**Impact of Digital Trade on Export Competitiveness: Evidence from Chinese Enterprises Using FEM**

***Abstract***

Digital trade has become one of the most important parameters in global trade in recent times. The presence of digital trade helps smaller businesses integrate into international models. However, the micro-level impact of firms’ digital trade capabilities on their export competitiveness remains unknown. To address this issue, this paper uses firm-specific data from China and analyses the impact of digital trade score on export competitiveness. Doing so, 9705 firm-year observations were analysed between 2013 and 2023. A FEM Model and GMM Model was utilised to analyse the same. The analysis found that the digital score has a negative impact on the competitiveness of exports by 13.54 per cent. GMM found a negative impact of 6.29 per cent. Factors such as intangible assets impacted exports positively, whereas ROA and leverage had a negative impact.

**Keywords:** Digital Trade, Export Competitiveness, ROA, Leverage, Fixed Effects Model

1. **Introduction**
   1. **Background of Digital Trade**

In recent times, there has been a significant change in the trends of global trade advocated by the emerging economies. The study by Khan (2024), has revealed that the growth of the Internet age has made it possible for small businesses to engage in international trade. This increases the inclusion of business within global trade, and also expands the horizon of global trade. Moreover, the same paper by Khan (2024), reveals that the use of digital innovations reduces the costs, and enhances the volume of trade. This creates a substantial revolution in the trading world globally. As per Meltzer (2019), digital trade is expected to reach USD 11 trillion by 2025 as it has been transforming the global value chains. It created the modern global economy which facilitates innovation. Therefore, digital trade has been one of the most important evolutions in the trade sector. China has been one of the leaders in digital trade, as there was a state-level change induced within the institutions of China to drive data-driven growth (Zhang, 2024). This forced a transformation towards a new economic growth model which relied on high-quality development. Moreover, another report by the State Council (2024), has revealed that the Chinese digital trade has increased by 8.5 per cent year-on-year to USD 387.5 billion in 2023. This has been a record high in the nation and has further shown the dominance of China within digital trade.

Despite the emergence of the digital economy, there are substantial gaps as there is a low level of understanding of micro-level analysis of how digital trade affects export performance in emerging economies. This paper addresses the same gap by utilising a panel data regression analysis across the digital trade drivers and the export performance of firms over time.

* 1. **Research Aim**

The key research aim of the paper is to examine the impact that the digital capabilities of firms have on the export competitiveness of Chinese enterprises. Moreover, the paper also aims to analyze how firm-level characteristics such as Leverage, ROA and presence of Intangible assets influence the relationship between digital trade and the export performance of Chinese enterprises.

* 1. **Research Question**

The primary research question of the paper is to analyse whether digital trade impacts the export competitiveness of Chinese enterprises, using firm-level panel data and a fixed-effect model approach.

* 1. **Summary of the Research**

This research article introduces the background of digital trade in the first chapter and also highlights the problem statement and the research aim. Based on this, the theoretical framework of the Resource-Based View of the Firm, along with Internationalisation theory, is considered for the empirical literature. Furthermore, an empirical design based on the Fixed Effects Model is also considered in the research. The findings are presented in the fourth chapter, and the results are discussed in the fifth chapter. Finally, a summary of the conclusion as well as the policy insights and limitations are presented in the sixth chapter of the study.

1. **Literature Review** 
   1. **Theoretical Framework** 
      1. **Resource-Based View of the Firm**

The resource-based view is a theory that can be used to understand why businesses adopt digital trade. As per Giustiziero et al. (2023), firms adapt digital technology resources, as it is key to gaining a comparative advantage. Adaptation to technological changes provides firms with the opportunity to gain economies of scale. This helps them to improve their output while controlling costs. Moreover, the enhanced output could also be exported, thereby leading to greater export growth. Hence, this shows that the adaptation of digital resources could help firms to enhance their export competitiveness.

* + 1. **Internationalization Theory**

The internationalisation theory is another important framework that shows the relation between exports and firm dynamism. The study by Ipsmiller and Dikova (2021) has revealed that internationalisation improves the capabilities of a firm in the production process. This is done through a learning curve, as internationalisation exposes the firms to various exogenous shocks. Hence, this makes the firms more dynamic in nature, which allows them to increase their exports despite maintaining their revenue levels. Hence, using the internationalisation theory, it can be understood that exports allow firms to learn and improve their export competitiveness.

