Digital Economy and Export Product Switching

Abstract: Leveraging data from ASIF, the Chinese Custom Database, and the China City Statistical Yearbook, this paper develops a comprehensive city-level digital economy index to assess its impact on Chinese export enterprises' product switching. The results show that: First, there are regional disparities in digital economy's development, with a distinct "East-Central-West" and "Coastal-Inland" divide, indicating uneven progress across regions. Second, digital economy significantly promotes Chinese export enterprises' product switching, particularly through the introduction of new products. At the same time, its influence varies across firm types, with high-tech, private, general trade and eastern enterprises showing the most pronounced effects. Third, this paper identifies innovation and information cost reduction as key mechanisms through which digital economy enhances export product switching.
Keywords: digital economy; product switching; innovation effect; information cost reduction effect

I. Introduction

Digital economy, a transformative force, is reshaping production, lifestyle, and governance, thereby altering the global economic landscape and patterns of international competition. Recognizing the huge potential of digital market and the swift global progress in this field, China's "The 14th Five-Year Plan" clearly emphasizes the strategic integration of digital technologies with industry and trade. The Chinese government prioritizes accelerating digital economic development, aiming to foster deeper integration with the real economy and establish a globally competitive digital industry cluster. By 2021, China's digital economy had grown to 45.5 trillion yuan, contributing 39.8% to the GDP, and ranking as the world's second-largest digital economy.

Export trade is pivotal to a nation's economic vitality, with its scale and structure reflecting the country's economic development and international competitiveness. China's export trade, a significant driver of economic growth since the reform and opening-up, now faces challenges such as slower growth, structural transformation, and inadequate support for high-tech industries. The COVID-19 pandemic and trade frictions have exacerbated these issues. In this context, enterprises may diversify their export products to maintain stability, raising the question of digital economy's impact on export product switching. This paper investigates the channels through which digital economy affects such switching and its heterogeneous impact on different types of enterprises, as well as its potential to promote high-quality development.

This paper provides marginal contributions in the following four aspects: (i) Expanding the existing research on export product switching. While previous studies have examined various factors influencing export product switching, such as enterprise size, age, and trade liberalization, there is a dearth of research that investigates the micro-level impact of digital economy on export product switching. This paper aims to address this gap by constructing digital economy indexes and analyzing its potential influence through two channels: innovation and information cost reduction. (ii)Enriching digital economy research. this paper introduces a novel approach to measuring digital economy at the city level by employing an entropy value method. This method provides a more objective assessment of digital economy's development from 2007 to 2013, enhancing the empirical understanding of its regional dynamics and disparities. (iii) Exploring new mechanisms. By focusing on the effects of innovation and information costs, this study deepens the understanding of how digital economy influences micro-level economic activities. It reveals the pathways through which digital advancements can lead to export product diversification and innovation, offering valuable insights that complement existing research. (iv) Policy Relevance. Beyond academic analysis, this paper's findings have practical implications for policymakers. By examining the mechanisms of export product switching, it provides insights into the broader economic impacts of digital economy. This information is crucial for assessing policy outcomes and for the development of strategies that leverage digital technologies to optimize trade structures and foster high-quality economic development.

This paper is organized as follows: the second part is the literature review and theoretical analysis; the third part is empirical evidence; the fourth part is the research design; the fifth part is the empirical results; the sixth part is the upgrading effect of digital economy; and finally, conclusion.

II. Literature Review and Theoretical Analysis

1. Literature review

There are three main branches of literature related to this research, each providing a foundation for the research presented in this paper.One of which is the measurement of digital economy indicators. The measurement of digital economy has been a topic of significant interest, yet the absence of a universally accepted statistical standard has led to a diversity of approaches. Scholars have employed various methods to quantify digital economy, such as constructing comprehensive indices to reflect its development (Liu et al., 2020; Zhao et al., 2020; Bo & Zhang, 2021), and measuring its growth incrementally (Xu & Zhang, 2020; Cai et al., 2021; Bai et al., 2022). Despite these efforts, the lack of a standard framework has resulted in a proliferation of indicators, indicating the need for further refinement and consolidation.

Furthermore, theoretical and empirical studies have explored digital economy's role in reducing information and transaction costs in the trade process (Sun, 2020) and enhancing enterprise innovation activities (Zhao et al., 2020). Empirical research has primarily focused on the direct effects of digital economy on export efficiency and growth. For instance, Fan (2021) found that digital economy can effectively reduce the loss of export efficiency in China, while Zhong and Wang (2022) demonstrated that it promotes the growth of export trade in Chinese cities. Digital economy's transformative potential for export upgrading has also been recognized, with studies showing that it can mitigate distortions in the allocation of labor and capital factors, leading to industry upgrading (Ma & Ning, 2020). Additionally, Du et al. (2022) found that digital transformation improves the quality of export products, and Xie & Wang (2022) reported that digital economy significantly enhances the quality of enterprises' export products. Xia et al. (2022) found that digital economy positively affects export technical complexity at the provincial level. These studies provide valuable insights into digital economy's impact on export behavior and upgrading. However, there is a gap in the literature regarding digital economy's influence on export product switching and its potential to facilitate export upgrading, which this paper aims to address.

