The Effect of Software Registration on Manufacturing Export *

Qingqing Niu [†1], Zhi Shao [‡1], and Wentao Wu[§1]

[1]College of Business, Shanghai University of Finance and Economics, Shanghai, China

Abstract

Considering the pivotal role of the software industry in the digital economy, this paper investigates the effect of software registration on China's manufacturing exports from 2000 to 2013 against the backdrop of rapid growth in the digital economy and international trade. Our results indicate a positive association between software registration, a unique proxy for digital economy development, and manufacturing firm exports. This finding remains robust across various tests, including Bartik IV estimation, different estimators, and subsample analyses. Mechanism analysis suggests that software registration may bolster exports by reducing firms' production and operational costs while mitigating information frictions in international markets, thereby incentivizing firms to expand their export activities to diverse markets. Furthermore, extended analyses reveal heterogeneous impacts across firm ownership, regions, industries, and destinations. Overall, our findings underscore the significant linkage between software registration and firm exports, providing a novel perspective on the digital economy's influence on international trade.

Keywords: *Digital Economy; Software Registration; Exports; Manufacturing Firms*
JEL classification: *L86, F14, R11, D83*

---

*We acknowledge the financial support from the Shanghai University of Finance and Economics (SUFE) Graduate Innovation Fund Project and SUFE Trade Theory & Policy Research Group. All errors are on our own.

†Qingqing Niu, qqingniu@163.com, College of Business, Shanghai University of Finance and Economics, Shanghai, China

‡Zhi Shao, shaozhi.yctx@gmail.com, College of Business, Shanghai University of Finance and Economics, Shanghai, China

§Wentao Wu, **Corresponding author**, alphene@yeah.net, College of Business, Shanghai University of Finance and Economics, Shanghai, China

1 Introduction

The importance of the digital economy in global economic activities is increasing. Recent literature has extensively focused on the impact of digital economy development or network infrastructure on the real economy, especially on trade activities (see, for example, Lederman and Zouaidi, 2022; Zhang et al., 2023; Herman and Oliver, 2023). In fact, whether it is network infrastructure, cloud computing platforms, data storage and processing systems, or various applications, they all rely on software support. Despite being an essential component of the digital economy, the economic effects of digital software are seldom emphasized, yet its global development momentum is undeniable. Taking China as an example, it achieved a remarkable milestone in 2022 with 1.8 million computer software copyrights registered, maintaining a record of over one million for the fifth consecutive year, representing a twelvefold increase compared to 2012.[1]

China, as the world's largest exporter, has transformed into the global factory, with exports steadily growing since its accession to the WTO in 2001. While research on China's manufacturing exports has received extensive attention (Kee and Tang, 2016; Brandt et al., 2017; Chor et al., 2021), there remains a gap in exploring how software iteration influences firm exports. Given the revolutionary impact of digital economy on trade (Fan et al., 2018; Goldfarb and Tucker, 2019), this study aims to fill this gap by revealing how the development of software in the digital economy affects Chinese manufacturing firms' exports. Specifically, we address two issues: the impact of software registration on manufacturing exports and the potential channels through which software registration affects firm exports.

We compiled a comprehensive dataset combining software copyright application information from the Chinese National Copyright Administration (CNCA) with firm export data from the General Administration of Customs for regression analysis. Our results indicate that software registration significantly boosts manufacturing firms' exports at the city-industry level, suggesting that regions and industries with more software registrations experience greater export growth compared to their counterparts. To address endogeneity concerns, we instrument city-industry software registration using Bartik IV, constructed based on the differential exposure of regional industries to specific category of software's total growth rates at the national level. The 2SLS results align with the benchmark, supporting the proposition that software registration promotes firm exports after validating the instrumental variables' effectiveness. We employ various robustness

[1]Source: Analysis Report on the Registration of National Computer Software Copyrights in 2022 released by the China Copyright Protection Center.

measures, including alternative explanatory variable measurements and the exclusion of processing trade, trade intermediaries, and relocated firms. After controlling for other confounding effects, we confirm two potential export promotion mechanisms resulting from software registration at the firm level: cost reduction and alleviation of information friction. Additionally, we examine heterogeneous effects across firm ownership, regions, industries, and destinations.

The contribution of this study is twofold. Firstly, we offer a unique perspective by exploring the impact of digital economic development on trade, specifically through software registration. While existing literature has predominantly focused on the influence of digital infrastructure on trade, overlooking the role of software (Freund and Weinhold, 2004; Bojnec and Ferto, 2010; Ferro, 2011; Yadav, 2014), we fill this gap. By constructing a measure of digital economy development at the city-industry level using software registration data from CNCA, we provide micro-level evidence demonstrating the crucial role of knowledge outcomes from the digital economy in facilitating trade. Moreover, software registration can also be utilized in studies examining how the digital economy impacts other aspects of firm performance.

Secondly, our study contributes to understanding the relationship between the producer service industry and manufacturing. We illustrate that new types of producer service industries, exemplified by the software industry, significantly contribute to promoting manufacturing exports. Through iterative software applications, manufacturing firms can reduce production and operational costs and alleviate information frictions in global markets, enabling them to export more products to diverse markets. This enhances our understanding of the interplay between the producer service industry and the performance of the manufacturing sector.

The remainder of this paper is structured as follows: Section 2 reviews the existing literature. Section 3 introduces the identification strategy and describes the data construction. Section 4 presents our empirical findings on the impact of software registration on exports. Section 5 further analyzes the potential channels through which software registration promotes exports, including cost reduction and alleviation of information frictions. Finally, Section 6 concludes.

2 Literature Review

2.1 Digital economy and export

The positive impact of digital economy development on exports has garnered widespread recognition in existing literature. Several studies have delved into the role of the Internet at the national level in fostering overall trade (Freund and Weinhold, 2004; Wheatley and Roe, 2008; Bojnec and Ferto, 2010; Mallick, 2014; Chaney, 2014). For instance, Bojnec and Ferto (2010) discovered that the Internet can lower specific market entry costs for the food industry, thereby facilitating trade. Similarly, Mallick (2014) employed gravity models to illustrate the significant role of Internet infrastructure in promoting service trade. Moreover, Chaney (2014) revealed that widespread Information and Communication Technology (ICT) usage can bolster exports by reducing information search and distribution costs.

With the emergence of heterogeneous firm theories, researchers have begun to examine the impact of the Internet on firm exports at the firm level. Studies such as Mostafa et al. (2005) have found that entrepreneurial firms are more inclined to utilize the Internet to access export markets, leading to improved export performance. Additionally, Ricci and Trionfetti (2012) demonstrated that firms with higher productivity levels are more likely to export and benefit from foreign and domestic networks, as well as communication channels such as email and the Internet. Other studies, including Ferro (2011) and Yadav (2014), have further substantiated the positive impact of Internet usage on export activities, highlighting reductions in information-related costs and enhancements in export margins.

2.2 Intelligent robot and export

The relationship between intelligent robots and exports is a well-explored topic in the field of trade. While both intelligent robots and software are products of digital economic development, they offer distinct insights when compared. Industrial robots, being physical capital, can enhance processing precision (Frey and Osborne, 2017), reduce error rates, and improve capital returns (Graetz and Michaels, 2018). Their introduction often results in cost reductions and increased commodity supply, thereby fostering a country's exports (Artuc et al., 2023). For instance, Cao et al. (2021) analyzed Chinese manufacturing industry-level robot stock data to investigate the impact of robots on firm exports, revealing a significant positive effect. Additionally, DeStefano and Timmis (2024) demonstrated that robot diffusion increases the quality of exported products, with quality improvements being predominantly driven by the upgrading of initially lower-quality exports from both developed and developing countries.

