Economics Bulletin

Volume 45, Issue 4

Boosting export competitiveness through firm automation

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Abstract

This paper unravels the effect of automation on international competitiveness through exports. We conduct our empirical analysis using a sample of firms from the World Bank Enterprise Survey, which spans 40 developed and developing countries over 2016–2022. Employing the recursive bivariate probit model, the fractional probit model, and the Lewbel's IV method to deal with endogeneity and reverse causality, we find that automation spurs the extensive and intensive margins of exports. We find stronger effect in manufacturing, high-productivity firms, and developed economies. Overall, automation can enhance export, but its effectiveness hinges on complementary investments and enabling ecosystems that support inclusive, productivity-driven trade growth.

Acknowledgements The authors would like to thank the anonymous referees for their very helpful comments. Thanks to the DSI/NRF/Newton Fund Trilateral Chair in Transformative Innovation, the 4IR and Sustainable Development for its support. This work has been partially supported by the National Research Foundation of South Africa (Grant Number: REP_SARC180529336567).
Citation: Ariel Herbert Fambeu and Patricia Tchawa Yomi and Mireille Etogo Messomo, (2025) "Boosting export competitiveness through firm automation", *Economics Bulletin*, Volume 45, Issue 4, pages 1794-1808
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Submitted: June 10, 2025. **Published:** December 30, 2025.

1. Introduction

In the last two decades, automation technologies and other digital technologies have improved considerably, leading to the emergence of the Fourth Industrial Revolution (4IR). Firms are increasingly able to automate job tasks using advances in robotics, machine learning, the internet of things, cloud computing, and other forms of artificial intelligence (AI). Increasingly, however, automation technologies allow firms to perform tasks using software systems, dedicated machinery, or industrial robots instead of workers. According to Sostero (2020), automation technologies aim to replace human labor with machine input for specific tasks within economic processes. As of 2024, there are roughly 8.4 million robots in operation around the world, with 51% and 49% of manufacturing and service robots, respectively (IFR, 2024). Between 2021 and 2023, the annual installations exceeded 705,000 units, of which 71% were industrial robots. Asia remains the world's largest market for industries utilizing robotics and automation. In 2023, Asia/Australia accounted for 72% of annual installations of industrial robots, while Europe and the Americas accounted for 17% and 11%, respectively. The automotive (30%) and electronics (28%) industries were the largest robot adopters (IFR, 2024).

In this regard, the implications of automation for employment have received substantial attention. Filippi et al. (2023) and Restrepo (2024) provide a comprehensive review of more than 120 studies on automation and employment and find that the results in the literature are inconsistent and inconclusive. Recent research has also given us useful information about how automation technologies affect many things, such as productivity (Dinlersoz and Wolf, 2024; Stiebale, 2024; Xu et al., 2024), profit (Stiebale, 2024), operating performance (Liu et al., 2024), firm value (Li et al., 2024a), and the global value chain (Reddy, 2025). In this paper, we investigate another channel—whether automation leads to firm export—in both developed and developing economies.

Automation technologies adoption primarily impacts firm exports by enhancing firm productivity (Cao et al., 2025; Fambeu and Tchawa, 2023; Melitz, 2003) and product differentiation (DeStefano and Timmis, 2024; Verhoogen, 2008). Melitz (2003) and Bernard et al. (2004), using the concept of heterogeneous firms in trade, highlight how productivity gains from technology and innovation enable firms to cover fixed export costs. Automation technologies increase firm-level productivity by enabling more efficient production processes, hence reducing unit costs and improving worldwide competitiveness (Autor et al., 2013; Grossman and Rossi-Hansberg, 2008). Explicitly designed to achieve greater accuracy, many robots can incorporate sensors to identify product defects (Herakovic et al., 2011). The widespread diffusion of robotics in firms may lead to increases in the quality of products and, thus, a competitive advantage in the international market (DeStefano and Timmis, 2024). Similarly, in a model with heterogeneous firms and quality differentiation, Verhoogen (2008) showed that more productive firms produce higher-quality goods than less productive firms, and only the most productive firms enter the export market. Different levels of digitalization create this heterogeneity among firms.

This study aims to investigate the effect of automation on firm export. We contribute to the recent yet burgeoning strand of literature that examines the economic consequences of automation adoption. By focusing on firm exporting, we complement the scarce literature on the effect of automation on international trade. Specifically, our paper adds to the existing literature in three key areas. First, compared to existing studies, we use data from both developed and developing country firms. Indeed, similar research has been conducted in China (Huang et al., 2023; Li et al., 2024; Cao et al., 2025), Spain (Alguacil et al., 2022), etc. These studies found that the robot adoption significantly promotes firm export. On the other hand, the study by DeStefano and Timmis (2024) on developed and developing countries does not examine the effect on exports, but on the quality of export products. In addition, their study is macroeconomic. Their findings show that robot diffusion increases the quality of exported products. Given that developing countries typically export goods of lower quality, their findings indicate a stronger overall impact on these economies. Therefore, our study enables us to evaluate the effect of automation based on a country's level of development. This allows us to know whether automation promotes the catching up of developing countries or, on the contrary, contributes to widening the gap already existing in participation in international trade. Second, existing literature focuses on the exploration and analysis of the impact of robot adoption on the export tendency, value and product quality of firms, neglecting the analysis of the effect of robot adoption on the export intensity of firms. To bridge this gap, we explore how automation affects firms' exports by examining the extensive (probability of exporting) and intensive (level of foreign sales) margins of exports. Third, our paper provides how firms can leverage automation to enhance exports from a productivity perspective. It further reveals the underlying logic behind the differentiated effect of automation on firm exports, thereby creating conditions for firms to develop complementary elements alongside automation technologies.

The rest of this paper proceeds as follows: Section 2 introduces the details of the empirical strategy, including the data and our automation measure. Results are discussed in Section 3. Section 4 concludes the paper with policy implications.