* 1. **Evolution and Scope of Digital Trade**

Digital trade has been one of the most important cornerstones towards growth and innovation in global economies (Burri et al., 2024). This happens as digital trade removes barriers towards geographical limitations. As a result, it opens up new revenue streams for businesses by diversifying economic activities. In recent times, various global economies have introduced provisions to the institutional framework of digital trade (Burri et al., 2024). This included the signing of preferential trade agreements with special provisions towards e-commerce. Such provisions improve the global dynamics towards the digital capabilities of enterprises as well as the digital trade outcomes of the economy. Moreover, digital trade has also reshaped the trade landscape substantially. As per Ouyang (2024), the adaptation of digital technologies has reduced trade costs. This helps the firms enhance their production by forming new forms of trade. Digital evolution leads to a reduction in transaction costs, which in turn reduces the barriers in the industry. As a result, it benefits businesses indulging in global trade. China has been one of the major economies that implemented a data-driven internationalisation policy. As per Zhang (2024), China established digital databases and management frameworks to expand the horizon of trade. This comes as an upgrade to the innovation-driven development in China regarding trade (Zhang, 2024). This would provide Chinese enterprises with a greater level of global competitiveness. Moreover, the digital evolution combined with the structural benefits of the Chinese manufacturing sector would also present a greater level of export competitiveness to the firms based in China. Overall, this shows the scope and the evolution of digital trade.

* 1. **Empirical Evidence on Digital Trade and Exports**

The growth of digital platforms also has a substantial effect on the export levels. As per Li et al. (2018), the web presence of enterprises enhances exports by 7.7 percent on average across the first 3 years of adaptation. Furthermore, Li et al. (2023) also revealed that the adaptation of email usage increased exports by 2.9 percent across the first 3 years of implementation. In this paper, Li et al. (2023) use a Propensity Score Matching - Difference-in-Differences (PSM-DID) method for Chinese Industrial Enterprise Data spanning between 2004 and 2009. However, another paper by Erdey et al. (2024), found contrasting outcomes with respect to digital trade and exports. The paper by Erdey et al. (2024), found that digital affordance creates a negative impact of 27.184 per cent on the export levels. The results of the analysis is concluded using 13,251 firm-level observations from 19 OECD countries. The main reason for such a negative impact on exports is the structural disadvantages firms face with the implementation of digital tools. This leads to lower digital affordance, which eventually reduces the export levels of the firms. As a result, this shows that digital presence always do not have a positive impact on the export levels of firms.

The policies on digital trade served up by a country also play an important role in enhancing exports. As per Suh and Roh (2023), it has been understood that digital trade agreements have a positive effect on digital trade flows across economies. The conclusion has been understood in the study by using the TAPED database and implementing a Poisson Pseudo Maximum Likelihood (PPML) estimator function. This shows that as there is a growth in digital trade agreements across countries, there is also a chance for the export levels from the country to be enhanced. This is because of the direct correlation between trade flows and trade agreement under such circumstances. Digital intensity is also another important control factor for the digital trade and export relationship. As per Chiappini and Gaglio (2023), the digital intensity of the importing sector has a 3.15 per cent impact on bilateral trade flows. On the other hand, the digital intensity of importing industries has a 0.32 per cent impact on bilateral trade. However, the impact on imports is not statistically significant. This shows that the ability of a country to digitize its production, logistics, and trade infrastructure strongly enhances its export performance. As a result, investment in industry-specific digital tools can help to yield strong export gains.

Digital upgrading is also another important factor that helps the growth of trade exports from nations like China. A study by Liu et al. (2023), mention that digital trade development has a strong positive impact on the export technology complexity in nations such as China. It is realised that there is a 2.76 per cent positive impact on the export technology complexity. As a result, it can be implied that as digital trade develops, it strongly boosts the technological level of exports. This can be further helpful for Chinese firms to improve their export competitive advantage and also enhance their export levels. Overall, this shows that digital trade significantly impacts exports in the nation.