The other branch is mainly based on the theoretical model of heterogeneous firms to study the internal and external factors affecting firms' export product switching. The theoretical model of heterogeneous firms has been instrumental in understanding how firms respond to internal and external shocks through product switching. Firms are known to reallocate resources by adding new product categories, reducing existing ones, or a combination of both, in response to shocks (Bernard et al., 2010; Mayer & Melitz, 2014). This phenomenon is globally observed and has been studied extensively (Kawakami & Miyagawa, 2010; Goldberg et al., 2010; Miranda et al., 2012; Qian &

Wang, 2013; Yin et al., 2018; Feng, 2020). Research has also examined the influence of firm attributes, such as size (Bernard & Okubo, 2013) and age (Timoshenko, 2015), on export product switching. Furthermore, scholars have investigated the effects of changing external environments on export product switching. For example, Bernard (2011) and Eckel & Neary (2010) analyzed the impact of trade liberalization, finding that increased market competition leads firms to abandon marginal products in favor of those with lower marginal costs and stronger core competitiveness. Kang and Tian (2016) reinforced this viewpoint using Chinese data. Other studies have examined the impact of new market entry costs, destination market competitiveness, business cycles, external demand changes, host country factor endowments, foreign investment, industrial integration, and financing constraints (Miranda et al., 2012; Mayer & Melitz, 2014; Bernard & Okubo, 2015; Hu et al., 2017; Ma et al., 2014; Fan, 2018; Cheng, 2020; Sang et al., 2021). These studies have provided a comprehensive understanding of how external environmental changes affect firms' export product switching strategies.

This paper introduces digital economy as a novel external environmental factor that influences export product switching. Building upon the existing research, it aims to expand the understanding of the external factors that affect export product switching, particularly focusing on the role of digital economy in this process.

2. Theoretical analysis

(i) Digital economy and export switching

The integration of digital economy into modern production processes has introduced data as a novel factor, complementing traditional inputs such as labor, capital, and technology. This integration significantly influences how resources are allocated and how businesses operate.

Data, unlike traditional factors, possesses non-exclusivity, reproducibility, and shareability, which allows for more efficient production processes and the enhancement of output quality, thereby improving product structures. Moreover, the integration of data with traditional factors can lead to improvements in labor, knowledge, management, and technological efficiency, reducing the per-unit cost of production inputs and facilitating product switching (Xie et al., 2020; Ghasemaghaei & Calic, 2019).

Digital technologies, such as CNC machine tools, information platforms, and artificial intelligence, have revolutionized production, enabling enterprises to upgrade their production processes and shift towards intelligence and automation (DeStefano &

Timmis, 2021). These technologies also facilitate low-marginal-cost innovation in production technology (Nambisanet et al., 2017).

Furthermore, digital technology enhances firms' understanding of market demand, guiding the strategic development of new products and the implementation of export product switching. In digital economy, a closer connection with consumer demand directly influences the diversity of export products. Big data, cloud computing, and artificial intelligence enable enterprises to accurately gauge consumer demand for new products and technologies (Peng & Zhang, 2022), mitigating the transactional challenges of information asymmetry. This not only improves market acceptance for new products but also reduces the risks associated with product innovation (Song, 2020). By employing algorithms and machine learning, firms can analyze consumer behavior trends and shape consumer demand, ensuring that new products meet the growing demand for personalization. This innovation in product development positively impacts export product switching.

In conclusion, considering digital economy's influence on both production upgrading and export choices, this paper posits that digital economy is a key determinant in export product switching. Consequently, this paper proposes the following hypothesis:

Hypothesis 1: Digital economy positively influences export product switching.

(ii) The innovation effect of digital economy

In the contemporary business landscape, product innovation has become a critical strategy for enterprises to diversify their offerings and facilitate export product switching. This is particularly evident in digital economy era, where technologies such as big data, cloud computing, and the Internet of Things (IoT) significantly contribute to the innovation process. The seamless integration of these technologies necessitates efficient coordination and collaboration across various departments within an enterprise. However, internal communication barriers can lead to friction and increased costs, impeding the innovation process.

Digital economy has mitigated these challenges by leveraging network information platforms that enhance data exchange and communication across different internal systems. Shen & Yuan (2020) highlight that such platforms improve management structures and communication efficiency, thereby reducing innovation barriers and fostering innovation development (Calic & Ghasemaghaei, 2021). The adoption of platforms like DingTalk has been shown to increase internal collaboration efficiency by 50% within the first year and save nearly 1.5 million yuan in application development costs over three years (Forrester), demonstrating the transformative impact of digital tools on enterprise innovation.

Furthermore, digital economy has facilitated the transition from closed-source research to collaborative research, accelerating the dissemination of knowledge and technology (Paunov & Rollo, 2016). Enterprises can now learn from the advanced technologies of others, creating an environment conducive to technological innovation and minimizing the duplication of efforts and resource wastage. Cross-regional cooperation and the sharing of supply chain information and resources through network platforms have further accelerated the integration of innovation knowledge, enhancing the innovation capabilities of enterprises.

Digital economy has also shifted the paradigm of product research and development from experience-driven to data-driven (Johnson et al., 2017). The ubiquity of mobile internet has made it more accessible and cost-effective for enterprises to gather consumer feedback, enabling them to better understand and cater to personalized consumer demands (Tan et al., 2016). This shift has spurred enterprises to innovate technologically to produce products that meet these evolving needs.

In summary, digital economy acts as a catalyst for enterprise product innovation, which in turn leads to increased rates of product switching. Based on these insights, this paper proposes the following hypothesis:

Hypothesis 2: Digital economy provides the technical infrastructure for enterprise technological innovation, reduces internal barriers to innovation, fosters collaborative innovation, and expands the space for innovation, thereby encouraging enterprises to develop new products and achieve export product switching.

(iii) The Information Cost Effect of Digital economy

Traditional international trade theory emphasizes the role of geographic distance as a determinant of trade, with increased distance typically correlating with higher transportation costs and information costs (Huang, 2007; Allen, 2014). This dynamic makes it challenging for enterprises to identify potential customer groups, leading to increased export costs and adversely affecting export activities (Shi, 2016).

