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Estimating the Effects of Robotization on Exports

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Abstract

Digitalization and robotization are two essential aspects of modern technological advancement. Albeit, the former has gained scholastic attention of empirical trade economists, the latter has not. This paper, therefore, examines the impact of robotization on trade. Specifically, we estimate empirically the effect of robotization on total exports, and further examine its effect on the different export margins. We find robust evidence that robotization increases total exports, and this effect works both along the extensive (number of exported product varieties) and intensive margins (average value of exported product variety). Results obtained using the volume and price of exports suggest that the positive effect of robotization on the intensive margin is driven by increases in both the quantity and unit prices of exports. Redefining the margins as the number of market destinations and the number of product by market destination, our results also show a positive effect of robotization.

Keywords: *Robotization; Exports; Extensive and Intensive Margins*

JEL: *F14; O31; O33; O14*

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1. Introduction

Since the introduction of the steam engine during the industrial revolution, inquiries into the causes and consequences of technological change have attracted scholastic attention, policy-makers inclusive. In a similar vein, the recent surge of robotization or what Brynjolfsson and MCafee (2014) call the "Second Machine Age" has not gone unnoticed. Indeed, among the palpable characteristics of the 21st century is the continuous expansion in the adoption of robots on a daily basis and in almost every sphere of human life: from the versatile mobile robots in agriculture and manufacturing jeans to autonomous vehicles and 3D-printed buildings (Schlogl & Summer, 2018). Moreover, as argued elsewhere, there is hardly any reason to believe this current pace of robotization will slow in any time soon (Bandholz, 2016). Albeit much speculation and anxieties have been expressed on what the economy wide impact of robotization would be, academic research in this strand of literature is still in infancy with copious policy and scholastic attention paid predominantly on their consequences while neglecting their causes. More still, the few existing studies on the consequences of robotization focus chiefly on labor market outcomes, productivity improvement and ultimately, economic growth (Zeira, 1998; Acemoglu & Restrepo, 2017a & b; Aghion et al. 2017; Graetz & Michaels, 2017; IFR, 2017; Autor & Salomons, 2018; Chiacchio et al. 2018; Nomaler & Verspagen, 2018). This paper therefore contributes to this surging literature by quantifying the effect of robotization on exports. Importantly, by studying the exports effect of robotization, we analyze a possible implication productivity growth induced by robotization, and also underscore a channel through which robotization can affect economic growth.

Robotization as an essential aspect of the current wave of technological advancement is changing how and where products are produced. For instance, Tesla Motors has fully robotic and automated assembly lines for its electric cars and batteries. Also, the German sportswear producer Adidas currently offers the possibility of customized running shoes in an automated speed factory in Germany, in order to avoid weeks of shipping between the production site and the retail market. Whilst the foregoing examples are only suggestive, there is hardly any production process void of one automation process or the other with little or no human intervention in the recent times (Kroll et al. 2018). In addition, as suggested in the UNCTAD (2016) Brief, this is rather a global phenomenon than being specific to only developed countries as some may presume. Salient among other factors driving this wave of robotization is the heightened competition which firms face both globally and locally in tandem with the complex demands of consumers in the recent times.[1] Hence, advanced technology adoptions and applications becomes a panacea which producers, nay exporters use to meet these challenges in order to retain their market share and competitiveness either locally or globally. This argument is also consistent with a number of trade theories that emphasize the pivotal role of technology as a fundamental force in shaping the export flows and performances of a country (Posner, 1961; Krugman, 1985; Dosi et al. 1990). Along these lines, it is safe to argue that the surging expansion in the adoption and application of robots in the different stages of industrial processes influences the export flows and performances of a country.

[1] "Complex demand" is defined here as the demand for high-quality, customized goods and at a fair price.

The robotization of the industrial processes can enhance productivity either by reducing the number of input coefficient or by increasing production efficiency. Graetz and Michaels (2015), for instance, find that robotization increases productivity whilst Kroll et al. (2018) find that it increases both innovation and production efficiency. In either case, this is expected to ultimately bear on the country's export performance. This argument is consistent with the heterogeneous firm models of international trade which show a positive relationship between productivity and export performances (Melitz, 2003). It is also consistent with the trade literature which shows a positive association between innovation and export performances (Grossman & Helpman, 1989; 1991a; Chen, 2013). Furthermore, robotization of the industrial processes can lead to production flexibility, in that it lowers the costs of producing different products at the same time and ultimately, expand the varieties of exported products. The foregoing, whilst suggestive of export effects of robotization also indicates different ways it can affect export. For instance, a productivity growth induced by robotization will increase export along the intensive margin by increasing the average value of tradable goods. On the other hand, a flexible production induced by robotization will mostly increase export along the extensive margin by increasing the variety of tradable goods. Despite these obvious nexus, the surging literature on robotization is yet to examine its effect on trade and most importantly, exports.

To this end, this paper employs a state-of-the art gravity model to assess the effect of robotization on total exports, and further examining its effect on the different export margins by using data from the International Federation of Robotics (IFR, 2016) and from the CEPII databases between the periods 1995-2013. Our results indicate that a 10 percent increase in the exporters' adoption of robots will increase total export by 0.4 percent, on average. Decomposing this effect into the extensive (number of exported product varieties) and intensive margins (average value of exported product variety), we observe that the exports effects of robotization works along both margins. Results obtained using the volume and price of exports suggest that observed positive effect of robotization on the intensive margin is both quantity and price driven. The results are also robust to alternative definitions of export margins such as total number of market destinations and the number of market destinations by product. Our results therefore indicate that robotization leads to both export scoping and deepening.

Besides contributing to the surging literature on the economic impacts of robotization, this paper also contributes to different literature. This include studies which evaluate the relationship between (process) innovation and export (Van Beveren & Vandenbussche , 2010; Becker & Egger, 2013), advance manufacturing technology and firm performances (Stoneman & Kwon, 1996; Baldwin & Sabourin, 2002; Bourke & Roper, 2018; Kroll et al. 2018), and information communication technology (as an indication of technological advancement) and trade (Freund & Weinhold, 2004; Lin, 2015; Barbero & Rodriquez-Crepo, 2018). Our study also contributes to the literature on agile manufacturing and firm performance (see Gunasekaran et al. 2018 for a review of literature on this). It is related to the erstwhile literature on the effect of technological innovation on export competitiveness (Fagerberg, 1988; Amendola et al. 1993; Magnier & Toujas-Bernate, 1994; Amable & Verspagen, 1995). It is worth pointing out, however, that whilst this literature predominantly uses R&D and patent statistics to proxy technology level, we use the adoption of advance technologies – i.e. a non-R&D and non-innovation output factor – to capture technological level. Moreover, we focus on the different export margins. The rest of the paper is structured as follows: Section 2 presents the hypotheses that we test empirically. Section 3 outlines the econometric methods and data sources. Section 4 presents and discusses the results while Section 5 concludes.