* 1. **Digital Trade and Firm-Level Export Competitiveness**

The export competitiveness of a firm is also enhanced by the digital trade levels in a firm. This could be understood through a paper by Li and Wang (2024) who expressed that the digital exposure of a firm has a positive effect on the competitiveness of the firm as well. This could be understood as the broadband connection exposure of the firm leading to a 0.150 percent positive impact on the export competitiveness of firms. This could be understood using data in China for companies between 2010 and 2022. The main reason for such a positive impact is because of the competitive advantage that companies gain because of the Internet. Furthermore, Luo (2021) has also revealed that access to the digital world enables firms to access global resources. Hence, harnessing the same allows the firms to have a competitive advantage within the industry. Another paper by Wang et al. (2023), reveal that digital integration leads to a positive impact on export competitiveness for Chinese enterprieses. This value is also statistically viable at 99 per cent Confidence Interval. The findings are concluded by using a FE analysis. Moreover, the same study by Wang et al. (2023), also conclude that digital integration positively impacts export growth competitiveness by 0.1952 per cent while controlling for other economic factors. These insights imply that digital infrastructure development is key towards the improvement of export efficiency in the nation. This would help the Chinese firms to enhance their export levels and be more competitive in the foreign markets. Furthermore, Luo (2021) has also revealed that participation in digital trade provides for participation in a trade ecosystem. This harnesses substantial data analytics tools which can be useful for marketing purposes. On the other hand, Liu and Ananthachari (2023) have also argued that leveraging digital transformation allows enterprises to improve their innovation capabilities. This helps them to improve their export structure further and position themselves within the global value chain. Hence, this also allows the firms to gain a comparative advantage. These factors eventually enable firms to enhance their export competitiveness. Digital trade has also been integral towards improving export competitiveness. As per Li and Wang (2024), digital services trade has become an essential carrier of transnational knowledge spillovers. This has been key towards the stimulation of trade, as knowledge transfers from international entities can be helpful in improving the efficiency of the firms and the industry as a whole. As a result, this would also enhance the export competitiveness of the firms related.

However, the presence of a digital economy also often leads to increased uncertainty in export markets. The paper by Fan (2021) reveals that digital means reduce trade inefficiency by 0.370 percentage points. However, it also increases the uncertainty by 1.125 percentage points. This occurs as greater digitalization leads to a crowding of the markets by various firms. This increases firm-level competition, thereby increasing trade uncertainty. Furthermore, another study by Zhu and Ye (2024) finds that the interaction between Economic Policy Uncertainty and the digital economy has a positive impact of 0.783 percentage points on high productivity firms. This indicates that digitalisation moderates the negative effect of economic uncertainty created, but only for high-efficiency firms. This further indicates the risks faced by low-efficiency firms, as digital economy does not help much and may even widen risks faced toward exports. Therefore, this shows the nuanced impact of digital economy on the export levels of firms.

* 1. **Firm-Specific Factors and Export Levels**

Factors of the firms, such as the ROA, impact the exports of firms substantially as well. A paper by Hussain et al. (2024) reveals that the ROA and Exports of a firm are negatively correlated. The coefficient is −0.064 and is statistically significant. This is because such firms operate at a more profitable level in domestic markets. Moreover, operational costs could be increased when ventures into foreign markets. Hence, firms often stick to domestic markets, which leads to a negative correlation between ROA and Exports. The Chinese economy is also one of the largest domestic markets in the world. As per the World Bank (2021), the Chinese GDP stood at a purchasing power worth USD 29 trillion, representing 18.9 per cent of global GDP. This makes the domestic market of the country the largest in the world, which explains the firms operating more within domestic territory despite having high ROA. Furthermore, it is also understood that having a higher ROA is also integral towards having a greater export quotient. As per Szarzec et al. (2020), data shows that exporting firms have an ROA of 8.88 compared to non-exporting firms having an ROA of 8.33. This is concluded by analysing 1683 non-financial firms and using an ANOVA analysis of the data. The results imply that the exporting firms are more efficient at using their assets to generate profits. As a result, better financial health and export engagement is correlated.