Digital economy has transformed this landscape by mitigating the impact of geographic distance on trade and directly reducing information costs. The proliferation of digital technologies has integrated the global information market, enabling enterprises to access detailed market insights, consumer preferences, and competitor status with enhanced speed and accuracy through search engines (Hoag, 2006; Mondria et al., 2010). Additionally, consulting firms like McKinsey and Roland Berger provide enterprises with valuable information on trade procedures, legal regulations, and cultural nuances, significantly reducing the costs associated with market research.

In contrast to the traditional trading model, which relies on historical transaction data and suffers from information lag, digital economy offers a platform-based trading model that allows enterprises to showcase their business scope and product offerings through corporate websites, microblogs, and e-commerce platforms. This shift enables more accurate market forecasting and responsive export strategies.

Advanced technologies such as machine learning and big data further enhance the ability of enterprises to analyze consumer behavior, including search keyword frequency, consumption patterns, and browsing habits, to gain a comprehensive understanding of market demand (Buffington et al., 2017). These tools also facilitate data-driven decision-making (Li et al., 2020), allowing enterprises to optimize their goals and strategies.

In summary, the reduction in information costs facilitated by digital economy is expected to encourage enterprises to adapt their export product mix, leading to increased product switching. This insight forms the basis for the following hypothesis:
Hypothesis 3: Digital economy's reduction in information costs incentivizes enterprises to adjust their export product mix, thereby facilitating export product switching.

III. Empirical Evidence

To investigate the potential relationship between digital economy and export product switching, this paper leverages data from authoritative sources, including the China Statistical Yearbook, the China City Statistical Yearbook, and the China Internet Network Information Center (CNNIC). These data sets are employed to construct indicators of digital economy and to create a comprehensive map that illustrates the development levels of China's digital economy across different regions. Furthermore, data from the China Customs Import and Export Database is utilized to develop an export product switching indicator. The analysis of these data sets aims to reveal the correlation between digital economy and export product switching, providing insights into the potential influence of digital economy on export product diversification.

Figure 2 presents the development levels of China's digital economy in 2007 and 2013, indicating a general upward trend nationwide. Despite this growth, there is a notable disparity in digital economy's development across regions, following a pattern of "east-central-west" and "coastal-inland" in descending order. The uneven development of digital economy persists, with the eastern region benefiting from earlier growth due to the country's reform and opening-up policies. To address this imbalance, China has implemented policies such as the Western Development, the Revitalization of Northeast China, and the Rise of Central China. However, the full impact of these policies is still emerging, leading to varied economic conditions and corresponding levels of digital economy development in the eastern, central, and western regions.

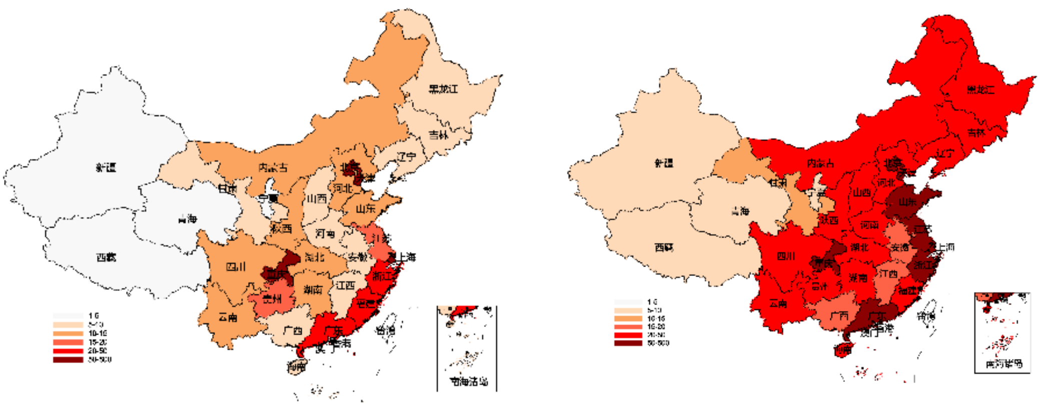

Figure 2: The development levels of China's digital economy（left 2007 right 2013）

Table 1: Annual Statistics of Enterprises Engaging in Export Product Switching

	add		drop		both		none	
year	Q	P	Q	P	Q	P	Q	P
2006-2007	64068	33.89%	17219	9.11%	85388	45.17%	22381	11.84%
2007-2008	62482	30.94%	23915	11.84%	86786	42.98%	28746	14.24%
2008-2009	65720	31.08%	24798	11.73%	90519	42.81%	30429	14.39%
2009-2010	78880	33.80%	23792	10.20%	96171	41.21%	34524	14.79%
2010-2011	77885	30.71%	29309	11.56%	105818	41.73%	40587	16.00%
2011-2012	80635	29.97%	30076	11.18%	115390	42.89%	42922	15.95%
2012-2013	86786	30.79%	34910	12.39%	111578	39.59%	48566	17.23%
average		31.60%		11.14%		42.34%		14.92%

Enterprises regularly adapt their product portfolios to optimize resource allocation and respond to shifting external demands. These adjustments typically manifest as expansions or contractions in the range of products offered. Table 1 provides a snapshot of the product switching behaviors observed among multi-product exporting enterprises. The data reveals that, on average, 31.6% of enterprises introduce new export products, and 11.14% reduce their export offerings. Notably, a substantial 42.34% of enterprises engage in both adding and subtracting products from their export portfolios. This pattern underscores the ubiquity of product switching, with over 85% of enterprises participating in at least one form of portfolio adjustment, highlighting the dynamic nature of global market requirements and strategic resource management.

Building upon the observed growth trends in digital economy and export product switching, this paper conducts a correlation analysis to examine the relationship between these two factors across various regions, as depicted in Figure 3. The results reveal a significant positive correlation in all regions, with the eastern region exhibiting an especially pronounced association.