In contrast, software serves as intangible capital for manufacturing firms. By distinguishing between these two types of inputs, a complementary perspective has been provided, enriching our understanding of how the software industry influences the export activities of manufacturing firms within the broader context of the digital economy.

2.3 Producer services and manufacturing

Our research also relates to the literature examining the impact of the producer service industry on the manufacturing sector. Arnold et al. (2011) emphasize the importance of service industry reforms in bolstering downstream manufacturing firms' performance. Their findings indicate that enhancements in the quality of external productive service inputs contribute to substantial growth in labor productivity and sales. Fernandes and Paunov (2012) investigates the effect of significant foreign direct investment (FDI) inflows in producer service sectors on the total factor productivity (TFP) of Chilean manufacturing firms, observing positive effects. Forward linkages from FDI in services account for 7% of the increase in Chile's manufacturing firms' TFP. Similarly, Lodefalk (2014) suggests that the intensity of a firm's services can influence its productivity and competitiveness abroad by facilitating connections to foreign markets and distinguishing its products from competitors. Additionally, Hoekman and Shepherd (2017) analyze the linkage between services and manufacturing productivity performance, finding compelling evidence for such a connection.

3 Empirical Strategy

3.1 Data and Description

Our analysis is based on detailed information on firm export activities and regional industry software applications. To achieve the empirical objectives of this paper, we constructed a unique analysis dataset by integrating data from different sources.

Firstly, we collected and organized software copyright information provided by the Chinese National Copyright Administration (CNCA). The software needs to be registered with the local copyright bureau to recognition and copyright protection in the market after the software been developed, and its information is subsequently disclosed on the official website of the CNCA. We obtained detailed information for each registered software, including the registration number (a unique identifier), software classification code, full name of the software, registration date (the time of software application), and copyright holder (the affiliated development company). To be specific, software classification codes comprise two sets of numerical values. One set delineates the category code of the software, reflecting specific software types such as system software, enterprise management software, statistical software, and informational software. [2] The other set denotes the industry code for the practical application of the software, aligning with 2-digit ISIC Rev.4 industries. We shall employ this data to construct indicators for the quantity of software registrations at the city-industry level, along with their corresponding instrumental variables.

In order to get the clean and unique city-industry level data, we remove duplicate applications and different versions of the same software. Then, matching the firm name to the firm-level database for location details of the software. Subsequently, based on the industry information provided by the software classification code, we aggregated the software applications at the city-industry level, resulting in a panel dataset for Chinese prefecture-level cities and ISIC industries at the 2-digit level.

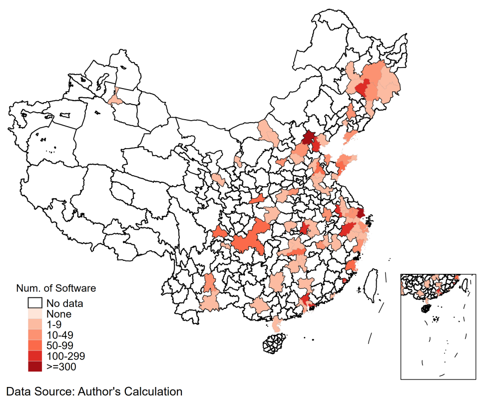
Secondly, we employed two different sources of firm-level databases. The first database is the Annual Survey of Industrial Firms(ASIF) database (1998-2013) provided by the National Bureau of Statistics of China, which includes all non-state-owned firms with annual sales at least 5 million RMB and all state-owned firms, discloses information including firm name, business characteristics, industry, geographical location and so on. The second firm-level database is the detailed micro-level trade data provided by the China Custom Trade Statistics database, including monthly firm-level trade data for products with each destination country from 2000 to 2013.

Ultimately, we compile the essential data required to support our empirical analysis by aligning the geographical details of firms and export product information with software application data. Prior to engaging in regression analysis, we conduct a concise descriptive analysis to illustrate the correlation between firm exports and the quantity of software applications in city-industries.

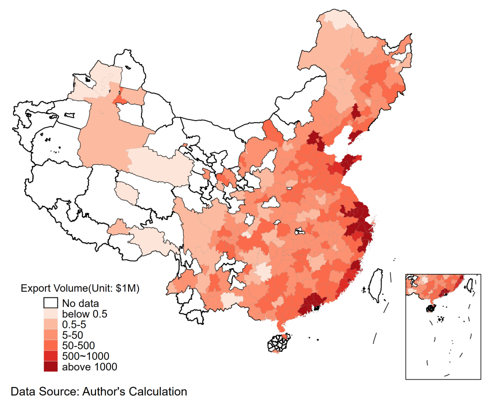
Figure 1 depicts the changes in software applications and total exports at the city level in China. Subfigures (a) and (c) present the spatial distribution maps of software application quantities for the years 2003 and 2013, respectively. Notably, the quantity of software applications in China exhibited substantial growth over the decade, albeit with minimal alterations in the primary growth cities. Furthermore, in 2013, the distribution of software applications extended to more cities compared to 2003. Subfigures (b) and (d) portray the

[2] For detailed category information, please consult the appendix of this paper.

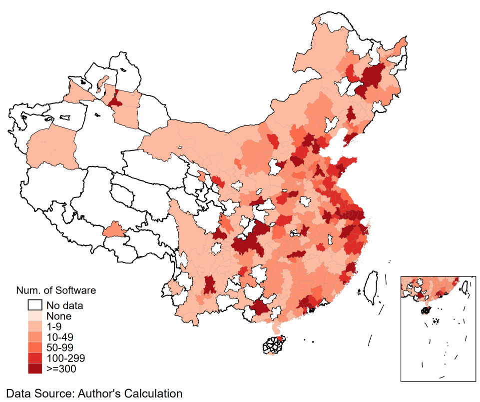
distribution maps of exports for the same years. In 2003, China's export cities were predominantly situated in coastal areas. A decade later, although coastal cities continued to dominate exports, inland cities also experienced a rapid increase in export volume.



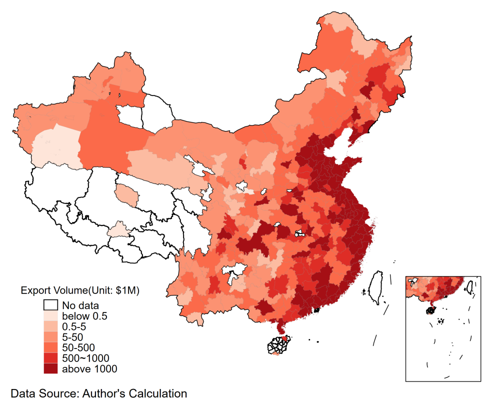
(a) Distribution of software across cities in 2003



(b) Distribution of exports across cities in 2003



(c) Distribution of software across cities in 2013



(d) Distribution of exports across cities in 2013

Fig. 1. The changing distribution of software and exports in Chinese cities

Note: This figure depicts the spatial distribution maps of software applications and export amounts at the city level in China for the years 2003 and 2013. The left two graphs show the trend of software application quantities in cities, while the right two graphs illustrate the trend of exports in cities. Data is sourced from the software copyright information provided by the Chinese National Copyright Administration, after being curated by the authors, and enterprise-level aggregated export information at the city level.

Our analysis reveals a discernible correlation. Firstly, the primary distribution of cities with software applications spatially coincides with the primary distribution of cities engaged in exports. Secondly, cities witnessing substantial growth in software applications also demonstrate a noticeable trend of export expansion. These initial data characteristics underscore a meaningful correlation between regional software applications and firm export patterns.

Lastly, we also collected supplementary information on cities and export destination countries from the China City Statistical Yearbook and the CEPII Gravity Database respectively. Further elaboration on this supplementary data will be provided in the subsequent sections.

