Ca' Foscari University of Venice

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Keywords
Technological complexity, international organization, export diversification

JEL Codes
F14, F23, L25, O33

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Abstract

This study investigates the relationship between technological complexity and international performance in small and medium-sized enterprises (SMEs) using data from a 2023 survey of firms in the Veneto region. We develop a Technological Complexity Index (TCI) to capture firms' adoption of advanced Industry 5.0 technologies. Our results reveal that higher TCI is associated with greater export intensity, broader geographical diversification, and reduced market concentration. Firms that adopt more comprehensive organizational strategies, such as product customization and post-sale services, also perform better internationally. Policy recommendations include targeted support for SMEs to enhance technological adoption through financial incentives and skills development programs.

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1. Introduction

The increasing globalization of markets and rapid advancements in digital and Industry 5.0 technologies are reshaping the way firms operate, particularly for small and medium-sized enterprises (SMEs). While large corporations have long dominated international trade, SMEs are increasingly expanding their presence in global markets, driven by technological innovation. However, the question remains: How do technological advancements, especially the complexity of adopted technologies, is associated with a firm's ability to compete internationally?

Based on a survey conducted in July 2023 among a representative sample of 2,000 Veneto companies, this paper provides an empirical investigation into the relationship between technological complexity and firms' international performance, with a particular focus on small and medium-sized enterprises (SMEs) in an industrial region. Leveraging firm-level data from a 2023 survey, we develop a Technological Complexity Index (TCI) that quantifies the technological sophistication of firms across various digital and Industry 5.0 technologies. Our findings reveal that higher TCI is strongly associated with improved export intensity, broader geographical diversification, and more balanced market penetration.

A good part of the literature states that digitalization connects people, companies, systems, products and services (Coreynen, Matthyssens and Van Bockhaven, 2017), thus creating opportunities for new ways of doing business with a potential strong impact especially in the manufacturing sector (Rymaszewska et al., 2017). Digital technologies, in fact, can provide fundamental support to innovation and marketing strategies, but they can also allow companies to organize and manage their business in a completely different way.

Considering the policy implications arising from our research, it is apparent that policymakers and industry stakeholders can gain valuable insights to cultivate an environment supportive of technological innovation and internationalization. Strategies promoting the diffusion of Industry 5.0 technologies should align with efforts to develop specialized skills and competencies within the workforce. Policymakers might explore options such as incentivizing training programs and fostering collaborations between educational institutions and industries to address the skills gap. Moreover, the recognition of geographical diversification as a crucial performance dimension suggests that policies encouraging exploration of global markets and providing resources for international market entry could bolster the resilience and competitiveness of local enterprises. Additionally, creating a supportive regulatory environment that accommodates and encourages the dynamic adoption of emerging technologies may play a pivotal role in propelling businesses in Veneto onto the global stage.

This study investigates the relationship between technological complexity and international performance, with a focus on SMEs from the Veneto region of Italy—an area renowned for its industrial strength. We propose a Technological Complexity Index (TCI) that quantifies the depth and breadth of firms' adoption of advanced technologies such as artificial intelligence, blockchain, the Internet of Things (IoT), and augmented reality. This index provides a novel analytical framework to explore how the complexity of adopted technologies affects firms' export intensity, geographical diversification, and market concentration. Although previous research has acknowledged the importance of digitalization in connecting firms to global markets, there has been less emphasis on the detailed relationship between technology diversity and complexity and the corresponding international success of SMEs. This study addresses this gap by examining both the quantity and sophistication of technological adoption, offering a richer perspective on how technology drives international expansion.

To rigorously examine these relationships, we employ several analytical techniques that enhance the robustness of our findings. First, we use the Economic Complexity framework (Hidalgo & Hausmann, 2009) to construct our Technological Complexity Index (TCI). This method allows us to capture not only the ubiquity of technologies but also their diversity, providing a comprehensive view of each firm's technological position. Next, we apply K-means clustering to group firms based on their international organizational practices. This clustering approach enables us to identify distinct patterns of organizational adaptation and link them to differences in international performance. By analysing the clusters, we uncover strategic variations in how firms manage their international operations, from minimal adjustments to highly customized approaches. Finally, to account for potential self-selection bias in firms' export decisions and technological adoption, we utilize the Heckman selection model.

In conclusion, our study not only unravels the intricate relationships between digital technology adoption, technological complexity, and international business functions but also provides valuable insights for policymakers, industry leaders, and academicians navigating the evolving landscape of Industry 5.0.

2. Relevant literature

a. Exporting and geographical scope at firm-level

The study of exporting and geographical outreach at the firm level is pivotal in understanding how businesses expand and thrive in international markets. Extensive research has explored various factors influencing export performance and geographical expansion, offering valuable insights into the complexities of international trade. Firm productivity plays a significant role in determining the number of export markets a firm can enter. Lawless (2009) provides a comprehensive analysis of firm export dynamics and the geography of trade, revealing that while firm productivity significantly influences market entry, the hierarchical model of market entry is not strongly supported by empirical data.

Export strategies in emerging markets face unique challenges and opportunities. Samiee and Chirapanda (2019) examine the international marketing strategies of firms in Thailand, highlighting that aligning export strategies with local market conditions significantly improves performance. Also, learning plays a pivotal role in a firm's success in exporting. Schmeiser (2012) investigates the gradual geographic expansion of firm exports, finding that firms typically enter new export markets slowly over time. This study highlights that learning from past export activities significantly influences future market entry decisions, with firms leveraging their export history to navigate new markets more effectively and making it a "structural" characteristic. Denis and Depelteau (1985) further emphasize the importance of market diversification and information acquired from business transactions in driving export expansion.

The internationalization pathways of small and medium-sized enterprises (SMEs) are obviously different from large ones. D'Angelo et al. (2013) provide empirical evidence that product innovation universally boosts SME export performance, while other factors like networking and external management have selective impacts depending on the geographical scope of internationalization. This is corroborated by Bodlaj, Kadic-Maglajlic, and Vida (2020), who demonstrate that both technological and organizational innovations, coupled with geographical diversification, significantly drive SME export growth. Geographical diversification impacts firm performance in complex ways. Boehe and Jiménez (2016) argue that the relationship between geographic export diversification and firm performance follows an S-curve when export intensity is low and an inverted U-shape when export intensity is high. This suggests that firms with high commitment to export markets benefit more from geographic diversification, which accelerates their learning curves and improves performance.