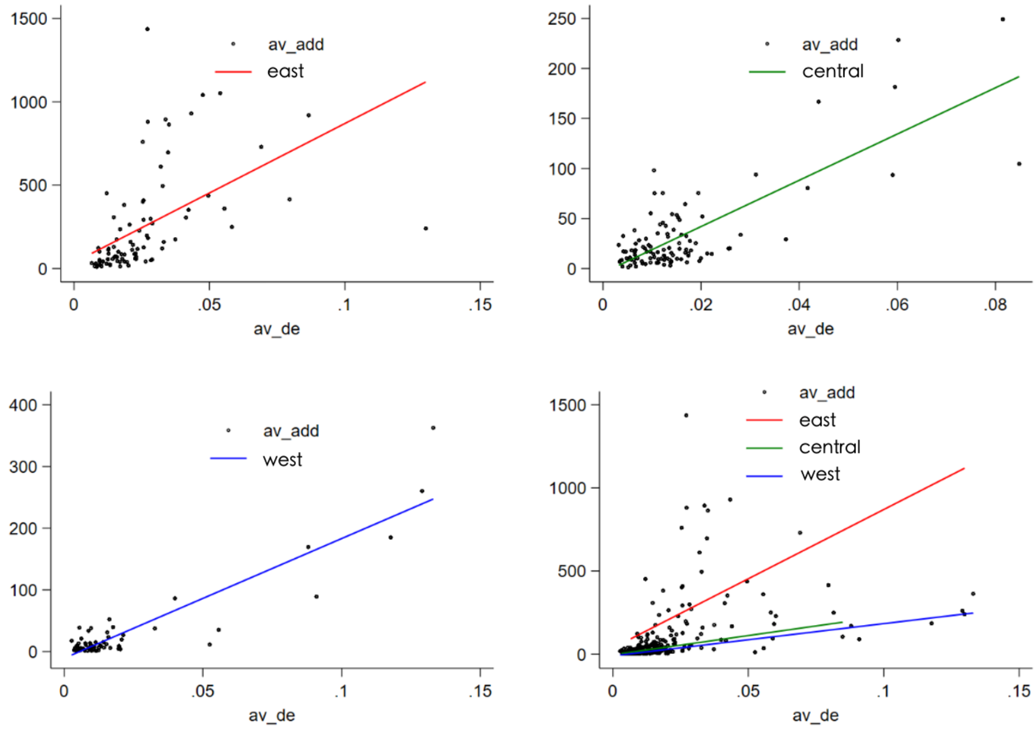

Figure 3: Relationship between Digital Economy Development and Enterprise Export Product Switching in Eastern, Central, and Western Regions

Based on the empirical observations above, it is evident that digital economy is experiencing a consistent upward trajectory, albeit with notable regional disparities in its development. The prevalence of export product switching is substantial, with over 85% of enterprises participating in this practice annually. Furthermore, a positive correlation between digital economy and export product switching is discernible, suggesting that digital economy significantly influences the dynamics of export product diversification. These findings prompt this paper to delve deeper into the mechanisms through which digital economy affects export product switching.

IV. Research Design

(I) Econometric Model

To examine the impact of digital economy on export product switching, this paper establishes the following econometric model:

$$switch_{ict} = \alpha_0 + \alpha_1 DE_{ct} + \gamma \sum X_{ict} + v_i + v_t + v_c + \varepsilon_{it}$$

where $switch_{ict}$ is the explained variable, that is, the export product switching rate of enterprise i in year t; DE_{ct} is the level of digital economy development in city c in year t; $\sum X_{ict}$ are control variables at the enterprise level, including:(1)Enterprise Age (lnage), Calculated as the logarithm of the current year minus the founding year of the enterprise plus one; (2)Enterprise Size (lnl), using the logarithm of the number of employees; (3)Capital Intensity of Enterprise (lncapital), using the logarithm of the ratio of total fixed assets to the number of employees; (4)Productivity of the Enterprise(lntfp), using the total factor productivity calculated using the OP method. v_i is individual fixed effects, v_t is year fixed effects, v_c is city fixed effects, and ε_{it} is the error term. The estimated coefficient of α_1 represents the magnitude of this effect.

(II) Measurement of Core Variables

1. Dependent Variable: Export Product Switching Rate

Adopting the approach of Bernard et al. (2011), the export product switching rate is divided into three indicators: product switching rate, product addition rate, and product reduction rate. These indicators are as follows: $totalrate = \frac{Add_{it} + Dele_{it}}{Product_{it-1}}$, $addrate = \frac{Add_{it}}{Product_{it-1}}$, $droprate = \frac{Dele_{it}}{Product_{it-1}}$, where Add_{it} represents the total number of products added by the enterprise in the current year; $Dele_{it}$ represents the total number of products reduced by the enterprise in the current year; $Product_{it-1}$ represents the total number of products of the enterprise in the previous year.

2. Explanatory Variable: Digital Economy

Following the methodology of Zhao et al. (2020) and Bai & Zhang (2021) for constructing digital economy indicators, and considering the availability of data, this paper measures digital economy from four dimensions: digital industry, digital infrastructure, digital users, and digital platforms. Digital Industry serves as an indicator of a city's digital development, encompassing the number of employees in sectors such as information transmission, computer services, and software industries, as well as the revenue generated by software businesses. Digital Infrastructure reflects the extent of a city's digital infrastructure, with a focus on metrics such as mobile phone exchange capacity, the length of long-distance optical cable lines, and the number of internet broadband access ports. Digital Users gauges the penetration and application of digital economy, incorporating measures like telecommunications revenue, the number of mobile phone users, and the number of internet broadband access users. Digital Platforms highlights the level of digitalization within urban network platforms, quantified by the logarithm of the number of domain names and websites.