2. Theory and Hypothesis Development

Economic inquiries into how technology adoption explains export performances is not entirely novel. This line of research is linked to two strands of literatures: neo-endowment and neo-technology trade literatures, respectively. The neo-endowment trade theories are a reformulation of the traditional trade theories such as the Hecksher-Ohlin model which assumes homogenous technology across countries and predicts that trade patterns depend solely on the relative differences in the factor endowment of countries. Specifically, while retaining the axiom of constant returns to scale, the neo-endowment trade literature extends the traditional trade theories by including non-price factors such as human capital and technology as an engine of export performance (Stern & Maskus, 1981; Sveikaukus, 1983; Gustavsson et al. 1999). On the other hand, the neo-technology trade literature considers differences in technology as a prime factor in explaining differential export performances either across sectors and/or across countries (Posner, 1961; Krugman, 1985; Dosi et al. 1990). In contrast to the traditional trade theories or the neo-endowment trade literature, in the neo-technology trade literature, patterns of trade between countries with symmetric conventional factor endowments can still differ due to differences in their production techniques (see Findlay & Grubert, 1959; Makussen & Svensson, 1983; Dollar, 1993; Trefler, 1995; Harrigan, 1997; Debaere, 2003). Salient in these models and as emphasized by Somers (1962) is that the level of technology both creates opportunities and acts as a new or better avenue of added value. In this case, the constant returns to scale assumed by traditional trade and neo-endowment theories may not be an absolute truth in itself.

According to Gourdon (2011), technology could influence trade in two ways. First, it can influence the efficiency in the use of factor inputs, thereby leading two countries with similar factors endowments but different inputs' efficiency to end up with different patterns of trade. Second, it can provide a competitive advantage in the production of some specific goods. Van Biesebroeck (2002) argues the adoption of a new technology by an existing plant can have a positive impact on productivity in two ways. The first is a potential level effect, that is, a onetime increase in productivity without long-run effect on productivity growth. The second is a dynamic effect because the plant will now produce according to a production function that shifts at a faster pace (p. 63).[2] In line with the Melitz (2003)'s heterogeneous firm model wherein firms vary by productivity and only the more productive ones self-select into the export market, these productivity gains due to [new] advanced technology adoption should ultimately serve as a source of the plants sustainable competitive advantage both domestically and abroad, which

[2] Van Biesebroeck (2002) further argues that the same two effects will apply if a plant with the old technology exits the sample, to be replaced by an entrant producing with the new technology

shift outward a country's export demand curve. This argument is corroborated by copious firm-level studies that find a positive association between advanced technology adoption and firm performances (Mechling et al. 1995; Bartelsman et al. 1998; Baldwin & Sabourin, 2002; Gomes & Vegas, 2013; Nair et al. 2013; Bourke & Roper, 2018; Kroll et al. 2018). The hypothesis, therefore, follows that:

H_o1: Advance technology adoption such as robots affects positively, a country's exports.

However, the international trade literature has shifted attention from a mere analysis of total trade (exports or imports) towards examining the different trade margins. From a pedagogical point of view, decomposition of trade, say, exports along the different margins enables us underpin how the variable of interest affects exports. From a policy perspective, such decomposition also enables us underscore the growth and welfare potentials of robotization. For instance, defining the extensive margin as varieties of traded products, a positive effect found at the extensive margin would imply that robotization is growth and welfare improving, since increases in the variety of traded products is assumed to be growth and welfare enhancing. This is because they increase the market share of the exporter, diversify exports and protect against trade shocks, among many others (Ndubuisi & Foster, 2018). Similarly, a positive effect on the intensive margin driven by quality upgrading would simultaneously increase unit prices and export quantities leading to positive welfare effects (Chen, 2013; Ndubuisi & Foster, 2018). However, an increase in the intensive margin that is driven by a fall in unit prices can lead to a deterioration in the terms of trade and possibly a negative effect on the welfare of exporters (Chen, 2013; Ndubuisi & Foster, 2018).

Robotization can affect the different export margins in diverse ways. Adoption and applications of robots in the industrial processes can reduce both the variable and marginal costs of production. It can also reduce the number of required inputs coefficient per unit of production. In either case, the affected firms are able to charge a fair price at home and abroad. This will increase the demand elasticity more than proportionally, thereby leading to an increase in the quantity of products sold both locally and abroad. The concatenation of these implies a positive effect of robotization on the intensive export margin. As an independent or complementing factor input, robotization can also make the machine aspects of production more efficient and effective. Kroll et al. (2018), for instance, note that the adoption of advanced robots transforms the work place into a man-machine cooperative working environment. As they argued further, this will in turn simplify complex activities for production employees improving the process speed and product quality and ultimately, the firm's productivity. Other things being equal, this product quality and firm productivity improvement will then translate into improvements in the average value of exported products or selection into (new) export markets. The efficiency and effectiveness of the industrial processes induced by the adoption and applications of robots can also enable producers, nay exporters "meet in time" the complex demands of consumers and thereby increasing the intensity of export flows. In tandem with the fair price charges robotization may induce, these associated efficient and effective productions also imply that exporters can serve a number of markets at the same time and at a (reduced) fixed cost. This leads to an increase in the extensive export margins in terms of either a wider variety of market being served or a selection into (new) markets due to a rise in the demand elasticity. Last but not the least, robotization of the industrial processes can lead to production flexibility, in that it lowers the costs of producing different products at the same time and ultimately, expand the varieties of exported products. The forgoing discussion leads to the hypothesis that:

> *H_o 2: Robotization increases the extensive and intensive export margins of a country.*

3. Econometrics Method and Data Sources

As noted in preceding sections, the overarching objective of this paper is to evaluate the effect of robotization on total exports. In addendum, the paper aims to decompose total exports into different export margins in order to underpin how robotization affects exports. Consequently, our research method follows Beverelli et al. (2015), in that it requires estimating both "$e\ i$" and "$e\ w$" regressions, respectively. Whereas the former requires estimating a bilateral trade flow model, the latter entails estimating a univariate export flow model. The subsequent sections delineate these models and how we estimate them empirically.

3.1. "e i regressions"

For the "$e\ i$ regressions", we employ the gravity model which has become a workhorse tool in the analysis of bilateral trade flows over the past 55 years. In its original form, the gravity model predicts bilateral trade flows as a function of country-pairs economic sizes and a vector of bilateral trade costs. We augment this model with a variable on exporter's stock of robots. The baseline equation that thus guides our analysis using the "$e\ i$ regressions" is formulated as:

$$TF_{eit} = \beta_o + \beta_1 LPCGDP_{et} + \beta_2 LPCGDP_{it} + \beta_3 LPOP_{et} + \beta_4 LPOP_{it} + \beta_5 LRobots_{et} \dots$$

$$+\gamma' Z_{ei} + \tau_t + \gamma_j + \varepsilon_{eit} \qquad \dots (1)$$

where β_o, ε_{eit}, and τ_t denote the intercept, the idiosyncratic error term, and time dummies, respectively. γ_j is a series of exporter and importer, and country-pair fixed effects to account for multilateral resistance terms (MRT).[3] $LPCGDP_{et}$ and $LPCGDP_{it}$ are exporter and importer logged gross domestic products whilst $LPOP_{et}$ and $LPOP_{it}$ are their respective population sizes. These variables are extracted from the World Bank development indicators. $LRobots_{et}$ is the logged stock of robots adoption in the exporting country and hence, β_5 is our parameter of interest. In line with our conjecture in section (2), we expect this to be positive in all "$e\ i$ regressions". Our data on the stock of robots is extracted from the International Federation of Robotics (IFR, 2016)