In conclusion, the success of firm-level exporting and geographical outreach is influenced by a combination of productivity, R&D investment, market-specific strategies, and learning processes from international activities. These insights are vital for firms seeking to enhance their export performance by effectively navigating the complexities of foreign markets.

b. Technological complexity and international activities

Technological complexity, as it pertains to the technologies employed by firms,[1] plays a crucial role in shaping their international activities. Firms leveraging advanced and complex technologies face unique challenges and opportunities in the global market, influencing their strategies and performance outcomes. Preece, Miles, and Baetz (1999) highlight that early-stage technology-based firms must navigate the complexity of foreign markets and global competition from their inception. Their study shows that resources necessary for international sales impact both the intensity and diversity of international activities. Interestingly, while attitudes towards foreign markets influence international intensity, achieving global diversity requires significant time and resources. This suggests that technological firms must be cautious about expanding too quickly without adequate preparation and support. Technological complexity also affects small and medium-sized enterprises (SMEs) in developing countries. Oyelaran-Oyeyinka and Lal (2006) discuss how SMEs adopt and utilize information and

[1] In this article, technological complexity, digitalization, and technological adoption are viewed as interrelated aspects of the same broader phenomenon within firms. Technological complexity refers to the sophistication of technologies that firms integrate, digitalization captures the shift towards digital processes, and technological adoption reflects the firm's uptake of these advancements. Given the interconnected nature of these processes in shaping a firm's technological trajectory, these terms will be used interchangeably throughout the article, acknowledging their conceptual overlap.

communication technologies (ICTs). Their findings show that increasing technological complexity requires skills upgrading and formal training, which are critical for enhancing firm performance. This underscores the importance of continuous learning and adaptation in managing complex technologies.

The internationalization processes of technology-intensive small firms often involve extensive networking and local embeddedness. Keeble et al. (1998) demonstrate that such firms in the Cambridge and Oxford regions engage in various international networks and processes. These firms exhibit high levels of both international and local networking, suggesting that successful internationalization is grounded in robust local collaborations and technological exchanges. Furthermore, the geographical distribution of technological activities is influenced by the complexity of technologies. Patel and Vega (1999) find that firms often locate their technological activities abroad in their core areas of strength, adapting products and processes to suit foreign markets. This strategic internationalization helps firms monitor and engage with new technological developments globally, maintaining their competitive edge. Finally, technological complexity also plays a role in the catch-up processes of latecomer firms. Hu and Zhang (2015) study Chinese pharmaceutical firms, showing that technological complexity extends the catch-up process, raises capability requirements, and necessitates extensive networking and institutional support. This suggests that firms facing high technological complexity must adopt evolutionary strategies that involve significant self-investment and collaboration to achieve technological advancement.
More recently, Cassetta et al. (2020) investigated Italian SMEs and the findings suggest that firms adopting advanced digital tools exhibit higher export propensity, as these technologies lower barriers to entry in foreign markets and improve international communication and transaction efficiency. Moreover, the study highlights the heterogeneity of digital technology adoption, where not all firms leverage the full potential of these innovations, often due to internal resource limitations or lack of digital capabilities.
Overall, the interplay between technological complexity and international activities underscores the importance of strategic planning, resource allocation, and continuous learning. Firms that effectively manage these aspects can enhance their technological capabilities and achieve greater success in the international market.

c. Beyond trade: digitalization and organization of international functions

Digital technologies, in fact, can provide fundamental support to innovation and marketing strategies, but they can also allow companies to organize and manage their business in a completely different way. In particular, in the digital age, scholars and practitioners have attributed to Industry 4.0 (I4.0) technologies a disruptive power that could have a dramatic impact on industries and competition on the one hand (Porter and Heppelmann, 2014; Vendrell-Herrero et al., 2017), and on the organizations themselves on the other side (Porter and Heppelmann, 2015). In fact, from this second point of view, I4.0 technologies can be implemented in different activities of the value chain, with potential impacts at different levels ranging from inbound logistics to after-sales assistance (Porter and Heppelmann, 2015). I4.0

technologies are also expected to enable and/or support manufacturer servitization (Kamp and Parry, 2017).
This relationship is attracting the attention of the literature but remains largely underexplored from an empirical point of view (Kowalkowski et al., 2017; Paiola, 2017a; Paiola 2017b). An exception, in relation to the manufacturing context, is the study by Coreynen, Matthyssens and Van Bockhaven, (2017) which demonstrates how specific digital technologies can guide companies along different servitization paths but require a dynamic configuration of the firm's resources. In all this, however, we could say that digitization and emerging technologies are radically transforming not only companies individually, but also the macroeconomic level, i.e. the global trade landscape, creating new opportunities for companies to export products and services (Baldwin et al, 2015).

RQ1: How is the technological complexity index related to international performance and geographical scope?

RQ2: How is the organization of international functions connected to technological complexity and geographical scope?

3. Empirical approach

a. Data sources, measurements and indexes

The dataset employed in this study is derived from a comprehensive survey conducted by Unioncamere Veneto in July 2023, which examined 2,000 firms across the Veneto region. The survey focused on three key dimensions: technology adoption, international presence, and organization of international functions. The analysis also incorporates data from the 2021 edition of the Archivio Statistico delle Imprese Attive (ASIA), an annual registry compiled by Istat. ASIA includes all economic units operating in the industrial and service sectors in Italy. This registry provides detailed information on the structure and performance of active firms, defined as those engaging in productive activity for at least six months during the year. The ASIA dataset offers granular insights into these firms' legal form, economic activity, number of employees (both dependent and independent), and the duration of their activity.

Additionally, we leverage data from CoE-web, an online platform managed by Istat that provides monthly updates on Italy's foreign trade statistics. CoE-web data is initially processed to comply with EU regulations and subsequently reviewed for accuracy. Its microdata version delivers precise details on Italy's import and export flows, with data disaggregated by sector (up to the NUTS-3 level) and by the geographical destination of traded goods. This dataset is enhanced by the REPRINT database, which tracks ownership patterns of multinational firms operating within Italy, allowing us to examine the extent of foreign direct investments (FDI). In this context, FDI is defined as the acquisition of control or significant influence in a company, leading to active involvement in its management and operations.