2. Methodology

2.1. Firm level data and variable measures

The data source comes from the World Bank Enterprise Surveys (WBES) database. The WBES currently operate in approximately 155 countries, offering a vast array of economic data on over 180,000 businesses. The WBES collects data by means of the stratified random sampling method based upon firm size, industry, as well as geographic region. The WBES has a broad array of business environment data covering topics such as exports, technologies, sales, and employment, among others. The WBES is administered to firm owners as well as top managers in the private sector. The survey covers formal private firms in both the manufacturing and service sectors. Although the data collected begins in 2006, information on automation technologies is available only from 2016. Therefore, we limited our analysis period to 2016–2022. We then cleaned the data by removing missing data, eliminating "don't know" spontaneous responses, and removing countries with fewer than five automated firms[1]. Our final sample consists of 8,340 firms across 40 economies[2].

The dependent variable of this paper is the export propensity of firms (*EXPP*). This binary variable takes the value 1 when a firm exports and 0 otherwise. In addition, this article draws on literature (Cao et al., 2025; Fambeu and Tchawa, 2023) measuring firm export intensity

[1] We excluded countries with fewer than five automated firms from the sample to ensure the robustness and reliability of our econometric analysis. Extremely small subsamples can lead to unstable estimates, inflated standard errors, and biased inference, particularly in disaggregated models or model including country-level heterogeneity. Moreover, including such limited cases may disproportionately influence the results without offering meaningful generalizable insights. This approach is consistent with Reddy et al. (2025), who also applied a minimum threshold for firm counts in cross-country automation studies to avoid distortions caused by very small samples.

[2] Table A1 (in the Appendix) presents the list of the countries.

(*EXPI*) to supplement the dependent variable. We measure the export intensity of a firm by the ratio of its total export volume to its current year's sales revenue.

The key independent variable in this study is firm automation. We use text analysis to ascertain whether a firm has implemented new automation technologies. The data on the firm's adoption of new technology is the initial source of information. In particular, we focus on the inquiry that requests a comprehensive explanation of the primary new or enhanced process that this institution has implemented within the past three years. The variable offers a concise summary of the firm's methodology. We identify firms that have automated the process through the text analysis of the supplied information. If the response includes any of the following words: "automation," "automated," or "robot," we identify automation activities. In addition, we manually reviewed the responses to confirm the sample firm's implementation of these technologies and to rule out the respondent's identification as a producer. Therefore, automation is a binary variable (*AUTO*) that is represented by 1 if a firm has automated any of its duties or implemented robots and 0 otherwise. Reddy et al. (2025) used the same method to identify automated firms. Table A2 (in the Appendix) provides more information about the automation adoption by sample firms. Table 3 gives a detailed description of all variables in the regression model. Table A3 (in the appendix) displays the descriptive statistical information for all variables, while Table A4 (in the appendix) shows the correlation analysis between variables.

Table 3: Variable definition

Variable	**Description**
Dependent variables	
EXPP	Dummy variable equal to 1 if the firm exports and 0 otherwise.
EXPI	Measure by the ratio of enterprise export value to sales volume.
Independent variables	
AUTO	Dummy variable equal 1 if the firm adopts any automation process and 0 otherwise (h6x)
LNLP	Log of Sales/Num. Permanent, Full-Time Employees at End of Last Fiscal Year
SIZE	Categorical variable that takes the value 1 if the firm employs less than 20 people (Small Enterprise-SE), 2 if the firm employs between 20 and 100 people (Medium Enterprise-ME), and 3 for larger firms (more than 100 employees) (Large Enterprise-LE).
LNAGE	Log of the age of the firm.
WEB	Dummy variable equal 1 for firm that has its own website, and 0 otherwise.
FDI	Dummy variable equal 1 if the share of foreign ownership in the firm is greater than or equal to 10%, and otherwise 0.
FINANCE	Dummy variable equal to 1 if the firm reports that access to finance is an obstacle to its current operations, and 0 otherwise.
FEMALE	Dummy variable equal 1 if there is at least one woman among the owners of the firm.
LNEXPER	Log of the number of years of experience of the top manager.
CORRUPT	Dummy variable taking the value 1 if the firm reports that corruption is an obstacle to its current operations, and 0 otherwise.
POLINST	Dummy variable taking the value 1 if the firm identifies political instability as an obstacle to its current operations, and 0 otherwise.

From Table A4, we observe that only 41% of sample firms are exporter firms. In addition, 8% of the firms in the sample are adopters of automation technologies. This low level of automation adoption is not surprising, as this technology, while increasing, is still in its early stages. Reddy et al. (2025) document a similar level of automation at the firm level, reporting that 5% of firms adopted automation technologies during 2016–2019. Moreover, the analysis of Table A4 shows that the correlation coefficients between the control variables are all less than 0.62, indicating that there is no high collinearity problem.

2.2. Empirical model

To examine the effect of automation technologies on firm export performance, the following econometric model (1) is constructed:

$$EXP_{jc} = \beta_0 + \beta_1 AUTO_{jc} + \beta_2 X_{jc} + \delta_j + \tau_c + \varepsilon_{ijc} \quad (1)$$

Among them, i represents the firm, j represents the industry, and c represents the country. *EXP* denotes the export performance, which is measured by extensive (probability of exporting, *EXPP*) and intensive (export intensity, *EXPI*) margins of exports. The key explanatory variable, $AUTO$, indicates whether a firm has adopted automation technologies. *X* captures other factors influencing the firm's export performance, including firm productivity, size, age, ICT, finance, the nature of ownership, the gender and experience of the manager, and the institutional quality (corruption and political instability). Additionally, δ_j and τ_c account for the industry and country fixed effects, respectively, while ε_{ijc} is the random perturbation term.