3.2 Identification

To investigate the impact of digital software registration on firm exports within a city-industry, we formulate the following identification equation:

$$\ln \text{Export}_{f,p,d,t} = \beta \ln \text{SoftReg}_{c,j,t} + \alpha_{f,t} + \lambda_{p,d,t} + \varepsilon_{f,p,d,t} \tag{1}$$

The dependent variable $\ln \text{Export}_{f,p,d,t}$ is the logarithm of the trade flow from firm f in city c, exporting product p to destination country d in year t (due to the right-skewed distribution of export data for Chinese firms, we followed existing literature and employed logarithmic transformation). The independent variable $\ln \text{SoftReg}_{c,j,t}$ is the logarithmic value of the software registration number introduced in industry j in city c during year t (city c's new software in j-th industry $+1$). It is important to note that industry j is derived from software data and statistically equivalent to 2-digit ISIC Rev.4 industry classification. Therefore, we enable each export HS6 product p to be associated with a unique industry j.

$\alpha_{f,t}$ represents firm-year fixed effects, absorbing time-varying firm-level characteristics that may influence export behavior. $\lambda_{p,d,t}$ denotes fixed effects at the HS6 product-destination country-year level, absorbing fluctuations in supply and demand in export markets. The inclusion of $\lambda_{p,d,t}$ concurrently controls for potential omitted variables at the industry level that may vary over time, such as technological shocks, labor demand, and supply shocks. Finally, $\varepsilon_{f,p,d,t}$ is the random error term. Due to the potential correlation of trade flows among different firms within the same city, standard errors are clustered at the city level.

The coefficient β captures the impact of the software development at the city-industry level on intra-city export trade among businesses. The validity of the estimated β hinges on the assumption that, digital software development in city industries is independent of other unobservable factors that could potentially impact firm export flows. The robustness of this assumption will be thoroughly examined in the forthcoming empirical analysis.

4 Results

In this section, we present the outcomes of the estimations derived from the linear regression model (Equation (1)). The initial subsection concentrates on assessing the influence of software registration at the city-industry level on trade among Chinese manufacturing firms. Subsequently, we investigate potential endogeneity concerns that could pose a threat to identification and mitigate potential estimation bias by constructing a Bartik instrument. Finally, we perform a series of sensitivity analyses to affirm the robustness of the results.

4.1 Baseline Results

This subsection delves into the discussion and presentation of estimates derived from Equation (1) and its extensions, with the aim of discerning the impact of city-industry level software applications on firm export behavior.

Table 1 provides the Ordinary Least Squares (OLS) estimates from Equation (1). The results underscore a significant effect of software registration on firm exports. In the first column, where we control for firm and year fixed effects to account for differences between firms that remain constant over time (including variations among firms in different cities) and common volatility factors in different years, the findings suggest that a 1 percent increase in the quantity of city-industry software applications corresponds to a 0.25 percent improvement in firm exports. In column (2), we included a range of firm-level characteristics, including firm output size, firm age, capital-labor ratio, state-owned and foreign ownership assets, as well as firm labor productivity (which are widely recognized as crucial in the operation of firms). We find that after incorporating these firm-level characteristics, the core coefficient remains significantly positive, and consistent with existing research, firm size and labor productivity are also positively correlated with export performance.

The magnitude of this effect increases when we introduce firm-year fixed effects in column (3). All time-varying firm characteristics including unobservable such as changes in overall sales strategies, which play a crucial role in firm export, are controlled by these fixed effects. Simultaneously, these effects eliminate differences at the city level that evolve over time, such as alterations in the city's foreign trade policies and immigration shocks.

In the fourth column, the effects diminish to 0.033 when we additionally control for fixed effects at the product-destination country-year level. This step accounts for variations in firm export growth across different industries or products, which can be driven by additional demand in export markets. The product-destination country-year level fixed effects incorporate demand-side factors, consistent with Aghion et al. (2022). The results indicate that neglecting demand-side factors would significantly exaggerate the effect in our sample.

A substantial body of research on firm exports often decomposes it into export quantity and export prices (Chen and Bao, 2023). Following this framework, we conducted an additional study in the appendix. In summary, we found that software registration activities exert an increase in the quantity of firms' export products but do not significantly affect the prices. One possible explanation is that we believe software or the digital economy primarily affects export behavior by influencing overall operating costs and information frictions for firms, rather than directly impacting the products themselves. This aligns with findings from existing literature, where the prices of firms' exported products are often more sensitive to the quality of inputs (Bas and Strauss-Kahn, 2015) and a range of characteristics of the destination countries (Fan et al., 2020). We will provide further discussion in the subsequent sections.

4.2 Endogeneity and IV Regression

The main endogeneity concern in this study stems from potential omitted variables. Although the baseline identification strategy controls for strict fixed effects to absorb potential time-varying factors at the firm and export market levels, there may still be time-varying factors at the city-industry level simultaneously affecting the number of software registrations in that city-industry and the corresponding export activities of manufacturing firms. For instance, if a city's dominant industries are technology-intensive manufacturing sectors such as automotive or medical instruments, the quantity of software applied in these dominant industries in the city and the exports of firms in these industries would be endogenously related. Unfortunately, due to extensive missing data on industry segmentation at the city level, we cannot simply control for these characteristics, hence constructing instrumental variables for 2SLS regression becomes a necessary choice in this study.

To address this concern, we construct a Bartik instrument using the category information of software in the software registration data (as shown in the appendix). Software categories such as enterprise management, transaction management and accounting are independent of regional and industry characteristics. Each industry incorporates various categories of digital software, and each category is not confined to a specific industry. In general, a Bartik IV (or shift-share IV) usually consists of two parts: "shifts" and "shares"

Table 1
Baseline Results

	(1) $\ln \text{Export}_{f,p,d,t}$	(2) $\ln \text{Export}_{f,p,d,t}$	(3) $\ln \text{Export}_{f,p,d,t}$	(4) $\ln \text{Price}_{f,p,d,t}$
$\ln \text{SoftReg}_{c,j,t}$	0.251***	0.309***	0.531***	0.033***
	(0.027)	(0.039)	(0.044)	(0.008)
Firm Size		0.221***		
		(0.047)		
Age		0.010		
		(0.014)		
Capital labor ratio		-0.000***		
		(0.000)		
Gov share		-0.095**		
		(0.042)		
Foreign share		0.002		
		(0.024)		
Labor productivity		0.000***		
		(0.000)		
N	15467956	8026338	15406408	14550533
Firm FE	Y	Y		
Year FE	Y	Y		
$\alpha_{f,t}$			Y	Y
$\lambda_{p,d,t}$			Y	Y
Adjust R^2	0.205	0.207	0.229	0.385

Note: Standard errors reported in brackets, are heteroskedasticity-robust and clustered at the city level. *** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

(Adao et al., 2019; Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). In this context, the "shock" (or shift) refers to the national annual growth rate $g_{i,t}$ of each category (i) of software. The "share" represents the ratio of the i-th category of software in a specific city-industry in the previous period, describing the extent to which industry j in city c is exposed to the growth rate of the i-th category of software. The construction is as follows:

$$IV_{c,j,t} = \sum_{i} \frac{\text{SoftReg}_{c,j,i,t-1}}{\text{SoftReg}_{c,j,t-1}} \times g_{i,t} \tag{2}$$

The validity of the Bartik instrument we constructed relies on the assumption that the overall growth rate of a specific category of software relative to regional firms' micro trade flows is exogenous. This is because the overall supply shock of a specific software category is less likely to be influenced by the characteristics of specific regional industries but is more likely to be influenced by the market demand from all potential industries nationwide that may use this software category. Thus it influences the trade behavior of corresponding firms only through the growth in the quantity of specific software category. This effectiveness builds upon our "shock design" Bartik IV (Borusyak et al., 2022), which, in turn, depends on two assumptions: (1) $g_{i,t}$ is as-good-as-random, and (2) there are a sufficient number of effective shocks. We follow the recommendations in Borusyak et al. (2022) to provide statistical descriptions of the shocks we use, supporting evidence for the validity of these assumptions.