Two critical variables in this study, which are based on our own estimations, warrant further explanation. First, we measure the geographic scope of firms' international presence using multiple indicators. These include the number of destination countries for exports and a Herfindahl-Hirschman Index (HHI) calculated over macro-geoeconomic blocs. A more sophisticated measure combines these dimensions to provide a comprehensive view of each firm's international diversification.

Second, the Technological Complexity Index (TCI) follows the methodology outlined in the literature on economic complexity and fitness (Hidalgo & Hausmann, 2009; Tacchella et al., 2012). This index accounts for both the diversity and ubiquity of technologies adopted by firms. Together, these data sources and measurement tools provide a robust framework for analyzing the technology adoption strategies and international expansion of Veneto firms.

Concluding, the exploitation of the survey data pertains mainly two dimensions: the above-mentioned technological ones, for which we use the 14 questions relative to the adoption or intention of adopting technologies, and the organization of international functions. From the latter, we specifically focus on six questions that report how firms approach foreign markets asking them the following:

1) Has the product system been customized?
2) Are ad-hoc documents used?
3) Do you have a dedicated office?
4) Do you provide post-sale customer services?
5) Has the logistics system been adapted?
6) Do you have strategic partners?

b. Firm-level technological complexity index (TCI)

The calculation applies the Economic Complexity (EC) algorithm to firm-level data, mapping firms' technological positions across 14 distinct technologies. We assign values of 1 to technologies that have already been adopted, 0.5 to technologies planned for adoption, and 0 for those not adopted. The firm-level Technological Capabilities Index (TCI) is then derived as a weighted average of these values, representing the extent to which firms have adopted or plan to adopt different technologies.

Our choice to use the Hidalgo and Hausmann (2009) algorithm, rather than the Economic Fitness algorithm proposed by Tacchella et al. (2012), merits clarification. While Tacchella's model is a significant refinement, its incorporation of non-linearities introduces complications in our dataset, particularly due to quasi-monopolies in certain technologies (e.g., the metaverse, which is utilized by only 9 firms in the sample). This creates substantial imbalances in the results, reducing the accuracy of the Economic Fitness approach. For this reason, the Hidalgo and Hausmann algorithm provides more solid outcomes in our context. To test the robustness of our TCI, we also calculate it with two key modifications: first, we include a base technology owned by all firms (e.g., laptops)[2], and second, we remove the 0.5 value assigned to technologies that firms intend to adopt but have not yet implemented. In doing so, the majority of our statistically significant results remain consistent.

The application of the economic complexity algorithm allows us to capture not only ubiquity and diversity but also to proxy for firm capabilities, which in the technological domain can be viewed as hierarchical. Firms that adopt more complex technologies are likely to have the capacity to adopt simpler ones as well, reflecting a capability ladder similar to that discussed in Coad et al. (2021).

c. Estimation approach

In this section, we will present the estimation techniques employed in the paper, specifically the computation of the technological complexity index, the econometric estimation and the clustering approach.

To address potential issues of self-selection into exporting and technological adoption, we employ the Heckman selection model (Heckman, 1979), which is a two-step procedure designed to correct for sample selection bias. This type of bias occurs when the decision to engage in an activity, such as exporting or adopting advanced technologies, is not random but rather influenced by unobserved characteristics that may also affect the outcome of interest (e.g., international performance or technological complexity). Ignoring such selection bias would lead to inconsistent and biased estimates, as firms self-select into exporting or technology adoption based on these unobserved factors. The model consists of two equations: an outcome equation describing the relationship between the outcome of interest, our export performance-related variables, and a vector of covariates X_i and a selection equation that describes the relationship between a binary participation decision, the joining of foreign markets, and a vector of covariates Z_i:

$$EXP\ outcomes_i = X_i'\beta + millsratio_i + \varepsilon_i$$

$$EXP\ decision_i = I\{Z_i'\gamma + u_i > 0\}$$

where X_i and Z_i depict the control variables described in the previous section and Z_i contains instrumental variables in addition to enhance identification of the model.

In the first stage of the Heckman model, we estimate a selection equation, using a probit model, where the dependent variable is whether or not a firm exports. This selection equation identifies the factors influencing the firm's decision to participate in this activity. The second

[2] This exploration stems from the reasonable suspect that the selection of technologies inquired in the survey may affect the results. Nevertheless, we stress how results are robust to this small variation and that more generally, this article contributes in methodological terms putting together tools and firm dimensions that are rarely analyzed all together.

stage corrects for the selection bias by including the inverse Mills ratio (IMR), derived from the first stage, as an additional explanatory variable in the outcome equation.

The Heckman model is particularly advantageous in contexts where self-selection is a concern, as it not only corrects for the bias but also provides insight into the determinants of participation. The inclusion of the IMR ensures that the estimation accounts for the non-random nature of the sample, which in our case is crucial for understanding how firms that export may differ from those that do not. Numerous studies have employed this approach to account for selection bias in firm-level analyses of internationalization and innovation (Wagner, 2007; Aw et al., 2011). In applying the Heckman model, we correct for any endogeneity that might arise from the decision to export. This allows also to more accurately estimate the impact of our variables of interest on key outcomes, such as export intensity, technological complexity, and international performance, and ensures that the observed effects are not driven by self-selection but reflect true underlying relationships.

By using the Heckman correction, we mitigate the risk of overlooking firms' unobserved characteristics (e.g., managerial ability, risk preferences) that could influence both the adoption of technologies and export behavior, making our estimates more reliable and robust to selection biases.

For clustering analysis, we apply K-means clustering to a set of binary variables. To determine the optimal number of clusters (k), we follow Makles (2012) and calculate the weighted sum of squares (WSS) for different values of k, ranging from 1 to 20. We find that using k=6 yields the largest kink in the WSS curve (Figure N). Furthermore, the η^2 statistic shows that the explained WSS increases from 42% for k=5 to 51% for k=6, with subsequent increases ranging only between 4% and 1%, indicating that k=6 is the most appropriate choice.

After computing the clusters, we incorporate them into a simple OLS regression model to explore potential relationships between the internal organizational clusters and our main variables of interest: technological complexity, export intensity, and geographical scope. For robustness, we replicated the analysis using smaller values of k, and the results remained consistent.