Given the nature of our dependent variable, measured as the propensity to export (or not), we use a probit regression model. On the other hand, since the dependent variable is export intensity (export turnover over total sales), the most appropriate model is the fractional probit model introduced by Papke and Wooldridge (1996). However, to overcome the heteroscedasticity problem, we use the robust form of the estimates. Furthermore, to take into account the endogeneity issue of the "automation" variable, we use a recursive bivariate probit estimation for the export propensity model and a fractional probit model for the export intensity model (Greene, 2012; Wooldridge, 2010). The recursive bivariate probit model is a two-step estmators. In the first stage, we model the probability of automation as a function of exogenous firm characteristics (productivity, size, age, ownership, sector dummies, etc.), thereby isolating the component of automation choice driven by observables. In the second stage, we include both the predicted probability from stage 1 and its residual as regressors in the export equation. By conditioning on the residual from the first-stage automation equation, we eliminate bias from unobserved factors that simultaneously affect automation and export outcomes. This approach replicates the logic of an instrumental variables strategy within a nonlinear probit setting (Greene, 2012; Wooldridge, 2010).

While the recursive bivariate probit model addresses endogeneity arising from omitted variable bias (e.g., unobserved productivity affecting both automation and export decisions), it does not by itself fully resolve potential reverse causality. For instance, a positive exogenous shock in foreign demand could enhance firms' revenues and access to capital, which in turn may facilitate automation investments.

To strengthen identification, we complement the recursive probit and fractional probit models with the heteroskedasticity-based IV approach proposed by Lewbel (2012). This method constructs instruments internally by interacting mean-centered exogenous regressors with the residuals from the first-stage regression of the endogenous variable. Under the assumption that the first-stage error is heteroskedastic, these generated instruments are correlated with the endogenous regressor but remain uncorrelated with the structural error term, thereby satisfying the relevance and exclusion conditions.

In our case, the potentially endogenous regressor is automation (AUTO). The first stage regresses AUTO on the set of exogenous firm-level covariates already included in the export equations (productivity, size, age, web presence, foreign ownership, access to finance, female ownership, manager experience, corruption, political instability, and country, industry, and year fixed effects). The constructed instruments take the form $\tilde{X} \times \hat{u}$, where $\tilde{X}$ are mean-centered exogenous regressors and $\hat{u}$ are the first-stage residuals.

For validity, the approach requires two conditions (see Baum & Lewbel, 2019): (i) relevance (the constructed instruments must be correlated with AUTO), which is achieved if the first-stage errors are heteroskedastic with respect to X, and (ii) exogeneity (exclusion restriction), which holds if the generated instruments are uncorrelated with the structural error in the export equation. The former is testable and expected in our cross-country, firm-level data, where heterogeneous technologies, sizes, and institutional environments naturally generate heteroskedasticity. The latter relies on the standard assumption that the included exogenous covariates are valid.

Taken together, the consistency of findings across the three econometric strategies (recursive bivariate probit, fractional probit, and Lewbel IV) helps mitigate concerns about endogeneity and reverse causality, and reinforces the robustness of our conclusion.

3. Results

3.1. Baseline results

Table 4 shows the results of the treatment impact of automation on the probability of export[3]. The estimated parameters show statistical significance across all three treatment impacts ($p < 0.05$). In the first column, which includes the entire sample, the ATE stands at 0.51. This indicates that the adoption of automation technologies enhances the probability of exporting by an average of 51 percentage points f or both adopters and non-adopters. The ATET parameter of 0.61 suggests that automated firms have a 61% higher probability of exporting compared to their non-automated counterparts. The ATEC of 0.07 indicates that the adoption of automation by non-adopters could potentially increase their propensity to export by 7 percentage points. Given that the ATE is lower than the ATET, this could indicate that automation adopters possess unobserved characteristics (international network, organizational capabilities, human capital, managerial capabilities or prior export experience), that amplify the technology's benefits. However, the effect of automation on the probability of exporting is found to be stronger in firms with higher productivity and in developed economies. These results align with theoretical models in which technology adoption reduces trade costs and improves productivity, enabling firms to overcome export market entry barriers (Bernard et al., 2018; Melitz, 2003). While the results hold across sectors, manufacturing firms show slightly larger effects, reflecting the greater tradability of goods and the suitability of automation for production processes (Autor et al., 2021). Figure 1 presents the marginal effects of all parameters as well as the treatment effects for the full sample case.

These findings suggest that automation can be a powerful tool for boosting exports, particularly for firms with complementary capabilities. However, policies aimed at increasing automation adoption should be accompanied by investments in infrastructure, trade logistics, institutional quality, workforce skills and managerial training to maximize the potential gains.

Table 4: Automation and the propensity to export (Treatment effects from recursive bivariate probit model)