To objectively weight and process each indicator of digital economy, this paper employs the entropy method, a technique that traditionally faces limitations when comparing across different years. To overcome this limitation, this paper adheres to the approach proposed by Yang & Chen (2015), which involves an enhanced panel entropy method. This method enables the analysis of process indicators across multiple time periods, offering a more dynamic and temporally robust assessment. The detailed composition of the sub-indicators for digital economy is presented in Table 2.

Table 2: Composition of Digital Economy Indicators

	Variables	Source
Digital Industry	the number of employees in information transmission, computer services, software industries	China City Statistical Yearbook
	revenue from software businesses	China Statistical Yearbook
Digital Infrastructure	mobile phone exchange capacity	China City Statistical Yearbook
	long-distance optical cable line length	
	internet broadband access ports	
Digital Users	telecommunications revenue	China City Statistical Yearbook
	the number of mobile phone users	
	the number of internet broadband access users	China Statistical Yearbook
Digital Platforms	the logarithm of the number of domain names	CNNIC
	the logarithm of the number of websites	

(III) Data Sources and Processing

The data for this study is sourced from multiple databases, including the China Industrial Enterprises Database (2007-2013), China Customs Import and Export Database (2006-2013), China Statistical Yearbook (2007-2013), China City Statistical Yearbook (2007-2013), and CNNIC (2007-2013). To address the complexity of the China Industrial Enterprises Database, panel data was cleaned using established methods from the literature (Cai, 2009; Nie, 2012). This process involved: 1. Excluding samples with missing key variables such as output value, sales revenue, fixed assets, and total assets; 2. Eliminating samples reporting less than eight employees or a negative age for imports; 3. Discarding samples with issues, such as depreciation in the current year greater than accumulated depreciation, total assets less than current assets, total assets less than the net value of fixed assets, and paid-in capital less than or equal to zero. Additionally, this paper requires to calculate total factor productivity of enterprises, which needs to address the absence of "intermediate input" data in the China Industrial Enterprises Database. Following the method of Chen (2018), we estimate "intermediate input" as follows: estimated value of "intermediate input" = "inventory" - "inventory of finished goods" + "main business cost" - "total wages payable for main business (or 'total wages payable for the year')" - "total welfare expenses payable for main business".

Given the need to integrate data from multiple databases, a merging process was initiated, starting with the enterprise name. To enhance the efficiency of the matching process, non-keywords such as "province," "city," "county," "company," and "limited liability" were removed from the enterprise names in both databases, as suggested by Yang (2015), resulting in a roughly 10% improvement in matching efficiency. For unmatched data, enterprise telephone numbers were used as a secondary step, capturing matches missed due to name discrepancies. The final Industrial-Export Database comprises approximately 40% of the total Customs data samples, providing a representative sample for analysis. The final stage involved matching the Industrial-Export Database with digital economy indicators.

Table 3: Descriptive statistics of all variables

Variables	count	mean	sd	min	p50	max
totalrate	1218384	1.03	4.86	0.00	0.67	1870.00
addrate	1218384	0.71	4.85	0.00	0.27	1870.00
droprate	1218384	0.32	0.29	0.00	0.33	2.00
DE	1369298	-2.80	1.14	-7.22	-2.97	-0.25
lnage	311639	2.30	0.54	0.00	2.30	7.61
lnl	311562	5.49	1.08	0.00	5.53	12.29
lncapital	309958	3.75	1.46	-6.27	3.79	15.13
tfp	309172	6.75	1.04	-5.16	6.69	12.57

The descriptive statistical results of all variables, with partial logarithmic processing, are presented in Table 3.

V. Regression Results and Analysis

(I) Benchmark regression

Following the econometric model, this paper investigates the impact of digital economy on the export product switching rate, product addition rate, and product reduction rate. To ensure a thorough analysis, the study incorporates relevant control variables and accounts for fixed effects at the individual, year, and city levels. The regression results, as depicted in Table 4, reveal the following:

Table 4: Benchmark Regression Results

	(1) totalrate	(2) totalrate	(3) totalrate	(4) totalrate	(5) totalrate	(6) addrate	(7) droprate
DE	-0.021	0.051***	0.052***	0.052***	0.053***	0.055***	-0.002
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.00)
lnage		-0.108***	-0.103***	-0.103***	-0.106***	-0.111***	0.005*
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.00)
lnl			-0.019***	-0.020***	-0.020**	-0.013*	-0.007***
			(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
lncapital				-0.002	-0.002	-0.001	-0.002**
				(0.01)	(0.01)	(0.01)	(0.00)
tfp					0.001	0.007	-0.006***
					(0.01)	(0.01)	(0.00)
_cons	0.975***	1.087***	1.182***	1.201***	1.199***	0.870***	0.329***
	(0.07)	(0.07)	(0.08)	(0.09)	(0.10)	(0.10)	(0.02)
R^2	0.399	0.292	0.292	0.298	0.297	0.263	0.429
City_fixed	YES	YES	YES	YES	YES	YES	YES
Year_fixed	YES	YES	YES	YES	YES	YES	YES
Individual_fixed	YES	YES	YES	YES	YES	YES	YES
N	1202517	289082	289007	287292	286526	286526	286526

Columns (1) to (5) focus on the export product switching rate as the dependent variable. As control variables are sequentially added, it becomes evident that digital economy exerts a significant positive influence on export product switching. This indicates that digital economy empowers enterprises to diversify their export product offerings. In column (6), the export product addition rate (addrate) is the dependent variable, demonstrating a significant and positive effect of digital economy on the rate at which enterprises introduce new products. This suggests that digital economy aids in the development and introduction of new export products. However, column (7), which considers the export product reduction rate (droprate) as the dependent variable, presents a contrasting outcome. The coefficient for digital economy is not statistically significant, indicating that digital economy's impact on reducing existing export products is less pronounced.