Lastly, to examine whether the clusters exhibit a natural ordering in terms of technological complexity, we conduct a non-parametric trend test based on ranks across the ordered clusters. Specifically, we use Cuzick's (1982) test, an extension of the Wilcoxon rank-sum test, to assess whether technological complexity follows a systematic trend across the clusters.

d. Descriptive statistics

The descriptive statistics in Table 1 highlight the significant heterogeneity among firms in terms of export activities, technological capabilities, and firm characteristics. Export intensity varies widely, with a small number of highly export-intensive firms skewing the average, while most firms are more modest in their international reach, typically exporting to only a few countries. This concentration is further confirmed by the high export Herfindahl-Hirschman Index (HHI), indicating that many firms rely on a few key markets.

Table 1. Descriptive statistics of the sample.

Variable	Mean	Median	Min	Max	N
Export intensity (€/employee)	119’750.4	58’356.98	12.44	3467907	815
Export destination countries	7.37	3	1	102	
Export HHI by macro-block	5311.42	4404.57	1890.07	10000	
Geographical diversification index	0.002	0.0007	0.0001	0.0447	
Technological complexity index	-0.003	0.001	-1.788	4.901	1365
Number of adopted technologies	2.104	2	0	14	1612
Exporter status (binary)	0.506	1	0	1	
Subject to FDI (binary)	0.122	0	0	1	
Artisanal production (binary)	0.336	0	0	1	
Size (employees)	45.104	19.91	0	7927.06	
Age (years)	28.831	28	3	102	

In terms of technological sophistication, the firms exhibit notable differences. While some firms have adopted numerous advanced technologies, a considerable portion remains less technologically complex, as indicated by the wide range in the number of adopted technologies. The presence of artisanal production in over a third of firms suggests that traditional industries play a role in the sample, which may influence the overall low levels of technological adoption. Firm size and age show a similar pattern of skewness, with most firms being small, but a few large firms significantly influencing the averages. Overall, the data indicate that while a few firms are highly advanced in their export and technology strategies, the majority are smaller, less diversified, and more dependent on traditional or concentrated markets.

4. Empirical results

a. Exploratory data analysis

To provide an initial overview of technological complexity across industries, we examine the average Technological Complexity Index (TCI) by aggregated industrial sector, as shown in Table 2. The TCI offers insight into the level of technological sophistication of firms within each sector, where values closer to zero represent the overall sample mean, negative values indicate below-average complexity, and positive values suggest above-average complexity.

Sectors with lower mean TCI values, such as Textiles, clothing, and footwear (-0.235) and Wood and furniture (-0.173), indicate that firms in these industries generally adopt fewer advanced technologies, often relying on labor-intensive and standardized processes. These results align with findings by Tybout (2000), who highlighted that firms in traditional manufacturing sectors are less likely to invest in sophisticated technologies due to cost constraints and limited competitive pressures. Such firms typically face high capital costs for technology upgrades and are often constrained by low-skilled labor pools, limiting their ability to scale technological complexity and productivity.

Industries with mid-level TCI values, like Metals and metal products (-0.027) and Rubber and plastics (0.089), demonstrate a blend of firms—some adopting higher-complexity production technologies and others maintaining less advanced practices. The distribution of TCI within these sectors reflects varying degrees of technology adoption that are often related to firm size and resource availability. Studies on technology adoption in the metals industry (Sutton, 2012) reveal that larger firms are more capable of integrating advanced technologies like automated casting and CNC machinery, which drives sectoral competitiveness and productivity gains. Smaller firms in these sectors, however, tend to lag due to financial constraints and lack of access to skilled labor, further contributing to the observed variability in TCI scores within these industries.

The highest TCI values are seen in sectors like Electrical and electronic machinery (0.199) and Mechanical machinery and equipment (0.123), where firms demonstrate significant adoption of advanced technologies, including automation, precision engineering, and AI-based quality control systems. Firms in these technology-intensive industries benefit from high demand for specialized and complex products, enabling them to capitalize on economies of scale and technological learning curves. Bresnahan, Brynjolfsson, and Hitt (2002) emphasize that firms within high-tech sectors experience greater returns on technology investments, as these sectors are inherently better suited for digital transformation and R&D-driven innovation, which enhances both firm and industry productivity. This high TCI reflects these firms' advanced technological capabilities, which further solidifies their position as contributors to economic complexity and broader industrial growth.

Table 2. Average TCI by aggregated industrial sector

Sector	**Mean**	**SD**	**N**
Textiles, clothing, footwear	-0.235	1.026	159
Wood and furniture	-0.173	0.939	137
Food, beverages, tobacco	-0.173	0.801	86
Metals and metal products	-0.027	0.976	372
Jewellery	-0.011	0.604	15
Marble, glass, ceramics, other non-metallic minerals	0.050	1.082	56
Eyewear	0.074	0.959	62
Rubber and plastics	0.089	0.858	96
Mechanical machinery and equipment	0.123	0.961	190
Transportation equipment	0.133	1.117	25
Electrical and electronic machinery	0.199	1.031	93
Paper and printing	0.235	1.072	56
Other	0.423	1.310	18
Total	**-0.003**	**0.982**	**1365**

Overall, these findings illustrate significant variation in technological complexity across sectors, with traditional manufacturing industries generally lagging behind more technology-intensive fields. Also, the standard deviation values suggest that in line with the stylized fact about sectoral heterogeneity (Dosi et al., 2010), sectors exhibit considerable variability not only across, but also within them. This variation in TCI aligns with expectations, as sectors that rely more heavily on advanced machinery or digital technologies tend to have higher levels of technological complexity, while those rooted in artisanal or conventional manufacturing processes show lower scores (European Commission, 2019).

Shifting our attention to the export dimension, we analyse how TCI varies across exporter status in Table 3. The table shows that exporters, with a higher average TCI (0.109) than non-exporters (-0.169), are more technologically advanced. This distinction highlights the economic relevance of technological sophistication in driving firms' ability to compete globally. Exporters benefit from greater innovation, aligning with economic theories like Melitz (2003), which link higher productivity to successful export participation. The greater variability in non-exporters' TCI suggests uneven technological adoption, possibly due to limited resources or incentives for innovation.