Table 2
Shock summary statistics

	(1)	(2)
mean	0.301	-0.000
s.d.	0.848	0.823
IQR	0.826	0.753
Residualized on year FE		Y
1/HHI across shocks	76.614	76.614
Largest share weight	0.036	0.036
# No. of shocks	705	705
# No. of soft categories	78	78

Note: This table summarizes the distribution of software growth shocks g_{it} across all software categories i and periods t. All statistics are weighted by the average city-industry exposure shares e_{cjt}, which are measured from city-industry level $\text{SoftReg}_{c,j,t}$. Column (2) residualizes software growth shocks on period indicators.

Table 2 shows a detailed statistical description of the shocks, i.e., the growth rate shocks $g_{i,t}$ for different categories of software, which were actually used in our sample. It is evident that the standard deviation and interquartile range of $g_{i,t}$ are approximately 2-3 times the mean, indicating that the shocks we use are sufficiently dispersed. Furthermore, there is substantial differentiation in the performance across different categories, alleviating concerns regarding the correlation between the growth in software quantity and its category.

To further investigate the validity of our assumptions, particularly relaxing the first assumption allowing for autocorrelation in shocks, the second column of Table 2 shows that the residuals continue to exhibit sufficient variability in the sample after controlling for period fixed effects. Importantly, the effective shock count (1/HHI) is 76.614, with the maximum share value only reaching 0.036. [3] This indicates that our Bartik IV identification strategy is not reliant on a few dominant specific category software growth rates. The effective number of shocks used for identification approaches the number of all software categories, and these categories are sufficiently dispersed across cities, dispelling suspicions of correlated shocks among different cities.

Table 3
Bartik IV Regression

	OLS	2SLS	
	(1)	(2)	(3)
	$\ln \text{Export}_{f,p,d,t}$	$\ln \text{SoftReg}_{c,j,t}$	$\ln \text{Export}_{f,p,d,t}$
Bartik IV	0.091***	0.404***	
	(0.034)	(0.138)	
$\ln \text{SoftReg}_{c,j,t}$			0.226***
			(0.079)
$\alpha_{f,t}$	Y	Y	Y
$\lambda_{p,d,t}$	Y	Y	Y
N	4852289	4852289	4852289

Note: The first column presents the reduced-form estimates of the Bartik instrument's effects on the dependent variable. Columns (2) and (3) display the 2SLS regression results, where column (2) corresponds to the first-stage regression results, and column (3) presents the IV estimation results. All regressions control for firm-year fixed effects and product-destination country-year fixed effects. Standard errors are clustered at the city level and reported in parentheses. *** p < 0.01. ** p < 0.05. * p < 0.1.

We employ the Bartik IV constructed based on Equation (2) to address potential endogeneity issues in the baseline identification. The first column of Table 3 shows the city-industry exposed to higher software growth rates significantly exhibit larger export values by applying instruments in OLS. To further test the instruments efficiency, we extend OLS into 2SLS to show the first stage results. The first stage shows that the Bartik IV is significantly positive, confirming that the instrument satisfies the necessary relevance conditions (column (2)). The second-stage reveals that the 2SLS estimates are consistent with the baseline results (column (3)). This indicates that after using the instrument to eliminate potential endogeneity interference, our baseline conclusion remains valid. These evidences suggest a causal relationship between software quantity and export.

[3] The share is transformed to the type level based on the equivalence moment condition (Borusyak et al., 2022), so 1/HHI reflects the degree of dispersion of the transformed share.

4.3 Robustness

4.3.1 Alternative explanatory variable

In our baseline regression, we utilized the increment in software quantity at the city-industry level as a proxy for digital economic development. However, a potential concern arises that this increment may primarily reflect contemporaneous activity in the digital economy for the city-industry, rather than fully capturing the cumulative level of digital economic development. Cities and industries with larger existing software quantities may exhibit greater growth potential in digital software, consequently leading to higher observed increments in the data. To address this concern, we computed the logarithm of the software stock applied for at each city-industry level as an additional core explanatory variable. This variable aims to investigate its impact on internal firm export activities.

The results of this examination are reported in the first column of Table 4. Our findings indicate that the software stock at the city-industry level also effectively promotes internal firm export activities. Whether considering the activity level or the cumulative scale of applications. Our results consistently underscore the driving role of digital economic development in city-industries for internal manufacturing industry exports.

4.3.2 Excluding processing trade

Following China's accession to the WTO, Chinese firms significantly integrated themselves into the global value chain through extensive processing trade, which typically constitutes a substantial share of total exports. However, it's crucial to note that fluctuations in processing trade are more likely influenced by overseas customers rather than changes on the domestic supply side. Therefore, export firms engaged in processing trade may exhibit less sensitivity to local industry's digital economic development compared to other export firms. Nevertheless, there's a noticeable trend in the growth of China's processing trade exports, as observed in previous studies (Manova and Yu, 2016; Dai et al., 2016). This trend could potentially yield a significantly positive "pseudo result" in the data, as it might be correlated with the quantity of software applications at the city-industry level.

To address concerns stemming from export firms engaged in processing trade, we refine the regression sample to exclude processing trade exporters. The results of this analysis are presented in the second column of Table 4. Despite a reduction in sample size by approximately one-third compared to the baseline results, the estimated coefficients remain similar in magnitude. This indicates that our estimates are less likely to be influenced by the "processing trade" export type, and our conclusions remain robust even after excluding the processing trade sample.

Table 4
Robustness Check

	(1) $\ln \text{Export}_{f,p,d,t}$	(2) $\ln \text{Export}_{f,p,d,t}$	(3) $\ln \text{Export}_{f,p,d,t}$	(4) $\ln \text{Export}_{f,p,d,t}$
$\ln \text{SoftStock}_{c,j,t}$	0.038*			
	(0.022)			
$\ln \text{SoftReg}_{c,j,t}$		0.034***	0.033***	0.033***
		(0.008)	(0.008)	(0.008)
N	4852289	9886183	13958951	14535724
$\alpha_{f,t}$	Y	Y	Y	Y
$\lambda_{p,d,t}$	Y	Y	Y	Y
Adjust R^2	0.390	0.392	0.386	0.385

Note: Standard errors are clustered at the city level and reported in parentheses. *** p < 0.01. ** p < 0.05. * p < 0.1.

4.3.3 Eliminate trade intermediaries

Another concern regarding the reliability of the baseline results stems from the presence of trading intermediary firms in the data. In practice, due to incomplete information on export markets, Chinese firms selling products to other countries or regions often do not directly pass through customs. Instead, they utilize trading intermediaries for indirect exports. These trading intermediaries engage not only in indirect export activities but also conduct direct exports leveraging their information advantage. This can directly lead to miscounting of the firm's export behavior, introducing measurement errors. It is crucial to emphasize that trading intermediaries in China contribute to approximately one-fourth of China's total exports. This substantial contribution could have a significant impact on the estimates in our sample.

To address the potential estimation bias introduced by trading intermediaries in the sample, we first identified trading intermediary firms in accordance with Ahn et al. (2011). Subsequently, we excluded them from the sample used in the baseline regression. We find that even after removing trading intermediaries, the coefficient of the core explanatory variable remains significantly positive (Column (3) of Table 4). This indicates that the promotional effect of regional industry's digital software registration on internal firm export activities remains robust and unaffected by the presence of trading intermediaries.