[3] MRT are unobserved price indices which go beyond bilateral trade costs that influence trade. Put differently, they are barriers that each of countries *e* and *i* face in their trade with all their trading partners, including domestic or internal trade (Adam & Cobham, 2007). This is in contrast to bilateral trade resistance which is the size of the barriers to trade between countries *e* and *i* (Adam & Cobham, 2007; also see Anderson & van Wincoop, 2003).

consolidated statistics on industrial robot supplies and actual robot installations.[4] $'Z_{ei}$ is a vector of trade costs which we capture using, bilateral distance (DIST), adjacency (CONTIG), Colony, official common language (COMLAN), and membership in a similar trade agreement (FTA). These variables are all extracted from the CEPII database. With the exception of Distance which is measured in kilometers per distance, these other variables are dummies which take the value of one if the country-pairs are common in those dimensions and zero otherwise. $TF_{eit}$is the value of exports from country e to country i in period t. Our examination of TF_{eit} in the *"e i regressions"* includes total exports, and the extensive and intensive export margins, respectively. To decompose total exports into the different margins in the *"e i regressions"*, we follow Dutt et al. (2013) to define the extensive export margin as a simple count of the number $N_{ei,t}^{HSO}$of HS-0 products exported from e to i in period t. The intensive margin, $\bar{x}_{ei,t} = TE_{ei,t}^{HSO} / N_{ei,t}^{HSO}$, is then the average value of exports per product. The total export $TE_{ei,t}^{HSO}$, is therefore given as the product of both margins:

$$TE_{ei,t}^{HSO} = \bar{x}_{ei,t} * N_{ei,t}^{HSO} \qquad \ldots (2)$$

Equation (2) suggests that the construction of both margins follow a linear decomposition such that if both margins are in logs, any linear operator should give estimates which when summed will add-up to the corresponding estimate for total exports.

The estimation of the *"e i regression"* proceeds in four steps. First, we estimate the model using logit in order to underscore whether robotization exerts any significant influence on a country's likelihood to export. Second, we estimate the effect of robotization on total exports using the within-fixed effects (FEM) estimator and Ordinary Least Squares (OLS) with importer and exporter fixed-effects. The gains of the former over the latter are highly emphasized in the literature particularly for a time varying panel gravity models such as equation (1) (Baldwin & Taglioni, 2006). Among other things, this includes solving endogeneity related issues due to omitted variables that may arise either due to the omission of MRTs and/or other time invariant variables. To further probe whether our baseline results are influenced by the potential omission of MRTs, we implement the *Bonus Vetus OLS* proposed by Baier and Bergstrand (2009).[5] Zero bilateral trade flows are commonly observed when using gravity model (Helpman et al. 2008) and can bias the results if the zero trade flows are not missing at random. In addition, Santos and Tenreyro (2006) advance that trade data are highly heteroskedastic and hence, impairing a rightful inference using OLS. To probe issues, we log the trade variables using the inverse hyperbolic function in order to preserve the zero trade observations and re-estimate equation (1) using OLS and FEM estimators. To address the heteroskedasticity problem, we implement the Harvey model which has being adopted by Martinez-Zarzoso and Marquez-Ramos (2008) to address similar issue. Lastly, we also employ the Poisson-Pseudo Maximum Likelihood (PPML) which has being suggested by Santos and Tenreyro (2006). Our PPML includes estimating our models using both importer and exporter fixed-effects and

[4] See Graetz & Michaels (2015) for detailed description of data.

[5] This method is a linear approximation of the MRT, which results in a reduced form gravity equation that can be estimated by Ordinary Least Squares (OLS). It essentially requires subtracting the average trade costs of all countries from the sum of the average trade costs of the two countries

country-pairs fixed effects following Westerlund and Fredrik (2009). It is worth pointing out that the estimates using the PPML addresses both the zero trade and heteroskedasticity issues initially mentioned. As a fourth step, we estimate the effect of robotization on the quantity and price of exported goods. And as a final step in the *"e i regression"*, we re-estimate equation (1), albeit this time, with a focus on the different export margins. Standard errors are all clustered at the country-pairs.

3.2. *"e w regressions"*

For the *"e w regressions"*, we either collapse the product and/or importer dimension in our bilateral trade data thereby reducing the analysis into a univariate export flow model. The baseline equation that guides this analysis is thus:

$$tf_{et} = \alpha_o + \alpha_1 LPCGDP_{et} + \alpha_3 LPOP_{et} + \alpha_4 LRobots_{et} + \tau_t + \gamma_j + \mu_{et} \quad \ldots (3)$$

where α_o, μ_{et}, τ_t and γ_j denote the intercept, the idiosyncratic error term, time dummies, and country fixed-effects, respectively. All other variables retain their definition as in equation (1). α_4 is the parameter of interest and we expect it to be positive in all *"e w* regressions in line with our conjectures in section (2). tf_{et} represents possible trade outcomes which vary only by the exporter. We consider six outcomes variable in the *"e w regression"*: (i) total number of market destinations; (ii) Average value of product to all market destinations; (iii) Average quantity of product to all market destinations; (iv) number of market destinations by product; (v) number of market destinations by quantity per product; and (vi) number of market destinations by value per product. To empirically estimate the model, we adopt both Poisson estimator for the cases of count data and within-fixed effects estimator in cases where we do not deal with count data.

Table (1) presents summary statistics of all the variables employed in both the *"e i"* and *"e w"* regressions. In both cases, the choice of the sample of countries, and time period is primarily informed by data availability. Specifically, our gravity model includes export flows from 71 countries to 175 countries for the period 1995-2013. For the *"e w"* regressions, we consider all market destinations in the CEPII trade data and hence, for the variables on total number of market destinations and number of market destinations by product, their respective maximum values exceed the number of importing country (i.e. 175) in the *"e i"* regressions. Figure (1) plots the time trends of the exporters' adoption of robots over the sample period. As expected, the graph shows an upward trend over time. Finally, Figure (2) plots the total exports over the exporters' adoption of robots. Both are the averages of the respective variables over the sample period and units. Interestingly, we observe a strong positive correlation between total export flow and the stock of robots. This thus presents a first piece of evidence of a positive association between the two variables as conjectured in section (2).

Table 1- Summary Statistics

Variables	Observation	Mean	Std. Dev.	Min	Max
Log Total Export Value	205,142	9.512	3.449	0	19.852
Log Number of Product	205,142	4.598	2.210	0	8.504
Log Average Value of Product	205,142	4.914	1.727	0	13.857
Log Average Unit Price	204,399	4.066	1.681	-5.845	13.891
Log Export Volume	204,399	8.792	4.00	-9.907	20.469
Number of Market Destinations	1,349	175.094	35.15	36	218
Log Average Product to all Markets	1,349	3.065	0.185	2.256	3.702
Log Average Quantity to all Markets	1,349	12.579	1.434	7.491	15.66
Number of Markets Destinations by Product	5,134,997	20.989	27.723	1	212
Log Number of Markets Destinations per Product	5,134,997	4.714764	3.520	-14.71	20.491
Log Number of Markets Destinations per Quantity	5,134,997	2.512342	2.766	-14.71	18.767
Log Robots (Stocks)	205,142	5.483	4.2161	0	13.624
Log Bilateral Distance	205,142	8.646	0.812	4.107	9.885
Log Exporter Population	205,142	2.945	-1.665	1.318	7.213
Log Importer Population	205,142	1.896	-2.014	4.685	7.213
Log Exporter Per Capita GDP	205,142	9.215	1.314	5.663	11.521
Log Importer Per Capita GDP	205,142	8.180	1.616	4.171	11.521
Colonial Ties	205,142	0.022	0.147	0	1
Common Border	205,142	0.021	0.144	0	1
Common Official Language	205,142	0.108	0.310	0	1
Trade Agreement	205,142	0.205	0.404	0	1