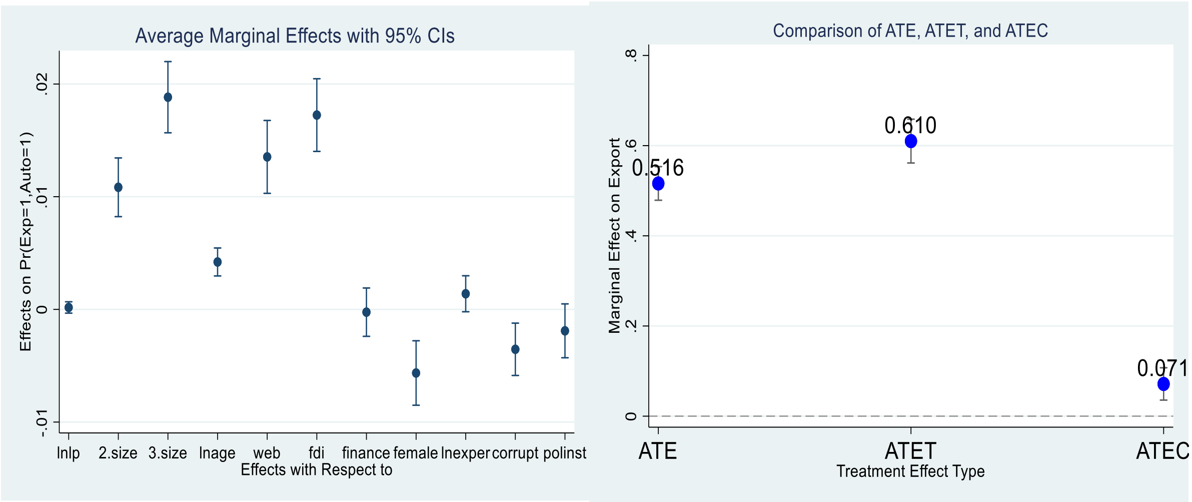
	All	**Manufacturing**	**Services**	**LProd**	**HProd**	**LMIC**	**UMIC**	**HI**
ATE	0.516***	0.423***	0.341***	0.453***	0.484***	0.042*	0.177**	0.324***
	(0.018)	(0.023)	(0.201)	(0.051)	(0.023)	(0.032)	(0.043)	(0.087)
ATET	0.610***	0.566***	0.353***	0.514***	0.605***	0.103**	0.132**	0.363**
	(0.024)	(0.037)	(0.069)	(0.056)	(0.033)	(0.027)	(0.039)	(0.118)

[3] Table A5 (in the Appendix) presents the coefficients from the bivariate recursive model.

ATEC	0.071	0.043**	-0.017	0.026	0.011	-0.081**	-0.025	0.066***
	(0.017)	(0.020)	(0.033)	(0.026)	(0.023)	(0.040)	(0.027)	(0.025)

ATE=Average treatment effect; ATET=Average treatment effect on the treated; ATEC=Average treatment effect on conditional probability; LProd=Lower Productivity; HProd=Higher Productivity; LMIC=Lower-Middle-Income; UMIC=Upper-Middle-Income; HI=High Income; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Figure 1: Marginal and treatments effects of automation on export (All)



Sources: authors, from WBES

Table 5 displays the marginal effects of a binary automation indicator (AUTO) on export intensity, measured as the share of export sales in total firm sales, estimated via a fractional probit model with an endogenous regressor. The overall marginal effect indicates that automation is associated with a 5.2 percentage point increase in export intensity among all firms, holding other factors constant. Notably, the effect of automation varies significantly by sector. The manufacturing subgroup shows a positive and significant effect, while service firms see a small, negative but statistically insignificant effect. This suggests that automation is more relevant to export-oriented goods producers, whereas service sectors may rely more heavily on digital platforms or intangible assets.

Stratification by productivity reveals a strong heterogeneity in the effects of automation: high-productivity firms experience greater gains than low-productivity firms. Specifically, automation leads to an increase in export intensity of 6% for high-productivity firms compared to 3% for low-productivity firms. This pattern reflects the “productivity premium” phenomenon, where automation yields greater benefits when firms already possess organizational capabilities that amplify the effect of technological adoption (Bernard and Jensen, 1999). The smaller effect observed for low-productivity firms is consistent with “self-selection” theories in international trade, which argue that only the most productive firms can overcome the fixed costs associated with exporting (Bernard et al., 2018). These findings are consistent with the broader empirical literature that links digital and automation adoption to export performance. For instance, Alguacil et al. (2022) demonstrated that robot adoption improves export performance in Spain by boosting total factor productivity. Similarly, Li et al. (2024b) and Yuanyuan et al. (2025) provide evidence from China showing that automation significantly increases both the export share and the sales value of firms, plausibly due to improvements in productivity and product quality. Huang et al. (2023) and Cao et al. (2025) also confirm the positive association between automation and export competitiveness. Añón Higón and Bonvin (2024) argue that productivity has a more significant impact on Spanish firms' trade behavior than the direct effect of digitalization itself, highlighting the importance of internal firm capabilities in translating automation into export success.

The analysis by income group further reveals a sharp divide. In high-income countries (HICs), automation has a large and statistically significant positive effect on export intensity. However, in lower-middle-income (LMICs) and upper-middle-income countries (UMICs), the effects are statistically insignificant. This supports the notion of an "automation divide" (Cirera et al., 2021), where automation benefits accrue disproportionately to countries with higher digital readiness and institutional capacity. Cerutti et al. (2025) similarly highlight that infrastructure and institutional weaknesses in lower-income settings limit the potential gains from automation, even when the technology is available.

Overall, the empirical results from Table 5 underscore that automation raises export intensity primarily within manufacturing, among more productive firms, and in higher-income contexts. This suggests that firm capability building (e.g. complementing automation with training and organizational restructuring) and ecosystem investments (digital infrastructure, governance, logistics) are essential to translating automation into trade benefits, particularly in developing economies.

Table 5: Automation and the intensity of exports (Marginal effects from fractional probit model)