4.3.4 Address transition

We also address concerns regarding potential confounding effects introduced by the relocation of export firms across different cities. In our baseline regression, we control for time-varying factors at the city level by incorporating firm-year fixed effects. However, this approach assumes that each firm strictly corresponds to a single city. If there are firms with changing geographic information over time, solely controlling for firm-year fixed effects may not fully eliminate the impact of city-level unobservable factors. These factors may include improvements in urban transportation infrastructure, enhancements in legal systems, and other variables that could simultaneously influence both software registration and firm exports.

To mitigate potential confounding effects, we identify firms with changes in their geographical location using their geographic information. Subsequently, we exclude these firms from the baseline sample. The last column of Table 4 presents the regression results based on this subsample. Remarkably, even after excluding firms with changing addresses, the software registration at the city-industry level continues to significantly promote the export intensity of internal firms. This underscores the robustness of our findings against the potential influence of firm relocations.

5 Further Discussion

This section further explores the underlying mechanisms through which software registration promotes firm export activities. Additionally, Furthermore, we investigate the heterogeneous effects at the firm, regional, and industry levels. This analysis aims to provide more comprehensive evidence to bolster the baseline conclusions. By exploring these mechanisms and examining the nuances of the effects across different dimensions, we aim to enhance our understanding of how software registration influences firm export activities and strengthen the robustness of our findings.

5.1 Underlying Mechanisms

The development of the digital software at the city-industry level enhances firms' export capabilities through two distinct perspectives. Firstly, it leads to a reduction in production and operational costs for manufacturing firms. Secondly, lots of software mitigate information frictions for exporters in foreign markets. Our findings are reinforced by micro-level evidence at the firm level that supports these two mechanisms. By elucidating how digital economic development influences firms' export capabilities from these perspectives, we provide a comprehensive understanding of the mechanisms underlying the observed effects.

5.1.1 Reduce production and operating costs

The development of the digital economy, particularly with the emergence of digital software, is often regarded as a technological breakthrough in productive service industries (Arora and Gambardella, 2005). These software applications can be seamlessly integrated into the production and operational processes of manufacturing firms, thereby enhancing production efficiency and reducing internal coordination costs. For example, the introduction of design and manufacturing software can significantly decrease labor costs by substituting manual labor. Similarly, the adoption of financial software and application systems can streamline tracking of sales processes and customer activities, leading to a reduction in sales costs. Additionally, company management software and other business applications can greatly decrease management costs by improving communication and collaboration efficiency.

Production cost is a critical factor influencing export decisions for firms (Melitz, 2003; Eaton et al., 2011). The development and widespread use of digital software have substantially lowered production and operational costs for manufacturing firms. This has assisted previously unable-to-export firms in surpassing productivity or cost thresholds, enabling them to enter global markets and increase their export volumes. Thus, the advent of digital software plays a key role in facilitating the entry of firms into global markets and expanding their export activities. [4]

To test above cost effects, we estimate the following mechanism identification equation:

$$Mech_{f,j,t} = \beta \ln \text{SoftReg}_{c,j,t} + \mathbf{X}'\xi + \delta_f + \mu_{j,t} + \varepsilon_{f,j,t} \tag{3}$$

Where $Mech_{f,j,t}$ represents various mechanism variables, reflecting the levels of different costs or other mechanism features for firm f in industry j at time t. Since we are unable to control for firm-year fixed effects (which would absorb all variations in the mechanism variables), we instead control for certain firm-year characteristics, including firm output size, age, capital-labor ratio, state-owned and foreign assets, and the labor productivity. Additionally, we control for firm fixed effects and industry-year fixed effects to account for time-invariant differences among firms and overall supply-demand

[4] We posit that the integration of productive service industries like digital software does not directly help firms improve product quality, hence may not be reflected in changes in export prices, as indicated in Column (1) of Table A3.

fluctuations in the industry.

Table 5
Mechanism: Reduce production and operating costs

	(1) Labor Cost	(2) Selling Cost	(3) Operating Cost	(4) Management Cost
$\ln \text{SoftReg}_{c,j,t}$	-0.022**	-0.049***	-0.020**	-0.031***
	(0.010)	(0.009)	(0.008)	(0.008)
N	329955	329979	306990	329413
Controls	Y	Y	Y	Y
δ_f	Y	Y	Y	Y
$\mu_{j,t}$	Y	Y	Y	Y
Adjust R^2	0.861	0.872	0.804	0.865

Note: Standard errors are clustered at the city level and reported in parentheses. *** p < 0.01. ** p < 0.05. * p < 0.1.

We examine the aforementioned mechanisms using information on firm costs provided by the Annual Survey of Industrial Production Database. Table 5 presents the results of tests for labor costs (wage payments), sales costs, operational costs, and management costs. In column (1) of Table 5, we find that local digital software registration significantly reduces firms' labor wages, which aligns with the notion that digital applications replace labor ((Acemoglu and Restrepo, 2020)). Furthermore, the growth of software at the city-industry level also significantly reduces export firms' sales costs, operational costs, and management costs (Columns (2) to (4) of Table 5). This confirms that the decrease in production and operational costs enables firms to achieve economies of scale, thereby enhancing export levels.

5.1.2 Reduce export information friction

The development of the digital software not only reduces costs for firms but also expands their channels of information. Export decisions heavily rely on obtaining information about destination markets (Fernandes and Tang, 2014; Dickstein and Morales, 2018). Given the costly nature of information transmission due to limited geographical distance, firms often cautiously search for destination markets. However, the internet and the software industry effectively alleviate this concern. Simple information retrieval and online business communication enable firms to access a wealth of market information, significantly reducing information frictions in export markets and leading to an increase in the marginal expansion of firm exports.

Directly identifying the information cost is challenging due to limited data availability. However, the reduction in information frictions implies that firms can improve product turnover efficiency. As capacity enhancement takes time, firms can quickly respond to new market demands by adjusting inventory, resulting in reduced inventory levels. Additionally, firms can export a greater variety of products to multiple destination markets. This paper employs inventory, HS6 product variety, and destination markets to indirectly capture information friction costs. The results are reported in Table 6.

Firstly, we examine the impact of city-industry level software application growth on firm inventory. Column (1)'s result validates this hypothesis, indicating that the development of the software indeed reduces the inventory of export firms, with statistical significance at the 10% level. Next, we further verify the influence of city-industry level software growth on the marginal expansion of firm exports. We find that firms in regions and industries with faster software growth tend to export more products (as shown in Column (2)). Additionally, the results in Column (3) confirm that these export firms also have access to more export markets. This indicates that the development of the digital economy does help firms export more products and serve more markets.

Table 6
Mechanism: Reduce export information friction

	(1) Inventory	(2) HS6 Product Num	(3) Export Market Num
$\ln \text{SoftReg}_{c,j,t}$	-0.017*	0.249**	1.004***
	(0.010)	(0.112)	(0.344)
N	323218	330087	330087
Controls	Y	Y	Y
δ_f	Y	Y	Y
$\mu_{j,t}$	Y	Y	Y
Adjust R^2	0.815	0.669	0.649

Note: Standard errors are clustered at the city level and reported in parentheses. *** p < 0.01. ** p < 0.05. * p < 0.1.

5.2 Heterogeneous Effects

5.2.1 Heterogeneity of firm ownership

Chinese firms often exhibit significant differences in market performance due to substantial variations in ownership types, leading to diverse reactions in terms of the purpose and efficiency of using digital software.

State-owned enterprises (SOEs) typically undertake economic tasks to hedge economic fluctuations and stabilize employment. They tend to participate in market activities according to established development plans, experiencing less impact from market shocks. Private firms, on the other hand, are more susceptible to changes in the market environment and often demonstrate more flexible economic behavior. Therefore, we expect private firms to be more affected by the development of the software industry. Foreign-investment enterprises (FIEs), on the other hand, focus more on labor-intensive processing trade due to relatively low-cost labor and land rent in China. Their exports may be more limited by orders from their home countries. Consequently, the likelihood of being influenced by the development of the digital software is lower for FIEs. Finally, joint ventures (JVs) share characteristics with SOEs and may face challenges in adopting effective measures in response to the software registration due to differences in internal governance concepts.