Table 3. Average TCI by exporter status

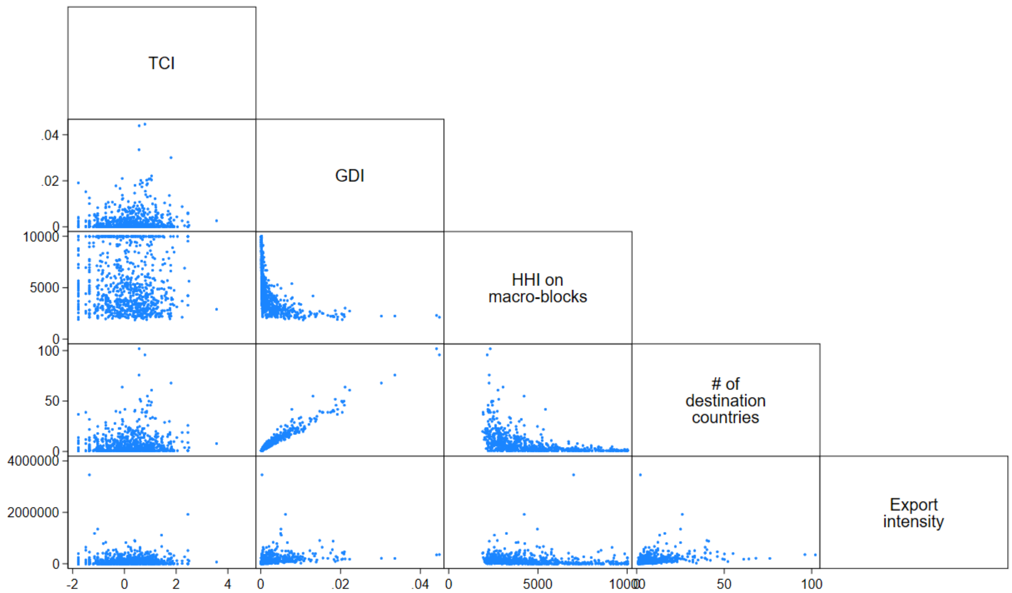
	Mean	SD	N
Exporter	0.109	0927	815
Non-Exporter	-0.169	1.036	550
Total	**-0.003**	**0.982**	**1365**

Finally, before moving to the regression results, we fully introduce and integrate our geographical dimension with the above-explored technological one. The pairwise correlation matrix in Table 4 shows that technological complexity (TCI) is positively correlated with geographical diversification (0.1348*) and the number of destination countries (0.1429*), suggesting that firms with higher technological sophistication tend to export to more diverse markets.

Table 4. Pairwise correlation matrix among technological and geographical variables.

	(1)	(2)	(3)	(4)	(5)
(1) TCI	1				
(2) Geographical diversification	0.1348*	1			
(3) HHI macro-block	-0.1022*	-0.4720*	1		
(4) # of destination countries	0.1429*	0.9752*	-0.4731*	1	
(5) Export intensity	0.0380	0.3245*	-0.2557*	0.3862*	1

Conversely, TCI is negatively correlated with the Herfindahl-Hirschman Index (HHI) for macro-blocks (-0.1022*), implying that firms focused on fewer regions show less technological complexity. These correlations highlight the interplay between innovation and market expansion, aligning with theories that link technological capability to broader export markets (Helpman, 1998).



b. Regression results

Table 5 presents the results from regressions examining the relationship between firm characteristics and various export outcomes, including exporter status, export intensity, number of export destination countries, export concentration (as measured by the macro-level Herfindahl-Hirschman Index, HHI), and geographical diversification. In line with the literature, firm size, plays a crucial role across all export-related variables. Larger firms are significantly more likely to be exporters, export to more countries, and show greater geographical diversification. While size does not have a large effect on export intensity (exports per employee), it is strongly associated with broader market reach and lower export concentration, suggesting that larger firms tend to diversify their export portfolios across multiple regions.

Firm age presents a more nuanced picture. Older firms are more likely to engage in exporting, although the relationship between age and export status is non-linear. The quadratic term suggests that the likelihood of exporting increases as firms age but tapers off at a certain point, potentially reflecting challenges that older firms may face in maintaining international competitiveness. However, age does not appear to influence export intensity, geographical diversification, or concentration significantly.

Table 5. Results from the selection model estimated through Heckman (1974).					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	Selection equation	**Outcome equations**			
VARIABLES	**Exporter status**	**Exp.int**	**# countries**	**macro HHI**	**GDI**
Size (in logs)	0.530***	0.0768	0.533***	-0.133***	0.659***
	(0.0719)	(0.115)	(0.0829)	(0.0228)	(0.0954)
Age	0.0182**	-0.000236	-0.00229	-0.00610	0.00329
	(0.00856)	(0.0199)	(0.00859)	(0.00406)	(0.0114)
Age squared	-0.000226*	9.94e-05	4.54e-05	8.68e-05	-3.51e-05
	(0.000136)	(0.000288)	(0.000122)	(5.86e-05)	(0.000162)
Subject to FDI	1.335***	1.129***	0.464***	-0.0606	0.514***
	(0.227)	(0.196)	(0.118)	(0.0404)	(0.145)
1 or 2 adopted technologies [ref.cat. "no technologies"]	0.741***				
	(0.101)				
3+ adopted technologies [ref.cat. "no technologies"]	0.973***				
	(0.0925)				
Artisanal production	-0.381***				
	(0.0768)				
TCI		**0.168***	**0.118****	**-0.0338***	**0.151****
		(0.0993)	**(0.0424)**	**(0.0193)**	**(0.0579)**
Constant	-2.476***	9.831***	-0.577	8.962***	-9.489***
	(0.258)	(0.614)	(0.472)	(0.113)	(0.507)
Rho		-0.146	-0.359	0.284***	-0.384*
		(0.113)	(0.268)	(0.102)	(0.200)
log(sigma)		0.766***	-0.0683	-0.750***	0.271***
		(0.0346)	(0.0441)	(0.0244)	(0.0375)
Selected observations			815		
Non-selected observations			797		
Observations			1,612		

Notes: standard errors in parentheses, significance stars as follows *** p<0.01, ** p<0.05, * p<0.1. For the sake of brevity, we only report one of four estimated selection equations because of the almost equivalence of the coefficients. All the dependent variables of the outcome equations are in logs. Errors are clustered at the 5-digit ATECO industry level.