VARIABLES	(1) All	(2) Manufacturing	(3) Services	(4) LProd	(5) HProd	(6) LMIC	(7) UMIC	(8) HIC
AUTO	0.052***	0.040***	-0.009	0.035**	0.061***	0.011	0.017	0.060***
	(0.010)	(0.013)	(0.017)	(0.014)	(0.013)	(0.031)	(0.015)	(0.013)
LNLP	0.002**	0.007***	0.004**	0.008	0.007**	-0.007	0.006***	0.016***
	(0.002)	(0.002)	(0.002)	(0.006)	(0.003)	(0.005)	(0.002)	(0.003)
SE								
ME	0.070***	0.093***	0.020**	0.066***	0.068***	0.045**	0.033***	0.089***
	(0.006)	(0.010)	(0.008)	(0.009)	(0.010)	(0.018)	(0.009)	(0.010)
LE	0.151***	0.198***	0.033***	0.179***	0.124***	0.136***	0.105***	0.173***
	(0.009)	(0.013)	(0.010)	(0.014)	(0.012)	(0.024)	(0.013)	(0.014)
LNAGE	0.008**	0.003	-0.003	-0.001	0.015***	-0.022*	-0.001	0.017***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.011)	(0.006)	(0.005)
WEB	0.009	0.008	0.022*	0.011	0.009	-0.015	0.012	0.018
	(0.010)	(0.014)	(0.012)	(0.013)	(0.014)	(0.019)	(0.013)	(0.018)
FDI	0.133***	0.176***	0.066***	0.116***	0.139***	0.095***	0.091***	0.145***
	(0.008)	(0.011)	(0.010)	(0.012)	(0.010)	(0.022)	(0.012)	(0.012)
FINANCE	-0.012*	-0.028***	-0.007	-0.013	-0.008	0.000	-0.032***	0.007
	(0.006)	(0.009)	(0.008)	(0.009)	(0.009)	(0.017)	(0.009)	(0.009)
FEMALE	-0.023***	0.001	-0.036***	-0.020*	-0.019	0.003	0.003	-0.055***
	(0.009)	(0.013)	(0.010)	(0.011)	(0.014)	(0.022)	(0.012)	(0.014)
LNEXPER	0.003	0.001	0.008	0.001	0.005	0.030**	0.021***	-0.012*
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.014)	(0.008)	(0.006)
CORRUPT	-0.036***	-0.058***	0.002	-0.024**	-0.044***	0.001	0.002	-0.032***
	(0.007)	(0.010)	(0.008)	(0.010)	(0.011)	(0.023)	(0.011)	(0.011)
POLINST	-0.000	0.004	-0.004	-0.002	0.002	-0.023	0.003	0.007
	(0.007)	(0.010)	(0.009)	(0.009)	(0.011)	(0.022)	(0.012)	(0.010)
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes			Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,010	4,620	3,390	4,006	4,004	1,104	2,731	4,175

SE=Small Enterprise; ME=Medium Enterprise; LE=Large Enterprise, LProd=Lower Productivity; HProd=Higher Productivity; LMIC=Lower-Middle-Income; UMIC=Upper-Middle-Income; HI=High Income; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

3.2. Robustness test

To assess the robustness of our baseline estimates from recursive bivariate probit and fractional probit models, Tables 6 and 7 report results using Lewbel's (2012) heteroskedasticity-based IV estimator, for export propensity and intensity, respectively. This method constructs internal instruments from heteroskedasticity in the first-stage residuals and is particularly useful when external instruments are unavailable or weak (Baum and Lewbel, 2019). The Tables 6 and 7 report also the Stock–Yogo weak-instrument test and the Sargan overidentification test, which provide support for instrument strength and validity.

For export intensity, the IV coefficient on automation is still positive and significant. Subsample estimates remain economically significant, whereas the coefficient in services loses significance, suggesting automation's effects on export margins are more compelling in tradable manufacturing and among more capable firms. These results support emerging evidence that automation enhances firm performance and export market entry, especially in advanced productivity settings and high-income contexts. They also illuminate the heterogeneity documented in global studies: automation's payoffs on export quality and participation materialize more fully when supported by institutional and digital readiness (DeStefano and Timmis, 2024). Collectively, the IV estimates corroborate our main findings while offering a more conservative and causally credible assessment. This underscores that automation's export advantage is context-dependent and strongest where underlying firm capabilities and national infrastructure facilitate its effective use.

Table 6: Automation and the propensity to export (heteroskedasticity-based IV (Lewbel, 2012))

VARIABLES	(1) All	(2) Manufacturing	(3) Service	(4) LProd	(5) HProd	(6) LMIC	(7) UMIC	(8) HIC
AUTO	0.198***	0.148**	0.414***	0.112***	0.135***	0.108	0.024	0.160***
	(0.054)	(0.058)	(0.131)	(0.029)	(0.036)	(0.078)	(0.054)	(0.038)
LNLP	0.003	-0.004	0.009**	0.023**	-0.006	0.004	-0.001	0.035***
	(0.003)	(0.003)	(0.004)	(0.010)	(0.004)	(0.008)	(0.003)	(0.006)
SE								
ME	0.113***	0.143***	0.021	0.117***	0.105***	0.094***	0.076***	0.140***
	(0.012)	(0.017)	(0.016)	(0.016)	(0.017)	(0.030)	(0.019)	(0.017)
LE	0.212***	0.257***	0.041*	0.246***	0.183***	0.249***	0.205***	0.224***
	(0.015)	(0.019)	(0.021)	(0.021)	(0.019)	(0.036)	(0.023)	(0.022)
LNAGE	0.048***	0.045***	0.020**	0.034***	0.060***	0.023	0.050***	0.045***
	(0.006)	(0.008)	(0.008)	(0.009)	(0.009)	(0.018)	(0.011)	(0.008)
WEB	0.144***	0.168***	0.114***	0.121***	0.168***	0.058**	0.138***	0.122***
	(0.015)	(0.019)	(0.023)	(0.022)	(0.022)	(0.029)	(0.024)	(0.027)
FDI	0.189***	0.207***	0.158***	0.167***	0.197***	0.130***	0.159***	0.173***
	(0.015)	(0.020)	(0.020)	(0.023)	(0.018)	(0.035)	(0.023)	(0.022)
FINANCE	-0.006	-0.022	-0.014	-0.024	0.014	0.022	-0.054***	0.034**
	(0.011)	(0.014)	(0.016)	(0.015)	(0.016)	(0.027)	(0.017)	(0.015)
FEMALE	-0.064***	-0.018	-0.089***	-0.049**	-0.079***	-0.003	-0.041*	-0.087***
	(0.014)	(0.019)	(0.020)	(0.019)	(0.021)	(0.035)	(0.021)	(0.021)
LNEXPER	0.014*	0.016	0.021*	0.002	0.027**	0.024	0.044***	-0.012
	(0.008)	(0.010)	(0.012)	(0.012)	(0.011)	(0.021)	(0.014)	(0.011)
CORRUPT	-0.048***	-0.071***	0.007	-0.044***	-0.048***	0.019	0.010	-0.028*
	(0.012)	(0.016)	(0.017)	(0.017)	(0.018)	(0.033)	(0.022)	(0.017)
POLINST	-0.023*	-0.008	-0.034**	-0.030*	-0.017	-0.032	0.009	-0.024
	(0.012)	(0.016)	(0.017)	(0.017)	(0.018)	(0.033)	(0.024)	(0.016)
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes			Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-Yogo	125.494	97.162	33.589	1964.671	397.073	109.430	114.413	344.822
Sargan	0.150	0.190	0.123	0.170	0.356	0.204	0.483	0.444
Observations	8,010	4,620	3,390	4,006	4,004	1,104	2,731	4,175