In summary, the findings align with the theoretical expectations and Hypothesis 1, confirming the pivotal role of digital economy in facilitating export product switching. The primary effect is observed through the addition of new products rather than the reduction of existing ones.

(II) Robustness Test

To ensure the robustness of the benchmark regression results, this paper addresses potential variations in digital economy indicators and the impacts of significant event shocks. Two strategies are employed for the robustness test: first, by substituting the core explanatory variable; and second, by altering the regression sample period.

1. Replacing the core explanatory variable

Digital economy indicators in this paper offer a comprehensive evaluation of urban digital economic development. However, the construction and methodology of these indicators could potentially affect the reliability of the empirical outcomes. To address this, this paper adopts the measurement approach of Zhao et al. (2020) for the robustness test. Due to the absence of a composite indicator, the test utilizes data from the years 2011 to 2013. The results, presented in columns (1) to (3) of Table 5, confirm that the direction and statistical significance of the core explanatory variable remain consistent, corroborating the conclusions of the benchmark regression. This reaffirms that digital economy significantly facilitates export product switching.

Table 5: Robustness Test Results

	(1)	(2)	(3)	(4)	(5)	(6)
	totalrate	addrate	droprate	totalrate	addrate	droprate
DE2	0.124***	0.111**	0.013**			
	(0.05)	(0.05)	(0.01)			
DE				0.065***	0.066***	-0.001
				(0.02)	(0.02)	(0.00)
R^2	0.380	0.355	0.520	0.340	0.312	0.464
Controls	YES	YES	YES	YES	YES	YES
City_fixed	YES	YES	YES	YES	YES	YES
Year_fixed	YES	YES	YES	YES	YES	YES
Individual_fixed	YES	YES	YES	YES	YES	YES
N	131382	131382	131382	200602	200602	200602

2. Changing the Sample Period

The initial sample period, spanning from 2006 to 2013, was extracted from the China Customs Import and Export Database. However, given the profound impact of the 2008 financial crisis, it is imperative to evaluate the robustness of the findings considering this significant economic event. To this end, this paper re-estimates the model using data from the post-crisis period, specifically from 2009 to 2013. The results, depicted in columns (4) to (6) of Table 5, demonstrate that the estimated coefficient for digital economy remains significantly positive. These findings further corroborate the conclusion that digital economy exerts a positive influence on export product switching.

(III) Endogeneity Test

This paper recognizes the potential bidirectional causality between digital economy and export product switching. On one hand, digital economy could act as a catalyst for export product switching. On the other hand, successful export product switching might benefit enterprises, which in turn increases investments in information technology hardware and software, ultimately elevating the overall level of digital economy. Additionally, this paper faces data limitations and the possibility of omitted variables. To address these challenges and strengthen the robustness of the regression analysis, the paper employs an instrumental variable (IV) method.

Drawing inspiration from Huang et al. (2019), this paper utilizes the number of post offices per million people in each city in 1984 as an instrumental variable for digital economy. To adapt this IV for panel data econometric analysis, this paper follows the strategy outlined by Nunn & Qian (2014), introducing a time-varying component. Specifically, the total volume of postal and telecommunication services in each province in the previous year is used to capture the dynamic nature of digital economy, resulting in an interaction term of two variables. The validity of this instrumental variable is supported by the belief that historically regions with a higher number of post offices are likely to have a higher digital economy level today. The historical number of post offices is expected to have a diminishing impact on export product switching, while the total volume of postal and telecommunication services in each province indirectly affects export product switching through digital economy. Thus, this instrumental variable satisfies the criteria of being "strictly exogenous" and "strongly relevant."

The regression results, presented in Table 6, confirm the validity of digital economy's impact on export product switching. Furthermore, the null hypothesis test for "insufficient identification of the instrumental variable" yields a p-value of 0.00 for the K-Paaprk LM statistic, leading to the rejection of the null hypothesis. In the context of the weak instrument variable identification test, the K-Paaprk Wald F statistic surpasses the critical value at the 10% level of the Stock-Yogo weak identification test.

Collectively, these tests affirm the appropriateness of employing the interaction term in the analysis.

Table 6: Endogeneity Test Results

	(1)	(2)	(3)
	totalrate	addrate	droprate
IV	0.279**	0.326**	-0.047**
	(0.14)	(0.14)	(0.02)
R^2	0.299	0.263	0.427
K-Paaprk LM	6869	6869	6869
	(0.00)	(0.00)	(0.00)
K-Paaprk Wald	5341	5341	5341
	(16.38)	(16.38)	(16.38)
Controls	YES	YES	YES
City_fixed	YES	YES	YES
Year_fixed	YES	YES	YES
Individual_fixed	YES	YES	YES
N	258153	258153	258153

(4) Heterogeneity Analysis

The previous sections have established that digital economy significantly fosters export product switching. This section delves into the heterogeneity of this impact across enterprises with varying technology types, ownership structures, and geographical locations.

1. Heterogeneity in Technology Intensity

Following Jeon (2013), enterprises are classified into four categories based on their technology intensity: low, medium, medium-high, and high. As illustrated in Table 7, the coefficients of DE in columns (10) and (11) are statistically significant at the 5% level, indicating that digital economy exerts a more pronounced effect on export product switching among high-technology-intensive enterprises compared to those in lower technology categories.

The possible interpretation is that high-technology-intensive enterprises, predominantly in advanced manufacturing, already equipped with advanced technological capabilities and sophisticated equipment, are more adept at integrating intelligent devices and data analytics into their operations. Consequently, digital economy aids these enterprises in the development of new products.