Firms that are subject to foreign direct investment (FDI) show robust export performance. These firms are more likely to export, with higher export intensity and a broader range of export destinations. The positive effects of FDI extend to geographical diversification, as FDI-backed firms are better able to expand into multiple regions. This is consistent with the idea that FDI provides the necessary resources and international networks that enhance a firm's ability to compete globally. Additionally, these firms exhibit lower export concentration, further confirming that FDI helps firms diversify their market presence.

The adoption of technology also emerges as a critical factor. Firms that have adopted one or more technologies are significantly more likely to export than those without any technological adoption. This supports the view that technological capabilities enhance a firm's competitiveness and ability to enter international markets. In addition to improving the likelihood of exporting, higher levels of technological complexity (as captured by the Technological Complexity Index, TCI) are associated with a broader export reach and greater geographical diversification. Technologically advanced firms tend to export to more countries and distribute their exports more evenly across markets, as reflected in the negative relationship between TCI and the export concentration index (HHI).

Artisanal firms, by contrast, are less likely to export. This result suggests that the nature of artisanal production, often characterized by smaller-scale, localized production and lower levels of technology, does not lend itself easily to international expansion. These firms may face structural limitations that prevent them from reaching global markets, highlighting the challenges faced by traditional sectors in an increasingly globalized and technologically driven economy.

c. Insights from firms' international organization

To further explore insights regarding firms' international organization, we apply a K-means clustering approach based on their responses to key questions outlined in section 3a. These questions relate to various aspects of firms' adaptation strategies in foreign markets, including whether they customize their product systems, use ad-hoc documents, establish dedicated offices, provide post-sale services, adapt their logistics, or engage with strategic partners. This method allows us to group firms based on commonalities in their organizational practices, shedding light on distinct patterns of internationalization.

Table 6. K-mean based clusters on firms' international organization

Cluster	Considering foreign markets, has the product system been customized?	are ad-hoc documents used?	do you have a dedicated office?	do you provide post-sale customer services?	has the logistics system been adapted?	do you have strategic partners?	n
1	0%	0%	0%	0%	0%	0%	59
2	0%	0%	0%	100%	55%	21%	156
3	54%	0%	0%	0%	96%	38%	63
4	57%	0%	100%	85%	90%	55%	199
5	100%	0%	40%	75%	0%	42%	85
6	86%	75%	57%	96%	94%	73%	281
Total	56%	26%	47%	79%	71%	49%	773

Note: not all the exporting firms answered completely to the survey questions, thus in this subsequent analysis there is a moderate loss of 42 observations with respect to the exporting sample used for the regression.

The results of this clustering, as presented in Table 6, show how firms align into six distinct clusters based on their degree of adaptation to international market demands. Each cluster represents a different combination of responses across the six variables, revealing heterogeneity in how firms manage their international operations. The clustering method optimally partitions the firms, ensuring that within-cluster similarity is maximized while between-cluster differences are emphasized. Table 7 characterizes from a managerial and economic standpoint each cluster.

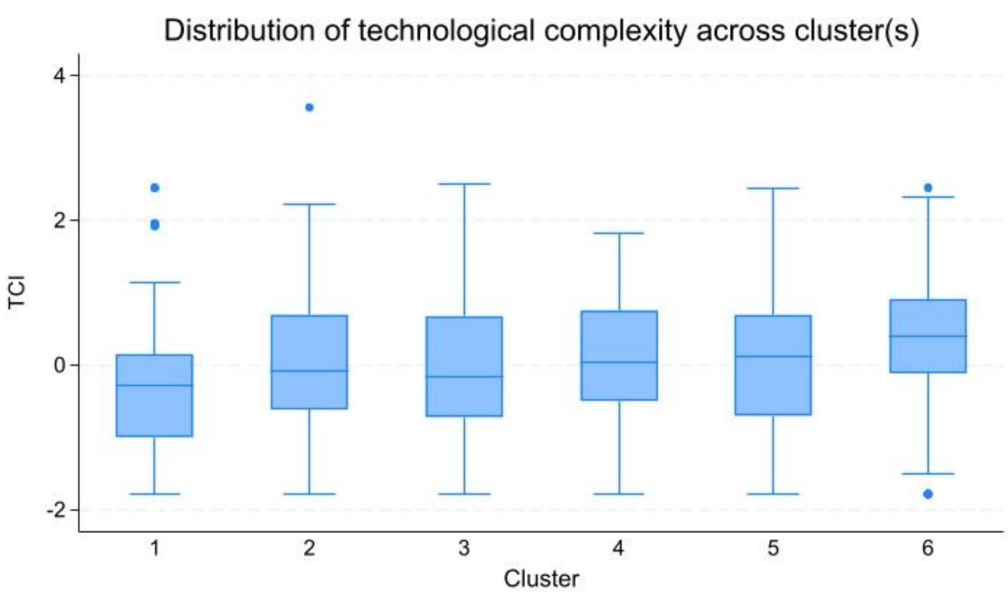
Table 7. Clusters description.

Cluster ID	Short name	Description
1	Minimal International Customization	These firms adopt a standardized approach with minimal adaptation for foreign markets, possibly indicating limited international engagement or resource constraints.
2	Post-Sale Service Focus	Focus on customer satisfaction through post-sale services and logistical adaptations, with some strategic partnerships, likely to maintain customer relationships abroad.
3	Partial Customization and Logistics Adaptation	These firms prioritize product customization and logistics to meet foreign market demands, supported by strategic partnerships.
4	Comprehensiv e Organizational Adaptation	These firms exhibit a well-rounded approach to international markets, with extensive customization and dedicated resources, reflecting a strong commitment to internationalization.

5	Product Customization Focus	Strong emphasis on product customization, with moderate use of other internationalization practices, indicating a product-centric strategy for foreign markets.
6	Highly Adapted and Supported Firms	These firms show extensive adaptation and support for international operations, reflecting sophisticated and well-resourced international strategies.

Overall, Clusters 4 and 6 indicate a comprehensive approach, whereas Clusters 1 and 2 show more selective adaptations. This clustering analysis offers a systematic way to classify firms based on their international organization, enabling us to draw meaningful distinctions between those that pursue standardized approaches and those that engage in more tailored, resource-intensive adaptations for foreign markets. These clusters form the basis for further examination of how organizational strategies relate to other key performance indicators, such as export intensity, geographical diversification, and technological complexity, which are be explored below.