Moreover, leverage is another factor that impacts firms' export share. A study from India found that a greater leverage ratio creates a decline in export share by 0.0320 with lag effects (Padmaja & Sasidharan, 2021). This is because exporting firms need to incur some level of transaction costs. However, having high leverage means a debt overhang. This does not allow firms to export in the market as they have a high level of debt. Another paper by Faruk and Subudhi (2019), has found that leverage has a mixed impact on the export performance of firms. The paper found that firms with a moderate level of leverage have a positive impact on the export operations. However, it is also mentioned that firms with excessive leverage have an increased exposure to financial risks, and this can affect the export ability of the firms. This shows that financial autonomy is extremely important for firms in order to maintain their export levels. The presence of excessive leverage constrains their investment decision towards internationalisation. As a result, this also indicates that firms need to control for their leverage levels in order to maintain their export levels.

* 1. **Gap in Literature**

Despite the widely considered study of digital trade on exports, there is a substantial gap, as there has been limited micro-level analysis using firm-level data from China. Papers like Edrey et al. (2024) used 13,251 firm-level observations from OECD nations. Hence, there might be unexplored relationships for Chinese enterprises. This would be addressed in this paper as it aims to analyse how the digital fronts of enterprises impact competitiveness for exports of companies based in China.

* 1. **Research Hypotheses**

The research Hypotheses are as follows:

HA: Digital capabilities of firms have a negative effect on their export competitiveness.

HB: Leverage, ROA and Intangible Asset can significantly impact export competitiveness.

1. **Methodology**

This particular research follows a quantitative research design and uses a statistical analysis. Data for Chinese enterprises for export levels and firm-specific characteristics have been considered from the CSMAR (2025) database and the Wind (2025) database. On the other hand, the data for the digital score has been created using 25 secondary indicators and an entropy method from the NBS (2024). Using these variables, a Fixed Effects Model (FEM) will be used for the analysis of the data. Using FEM will help the paper control for unobserved heterogeneity (Bonhomme et al., 2022). Thus, it would be viable to understand firm-specific traits that may affect competitiveness.

The variables and abbreviations used in the research is as follows in Table 1:

Table 1: Variable List and Abbreviations for Base Model

|  |  |  |
| --- | --- | --- |
| **Variable** | **Meaning** | **Abbreviation** |
| ***Dependent Variable*** |  |  |
| Export Growth Rate | The ratio of business income to overseas revenue | EXPG |
| ***Independent Variable*** |  |  |
| Score | Digital Trade and Integration Score | SCR |
| ***Control Variables*** |  |  |
| Intangible Assets | Share of Assets which are in Intangible form | INTG |
| Return on Assets | Net Income on Total Assets | ROA |
| Leverage | Total Liabilities against Total Assets | LEVR |

The empirical model used in the paper is as follows:

Equation 1: Empirical Modelling using EXP, SCR, INTG, ROA and LEVR

Here, the components represents the firm-level impact from panel data analysis, and the component represent the time period of the variable within the study. However, this baseline model using the basic firm-level specification might face issues with respect to endogeneity. As per Cordero et al. (2013), the endogeneity issue arises when the explanatory variable used is correlated with the error term. In this case, there could be a bi-directional relation between the score and the export rate of the firms, as the firms that export could also invest in greater digital tools. The same is mentioned in Wang (2023), which reveal that firms have greater export competitiveness with digital growth. As a result, this puts the model at risk of reverse causality. Moreover, the variable *SCR* is created using an entropy method based, and also face the risk of measurement error. Under such circumstances, the OLS assumes that the regressors are perfect indicators in nature. As a result, to address the weaker assumptions made by the OLS Model, the GMM Model is considered. In order to control for the endogeneity problem, the System GMM is used as it introduces more instruments for the lagged dependent variable (Yitayaw et al., 2023). As a result, the GMM Model controls for the potential issues of endogeneity and reverse causality.

Model 1 focuses on core firm-level drivers of export competitiveness, it lacks controls for trade costs, sector-specific heterogeneity, and digital operational efficiency. To address these gaps, Model 2 introduces financial and structural variables (CMIR, DLCR, ATO). Sectoral controls are also considered under this model. Furthermore, an OLS and a GMM is again analysed for the second model using trade Cost, efficiency and industry effects. The new variable list is shown in Table 2.