Dependent variable: propensity to export (1 if the firm exports, 0 otherwise); SE=Small Enterprise; ME=Medium Enterprise; LE=Large Enterprise, LProd=Lower Productivity; HProd=Higher Productivity; LMIC=Lower-Middle-Income; UMIC=Upper-Middle-Income; HI=High Income; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 7: Automation and the intensity of exports (heteroskedasticity-based IV (Lewbel, 2012)

VARIABLES	(1) All	(2) Manufacturing	(3) Service	(4) LProd	(5) HProd	(6) LMIC	(7) UMIC	(8) HIC
AUTO	0.148***	0.106***	0.092	0.045***	0.091***	0.070	0.014	0.082***
	(0.030)	(0.032)	(0.058)	(0.017)	(0.021)	(0.053)	(0.032)	(0.022)
LNLP	0.001	0.006***	0.003*	0.006	0.005**	-0.007	0.005***	0.016***

	(0.001)	(0.002)	(0.002)	(0.006)	(0.003)	(0.005)	(0.002)	(0.003)
SE								
ME	0.064***	0.088***	0.018**	0.062***	0.065***	0.051**	0.029***	0.083***
	(0.007)	(0.011)	(0.008)	(0.009)	(0.011)	(0.021)	(0.011)	(0.010)
LE	0.143***	0.188***	0.026***	0.178***	0.118***	0.139***	0.105***	0.178***
	(0.009)	(0.012)	(0.010)	(0.012)	(0.012)	(0.023)	(0.012)	(0.013)
LNAGE	0.009**	0.005	-0.003	-0.001	0.018***	-0.024**	-0.003	0.018***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.011)	(0.006)	(0.005)
WEB	-0.005	-0.008	0.014	0.003	-0.007	-0.029	0.002	0.015
	(0.009)	(0.013)	(0.010)	(0.012)	(0.013)	(0.018)	(0.011)	(0.016)
FDI	0.177***	0.224***	0.086***	0.162***	0.179***	0.112***	0.138***	0.186***
	(0.009)	(0.013)	(0.011)	(0.014)	(0.012)	(0.025)	(0.014)	(0.013)
FINANCE	-0.010	-0.026***	-0.006	-0.013	-0.008	0.001	-0.035***	0.008
	(0.007)	(0.009)	(0.008)	(0.009)	(0.010)	(0.018)	(0.010)	(0.009)
FEMALE	-0.019**	0.003	-0.030***	-0.018	-0.017	0.006	0.004	-0.046***
	(0.008)	(0.012)	(0.009)	(0.011)	(0.013)	(0.022)	(0.011)	(0.013)
LNEXPER	0.000	-0.002	0.009	-0.000	0.001	0.029**	0.025***	-0.014**
	(0.005)	(0.007)	(0.006)	(0.007)	(0.007)	(0.013)	(0.008)	(0.007)
CORRUPT	-0.036***	-0.058***	0.003	-0.024**	-0.048***	0.002	-0.003	-0.031***
	(0.007)	(0.011)	(0.009)	(0.010)	(0.011)	(0.021)	(0.012)	(0.010)
POLINST	-0.000	0.004	-0.005	-0.003	0.000	-0.028	0.003	0.007
	(0.007)	(0.011)	(0.009)	(0.010)	(0.011)	(0.022)	(0.013)	(0.010)
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes			Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-Yogo	125.215	97.069	33.461	1975.416	397.198	109.586	114.458	344.474
Sargan	0.146	0.121	0.166	0.073	0.574	0.126	0.216	0.208
Observations	8,010	4,620	3,390	4,006	4,004	1,104	2,731	4,175
R-squared	0.140	0.194	0.041	0.126	0.187	0.107	0.125	0.183

Dependent variable: intensity of exports (export sales/total sales); SE=Small Enterprise; ME=Medium Enterprise; LE=Large Enterprise, LProd=Lower Productivity; HProd=Higher Productivity; LMIC=Lower-Middle-Income; UMIC=Upper-Middle-Income; HI=High Income; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

4. Conclusion

This study aimed to assess the effect of firm-level automation on export in Sub-Saharan African economies. Using cross-sectional Enterprise Survey data on formal firms surveyed from 2011 to 2022, we applied recursive bivariate probit and fractional probit models on both export propensity and intensity. To strengthen identification and address endogeneity and reverse causality, we implemented Lewbel's heteroskedasticity-based IV method, which constructs internal instruments in the absence of external valid instruments, helping correct for endogeneity bias. Our main findings show that automation significantly boosts export participation. Moreover, this positive effect of automation is stronger in manufacturing, in firms with higher productivity, and in developed countries. Policy implications emerge clearly. Digital infrastructure investments, such as broadband expansion and public digital backbone building, are critical to translate automation into export gains. By digitalizing customs, implementing single-window systems, and reducing non-tariff barriers, trade facilitation reforms will amplify returns to automation. Technical assistance, organizational upgrading, and skill development are necessary to ensure that productivity firms can leverage automation effectively. The public sector should coordinate automation support with broader development interventions such as energy reliability, trade infrastructure, and access to finance to avoid exacerbating trade-related inequality.