Table 7: Heterogeneity Regression Results Based on Technology Intensity

	low-technology			medium-technology		
	(1)	(2)	(3)	(4)	(5)	(6)
	totalrate	addrate	droprate	totalrate	addrate	droprate
DE	0.013	0.027	-0.014***	0.019	0.005	0.014*
	(0.03)	(0.03)	(0.00)	(0.02)	(0.03)	(0.01)
R2	0.335	0.311	0.454	0.364	0.271	0.394
Controls	YES	YES	YES	YES	YES	YES
City_fixed	YES	YES	YES	YES	YES	YES
Year_fixed	YES	YES	YES	YES	YES	YES
Individual_fixed	YES	YES	YES	YES	YES	YES
N	93211	93211	93211	46542	46542	46542
	medium-high-technology			high-technology		
	(7)	(8)	(9)	(10)	(11)	(12)
	totalrate	addrate	droprate	totalrate	addrate	droprate
DE	0.044	0.041	0.003	0.457***	0.463***	-0.006
	(0.03)	(0.03)	(0.01)	(0.09)	(0.09)	(0.01)
R^2	0.292	0.236	0.441	0.284	0.264	0.449
Controls	YES	YES	YES	YES	YES	YES
City_fixed	YES	YES	YES	YES	YES	YES
Year_fixed	YES	YES	YES	YES	YES	YES
Individual_fixed	YES	YES	YES	YES	YES	YES
N	79628	79628	79628	26143	26143	26143

2. Heterogeneity in Enterprise Ownership

According to the ownership classifications in the China Customs Import and Export Database, enterprises are categorized into state-owned enterprises (including collective enterprises), private enterprises, and foreign-funded enterprises (including Sino-foreign joint ventures, foreign-owned enterprises, and Sino-foreign cooperative enterprises). Table 8 reveals that digital economy significantly influences the export product switching of private enterprises, as evidenced by the results in columns (4) and (5). In contrast, the impact on state-owned and foreign-funded enterprises is not statistically significant. This disparity can be rationalized by the market-oriented nature of private enterprises, which, compared to their state-owned and foreign-funded counterparts, exhibit a higher degree of marketization. This market-driven characteristic enables private enterprises to respond more swiftly and effectively to market demands shaped by digital economy, facilitating the adjustment of their product offerings.

Table 8: Heterogeneity Regression Results Based on Enterprise Ownership

	state-owned			private			foreign-funded		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	totalrate	addrate	droprate	totalrate	addrate	droprate	totalrate	addrate	droprate
DE	-0.001	-0.013	0.013	0.126^{***}	0.128^{***}	-0.002	0.002	0.008	-0.006
	(0.08)	(0.08)	(0.01)	(0.04)	(0.04)	(0.00)	(0.02)	(0.02)	(0.00)
R^2	0.232	0.203	0.451	0.331	0.309	0.443	0.384	0.292	0.456
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
City_fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year_fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual_fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	19016	19016	19016	99846	99846	99846	115020	115020	115020

3. Heterogeneity in Trade Patterns

Drawing on Qian et al. (2013), this paper categorizes export processing trade, processing trade with imported materials, and assembly trade with supplied materials under the umbrella of 'processing trade.' Empirical tests are then conducted on sub-samples of processing trade and general trade enterprises. Table 9 shows that digital economy significantly influences the export product switching of general trade enterprises, while its impact on processing trade enterprises is not statistically significant. This discrepancy can be attributed to the nature of processing trade enterprises, which operate in a 'both-ends-outside' trade model, where their product decisions are heavily influenced by external market demands. Consequently, the domestic digital economy has a limited effect on the export product switching decisions of processing trade enterprises.

Table 9: Heterogeneity Regression Results Based on Trade Patterns

	processing trade			general trade		
	(1)	(2)	(3)	(4)	(5)	(6)
	totalrate	addrate	droprate	totalrate	addrate	droprate
DE	0.057^{***}	0.059^{***}	-0.003	-0.038	-0.035	-0.003
	(0.02)	(0.02)	(0.00)	(0.03)	(0.03)	(0.01)
R^2	0.298	0.251	0.434	0.490	0.439	0.496
Controls	YES	YES	YES	YES	YES	YES
City_fixed	YES	YES	YES	YES	YES	YES
Year_fixed	YES	YES	YES	YES	YES	YES
Individual_fixed	YES	YES	YES	YES	YES	YES
N	231030	231030	231030	37619	37619	37619

4. Heterogeneity in Regions

This study conducts a geographical analysis by classifying enterprises into three regions: eastern, central, and western China. Table 10 confirms the previously identified regional disparities in the development of digital economy. The regression results indicate that digital economy significantly influences the export product switching of enterprises in the eastern region. However, this significant impact is not observed for enterprises located in the central and western regions.

Table 10: Heterogeneity Regression Results Based on Regions

	east			center			west		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	totalrate	addrate	droprate	totalrate	addrate	droprate	totalrate	addrate	droprate
DE	0.026**	0.029**	-0.003	-0.042	-0.038	-0.004	0.469	0.474	-0.005
	(0.01)	(0.01)	(0.00)	(0.06)	(0.06)	(0.01)	(0.51)	(0.51)	(0.01)
R^2	0.315	0.260	0.426	0.268	0.233	0.448	0.283	0.278	0.483
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
City_fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year_fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual_fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	261322	261322	261322	17725	17725	17725	7479	7479	7479

(5) The mechanism analysis

As mentioned above, we have concluded that digital economy prompt export product switching. In this section, this paper further explores the impact mechanism. Accordingly, to test Hypotheses 2 and 3 presented earlier in this paper, we adopt the approach of He et al. (2021) for impact mechanism analysis. This involves incorporating interaction terms between digital economy and influencing factors to analyze the mechanism. The econometric model is established as follows:

$$switch_{ict} = \alpha_0 + \alpha_1 DE_{ct} + \alpha_2 DE \cdot M_{ict} + \gamma \sum X_{ict} + v_i + v_t + v_c + \varepsilon_{it}$$

Where M_{ict} represents the effects of innovation (innovation) and information costs (info). The innovation effect is measured by taking the logarithm of the total number of patents plus one. The information cost effect, following the approach of Shi & Jin (2019), uses the variance of market prices as a proxy.