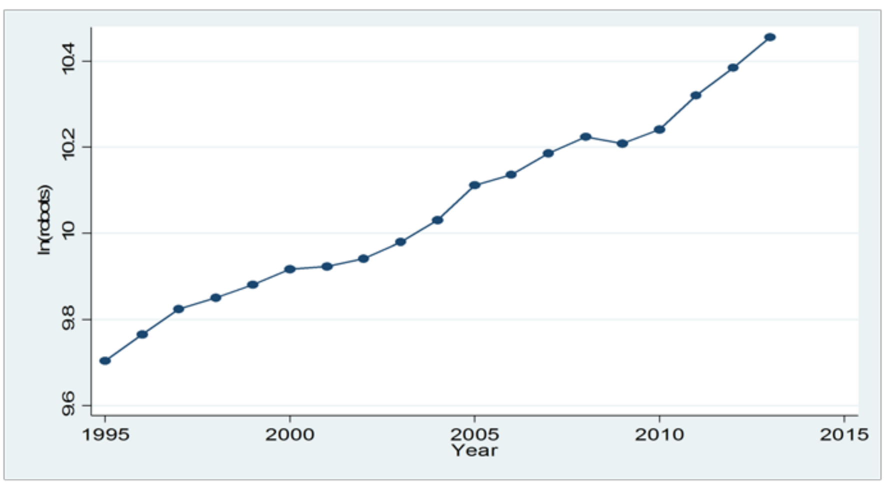

Figure 1: Trend in Robots' Adoption

Note: Robots is logged using the inverse hyperbolic function as $ln\left[robots + \left(\sqrt{robots^2 + 1}\right)\right]$. Observation comprises the mean value of stock of robots in 71 countries between the periods 1995-2013.

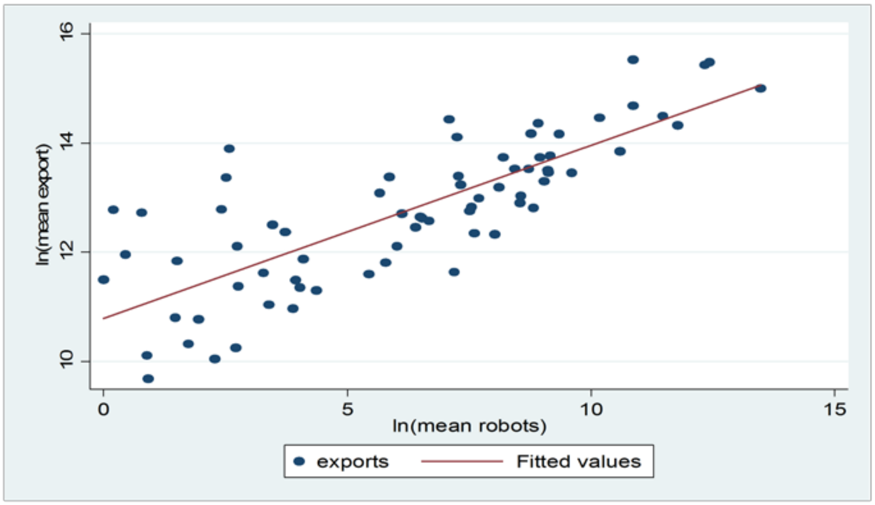

Figure 2: Robotization and Exports
Note: Robots is logged using the inverse hyperbolic function as $ln[robots + (\sqrt{robots^2 + 1})]$. Observation comprises the mean values of export from and the stock of robots in 71 countries between the periods 1995-2013.

Table 2 – Baseline Regression: Robotization and Bilateral Exports

	Logit		OLS		FEM	
	[1]	[2]	[3]	[4]	[5]	[6]
$\beta_{lnrobots}$	0.183***	0.104***	0.046***	0.035***	0.047***	0.035***
	[0.008]	[0.009]	[0.003]	[0.003]	[0.003]	[0.003]
$\beta_{lngdppce}$	0.603***	0.783***		0.498***		0.549***
	[0.025]	[0.034]		[0.025]		[0.024]
$\beta_{lngdppci}$	0.664***	0.781***		0.742***		0.781***
	[0.017]	[0.024]		[0.021]		[0.020]
β_{lnpope}	0.622***	0.987***		0.950***		1.151***
	[0.018]	[0.026]		[0.080]		[0.072]
β_{lnpopi}	0.596***	0.894***		0.677***		0.752***
	[0.013]	[0.017]		[0.063]		[0.060]
$\beta_{lndistw}$	-0.701***	-0.983***		-1.455***		
	[0.040]	[0.056]		[0.024]		
β_{border}	-1.405***	-2.034***		0.313***		
	[0.290]	[0.379]		[0.107]		
β_{comlan}	0.913***	1.431***		0.642***		
	[0.089]	[0.137]		[0.043]		
β_{colony}	-0.395	0.396		0.990***		
	[0.439]	[0.434]		[0.088]		
β_{FTA}	0.633***	0.619***		0.221***		0.093***
	[0.089]	[0.086]		[0.029]		[0.016]
Observations	234,726	234,726	205,142	205,142	205,142	205,142
R-squared	0.384	-	0.724	0.810	0.298	0.333

Robust standard errors clustered at the country-pair in squared brackets; All regression contains unreported constant terms and year fixed-effects; ***p<0.01, ** p<0.05, *p< 0.10; Robots is logged using the inverse hyperbolic function as $ln[robots + (\sqrt{robots^2 + 1})]$.

4. Results and Discussion

This section presents the estimation results showing the effects of robotization on total exports, and export margin differentials. The section first presents the results on the effect of robotization on total export, followed by subsections on alternative estimation strategies and using export volume and prices. The section ends with the results on the effect of robotization on the exports margins while using the *"e i"* and *"e w"* regressions, respectively.

4.1 The total exports effects of robotization

Table 2 displays the result on the exports effect of robotization, using total export value. Columns (1) - (2) show the estimation results from the Pooled and Random-Effects Logit regression models, respectively. The dependent variable in both cases is a binary variable representing trade existence, which equals one if a country-pair has positive trade in a year and zero otherwise. The coefficient of robots is positive and statistically significant in all cases, suggesting that adopting robots in a country increases the propensity to export. More importantly, as our data sums to the country level, the result further leads to the conclusion that increasing robotization is trade creating (i.e. by increasing the number of importing trade links) and preserving (i.e. by sustaining existing importing trade links). The trade creating and preserving effects of robotization can occur in variant ways, two of which include: mass customization and flexible production. Mass customization involves the [firm's] capability to swiftly design, produce and deliver a high volume of different products that meet specific customer demands without tradeoffs in cost, delivery and quality (Gunasekaran et al. 2018). On the other hand, flexible production refers to the capability to lower the cost of producing multiple product lines within a plant (Lileeva & Van Biesebroeck, 2015). Both factors are emphasized in the firm level literature to largely depend on a firm's ability to adopt [new] advanced technologies (Lileeva & Van Biesebroeck, 2015; Gunasekaran et al. 2018) such as, computer numerically controlled (CNC) machinery, among many others. Along this line, robotization by inducing mass customization as opposed to only mass production will increase the probability that the adopting firm nay exporter is able to satisfy the complex demand of consumers in current times thereby leading to the preservation of existing trade links. Applications of robots in the industrial processes can also incentivize market diversification due to the reduced costs in the production of precise and high-quality products to satisfy consumers' complex demands in good time. More so, the reduced marginal cost of production associated with the adoption of advanced technology – i.e. flexible production – implies that the adopting firm can engage in diverse production activities thereby creating an avenue for a wider market.