These insights suggest that automation has considerable potential to enhance formal firms' export orientation, but its effectiveness depends critically on complementary capabilities and enabling ecosystems. Development strategies should therefore promote holistic digital and trade reform agendas to stimulate inclusive export growth.

While our estimation strategy addresses omitted variable bias using a recursive bivariate probit model and Lewbel's IV method, it may not fully eliminate concerns about reverse causality. For instance, firms experiencing export success due to exogenous demand shocks may later adopt automation, implying that exports drive automation, not the reverse. Although our cross-sectional design and model specification mitigate simultaneity concerns, the lack of panel data limits our ability to establish temporal order. We acknowledge this limitation and suggest that future research use longitudinal data or policy-driven instruments to more precisely identify the direction of causality between automation and exports.

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Appendix

Table A1: List of the countries

Country	Survey year	Firms	Country	Survey year	Firms	Country	Survey year	Firms	Country	Survey year	Firms
Albania	2019	92	Denmark	2020	611	India	2022	203	Netherlands	2020	374
Argentina	2017	351	Ecuador	2017	198	Ireland	2020	210	Nicaragua	2016	123
Austria	2021	148	ElSalvador	2016	143	Italy	2019	64	Peru	2017	505
Belarus	2018	143	Estonia	2019	84	Kazakhstan	2019	195	Poland	2019	110
Belgium	2020	214	Finland	2020	486	Kenya	2018	263	Portugal	2019	80
Bolivia	2017	156	France	2021	517	Kyrgyz Republic	2019	95	Romania	2019	163
Bosnia and Herzegovina	2019	105	Germany	2021	627	Latvia	2019	172	Russia	2019	149
Bulgaria	2019	97	Greece	2018	93	Lithuania	2019	79	Serbia	2019	103
Colombia	2017	518	Guatemala	2017	159	Malaysia	2019	180	Slovak Republic	2019	36
Czech Republic	2019	146	Hungary	2019	104	Moldova	2019	76	Slovenia	2019	208

Table A2: Description of all the automation technologies that firms have adopted

"We Have Automated Our Sales System" "- Which Means Sales On Social Media. Customers Can Sign Up On Social Media And Get A Special Price."
A Bagging Process Went Fully Automated
A Better Management Program And Distribution Planning: It'S Automatic And It'S Faster
A Better, Faster And Automatic Way Of Registerings, Inventories And Sales/ Selling Method
A Bigger Degree Of Automation In Production
A Bread Line That Works More Automatically
A Digital Process In An Online Store Where The Customer Gets Defined What They Want, The Process Automated
A Fully Automatic Filling Can Weigh Everything And Make Sausage.
A Machine That Makes The Product Without Operators, Injects The Filling And The Like That Happens Automatically. Only The Start-Up And Shutdown Of The Machine Is Done By Our People In The Morning And In The Evening.
A Modern Automated Fabric Cutting Line Has Been Purchased. It Allows Cutting Of Piece Goods In Large Quantities. Also Modern Sewing Machines Have Been Purchased.
A New Automated Logistics Process Has Been Introduced. Gaps In Logistics Can Be Detected And Prevented. What Occasionally Goes / Went Wrong Can Also Be Resolved Better And Faster
A New Automatization Of Production Process Has Been Implemented
A New Graging Machine That Does It Automatically
A New Line In The Carpentry. Automatic Line For Chipboard Processing
A New Modern And Half-Way Automated Switching Center
A New Spraying Method For Concrete Processing: The Use Of A Spraying Robot For Processing Shotcrete
A Packaging Robot That Packs Steel Coils With Reinforced Plastic
A Part Of Our Production Means Has Been Automated
A Robot Has Been Developed To Replace Manual Work, And A Robot Has Been Purchased.
A Robot Machine For Painting
We Use New Automatic Machines To Process Meat
We Use New Software To Automatically Process Orders
We have a robot for one part of the production
Welding Methods Have Been Further Automated
Welding Robot.
Went From Plasma Cutting To A Lazer Controlled System Which Is Automated.
Work Has Been Automated
Automate some processes
Automatic fillers and automatic encoders
Automatic raw material supply and machine expansion to 17 and 22
Billing automation process
Finest colour spray auto machine
High volume quantity automatic water tank production machine
Mixer machine automatic for ease of mixing
New automated packaging line
New generation automatic wire cutting equipment
Optimization in automated plants
Sub zero chillers, automation system, tanks vessles
The automated production line
Use automatic machine

Table A3: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
EXPP	8,340	0.4125899	0.4923297	0	1
EXPI	8,340	0.1650612	0.292788	0	1
AUTO	8,340	0.0845324	0.2782012	0	1
LNLP	8,206	12.9433	2.131834	6.345929	23.12301
SE	8,340	0.364988	0.4814557	0	1
ME	8,340	0.3761391	0.4844446	0	1
LE	8,340	0.2588729	0.4380419	0	1
LNAGE	8,339	3.057382	0.8900374	0	7.615791
WEB	8,340	0.8407674	0.3659148	0	1
FDI	8,223	0.1420406	0.349113	0	1
FINANCE	8,340	0.5015588	0.5000275	0	1
FEMALE	8,329	0.1606435	0.3672239	0	1
LNEXPER	8,258	3.018482	0.6520204	0.6931472	4.26268
CORRUPT	8,340	0.5058753	0.4999955	0	1
POLINST	8,340	0.6151079	0.486599	0	1