Table 2: Variable List and Abbreviations for Extended Model

|  |  |  |
| --- | --- | --- |
| **Variable** | **Meaning** | **Abbreviation** |
| ***Dependent Variable*** |  |  |
| Export Growth Rate | The ratio of business income to overseas revenue | EXPG |
| ***Independent Variable*** |  |  |
| Score | Digital Trade and Integration Score | SCR |
| ***Control Variables*** |  |  |
| Intangible Assets | Share of Assets which are in Intangible form | INTG |
| Return on Assets | Net Income on Total Assets | ROA |
| Leverage | Total Liabilities against Total Assets | LEVR |
| Market Dependence | Capital Market Intensity Ratio | CMIR |
| Asset Efficiency | Asset Turnover Ratio | ATO |
| Financial Structure | Debt to Long-Term Capital Ratio | DLCR |
| Industry Specification | Industrial Code | INDUST |

The usage of CMIR helps to understand the capital dependency whereas, the usage of ATO indicates the export efficiency using digital technology investments. Furthermore, the DLCR helps to understand the investment capacity as well as the financial risk tolerance of the firms.

The empirical model used in the paper is as follows:

Equation 2: Empirical Modelling using EXP, SCR, INTG, ROA, LEVR, CMIR, ATO and DLCR and INDUST

The industry classification (INDUST) is further specified under various subgroups using industry code. The classification is provided in Appendix 1. Under the circumstances of industry classification, the Manufacturing has been considered as a benchmark and the Utilities/Construction as well as Services/Others are measured against it.

Overall, these models provide a more comprehensive view of how digital transformation, financing structure, and industry type interact to shape firm-level export outcomes.

1. **Empirical Results**
   1. **Core Model: Basic Firm-Level Specification**

A summary of statistics is first analysed for the variables used in the paper. Table 3 discloses the statistical table.

Table 3: Statistical Summary of the Variables EXP, SCR, INTG, ROA, and LEVR

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| *Variable* | *EXP* | *SCR* | *INTG* | *ROA* | *LEVR* |
| **OBS** | 9705 | 9705 | 9705 | 9705 | 9705 |
| **Mean** | 0.2592 | 0.1637 | 0.0451 | 0.0337 | 0.4439 |
| **SD** | 0.5011 | 0.1168 | 0.0395 | 0.0649 | 0.1909 |
| **MIN** | 0.0000 | 0.0046 | 0.0000 | -0.3750 | 0.0462 |
| **MAX** | 25.5620 | 0.5648 | 0.3428 | 0.2552 | 0.9246 |

The summary table 3 shows that in total, there is a total of 9705 firm-year observations for each indicator. The EXP comes at an average of 0.2592 with a deviation of 0.5011. This shows that the EXP has been within a certain bound for firms based in China, as they export approximately 25.92 per cent of their productivity. SCR has an average rating of 0.1637. This comes with a variability of 0.1168. Hence, this shows that firms are at a moderate stage of digital readiness. Moreover, the variability of 0.1168 indicates noticeable differences in digital readiness across firms. INTG has a mean of 0.0451, and the SD of INTG is 0.0395. This means that firms have only a proportion of 4.51 per cent of intangible assets out of total assets. This is a significantly small proportion, showing that firms still rely on tangible assets. This also shows the scope of digital assets in the future. The SD of 3.95 per cent indicates that some firms hold significantly higher levels of intangible assets than others. The average value for ROA is 0.0337. The standard deviation for ROA is 0.0649. This indicates modest profitability across firms, suggesting limited earnings relative to assets. However, the SD implies substantial variation in financial performance across firms. Finally, the LEVR has a mean of 0.4439 and an SD of 0.1909. This indicates that firms finance nearly half of their assets through debt.

With the summary statistics described, the study now tends towards the FEM Model Analysis as per Equation 1.

Table 4: FEM Regression Analysis, Dependent variable: EXPG, Independent Variables: SCR, INTG, ROA, LEVR

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| ***Variable*** | ***SCR*** | ***INTG*** | ***ROA*** | ***LEVR*** | ***CONST.*** |
| **COFF** | -0.1354 | 0.9276 | -0.4115 | -0.1223 | 0.3077 |
| **S. ERR** | 0.0639 | 0.2246 | 0.0971 | 0.0526 | 0.0286 |
| **T-STAT** | -2.1200 | 4.1300 | -4.2400 | -2.3200 | 10.7600 |
| **P-VAL** | 0.0340 | 0.0000 | 0.0000 | 0.0200 | 0.0000 |
| **L. CI** | -0.2607 | 0.4874 | -0.6018 | -0.2254 | 0.2516 |
| **U. CI** | -0.0102 | 1.3678 | -0.2211 | -0.0191 | 0.3637 |