The economic behavior differences arising from diverse ownership types necessitate an examination of the heterogeneous impact of software registration on firm exports from this perspective. By understanding how ownership types shape firms' responses to the digital economy, we can better comprehend the varied effects of software registration on export performance across different types of firms.

Following the firm ownership type, we divide the sample into four groups: state-owned enterprises, private firms, foreign-investment enterprises, and joint ventures. Table 7 reports the results. Consistent with our hypotheses, we find that the export activities of private firms are more sensitive to the software registration (as shown in Columns (2)). While state-owned enterprises and foreign-funded enterprises show some improvement in export values (Columns (1) and (3)), the overall impact is not significant. Joint ventures even experience a slight decline in export values, though not significant (Columns (4)). These findings suggest that private firms, with their greater flexibility and responsiveness to market changes, are more likely to benefit from the development of the software compared to other ownership types. Conversely, state-owned enterprises, foreign-investment enterprises, and joint ventures may face challenges or have different priorities that limit the positive impact of software registration on their export activities.

Table 7
Heterogeneous Effects of Firms

	$\ln \text{Export}_{f,p,d,t}$			
	(1)	(2)	(3)	(4)
	State-owned	Private	Foreign	Joint
$\ln \text{SoftReg}_{c,j,t}$	0.015	0.052***	0.015	-0.009
	(0.034)	(0.017)	(0.011)	(0.027)
N	493724	4683886	5543486	2947403
$\alpha_{f,t}$	Y	Y	Y	Y
$\lambda_{p,d,t}$	Y	Y	Y	Y
Adjust R^2	0.485	0.422	0.381	0.348

Note: This table presents heterogeneous treatment effects based on firm ownership types. Column (1) includes data on exports from all state-owned firms, Column (2) focuses on exports from all private firms, while Columns (3) and (4) correspond to exports from foreign-investment firms and joint ventures, respectively. Standard errors in parentheses are clustered at the city level. *** p < 0.01. ** p < 0.05. * p < 0.1.

5.2.2 Regional heterogeneity

Different cities exhibit significant differences, particularly in a country like China with complex geographic locations and uneven regional economic development. Therefore, the supporting facilities in different regions, especially the construction of digital infrastructure, vary greatly, thereby affecting the impact of local software registration on firm exports. Exploring the heterogeneous treatment effects on firm exports across different dimensions of Chinese cities will greatly enrich our study.

In Panel A of Table 8, we first examine the differentiated impact of city location characteristics on the influence of software registration on firm exports. We categorize Chinese cities into Eastern and non-Eastern regions (Central and Western regions), following China's official geographical division. As the majority of China's population and economic activities are concentrated in the Eastern region, Eastern cities attract more firms to engage in export activities. We find that the construction of the digital economy at the city-industry level significantly promotes export performance for all cities (Columns (1) and (2)). Interestingly, firms in non-Eastern cities are more sensitive to the local development of the digital software. Following the mechanism test, this may be because firms in the Central and Western regions often face higher export costs and information barriers, making the local software registration more beneficial for these firms.

We also differentiate cities as coastal and inland cities. Coastal cities, with favorable

Table 8
Heterogeneous Effects of Cities

	ln $\text{Export}_{f,p,d,t}$			
Panel A	(1) East Region	(2) Other Region	(3) Coastal city	(4) Inland city
ln $\text{SoftReg}_{c,j,t}$	0.030***	0.071***	0.028***	0.043***
	(0.008)	(0.023)	(0.010)	(0.013)
N	13352742	1047640	9655579	4546390
$\alpha_{f,t}$	Y	Y	Y	Y
$\lambda_{p,d,t}$	Y	Y	Y	Y
Adjust R^2	0.381	0.515	0.373	0.428
Panel B	(5) High RD level	(6) Low RD level	(7) High IS level	(8) Low IS level
ln $\text{SoftReg}_{c,j,t}$	0.031***	0.027	0.024**	0.022
	(0.008)	(0.025)	(0.010)	(0.014)
N	10787125	3605313	9646648	4570681
$\alpha_{f,t}$	Y	Y	Y	Y
$\lambda_{p,d,t}$	Y	Y	Y	Y
Adjust R^2	0.394	0.373	0.389	0.393

Note: This table presents heterogeneous treatment effects concerning urban geographical locations and the level of development in productive services. In Panel A, we present the heterogeneous regression results based on urban geographical factors, while Panel B displays the heterogeneous regression results based on the level of development in productive services. The categorization of urban geographical factors primarily follows the official geographical division standards provided by the Chinese government. The classification of the level of development in productive services is based on the mean values of the respective indicators. Standard errors in parentheses are clustered at the city level. *** p < 0.01. ** p < 0.05. * p < 0.1.

geographical locations, often undertake more export activities due to lower trade costs, and accessing export markets is more convenient for them. Columns (3) and (4) of Table 8 report the regression results for the samples of coastal and inland cities. Consistent with the earlier conclusion, the growth of software applications at the city-industry level promotes exports for both coastal and inland cities, but exports from inland cities are more sensitive to this growth. This suggests that local software registration will favor the inland economy and develop more advantage industry for export.

Secondly, we further investigate the heterogeneous impact of differences in the development of cities in the productive services sector on treatment effects in Panel B of Table

8. As we know, digital software assists firms' production and exports primarily through embedding in regional productive services. In order to reflect the level of development of local productive services, this paper uses local R&D investments as a proxy. We expect that cities with higher R&D investment levels will have more developed productive services, thus promoting firms' production and exports. It can be observed that the enhancing effect of the digital economy or software registration on firm export activities mainly occurs in cities with high R&D investment levels (as shown in Columns (5)), while in cities with lower R&D investment levels, the effect is not significant (see Columns (6)).

Furthermore, we specifically analyze the development of information services (IS) industry in cities for the robustness of productive services. By calculating the average employment in the information services industry in different cities, we categorize cities into high and low levels of information services industry development. The last two columns of Table 8 show the corresponding results. Consistent with the earlier inference, the growth of software applications significantly promotes firm exports only in cities with a high level of development in the information services industry.

5.2.3 Industry heterogeneity

The factor density of a product is a key factor affecting a firm's exports, with inherent differences in the intensity of production factors and production technology in the manufacturing industry. To examine the impact of software usage in different manufacturing industries on enterprise exports, we categorizes industries into high-tech and low-tech, labor-intensive, and capital-intensive industries.

According to the mechanism outlined in this paper, digital software registration primarily reduces the production and export costs of firms by enhancing the technological capabilities of the productive service industry. This requires the presence of a certain foundation of technology-intensive productive service demand within the industry. Put differently, the sensitivity of export activities in different industries to the software registration within the industry is not uniform.

Firstly, we classify the export industries in the sample into high-tech and low-tech industries based on the OECD classification of high-tech sectors. [5] High-tech industries exhibit a much higher demand for technology-intensive productive services compared to low-tech industries such as apparel manufacturing and food manufacturing. The re-

[5]High-tech industries include pharmaceutical manufacturing, transportation equipment manufacturing, electronic and communication equipment manufacturing, computer equipment manufacturing, medical and precision instrument manufacturing, and information chemical manufacturing, while the rest are categorized as low-tech industries.

gression results for the sub-sample are reported in columns (1) and (2) of Table 9. The development of the software enhances the exports of firms in both high-tech and low-tech industries, with a more pronounced effect on exports in high-tech industries.

