting of the investment and the capital stock.

Finally, we define $V_{it} = \ln Y_{it} - \hat{\beta} \cdot \ln L_{it}$, and estimate the following equation

$$V_{it} = \alpha \cdot \ln K_{it} + g\left(\phi_{t-1} - \alpha \cdot \ln K_{it-1}\right) + \mu_{it} + e_{it} \tag{7}$$

where $g(\cdot)$ is a function containing ϕ and lags of the capital stock that can be estimated by higher-degree polynomials of $\phi_{t\text{-}1}$ and Ln $K_{t\text{-}1}$. In the actual estimation process, it is necessary to use the nonlinear least squares method to ensure that the estimated coefficients of the capital stock are always consistent, both in the current period and in the lagged period. When the estimation results of Equation (7) are obtained, all coefficients in the production function can be computed. This allows us to obtain the logarithm of the residuals by fitting the equation Ln Y=Ln A+α Ln K+β Ln L to obtain the logarithm of total factor productivity.

As stated above, the OP method can obtain the consistent estimates of total factor productivity at the firm level. However, the method assumes that the investment and total output need to maintain monotonical relationship at all times, so sample firms with zero investment cannot be estimated. In reality, some firms do not have positive investment every year, so using the OP method requires removing these firms from the sample. The improvement of the LP method is using the intermediate goods input to replace the investment as the proxy variable, which can avoid the problem that the TFP of the firm cannot be estimated due to zero investment.

According to the above methods, we obtain the data of A-share listed manufacturing enterprises in China to measure the TFP of firms. The paper uses operating incomes to represent total output, net fixed assets to represent capital input, and total number of employees to represent labor input. In addition, in the OP method measurement, the investment is represented by cash paid for the purchase and construction of fixed assets, intangible assets and other long-term assets; in the LP method measurement, the intermediate goods input is represented by "operating costs + selling expenses + administrative expenses + financial expenses - depreciation and amortization - cash paid to employees and cash paid for employees".

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Declarations

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