The FEM Analysis as per Table 4, present that SCR has a coefficient of -0.1354. This remains statistically viable (P-VAL<0.05). This represents that as the SCR in digital trade for firms increases in China by 1 indicator point, the EXPG reduces by 13.54 per cent. This indicates that as the firms are more digitally integrated in the Chinese economy, their export competitiveness falls. The INTG has a coefficient of 0.9276 and is significant (P-VAL<0.05). This means that as the number of intangible assets rises within the economy, the export growth of the firms in the nation also rises. ROA also has a negative impact on EXPG by 0.4115 percentage points. This is statistically acceptable as (P-VAL<0.05). This indicates that firms with higher returns have an adverse impact on their exporting competitiveness. Similarly, LEVR also negatively impacts EXPG by 0.1223 and is statistically viable (P-VAL<0.05). As leverage for firms increases, their export growth rate reduces, reducing competitiveness. Overall, these factors show that as ROA and LEV increase, the EXPG reduces for firms based in China.

The GMM Estimation for the Core Model in the study is shown in Table 5.

Table 5: GMM Estimation of Core Model

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| ***Variable*** | ***L1.EXP*** | ***SCR*** | ***INTG*** | ***ROA*** | ***LEVR*** | ***CONST.*** |
| **COFF** | -0.2244 | -0.0629 | -0.3915 | -0.2103 | -0.0451 | 0.4232 |
| **S. ERR** | 0.0343 | 0.0296 | 0.0877 | 0.0499 | 0.2509 | 0.0332 |
| **T-STAT** | -6.5400 | -2.1200 | -4.4600 | -4.2200 | -0.1800 | 12.7400 |
| **P-VAL** | 0.0000 | 0.0340 | 0.0000 | 0.0000 | 0.8580 | 0.0000 |
| **L. CI** | -0.2917 | -0.1210 | -0.5636 | -0.3083 | -0.5376 | 0.3580 |
| **U. CI** | -0.1571 | -0.0047 | -0.2193 | -0.1124 | 0.4474 | 0.4884 |
| **AR (1)** | 0.363 |  |  |  |  |  |
| **AR (2)** | 0.131 |  |  |  |  |  |

The GMM estimation shows that the factors such as L1.EXP has a negative impact on the EXP growth with a coefficient of -0.2244. The SCR, INTG, ROA and LEV also has a negative impact of -0.0629, -0.3915, -0.2103 and -0.0451 respectively on Export Growth. However, LEV is not significant (P-VAL>0.05).

* 1. **Extended Model: Trade Cost, Efficiency and Industry Effects**

The study also considers an extended model to account for the sectoral effects. This helps to address potential issues with omitted variable bias. As a result, this extended model also uses two specifications using the OLS Regression Model and the Dynamic GMM Model. The results of the OLS Regression model for the extended model are shown in Table 5.

Table 6: FEM Regression Analysis, Dependent variable: EXPG, Independent Variables: SCR, INTG, ROA, LEVR, CMIR, ATO, DLCR

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| ***Variable*** | ***SCR*** | ***INTG*** | ***ROA*** | ***LEVR*** | ***CMIR*** | ***ATO*** | ***DLCR*** | ***Utilities/Construction*** | ***Services/Others*** | ***CONST.*** |
| **COFF** | 0.0951 | 0.1968 | -0.3136 | -0.1870 | 0.0095 | -0.0255 | 0.1083 | 0.0065 | -0.0781 | 0.3214 |
| **S. ERR** | 0.0353 | 0.2525 | 0.0984 | 0.0364 | 0.0123 | 0.0085 | 0.0406 | 0.0139 | 0.0140 | 0.0239 |
| **T-STAT** | 2.6900 | 0.7800 | -3.1900 | -5.1300 | 0.7700 | -2.9900 | 2.6700 | 0.4700 | -5.6000 | 13.4600 |
| **P-VAL** | 0.0070 | 0.4360 | 0.0010 | 0.0000 | 0.4420 | 0.0030 | 0.0080 | 0.6370 | 0.0000 | 0.0000 |
| **L. CI** | 0.0259 | -0.2982 | -0.5065 | -0.2584 | -0.0146 | -0.0422 | 0.0287 | -0.0206 | -0.1054 | 0.2746 |
| **U. CI** | 0.1643 | 0.6918 | -0.1206 | -0.1156 | 0.0335 | -0.0088 | 0.1878 | 0.0337 | -0.0507 | 0.3682 |