Table 9
Heterogeneous Effects of Industries

	$\ln \text{Export}_{f,p,d,t}$			
	(1)	(2)	(3)	(4)
	High Tech	Low Tech	Labor Intensive	Capital Intensive
$\ln \text{SoftReg}_{c,j,t}$	0.038**	0.020**	0.007	0.030***
	(0.019)	(0.008)	(0.028)	(0.010)
N	5304640	9346008	4693971	9979863
$\alpha_{f,t}$	Y	Y	Y	Y
$\lambda_{p,d,t}$	Y	Y	Y	Y
Adjust R^2	0.357	0.442	0.355	0.401

Note: This table presents heterogeneous analysis results based on industry technological, labor, and capital intensity characteristics. Standard errors in parentheses are clustered at the city level. *** p < 0.01. ** p < 0.05. * p < 0.1.

Secondly, we categorize industries into labor-intensive and capital-intensive based on the capital-labor ratio. Labor-intensive industries, such as construction, agriculture, and mining, rely mainly on low-skilled labor for production, resulting in lower sensitivity to software registration and digital economic development. Conversely, capital-intensive industries exhibit the opposite characteristics. Column (3) shows that the impact of digital economic development on export promotion for labor-intensive firms is limited and statistically insignificant in labor-intensive industries. However, software registration significantly promotes the export activities of firms in capital-intensive industries (see Column (4)).

5.2.4 Destination heterogeneity

The impact of export demand is the main motivation for promoting firm exports (Aghion et al., 2022). Differences in demand preferences from different countries are also key factors affecting the export profits of firms. Examining the heterogeneity tests on these destination markets can provide more robust evidence for our mechanism analysis.

From the perspective of export destinations, gravity models typically assert that factors such as the size of the destination market, its income level, and the geographical distance can explain over 90% of trade volume between two locations (Bergstrand, 1985; Chaney, 2018). These trade theories suggest that exporting to markets with larger size, higher income levels, and closer geographical proximity is easier, since the export costs to these markets are lower. Conversely, exporting to small-scale markets, low-income markets, and distant markets is more sensitive to cost reductions. We verify these dimensions of heterogeneity in destination markets to provide further evidence supporting the theoretical mechanisms.

Table 10
Heterogeneous Effects of Countries

	$\ln \text{Export}_{f,p,d,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	Large Economy	Small Economy	High Income	Low Income	Far Shore	Near Shore
$\ln \text{SoftReg}_{c,j,t}$	0.021***	0.049***	0.018**	0.056***	0.039***	0.029***
	(0.007)	(0.011)	(0.008)	(0.012)	(0.009)	(0.008)
N	7774504	6649768	8640964	5784728	8407472	6020419
$\alpha_{f,t}$	Y	Y	Y	Y	Y	Y
$\lambda_{p,d,t}$	Y	Y	Y	Y	Y	Y
Adjust R^2	0.376	0.424	0.374	0.433	0.390	0.401

Note: This table presents regression results based on the heterogeneity of export destination markets. The basis for the economic and geographic classification of destination markets is sourced from CEPII's Gravity database. We categorize destination markets based on mean levels of relevant indicators into large and small economies, high and low-income markets, and near and distant markets. Standard errors in parentheses are clustered at the city level. *** p < 0.01. ** p < 0.05. * p < 0.1.

Specifically, we classify all export markets in the sample according to CEPII's Gravity database. Table 10 reports heterogeneity regression results based on the economic and geographic dimensions of destination countries. Firstly, we differentiate export destination markets into large and small economies based on the total economic size (GDP) of the destination country (whether it is above the average level). Columns (1) and (2) show the corresponding regression results, indicating that the software registration significantly enhances exports to all economies, with a more pronounced effect on exports to small-scale markets. Secondly, we categorize export markets based on the per capita income level of countries and regions into high-income and low-income markets, and display the corresponding regression results in columns (3) and (4). Consistent with our expectations, the software registration promotes exports to both high-income and low-income countries, but the effect is more pronounced for exports to low-income markets. Finally, we classify export markets based on the geographical distance between the destination market and China into near and distant markets, with the regression results for the respective samples shown in columns (5) and (6). Similarly, although the software registration enhances exports to all markets, firms exporting to distant markets are more sensitive to this change. All heterogeneity test results are consistent with our hypotheses, indicating the robustness of our mechanism analysis results.

6 Conclusion

In the extensive literature exploring the relationship between the digital economy and the real economy, the specific aspect of software development, a pivotal component of the digital economy, has been somewhat overlooked by scholars. This study addresses this gap by leveraging unique micro-level data on software applications to investigate the connection between city-industry level software applications and the export activities of manufacturing firms in developing countries.

Utilizing rigorous fixed-effects controls and constructing corresponding Bartik instruments, our findings reveal a significant positive relationship between the quantity of software applications at the city-industry level and the exports of domestic firms. This conclusion remains robust even after accounting for potential confounding effects. We propose that the development of the digital economy, as represented by software applications, primarily influences firm exports through two distinct channels. Firstly, the growth of digital software enhances the quality of industry-level productive services, thereby reducing the production and operational costs of manufacturing firms. Secondly, digital software stimulates firms to expand their export portfolio to more markets by mitigating frictions in export market information.

Further heterogeneity analysis deepens our understanding of how the digital economy fosters the export activities of real entities, providing robust evidence for the mechanisms mentioned. Our research contributes to a broader perspective on the interplay between the digital economy and the real economy, and we anticipate additional evidence from other countries in the future.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The work was supported by the Shanghai University of Finance and Economics Graduate Innovation Fund Project.

References

Acemoglu, D. and P. Restrepo (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy 128*(6), 2188–2244.

Adao, R., M. Kolesár, and E. Morales (2019). Shift-share designs: Theory and inference. *The Quarterly Journal of Economics 134*(4), 1949–2010.

Aghion, P., A. Bergeaud, M. Lequien, and M. J. Melitz (2022). The Heterogeneous Impact of Market Size on Innovation: Evidence from French Firm-Level Exports. *The Review of Economics and Statistics*, 1–56.

Ahn, J., A. K. Khandelwal, and S.-J. Wei (2011). The role of intermediaries in facilitating trade. *Journal of International Economics 84*(1), 73–85.

Arnold, J. M., B. S. Javorcik, and A. Mattoo (2011). Does services liberalization benefit manufacturing firms?: Evidence from the Czech republic. *Journal of International Economics 85*(1), 136–146.

Arora, A. and A. Gambardella (2005). The globalization of the software industry: perspectives and opportunities for developed and developing countries. *Innovation Policy and the Economy 5*, 1–32.

Artuc, E., P. Bastos, and B. Rijkers (2023). Robots, tasks, and trade. *Journal of International Economics 145*, 103828.

Bas, M. and V. Strauss-Kahn (2015). Input-trade liberalization, export prices and quality upgrading. *Journal of International Economics 95*(2), 250–262.

Bergstrand, J. H. (1985). The gravity equation in international trade: some microeconomic foundations and empirical evidence. *The Review of Economics and Statistics*, 474–481.

Bojnec, S. and I. Ferto (2010). Market-creating effect of the internet on food trade. Technical report.

Borusyak, K., P. Hull, and X. Jaravel (2022). Quasi-experimental shift-share research designs. *The Review of Economic Studies 89*(1), 181–213.

Brandt, L., J. Van Biesebroeck, L. Wang, and Y. Zhang (2017). Wto accession and performance of chinese manufacturing firms. *American Economic Review 107*(9), 2784–2820.

Cao, Y., S. Chen, and H. Tang (2021). Robots, productivity, and firm exports. *SSRN Working Paper*, No. 3980375.

Chaney, T. (2014). The network structure of international trade. *American Economic Review 104*(11), 3600–3634.

Chaney, T. (2018). The gravity equation in international trade: An explanation. *Journal of Political Economy 126*(1), 150–177.

Chen, W.-C. and X. Bao (2023). Technical barriers to trade and china's exports: firm-level evidence. *Applied Economics 55*(17), 1919–1938.