Next, Columns (3) - (6) report the results of the OLS and within-effect regression, respectively. Unlike in Column (1)-(2), the dependent variable here is total export value. The number of observation here is smaller than that of the Logit regressions because the sample in these regressions contains only country-pairs with positive trade. We first introduce our variable of interest in Column (3) and (5) without the gravity model variables. In both cases, the results suggest an unconditional positive effect of robotization on total export value which is distinguishable from zero at all conventional statistically significant levels. Interestingly, both the size of the coefficient and standard errors are similar. Introducing the gravity model variables in Column (4) and (6), the results remain unchanged qualitatively. Quantitatively, however, the size of the coefficient of robots is now somewhat smaller albeit in each column, we continue to observe a statistically significant positive effect of robots on total exports value. These results are therefore consistent to those of the Logit regression model reported in Columns (1) - (2). On the average, the results indicate that a 10 percent point increase in the adoption of robots in the exporting country will lead to a 0.4 percent point increase in total export. Although not reported, this statistically significant positive effect of robots on total export value is robust to excluding importer and exporter fixed-effects both jointly and/or independently. It is also robust to the exclusion of time-effects or by adding a constant when log transforming the robot variable i.e.$lnrobots_{it} = \ln(1 + robots_{it})$ as opposed to using the inverse hyperbolic function.[6]

Information and Communication Technologies (ICTs) and robotization comprise two essential aspects of technological advancement in the recent times. However, whilst the trade literature has begun to analyze the impacts of ICTs adoption on trade (Freund & Weinhold, 2004; Lin, 2015; Barbero & Rodriquez-Crepo, 2018), the literature is mute on the trade impacts of robotization. The results displayed in Table 2 thus provide the first piece of empirical contribution to this literature, with the results suggesting that robotization enhances exports. Our results corroborate with Lin (2015) who provides a benchmark estimate suggesting that a 10 percent increase in the proportion of internet users in the exporting country increases total export value by 0.4 percent. With our obtained point estimate of about 0.4, it could be argued therefore that both have an equal effect on exports. One explanation for this may be that they are complementing each other.[7] Indeed, Kroll et al (2018) advances that new digital technologies have additionally improved the effectiveness of automation, making a whole sequence of operations more flexible, smart and efficient (p.4). Our finding of a net positive effect of robots' adoption on export is also consistent with firm level studies suggesting that the adoption of advance technologies improves firm performance (Mechling et al, 1995; Kotha & Swamidass, 2000; Bare-Gil, et al. 2011; Bourke & Roper, 2016; Kroll et al. 2018).[8] However, unlike these firm level studies that are highly speculative on what comprises these [new] advanced technologies, our result itemizes adoption of robots such as automatically controlled, reprogrammable, multipurpose manipulator, and programmable, machines as sources of firm domestic and international competitiveness which will in turn push outward a country export demand curve.

[6] In all cases, the coefficient of robots is statistically significant at 1 percent significant level. With the exception of adding a constant term when we log transform the robot variable, the coefficient becomes larger in absolute terms. In the case of adding a constant term when we log transform the robot variable, the results are largely the same with those reported in Table 3. We however prefer estimates reported in Table 3 because they are superior in terms of the estimation strategies employed.

[7] Acemoglu & Restrepo (2017b) find the impact of robots on productivity and employment is distinct from that of the other types of IT capital and the total capital stock.

[8] Unlike most other studies, Kroll et al (2018) uses a detailed firm level data distinguishing between automation and digital technology adoption among German firms. However, the study only focuses on productivity and innovation performances of the sampled firms.

Regarding the control variables, with the exception of the border coefficient in Column (1) - (2), we obtain coefficients that are in line with the extant literature. Specifically, we obtain robust statistically significant positive coefficients on both the exporter and importer population, and a negative coefficient for bilateral distance. This suggests that bilateral trade between country pairs increases (decreases) with their country sizes (bilateral distances) as mirrored by the signs of population size (distance) coefficients. Their respective per capita GDPs are also consistently positive suggesting that high income countries trade more. Whilst the positive coefficient on the exporter per capita GDPs may reflect high productive capacity, the positive coefficient on the importer per capita GDPs may suggest diverse preferences which increases substitution of foreign goods with local goods as income increases. The coefficients for FTA and colony are positive and statistically significant, implying that being part of trade agreement or having colonial ties increases bilateral trade. The positively signed coefficients for COMLAN indicate that trade between bilateral pair increases if they share an official language (COMLAN).

Table 3 - Robotization and Total Exports: Alternative Estimation Strategies

	BOLS	BFEM	OLS	FEM	Harvey Model		PPML	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$\beta_{lnrobots}$	0.036***	0.036***	0.032***	0.032***	0.032***	0.035***	0.015***	0.020***
	[0.003]	[0.003]	[0.004]	[0.004]	[0.004]	[0.003]	[0.006]	[0.006]
$\beta_{lngdppce}$	0.516***	0.556***	0.650***	0.651***	0.650***	0.498***	0.622***	0.601***
	[0.025]	[0.024]	[0.031]	[0.031]	[0.031]	[0.025]	[0.039]	[0.030]
$\beta_{lngdppci}$	0.737***	0.779***	0.868***	0.867***	0.868***	0.742***	0.748***	0.767***
	[0.021]	[0.020]	[0.029]	[0.029]	[0.029]	[0.021]	[0.034]	[0.028]
β_{lnpope}	0.950***	1.149***	1.266***	1.266***	1.266***	0.950***	0.680***	0.797***
	[0.080]	[0.072]	[0.106]	[0.106]	[0.106]	[0.080]	[0.112]	[0.091]
β_{lnpopi}	0.604***	0.719***	1.160***	1.154***	1.160***	0.677***	0.406***	0.510***
	[0.063]	[0.060]	[0.099]	[0.099]	[0.099]	[0.063]	[0.142]	[0.107]
$\beta_{lndistw}$	-1.456***		-1.597***		-1.597***	-1.455***	-0.744***	
	[0.025]		[0.031]		[0.031]	[0.024]	[0.032]	
β_{border}	0.313***		-0.023		-0.023	0.313***	0.451***	
	[0.107]		[0.144]		[0.144]	[0.107]	[0.064]	
β_{comlan}	0.642***		0.812***		0.812***	0.642***	0.084	
	[0.043]		[0.057]		[0.057]	[0.043]	[0.063]	
β_{colony}	0.989***		1.033***		1.033***	0.990***	0.118	
	[0.088]		[0.113]		[0.112]	[0.088]	[0.104]	
β_{FTA}	0.217***	0.016	0.133***	0.114***	0.133***	0.221***	0.298***	0.006
	[0.035]	[0.020]	[0.038]	[0.020]	[0.038]	[0.029]	[0.045]	[0.027]
Observations	205,142	205,142	234,726	234,726	234,726	205,142	234,726	230,204
R-squared	0.810	0.333	0.801	0.241	-	-	0.888	

Robust standard errors clustered at the country-pair in squared brackets; All regression contains unreported constant terms and year fixed-effects; ***p<0.01, ** p<0.05, *p< 0.10; Robots is logged using the inverse hyperbolic function as $ln\left[robots + \left(\sqrt{robots^2 + 1}\right)\right]$. *Pseudo* R-*squared* reported in for Column (7).