Before associating these clusters to our variables of interest, on the technological and geographical side, we plot the distribution of the technological complexity index for each of the six identified clusters. As we can see, there exists a natural ordering of the technological endowments across the clusters, as also confirmed by formal testing reported in Table A2.



Switching to the regression results, Table 8 shows the relationship between the firms' international organizational clusters and our target variables: Technological Complexity Index (TCI), export intensity, macro-level export concentration (HHI), number of export destination countries, and geographical diversification index (GDI). The regressions use Cluster 1, the baseline group with minimal international adaptations, as the reference category.

Table 8. Regression results between our target variables and each cluster based on the form of international organization.

VARIABLES	(1) TCI	(2) Exp.int	(3) HHI macro	(4) # destination countries	(5) GDI
Cluster 2	0.245	-0.435	0.00683	-0.120	-0.127
[ref. cat. "Cluster 1"]	(0.179)	(0.413)	(0.0759)	(0.187)	(0.250)
Cluster 3	0.237	-0.166	0.110	-0.152	-0.262
	(0.210)	(0.513)	(0.0891)	(0.204)	(0.273)
Cluster 4	0.330*	0.943**	-0.327***	0.752***	1.079***
	(0.179)	(0.398)	(0.0731)	(0.183)	(0.238)
Cluster 5	0.324*	0.485	-0.231**	0.485**	0.716**
	(0.168)	(0.423)	(0.0906)	(0.209)	(0.281)
Cluster 6	0.607***	1.363***	-0.333***	1.000***	1.332***
	(0.150)	(0.357)	(0.0752)	(0.183)	(0.243)
Constant	-0.252*	10.04***	8.606***	0.819***	-7.787***
	(0.147)	(0.382)	(0.0676)	(0.169)	(0.224)
Observations			773		
R-squared	0.038	0.125	0.114	0.152	0.159

Notes: standard errors in parentheses, significance stars as follows *** p<0.01, ** p<0.05, * p<0.1. With the exception of TCI, all the dependent variables of the outcome equations are in logs. Errors are clustered at the 5-digit ATECO industry level.

Highly adapted and supported firms, which exhibit the most extensive organizational adaptations—such as product customization, dedicated offices, logistics adjustments, and strategic partnerships—stand out with significantly higher technological complexity and export intensity. They also reach more export destinations and demonstrate broader geographical diversification, while maintaining less concentrated export portfolios. This suggests that firms making the most substantial organizational changes are better positioned to penetrate international markets and diversify their operations.

Cluster 4 follows a similar pattern, with firms also benefiting from a range of organizational adaptations, such as offering post-sale services and logistics adjustments. These firms perform well in terms of technological complexity and export diversification, exporting to a wider array of markets. They also show less reliance on concentrated export markets, reinforcing the idea that a more adaptive international approach fosters broader market engagement.

Cluster 5, which involves firms with a product customization focus, also is associated with positive outcomes, though to a slightly lesser degree than Clusters 4 and 6. These firms show gains in both technological complexity and market diversification, supporting the notion that even partial international adaptation can lead to improved performance in foreign markets.

In contrast, Clusters 2 and 3, representing firms that adopt limited or uneven organizational changes, do not show significant benefits in terms of export intensity or diversification. These firms, which make only selective adjustments in their international strategies, tend to underperform relative to those that have embraced more holistic changes. Cluster 2 firms, in particular, show negative trends in export intensity, suggesting that minimal adaptations may hinder international success.

Overall, the results suggest that firms with more comprehensive and tailored international organizational strategies—such as those in Clusters 4, 5, and 6—tend to perform better in terms of technological complexity, export intensity, and market diversification. These findings reinforce the importance of holistic organizational adaptation when entering foreign markets, as greater customization and strategic alignment across logistics, post-sale services, and partnerships appear to support firms in achieving higher levels of export performance and broader market reach. In contrast, firms with minimal or selective adaptations are less competitive in international markets, as seen in Clusters 2 and 3.

5. Conclusions

This study sheds light on the interplay between technological complexity, organizational adaptation, and international performance in firms, drawing from a detailed analysis of export intensity, market diversification, and technological sophistication. The findings reveal that firms adopting comprehensive international organizational strategies—such as customizing their product systems, establishing dedicated offices, adapting logistics, and engaging in strategic partnerships—are better positioned to thrive in global markets. These firms exhibit higher technological complexity, broader geographical diversification, and more balanced export portfolios. Conversely, firms with limited organizational adaptations face challenges in competing internationally, with lower export intensity and market reach.

One of the most significant insights from this research is the clear relationship between a firm's technological complexity and its international success. Firms that invest in advanced technologies are more likely to expand into new markets and diversify their export activities. This highlights the need for firms to view technology adoption not as an isolated investment, but as an integral part of a broader international strategy. In doing so, they can improve both their competitive positioning and operational resilience in a globalized economy.

The findings from this study underscore the critical role of technological complexity and organizational adaptation in driving firms' international success. To enhance the global competitiveness of firms, particularly small and medium-sized enterprises (SMEs), policymakers should focus on promoting technological upgrading. SMEs often face barriers to adopting advanced technologies due to limited resources or expertise. Targeted government programs that provide financial support, such as subsidies for technology investments, tax incentives for research and development, and accessible innovation grants, can help bridge this gap. Additionally, support should be extended to traditional sectors, such as artisanal production, to facilitate their integration of digital technologies, ensuring that all firms, regardless of industry, can increase their technological complexity and competitiveness.

Organizational adaptation is equally vital. Firms that invest in customizing their product offerings, adapting logistics, and establishing strategic partnerships perform better in foreign markets. To encourage this, policymakers should develop initiatives that provide firms with the necessary tools and knowledge to optimize their internal organization for international operations. Export promotion agencies can play a pivotal role by offering consultancy services to help firms effectively structure their operations to meet the demands of foreign markets, particularly for firms with limited capacity to make these adjustments independently.

Moreover, policymakers should encourage firms to participate more actively in global value chains (GVCs), as involvement in these networks can foster both technological upgrading and export growth. Programs aimed at creating links between domestic firms and international GVCs—especially in technology-intensive sectors—can help firms move up the value chain and enhance their technological capabilities. Encouraging partnerships with foreign firms or facilitating foreign direct investment (FDI) can also be instrumental in driving knowledge transfer, which is essential for improving technological complexity and expanding international reach.