Chor, D., K. Manova, and Z. Yu (2021). Growing like China: Firm performance and global production line position. *Journal of International Economics 130*, 103445.

Dai, M., M. Maitra, and M. Yu (2016). Unexceptional exporter performance in China? the role of processing trade. *Journal of Development Economics 121*, 177–189.

DeStefano, T. and J. Timmis (2024). Robots and export quality. *Journal of Development Economics 168*, 103248.

Dickstein, M. J. and E. Morales (2018). What do exporters know? *The Quarterly Journal of Economics 133*(4), 1753–1801.

Eaton, J., S. Kortum, and F. Kramarz (2011). An anatomy of international trade: Evidence from French firms. *Econometrica 79*(5), 1453–1498.

Fan, H., Y. A. Li, S. Xu, and S. R. Yeaple (2020). Quality, variable markups, and welfare: A quantitative general equilibrium analysis of export prices. *Journal of International Economics 125*, 103327.

Fan, J., L. Tang, W. Zhu, and B. Zou (2018). The alibaba effect: Spatial consumption inequality and the welfare gains from e-commerce. *Journal of International Economics 114*, 203–220.

Fernandes, A. M. and C. Paunov (2012). Foreign direct investment in services and manufacturing productivity: Evidence for Chile. *Journal of Development Economics 97*(2), 305–321.

Fernandes, A. P. and H. Tang (2014). Learning to export from neighbors. *Journal of International Economics 94*(1), 67–84.

Ferro, E. (2011). Signaling and technological marketing tools for exporters. *World Bank Policy Research Working Paper* (5547).

Freund, C. L. and D. Weinhold (2004). The effect of the internet on international trade. *Journal of International Economics 62*(1), 171–189.

Frey, C. B. and M. A. Osborne (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change 114*, 254–280.

Goldfarb, A. and C. Tucker (2019). Digital economics. *Journal of economic literature 57*(1), 3–43.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift (2020). Bartik instruments: What, when, why, and how. *American Economic Review 110*(8), 2586–2624.

Graetz, G. and G. Michaels (2018). Robots at work. *Review of Economics and Statistics 100*(5), 753–768.

Herman, P. R. and S. Oliver (2023). Trade, policy, and economic development in the digital economy. *Journal of Development Economics 164*, 103135.

Hoekman, B. and B. Shepherd (2017). Services productivity, trade policy and manufacturing exports. *The World Economy 40*(3), 499–516.

Kee, H. L. and H. Tang (2016). Domestic value added in exports: Theory and firm evidence from China. *American Economic Review 106*(6), 1402–1436.

Lederman, D. and M. Zouaidi (2022). Incidence of the digital economy and frictional unemployment: International evidence. *Applied Economics 54*(51), 5873–5888.

Lodefalk, M. (2014). The role of services for manufacturing firm exports. *Review of World Economics 150*, 59–82.

Mallick, H. (2014). Role of technological infrastructures in exports: evidence from a cross-country analysis. *International Review of Applied Economics 28*(5), 669–694.

Manova, K. and Z. Yu (2016). How firms export: Processing vs. ordinary trade with financial frictions. *Journal of International Economics 100*, 120–137.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica 71*(6), 1695–1725.

Mostafa, R. H., C. Wheeler, and M. V. Jones (2005). Entrepreneurial orientation, commitment to the internet and export performance in small and medium sized exporting firms. *Journal of International Entrepreneurship 3*, 291–302.

Ricci, L. A. and F. Trionfetti (2012). Productivity, networks, and export performance: Evidence from a cross-country firm dataset. *Review of International Economics 20*(3), 552–562.

Wheatley, W. P. and T. L. Roe (2008). The effects of the internet on us bilateral agricultural trade. *Journal of International Agricultural Trade and Development 4*(2), 231–253.

Yadav, N. (2014). The role of internet use on international trade: Evidence from Asian and Sub-Saharan African enterprises. *Global Economy Journal 14*(2), 189–214.

Zhang, H., Q. Liu, and Y. Wei (2023). Digital product imports and export product quality: Firm-level evidence from china. *China Economic Review 79*, 101981.

Appendix

Overall, the sample includes most software categories, widely utilized in industry activities, enterprise management, project management, business operations, and other information processing tasks. The extensive use of these software tools in enterprise productivity services can enhance operational efficiency, as well as information gathering, processing, and communication capabilities. It is noteworthy that the distribution of software categories in the sample is quite diverse, providing a good starting point for constructing the Shift-share IV. We utilize the total growth rate of specific category software as the exogenous shock and the pre-share of specific categories in regional industries as the exposure level to construct the Shift-share IV. This is because the overall supply shock of a specific software category is less likely to be influenced by the characteristics of specific regional industries but is more likely to be influenced by the market demand from all potential industries nationwide that may use this software category.

Table A1
Software Categories in the Sample

Category code	Software category	Ratio
10000～10900	Basic software and underlying system	5.37
12000～19900	System related software	3.69
20000～20900	Middleware	2.17
30000～30105	General application	8.27
30106	Enterprise management	4.71
30107～30108	Auxiliary software	1.38
30109	Network information	0.84
30200	Industry application	10.28
30201	Government	1.23
30202～30205	Business software	3.91
30206	Communication software	1.26
30207～30211	Exclusive Software	6.58
30212	Accounting software	0.41
30213	Statistical software	0.58
30219	Other application software	2.63
30300～30309	Textual processing	1.75
30900	Other general software	0.7
31000～39900	Software development and support tools	2.23
40000	Embedded application	2.92
61000～64000	Science and engineering	7.1
65000	Transaction management	10.96
66000	Control software	5.16
66500～67500	Intelligent and simulation	6.05
68000	Security and confidentiality	0.92
68500	Social services	0.56
69000	Game	1.41
69900	Others	6.93
Total		100

Note: This table presents the distribution of software categories in our sample.

Table A2
Main Variable Summary Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
$\ln \text{Export}_{f,p,d,t}$	15,482,309	9.604204	2.780274	0	23.5117
$\ln \text{Volume}_{f,p,d,t}$	15,338,901	7.610798	3.339766	0	24.05424
$\ln \text{Price}_{f,p,d,t}$	15,338,900	2.04414	2.279647	-12.6975	20.13463
$\ln \text{SoftReg}_{f,p,d,t}$	15,482,318	0.724373	1.26305	0	6.698268
Bartik IV	4,852,289	0.179647	0.259814	0	1.634783
Labor Cost	518,288	8.340851	1.373068	0	16.99738
Selling Cost	643,642	10.78628	1.404899	0	19.16658
Operating Cost	641,435	7.073734	1.770105	0	17.07045
Management Cost	643,579	7.905068	1.469982	0	17.4721
Inventory	642,520	8.698616	1.799487	0	17.45033
HS6 Num	713,154	6.987349	14.03482	1	1129
Export Market Num	713,154	21.80158	51.86924	1	5961

Note: Labor Cost, Selling Cost, Operating Cost, Management Cost, Inventory, HS6-Product-Num and Export-Market-Num are firm-level variables, and all kinds of costs and inventories are in logarithmic form.

Table A3
Decomposition of firm exports

	(1)	(2)
	$\ln \text{Price}_{f,p,d,t}$	$\ln \text{Volume}_{f,p,d,t}$
$\ln \text{SoftReg}_{f,p,d,t}$	-0.007	0.037***
	(0.009)	(0.012)
N	14408242	14408243
$\alpha_{f,t}$	Y	Y
$\lambda_{p,d,t}$	Y	Y
Adjust R2	0.808	0.548

Note: Standard errors reported in brackets, are heteroskedasticity-robust and clustered at the city level. *** p < 0.01. ** p < 0.05. * p < 0.1.