4.2 How sensitive are the export effects of robotization to alternative estimation strategies?

Table 3 displays the results on the exports effect of robotization when we subject the results reported in Table 2 to alternative estimation strategies in order to address some empirical estimation concerns. Specifically, we address in this section issues pertaining to MRTs, zero trade flows that are common while estimating gravity model and heteroskedasticity which are pervasive in trade data. Starting with the control variables, we observe that their coefficients meet the *a priori* expected signs where statistically significant in all columns in the table. The interpretations of the coefficients are therefore in line with those discussed in section 4.1 and hence, we immediately proceed into the discussion of the coefficient of our variable of interest.

Column (1) displays the result when we implement the *Bonus Vetus OLS* as suggested by Baier and Bergstrand (2009) whilst in Column (2) we follow Foster et al. (2018) and Ndubuisi and Foster (2018) by including the adjusted trade costs variables into the within-effect model. As discussed in section 2, this estimation strategy serves as an additional robustness check that our results are not influenced by the omission of MRTs.[9] It is worth pointing out that the trade cost variables reported in Column (1) - (2) are not comparable to those of the subsequent columns since those of the latter have not been adjusted in line with Baier and Bergstrand (2009). In both Columns, we continue to observe a positive and statistically significant effect of robotization on total export value, at all conventional levels. Interestingly, the coefficient continues to suggest a point estimate of about 0.4 percent increase in total export for each 10 percent increase in the adoption of robots. Column (3) - (4), show the results when we re-estimate the unconditional effect of robotization on total exports using OLS and within-effect estimators while preserving the zero trade flows. Since the log of zero is undefined, we use the inverse hyperbolic function to log transform the dependent variable. The obtained results from this transformation are largely consistent to those reported in the preceding columns and in Table 2. In Column (5) - (6), we follow Martinez-Zarzoso and Marquez-Ramos (2008) in implementing the Harvey model as an attempt to probe whether our baseline results are influenced by heteroskedasticity. The difference between Column (5) and (6) is that all zero trade flows are dropped in the log transformation of the dependent variable in Column (5), whereas in Column (6) we adopt the inverse hyperbolic function. The results, despite this difference in the transformation of the dependent variable, continue to suggest a positive effect of robotization on total exports. More importantly, we observe a point estimate of 0.03 on average, which is a statistically significant at all conventional level. Although not reported, these results are also robust to further adjusting the trade costs variables following Baier and Bergstrand (2009) and excluding year fixed-effects and/or importer and exporter fixed-effects. Column (7) shows the result when we implement the PPML with importer and exporter fixed-effects. Unlike in the previous columns, the dependent variable here is in level. Santos-Silva and Tenreyro (2006), however, advances that

[9] An alternative approach here will be to use time-varying exporter and importer fixed-effects since it could be argued that the MRTs is not constant in a time series panel data like here. A problem associated with this approach is that including time-varying importer and exporter fixed effects in a large sample like in ours makes estimation difficult to achieve. The variable of interest her, robots, varies both across space and time implying that using time-varying importer and exporter fixed effects will make it impossible to estimate its effect.

the coefficients can be interpreted as elasticities. As earlier noted, the method has the dual advantage that it solves the zero trade flows and also the heteroskedasticity problem, hence the number of observation here equals those reported in Column (3) - (4).[10] Again, the emerging result from the column continues to suggest a positive effect of robotization on total exports which is distinguishable from zero at all conventional statistically significant levels. However, the size of the coefficient drops significantly to 0.015, from the average point estimates of 0.03 obtained in the preceding columns or 0.04 obtained in Table 2. To further account for unobserved heterogeneity while addressing both issues on heteroskedasticity and zero trade flows, Column (8) implements the PPML with the country-pair fixed-effects as suggested by Westerlund and Fredrik (2009). Doing so, the coefficient rises from 0.015 to 0.02 which is still lower than the average point estimates of 0.03 obtained in the preceding columns or 0.04 obtained in Table 2.

In summary, whilst we find the size of the coefficient of robots adoption varies across the alternative estimation strategies, the results presented in Table 3, generally, corroborate those in Table 2 in suggesting that robotization enhances total export value.

4.3 Export quantity and price effects of robotization

The results displayed in Tables 2 and 3 suggest that robotization increases total export value. However, the problem with such exercise is that we are usually unaware whether the effect is due to a price or quantity increase. Premised on our discussion in section (2), we however expect the effect to be both quantity and price driven wherein the latter signals quality improvements rather than monopoly pricing. Robotization can make production and logistic processes more effective and efficient. Advertently, these will increase both the quantity and variety of exported products. It should also improve the quality of goods. To the extent that prices signal quality, we would then expect a positive association between robotization and the prices of exported goods. To this end, Table 4 displays the results on the effect of robotization on export quantity and price. Whereas Panel A reports the result on the quantity of goods exported by country e to country i in period t, Panel B reports the results on the average unit price of those goods. Column (1) and (5) report the results using importer and exporter fixed-effects whilst Column (2) and (6) emerge when we control for country-pair fixed-effects using the panel within-effect estimator. In either of these columns, estimation is achieved by dropping the zero trade flows when log transforming the dependent variable. Similarly, Column (3) and (7) report the results using importer and exporter fixed-effects whilst Column (4) and (8) emerge when we control for country-pair fixed-effects using the panel within-effect estimator. However, in either of these Columns, we account for the zero trade flows and hence, estimation is achieved by using the inverse hyperbolic function when log transforming the dependent

[10] An alternative to this approach would be the 2-Stage modified Heckman selection model proposed by Helpman et al. (2008). The first stage comprises estimating a probit equation to predict the probability of having a positive export value based on some observable fixed costs. The predicted component of the resulting estimates is then used to control for the extensive margin and selection biases. The assumptions of this approach have, however, come under strict criticism in the literature (Santos-Silva & Tenreyro, 2008).

variable. Across each column in Panel A and B, we observe a strong statistically significant positive effect of adoption of robots on both the quantity and the unit price of exports. The results, therefore, confirm our conjecture that the export effects of robotization is both quantity and price driven. We re-emphasize that the latter signals quality improvements that are induced by adoption of robots rather than monopoly pricing.