Regression results, as presented in Table 11, demonstrate that for innovation, columns (1) to (3) display significantly positive coefficients in the interaction terms for totalrate and addrate. This suggests that enterprises with a higher capacity for innovation are advantaged by digital economy in the development of new export products.

Regarding information costs, columns (4) to (6) reveal significantly negative coefficients, indicating that enterprises with lower information costs are more likely to benefit from digital economy in terms of adding new products to their export portfolio. These findings underscore the multifaceted role of digital economy in influencing export product switching, as it both enhances enterprise innovation and reduces information costs, thereby facilitating the introduction of new products in export trade.

Table 11: Mechanism Analysis Results

	(1) totalrate	(2) addrate	(3) droprate	(4) totalrate	(5) addrate	(6) droprate
DE	0.050***	0.053***	-0.002	0.119***	0.138***	-0.019***
	(0.02)	(0.02)	(0.00)	(0.02)	(0.02)	(0.00)
DE×innovation	0.004**	0.004**	0.000			
	(0.00)	(0.00)	(0.00)			
DE×info				-0.004***	-0.006***	0.001***
				(0.00)	(0.00)	(0.00)
R^2	0.298	0.263	0.429	0.298	0.265	0.431
Controls	YES	YES	YES	YES	YES	YES
City_fixed	YES	YES	YES	YES	YES	YES
Year_fixed	YES	YES	YES	YES	YES	YES
Individual_fixed	YES	YES	YES	YES	YES	YES
N	286524	286524	286524	283531	283531	283531

VI. The Upgrading Effect of Digital Economy

The preceding sections have elucidated the impact and mechanisms of digital

$$upgrade_{ict} = \alpha_0 + \alpha_1 DE_{ct} + \gamma \sum X_{ict} + v_i + v_t + v_c + \varepsilon_{it}$$

economy on export product switching, demonstrating that digital economy exerts influence through two primary channels: enhancing enterprise innovation and mitigating information costs. Expanding the scope beyond export product switching, this paper further assesses digital economy's impact on export upgrading by analyzing the annual average export product quality and the average export technological complexity of enterprises. The following econometric model is established:

Where $upgrade_{ict}$ represents export product quality (TQ) and export technological complexity (ESI). The measurement of these variables is as follows:

TQ is measured following the approach of Khandelwal et al. (2013), where product quality is inferred using demand-side information. ESI is measured following the approach of Sheng & Mao (2017), which calculates a revised export sophistication index.

The regression analysis, as depicted in Table 12, provides strong evidence of digital economy's significant influence on export upgrading. Specifically, column (1) shows that a 1% increase in digital economy results in a 0.003 unit increase in the average export product factor density, indicating a trend towards higher quality products. Column (2) further supports this, with a coefficient of 0.147 for digital economy, which is statistically significant. This enhancement is attributed to the innovation effects catalyzed by digital economy. In essence, regardless of whether the dependent variables are export product quality or technological complexity, digital economy's coefficient remains significantly positive. This underscores that digital economy not only fosters export product switching but also propels export upgrading, enhancing both the quality and technological sophistication of export products.

Table 12: Upgrading Effect Results

	(1) TQ	(2) ESI
DE	0.003** (0.00)	0.147** (0.07)
R^2	0.727	0.700
Controls	YES	YES
City_fixed	YES	YES
Year_fixed	YES	YES
Individual_fixed	YES	YES
N	209489	217906

VII. Conclusion

This study, leveraging data from the China Customs Import and Export Database, China Industrial Enterprises Database, and China City Statistical Yearbook, offers a comprehensive analysis of digital economy's impact on export product switching in China, combining theoretical insights with empirical evidence. The results reveal a consistent growth in China's digital economy, albeit with significant regional disparities. The development of digital economy shows a gradient from the eastern coastal regions to the central and western areas, with most regions still in the early stages of development.

The empirical findings underscore a significant and positive influence of digital economy on the overall rate of export product switching and the rate of introducing new export products. This impact is particularly evident in enterprises characterized by high technological intensity, private ownership, and engagement in general trade, with a pronounced effect in the eastern regions of China. This paper identifies two primary mechanisms: the innovation effect and the information cost reduction effect. Digital economy fosters innovation, enabling enterprises to develop and introduce technologically advanced and higher-quality products, while also reducing information-related costs, which aids enterprises in adapting to rapidly changing market demands.

Furthermore, digital economy plays a pivotal role in facilitating export upgrading, characterized by a shift towards products of higher quality and greater technological complexity. These findings underscore digital economy's significant contribution to enhancing export competitiveness and driving economic growth.

The conclusions drawn from this research suggest several policy recommendations essential for harnessing the potential of digital economy in China:

Secondly, technological innovation is essential for both overall economic growth and the development of individual businesses in digital economy era. Enterprises should be encouraged to fully embrace digital technologies, transforming their production and management processes. Utilizing digital technologies for innovation, modernizing outdated technologies, and continuously upgrading export products can provide businesses with a competitive edge in the global market. Supporting enterprises in these endeavors is vital for fostering a dynamic and innovative business environment.

Thirdly, promoting a deep integration between the digital and real economies is vital for economic progress. This involves nurturing emerging digital industries and applying digital technologies to revitalize traditional industries. The goal is to drive industrial advancement, achieve high-quality development, and ensure sustained and stable economic growth. By intertwining the digital and real economies, policies can catalyze a comprehensive economic transformation, leveraging digital advancements for broader industrial and economic benefits.

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