From the results in Table 6, it is understood that factors such as SCR is significant with a coefficient of 0.0951 (P-VAL <0.05). The ROA is also significant at a -0.3136 percentage point impact (P-VAL<0.05). LEVR is also significant with a coefficient of -0.1870 percentage points and a (P-VAL<0.05). Furthermore, the extended model determined variables such as ATO and DLCR are also significant at a coefficient of -0.0255 and 0.1083. With a sectoral analysis, service and other sectors have a coefficient of -0.0781(P-VAL<0.05).

The GMM Estimation of the extended model has been shown in Table 7.

Table 7: GMM Estimation of Extended Model

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| ***Variable*** | ***L1.EXP*** | ***SCR*** | ***INTG*** | ***ROA*** | ***LEVR*** | ***CMIR*** | ***ATO*** | ***DLCR*** | ***CONST.*** |
| **COFF** | -0.2236 | -0.0608 | -0.1674 | -0.4333 | -0.3088 | 0.0347 | -0.0167 | 0.1989 | 0.4159 |
| **S. ERR** | 0.0330 | 0.0280 | 0.2577 | 0.0984 | 0.0687 | 0.0145 | 0.0199 | 0.0824 | 0.0394 |
| **T-STAT** | -6.7800 | -2.1700 | -0.6500 | -4.4000 | -4.5000 | 2.4000 | -0.8400 | 2.4100 | 10.5500 |
| **P-VAL** | 0.0000 | 0.0300 | 0.5160 | 0.0000 | 0.0000 | 0.0170 | 0.4010 | 0.0160 | 0.0000 |
| **L. CI** | -0.2883 | -0.1158 | -0.6733 | -0.6264 | -0.4435 | 0.0063 | -0.0557 | 0.0371 | 0.3386 |
| **U. CI** | -0.1589 | -0.0059 | 0.3384 | -0.2402 | -0.1740 | 0.0631 | 0.0223 | 0.3607 | 0.4933 |
| **AR (1)** | 0.353 |  |  |  |  |  |  |  |  |
| **AR (2)** | 0.134 |  |  |  |  |  |  |  |  |

The estimation shows that the factors such as L1.EXP and SCR are significant with a coefficient of -0.2236 and -0.0608. The ROA has a coefficient of -0.4333, and LEVR has a coefficient of -0.3088. Both of them are statistically significant (P-VAL<0.05). CMIR and DLCR are also significant as per the GMM estimation with a coefficient of 0.0347 and 0.1989 (P-VAL<0.05).

1. **Discussion**

The empirical analysis shows that the digital trade integration score has a negative impact on the export growth of firms in China. This is explained by the negative coefficient of -0.1354, which is significant in nature. The GMM estimation also supports the same however at a lower margin. As per the GMM estimation the coefficient remains negative and significant at −0.0608. The same could be explained using the research by Fan (2021), who reveals that digital trade integration reduces inefficiency within external trades but increases trade uncertainty. As a result, firms are opting for a more effective business model. Hence, there is a reduction in export levels, resulting in firms' export competitiveness also falling. Therefore, this confirms the rejection of Hypothesis HA. The presence of intangible assets leads to an increase in export competitiveness. Edrey et al. (2024) argue that intangible assets play a role in digital affordance. Hence, as the intangible assets for firms grow, they could enhance their digital affordance. This leads to a greater digital-trade-induced export growth. Finally, ROA and Leverage of firms have a negative impact on export growth. This can be explained using the literature by Hussain et al. (2024), who found a negative correlation between ROA and Exports. This is because firms that are doing well domestically would prefer to remain in the domestic market, as the international export market comes with transaction costs and trade uncertainty. On the other hand, Padmaja and Sasidharan (2021) reveal that high leverage means greater debt levels, which reduces the capacity for firms to invest in exporting ventures. Hence, this leads to a negative impact on export competitiveness. This shows that Firm-level characteristics moderate the relationship between digital trade and export performance. Hence, the Hypothesis HB is accepted.