Table 4 – Export Quantity and Price Effects of Robotization

	Panel A: Quantity				Panel B: Unit Price			
	OLS	FEM	OLS	FEM	OLS	FEM	OLS	FEM
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$\beta_{lnrobots}$	0.033***	0.036***	0.044***	0.045***	0.050***	0.015***	0.067***	0.023***
	[0.004]	[0.004]	[0.005]	[0.005]	[0.003]	[0.003]	[0.004]	[0.003]
$\beta_{lngdppce}$	0.283***	0.352***	0.469***	0.476***	0.563***	0.381***	0.543***	0.352***
	[0.035]	[0.033]	[0.035]	[0.035]	[0.028]	[0.020]	[0.031]	[0.022]
$\beta_{lngdppci}$	0.723***	0.771***	0.826***	0.824***	0.630***	0.186***	0.768***	0.300***
	[0.028]	[0.027]	[0.032]	[0.032]	[0.025]	[0.017]	[0.030]	[0.020]
β_{lnpope}	1.391***	1.587***	1.701***	1.699***	0.119	-0.034	0.385***	0.038
	[0.113]	[0.103]	[0.112]	[0.112]	[0.091]	[0.064]	[0.102]	[0.063]
β_{lnpopi}	0.899***	1.022***	1.498***	1.463***	0.408***	0.088*	0.837***	0.357***
	[0.087]	[0.082]	[0.110]	[0.110]	[0.075]	[0.053]	[0.099]	[0.063]
$\beta_{lndistw}$	-1.907***		-1.916***		-0.943***		-1.109***	
	[0.031]		[0.035]		[0.024]		[0.030]	
β_{border}	0.414***		0.236		-0.119		-0.459***	
	[0.130]		[0.157]		[0.125]		[0.153]	
β_{comlan}	0.635***		0.783***		0.812***		0.907***	
	[0.057]		[0.064]		[0.044]		[0.056]	
β_{colony}	1.181***		1.176***		0.780***		0.873***	
	[0.110]		[0.124]		[0.103]		[0.129]	
β_{FTA}	0.265***	0.083***	0.221***	0.113***	0.134***	0.074***	0.089**	0.091***
	[0.038]	[0.023]	[0.044]	[0.025]	[0.029]	[0.014]	[0.037]	[0.016]
Observations	204,399	204,399	234,726	234,726	204,399	204,399	234,726	234,726
R-squared	0.716	0.096	0.757	0.133	0.739	0.158	0.772	0.167

Robust standard errors clustered at the country-pair in squared brackets; All regression contains unreported constant terms and year fixed-effects; ***p<0.01, ** p<0.05, *p< 0.10; Robots is logged using the inverse hyperbolic function as $ln[robots + (\sqrt{robots^2 + 1})]$.

Table 5A - Robotization and Export Margins

	Panel A: Extensive Margin						Panel B: Intensive Margin					
	OLS	FEM	OLS	FEM	PPML		OLS	FEM	OLS	FEM	PPML	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
$\beta_{lnrobots}$	0.029***	0.031***	0.031***	0.031***	0.028***	0.027***	0.005**	0.004*	-0.001	-0.001	0.017*	0.018*
	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.002]	[0.002]	[0.003]	[0.003]	[0.010]	[0.010]
$\beta_{lngdppce}$	0.251***	0.280***	0.273***	0.277***	0.072***	0.230***	0.247***	0.268***	0.427***	0.422***	0.358***	0.343***
	[0.015]	[0.015]	[0.016]	[0.016]	[0.009]	[0.011]	[0.019]	[0.018]	[0.023]	[0.023]	[0.069]	[0.069]
$\beta_{lngdppci}$	0.449***	0.467***	0.484***	0.483***	0.154***	0.302***	0.293***	0.314***	0.401***	0.402***	0.205**	0.244***
	[0.014]	[0.013]	[0.016]	[0.016]	[0.008]	[0.010]	[0.016]	[0.015]	[0.020]	[0.020]	[0.086]	[0.084]
β_{lnpope}	0.280***	0.334***	0.396***	0.395***	0.080**	0.315***	0.671***	0.817***	0.948***	0.950***	0.529***	0.555***
	[0.046]	[0.042]	[0.053]	[0.053]	[0.040]	[0.039]	[0.066]	[0.059]	[0.073]	[0.073]	[0.152]	[0.151]
β_{lnpopi}	0.406***	0.475***	0.578***	0.558***	0.193***	0.351***	0.271***	0.278***	0.654***	0.675***	-0.238	-0.066
	[0.040]	[0.038]	[0.053]	[0.053]	[0.024]	[0.025]	[0.047]	[0.046]	[0.066]	[0.066]	[0.231]	[0.218]
$\beta_{lndistw}$	-1.014***		-1.018***		-0.572***		-0.441***		-0.616***		-0.244***	
	[0.018]		[0.020]		[0.018]		[0.013]		[0.018]		[0.056]	
β_{border}	-0.054		-0.124		-0.133**		0.367***		0.036		0.808***	
	[0.100]		[0.108]		[0.058]		[0.046]		[0.064]		[0.148]	
β_{comlan}	0.660***		0.658***		0.309***		-0.018		0.185***		-0.211**	
	[0.032]		[0.036]		[0.036]		[0.025]		[0.034]		[0.086]	
β_{colony}	0.804***		0.825***		0.503***		0.185***		0.219***		-0.143	
	[0.077]		[0.083]		[0.055]		[0.039]		[0.052]		[0.236]	
β_{FTA}	0.135***	0.061***	0.131***	0.068***	0.104***	0.011	0.086***	0.032**	-0.019	0.047***	0.207***	-0.013
	[0.021]	[0.010]	[0.023]	[0.012]	[0.022]	[0.008]	[0.017]	[0.013]	[0.023]	[0.015]	[0.063]	[0.029]
Observations	205,142	205,142	234,726	234,726	234,726	230,204	205,142	205,142	234,726	234,726	234,726	230,204
R-squared	0.826	0.301	0.836	0.246	0.768	-	0.584	0.165	0.623	0.149	0.426	-

Robust standard errors clustered at the country-pair in squared brackets; All regression contains unreported constant terms and year fixed-effects; ***p<0.01, ** p<0.05, *p< 0.10; Robots is logged using the inverse hyperbolic function as $ln[robots + (\sqrt{robots^2 + 1})]$.Pseudo R-squared reported for Columns (5) and (11). Extensive margin is a simple count of number of HS6 products exported by country e to country i. The intensive margin is the average value of the product.

4.4 The export margins effects of robotization: the "e i regressions"

Table 5A presents the first results on the effect of robotization on export margins. Whereas Panel A reports the result on the extensive export margin, defined as the number of products exported by country *e* to country *i* in period *t*, Panel B reports the results on the intensive margins, defined as the average value of the products exported from country *e* to country *i*. Columns (1), (3), (7), and (9) report the results using importer and exporter fixed-effects whilst Columns (2), (4), (8) and (10) emerge when we control for country-pair fixed-effects using the panel within-effect estimator. Whereas estimation is achieved for Columns (1) - (2) and (7) - (8) by dropping the zero trade flows when log transforming the dependent variable, estimation is achieved in Columns (3) - (4) and (9) – (10) by employing the inverse hyperbolic function when log transforming the dependent variable. Columns (5) and (11) emerge when we implement the PPML with importer and exporter fixed-effects whilst Columns (6) and (12) emerge when we further control for country-pair fixed-effects. In either of these Columns, the dependent variable is in levels.