Finally, improving data collection on firms' technological adoption and export behaviors is essential for designing more effective policies. By supporting regular, detailed surveys that capture the timing of technology adoption and its integration into business strategies, policymakers can gain a clearer understanding of the relationship between technological complexity and international performance. This will enable the development of more targeted support mechanisms, ensuring that firms receive the precise assistance they need to enhance their competitiveness in global markets.

a. Future research avenues

An important avenue for extending this research lies in integrating the value chain perspective by analyzing how technological complexity interacts with the nature of goods traded and their position in the value chain. By examining unitary values of exported and imported goods (i.e., value/quantity ratios) and categorizing them as investment, intermediate, or consumption goods, we could assess how technological complexity influences the sophistication of a firm's role in global supply chains. For instance, firms with higher TCI scores may be more likely to export high-value intermediate or investment goods, positioning themselves in more complex and value-added segments of international production networks. Such an analysis would provide valuable insights into how technological sophistication aligns with firms' strategic positioning in global value chains, deepening our understanding of the dynamics between technology and trade.

Complementarily, a promising future research direction is also to establish the causal relationship between TCI and international reach. By repeating the survey and collecting data on the timing of technology adoption, it would be possible to examine whether increases in technological complexity lead to expanded market reach and greater export intensity over time. This longitudinal approach would allow for a more robust understanding of how technological advancements impact internationalization, offering evidence of causality rather than mere correlation. Such research could substantiate the role of technological innovation as a key driver of international success, helping firms and policymakers tailor strategies to foster technological growth with measurable global outcomes.

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Appendix

The TCI values are derived from the averaging of the **technological complexity index** computed for each of the 14 technologies in the sample, which are ranked as follows:

Table A1 – The technological complexity values at technological-level

Technologies	TCI
Metaverse and creation of virtual interaction spaces along the value chain	6.889
Nanotechnologies and smart materials	4.901
Augmented/virtual reality	4.587
Blockchain systems	4.091
Artificial intelligence	3.730
Digital twin technologies	3.505
Additive manufacturing systems	2.446
Big data management and analysis	1.934
Industrial internet, IoT/IoM	1.856
Data and information integration across different production stages	0.107
RFID, barcode, tracking/tracing systems	0.092
Robotics and automation	-0.290
Cloud services	-0.931
Cybersecurity management	-1.788

The table provides an insightful breakdown of various technologies along with their respective densities and Technology Complexity Index (TCI), offering a glimpse into the technological landscape traversed by the sample firms in Veneto. Observing the TCI values, we discern a spectrum of technological complexity across different domains. Technologies such as "Metaverse and creation of virtual interaction spaces along the value chain" and "Nanotechnologies and smart materials" boast high PCI scores, indicating intricate and sophisticated technological frameworks. Conversely, technologies like "Cybersecurity management" and "Cloud services" exhibit negative PCI scores, suggesting relatively lower levels of complexity. The density values unveil the prevalence of each technology within the examined context. Technologies such as "RFID, barcode, tracking/tracing systems" and "Data and information integration across different production stages" demonstrate high densities, indicating widespread adoption and integration across various sectors. Conversely, technologies like "Metaverse and creation of virtual interaction spaces along the value chain" and "Digital twin technologies" exhibit lower densities, potentially signalling emerging or niche domains within the technological landscape.

Figure A1 – Optimal clustering number selection.

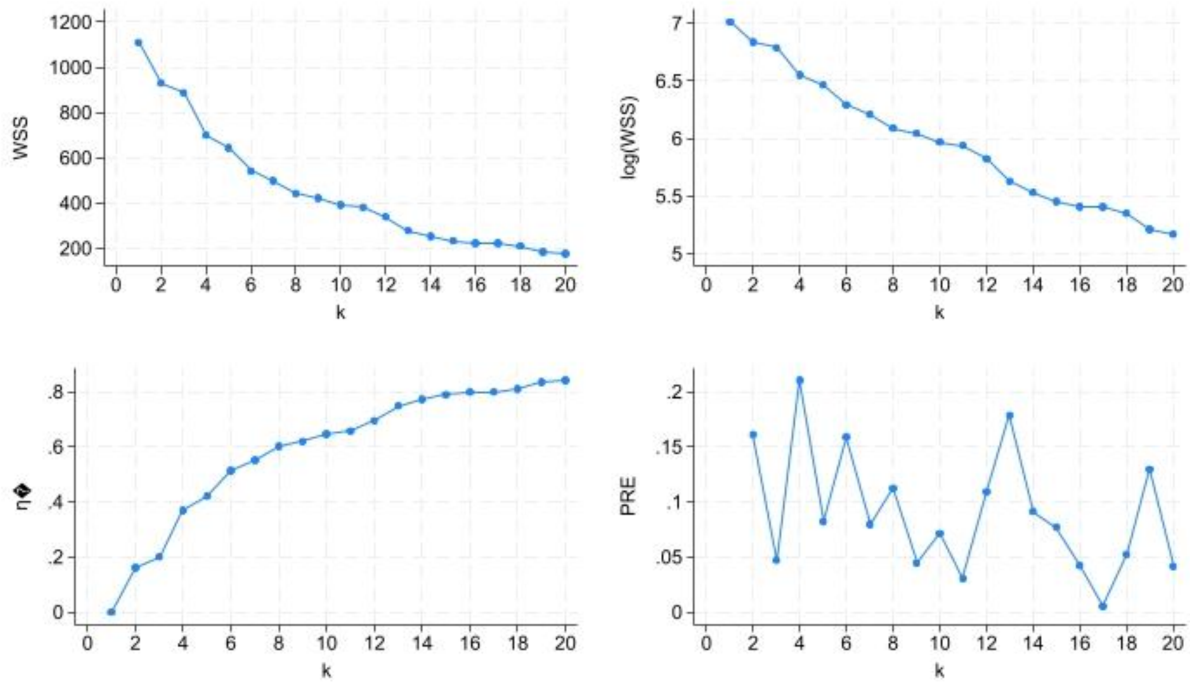

Table A2. Mean value of TCI across cluster and results of the Cuzick's test with rank scores

Cluster	Mean response score	Number of firms
1	-0.252	47
2	-0.008	145
3	-0.015	49
4	0.078	184
5	0.072	72
6	0.354	266
	statistic	75.298
	Std. Err.	13.448
	z	5.599
	Prob>|z|	0.000