The inclusion of additional control variables in the extended model shows that CMIR and DLCR have a positive impact on Export Growth. This is supported by Giustiziero et al. (2023), who emphasise that the competitive advantage of companies arises from hyper-specialisation and hyper-scaling. These are both instances of long-term investments as a result, these cause a positive impact on the export growth. Furthermore, Liu and Ananthachari (2023) argue that the success of digital transformation is contingent on absorptive capacity of the firm. Hence, this shows the role of capital structure on export growth. The inclusion of Services and Other Sectors are significantly less competitive in exports compared to manufacturing. This confirms the heterogeneity across industries. The same is shown by Ipsmiller and Dikova (2021), who argue that learning effects and internationalisation pathways vary by industries.

Given the findings of the paper, there are several policy implications that are also adjusted in this research. Firstly, it is understood from the findings that firms may lack the infrastructure or capabilities to leverage digital tools effectively. As a result, the government should invest in upgrading national digital infrastructure, with a particular focus on enabling small and medium-sized enterprises (SMEs) (Kadaba et al., 2023). This would help the adoption of commerce, cloud services, and international digital platforms efficiently across industries. The analsysis also show that the service-sector firms significantly underperform in export competitiveness compared to manufacturing. Hence, targeted policies towards the Sector-specific digital export platforms must be floated (da Costa Júnior et al., 2024).

1. **Conclusion**

In conclusion, it has been realised that digital trade has been one of the most integral innovations in recent global business. The growth of the digital age has allowed small firms to engage in international transactions. Despite this growth of digital trade, there is a substantial gap in understanding the micro-level impact of digital trade on export performance in emerging economies like China. In order to address the same, the paper uses 9705 firm-year observations for enterprises based in China. The analysis of the paper shows that the digital trade growth score of firms has a negative impact on export competitiveness. This is because the integration of digital trade also leads to uncertainties. Hence, firms prefer to protect their profit levels by adhering to the domestic economy. Furthermore, the other firm-specific factors, such as leverage, ROA, and intangible assets, moderate the relationship between digital trade scores and firms’ export competitiveness. Leverage and ROA impact export growth negatively, whereas the presence of intangible assets has a positive impact. This allows the paper to reject Hypothesis A and accept Hypothesis B.

The findings show that digital trade integration currently reduces export competitiveness by 13.54 per cent. Based on these insights, it is recommended that governments set out a policy regarding digitalisation on the basis of the digital affordances and leverage of the firms within an industry. Industries with high leverage might be negatively impacted through such a digitalisation process. Hence, the Chinese government can selectively target industries or sectors based on leverage and ROA to enhance export competitiveness through the digitalisation process. Moreover, it is also recommended to the government to reduce export barriers for firms with high ROA, as it would reduce the export uncertainty.

The paper face certain limitations as the FEM only controls for unobserved heterogeneity. However, there are instances when firm-specific factors do not change across years. This calls for using the Random Effects Model (REM), which assumes these individual-specific effects are random and uncorrelated with the independent variables. Hence, future studies could utilise more robust analyses like the REM.

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1.

2.

3.

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**Appendices**

Appendix 1: Industry Classification

Table 8: Industry Classification as per Industry Codes

|  |  |  |
| --- | --- | --- |
| **Original Industry Code** | **Sector Description** | **Grouped as** |
| C13–C42 | Manufacturing (e.g., electronics, machinery) | Manufacturing |
| D | Electricity, Gas, Steam, and Air Conditioning | Utilities/Construction |
| E | Water Supply, Waste Management | Utilities/Construction |
| F | Construction | Utilities/Construction |
| G | Wholesale and Retail Trade | Services/Others |
| I | Transportation and Storage | Services/Others |
| K | Financial and Insurance Activities | Services/Others |
| L | Real Estate Activities | Services/Others |
| M | Professional, Scientific, and Technical Services | Services/Others |
| N | Administrative and Support Services | Services/Others |
| Q | Health and Social Work | Services/Others |
| R | Arts, Entertainment, and Recreation | Services/Others |
| S | Other Service Activities | Services/Others |