Table A4: Matrix correlations

	EXPP	EXPI	AUTO	LNLP	SE	ME	LE	LNAGE
EXPP	1.0000							
EXPI	0.6727	1.0000						
AUTO	0.1139	0.1062	1.0000					
LNLP	0.0025	-0.0086	0.0063	1.0000				
SE	-0.2023	-0.2018	-0.0630	-0.0802	1.0000			
ME	0.0235	-0.0028	-0.0091	0.0068	-0.5887	1.0000		
LE	0.1964	0.2249	0.0792	0.0799	-0.4481	-0.4589	1.0000	
LNAGE	0.1788	0.1086	0.0560	-0.0037	-0.1951	0.0226	0.1894	1.0000
WEB	0.1704	0.0625	0.0474	0.0320	-0.1166	0.0193	0.1068	0.1314
FDI	0.1981	0.2705	0.0471	0.0619	-0.1685	-0.0550	0.2476	0.0372
FINANCE	-0.1017	-0.0976	-0.0436	0.0657	0.0121	-0.0046	-0.0081	-0.1033
FEMALE	-0.0930	-0.0587	-0.0344	-0.0360	0.0710	-0.0163	-0.0600	-0.0724
LNEXPER	0.0339	-0.0067	0.0123	-0.0093	-0.0195	0.0066	0.0142	0.2058
CORRUPT	-0.1519	-0.1339	-0.0704	0.1074	-0.0258	-0.0138	0.0437	-0.0743
POLINST	-0.1184	-0.0883	-0.0475	0.0734	-0.0278	-0.0186	0.0512	-0.0446

	WEB	FDI	FINANCE	FEMALE	LNEXPER	CORRUPT	POLINST
WEB	1.0000						
FDI	0.0310	1.0000					
FINANCE	-0.0544	-0.0736	1.0000				
FEMALE	-0.0642	-0.0304	0.0104	1.0000			
LNEXPER	0.0724	-0.0865	-0.0332	-0.0852	1.0000		
CORRUPT	-0.0768	-0.0539	0.3041	0.0115	-0.0015	1.0000	
POLINST	-0.0695	-0.0439	0.2829	0.0144	0.0160	0.5051	1.0000

Table A5: The effect of automation on export using the recursive biprobit model

VARIABLES	(1) All	(2) Manufacturing	(3) Service	(4) LProd	(5) HProd	(6) LMIC	(7) UMIC	(8) HIC
1.AUTO	1.680***	1.522***	1.421***	1.586***	1.629***	1.669***	1.474***	1.036***
	(0.099)	(0.113)	(0.376)	(0.234)	(0.126)	(0.339)	(0.270)	(0.343)
LNLP	0.005	-0.014	0.031**	0.053*	-0.016	0.007	-0.002	0.088***
	(0.007)	(0.009)	(0.012)	(0.029)	(0.012)	(0.025)	(0.010)	(0.017)
SE								
ME	0.297***	0.366***	0.075	0.317***	0.270***	0.337***	0.263***	0.359***
	(0.035)	(0.047)	(0.056)	(0.048)	(0.051)	(0.112)	(0.069)	(0.047)
LE	0.511***	0.630***	0.149**	0.608***	0.431***	0.705***	0.581***	0.566***
	(0.041)	(0.057)	(0.068)	(0.063)	(0.058)	(0.118)	(0.075)	(0.069)
LNAGE	0.120***	0.115***	0.067**	0.084***	0.153***	0.079	0.165***	0.115***
	(0.018)	(0.024)	(0.029)	(0.025)	(0.026)	(0.058)	(0.038)	(0.024)
WEB	0.385***	0.436***	0.387***	0.322***	0.460***	0.202**	0.445***	0.324***
	(0.045)	(0.058)	(0.079)	(0.063)	(0.066)	(0.096)	(0.080)	(0.077)
FDI	0.492***	0.521***	0.533***	0.459***	0.514***	0.381***	0.508***	0.471***

	(0.044)	(0.061)	(0.071)	(0.069)	(0.058)	(0.117)	(0.078)	(0.064)
FINANCE	-0.007	-0.035	-0.049	-0.064	0.057	0.083	-0.169***	0.095**
	(0.031)	(0.041)	(0.053)	(0.043)	(0.046)	(0.089)	(0.058)	(0.043)
FEMALE	-0.160***	-0.034	-0.309***	-0.110**	-0.217***	-0.011	-0.116	-0.231***
	(0.041)	(0.055)	(0.069)	(0.056)	(0.062)	(0.114)	(0.071)	(0.061)
LNEXPER	0.039*	0.031	0.069*	0.004	0.077**	0.069	0.123***	-0.028
	(0.023)	(0.030)	(0.040)	(0.033)	(0.033)	(0.068)	(0.047)	(0.032)
CORRUPT	-0.101***	-0.148***	0.009	-0.108**	-0.081	0.072	0.065	-0.073
	(0.034)	(0.045)	(0.058)	(0.047)	(0.051)	(0.106)	(0.070)	(0.048)
POLINST	-0.054	-0.018	-0.110*	-0.066	-0.047	-0.114	0.039	-0.062
	(0.035)	(0.045)	(0.058)	(0.048)	(0.051)	(0.108)	(0.078)	(0.044)
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes			Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rho	-0.729***	-0.746***	-0.621***	-0.662***	-0.718***	-0.763***	-0.673***	-0.344*
Observations	8,010	4,620	3,390	4,006	4,004	1,104	2,731	4,175

SE=Small Enterprise; ME=Medium Enterprise; LE=Large Enterprise, LProd=Lower Productivity; HProd=Higher Productivity; LMIC=Lower-Middle-Income; UMIC=Upper-Middle-Income; HI=High Income; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1