Starting with Panel A, the results, on the average, reveal a positive and statistically significant point estimate of about 0.03, across all specified columns. This indicates that a 10 percent increase in the adoption of robots in the exporting country increases the extensive export margin by 0.3 percent which accounts for about 83-187 percent increase in total exports. This result is consistent with our conjecture for the Logit regression model in Table 2 where we found that adoption of robots in the exporting country increases the probability of exporting. Specifically, among many ways robotization exerts a positive effect on the extensive margins is via mass customization and flexible production, as discussed in section 3.1.

In Panel B, we also obtain a statistically significant positive coefficient for robots adoption on the intensive export margin. Unlike in the case of the extensive margin however, the coefficient of adoption of robots is not statistically significant when we account for zero trade flows using the panel within fixed-effect or OLS with importer and exporter fixed-effects. More still, in cases where we observe an effect which is distinguishable from zero, the statistical significance of this effect is weak compared to those obtained for the extensive margin. This may suggest that the extensive margin is more responsive to variations in the level of adoption of robots as compared with intensive margin. This may be due to the reason that incumbent firms' nay exporters adopt robots in a bid to increase the variety of exported goods than increase the average value of the exported goods. This conjuncture seems founded, as the coefficients of adoption of robots are consistently higher for extensive margin than for intensive margin. Notwithstanding this, summing the results on the intensive margin with those on export quantities and unit prices in Table 4 lead to the conclusion that the observed positive effect of robotization on the intensive margin is both quantity and price driven. In line with our initial argument that the price signals more of quality improvement than monopoly pricing, we argue further that the positive effect induced by adoption of robots on the intensive margin of exports is demand driven.

In summary, our obtained result that robotization positively affects both margins of exports substantiates some of the findings in the extant literature on robotization. Among many others, extant studies suggest that robotization is productivity improving (Graetz & Michaels, 2015; 2017). In line with studies which delineate a nexus between productivity growth and export (Melitz, 2003), the results obtained in the preceding sections thus indicate that robots induced productivity growth leads to export. Some studies have also theoretically analyzed the economic growth potentials of robotization (Zeira, 1998; Aghion et al. 2017; Acemoglu & Restrepo, 2017b; Nomaler & Verspagen, 2018). Although these studies emphasis different paths through which robotization affects economic growth, this paper suggests improvement along the export margins as a possible channel through which robotization affects economic growth. It goes without saying that the role of either margin in driving economic growth has been emphasized in the literature (Romer, 1990; Aditya & Acharyya, 2013; Ndubuisi & Foster, 2018). More importantly, the results indicate robotization as a non-R&D factor that can induce and generate economic growth via increasing exports.

Table 5B – Robotization and Export Margins

	Panel A			Panel B		
	Poisson	FEM		Poisson	FEM	
	[1]	[2]	[3]	[4]	[5]	[6]
$\beta_{lnrobots}$	0.013***	0.018**	0.001	0.070***	0.010***	0.012***
	[0.004]	[0.008]	[0.003]	[0.001]	[0.001]	[0.001]
β_{lgdppc}	0.074***	0.549***	-0.023	0.254***	0.346***	0.121***
	[0.028]	[0.077]	[0.022]	[0.004]	[0.004]	[0.005]
β_{lpop}	0.075**	0.725***	0.100	0.236***	0.137***	0.420***
	[0.035]	[0.149]	[0.082]	[0.005]	[0.014]	[0.016]
β_{lck}	-0.013	-0.048	0.081**	0.049***	0.034***	0.102***
	[0.040]	[0.117]	[0.032]	[0.005]	[0.006]	[0.007]
Observations	1,349	1,349	1,349	5,192,898	5,192,898	5,134,997
R-squared	-	0.870	0.371	-	0.057	0.004

Robust standard errors clustered at the country level in squared brackets; All regression contains unreported constant terms and year fixed-effects; ***p<0.01, ** p<0.05, *p< 0.10; Robots is logged using the inverse hyperbolic function as $ln\left[robots + \left(\sqrt{robots^2 + 1}\right)\right]$.

4.5 The export margins effects of robotization: the "e w regressions"

Table 5B displays the results for the *"e w regression"*. Column (1) displays the results when we consider the number of markets served by country *e* in period *t* for all its traded products. Estimation is achieved using the Poisson method since the dependent variable is a count variable i.e. the number of market destinations. Columns (2) - (3) show the results on the effect of adoption of robots on the average value of product variety and the average quantity exported to all markets. With the exception of Column (3), which albeit positive is statistically insignificant, we obtain statistically significant evidence that robotization leads to market diversification at both the extensive and intensive (i.e. average value of product variety and the average quantity exported to all markets) margins. The results are thus largely consistent with those of the *"e i regression"*. Importantly, the results are also consistent to our initial argument that robotization is both trade creating and preserving.

Panel B displays the results on the extensive and intensive export margins based on export market destinations with Column (4) being when we consider, as a dependent variable, the number of market destinations by product. Estimation here is achieved using Poisson method. Column (5) emerges when we use average value of product by number of market destinations, whilst Column (6) emerges when we consider average quantity by number of market destinations. In either of these cases, estimation is achieved using the within fixed-effects estimator. Across each column in Panel B, we continue to observe a positive effect of robots adoption on the different margins of export. The results thus suggest that robotization increases export market diversification both at the intensive and extensive margins independent of how we define the margin. Our results are thus in tandem with our conjectures of a positive effect of robotization on exports, working along the extensive and intensive margins.

5 Conclusion

The fourth industrial revolution is eminent, and it promises to change the interface of humanity. While the socio-economic impacts of these new 'revolutionary' technological changes remain an open debate, if history is anything to go by, the very nature and ways people and economies communicate, learn and exchange knowledge and technologies are expected to change. Trade remains a conduit through which economies produce and exchange both tangible and intangible products – goods and services. The way products are produced, and traded in terms of routes and patterns, are, therefore, expected to evolve with these new technological advancements. Technological innovations, such as robots, are predicted to increase the production efficiency and effectiveness whilst reducing variable and marginal cost of production of economies and thereby driving the production of new, high quality and range of products for global exchange. With dearth of any empirical evidence assessing the international trade implications of robotization, this paper fills a gap in the literature by going beyond the labor market and productivity growth effects of robotization that is the obsession of extant studies.

This paper presented a first contribution to the literature by employing a gravity model, among other econometric approaches, to examine the total export, and the intensive and extensive export margins' implications of robotization. Using new panel data on robots from the International Federation of Robotics (IFR) database spanning the period 1995-2013 and across 71countries, our results show a generally positive relationship between robotization and total exports. The robustness of this result suggests that technological deepening, in terms of robot adoption, enhances the export performance of countries. Decomposing the positive effect of robotization on total exports into extensive and intensive margins, our results, generally, suggest that the exports effects of robotization works along both the extensive and intensive margins. That is, robotization leads to increases in the number of exported product varieties (extensive), as well as increases in the average value of exported product variety (intensive). These results imply that robotization leads to both export scoping and deepening. The estimation results using the volume and price of exports further suggests that the obtained positive effect of robotization on the intensive export margin is both quantity and price driven. Based on the efficiency and productivity effects induced by robotization, we argue that the positive price effect signals quality improvement in exports rather than economic agent rent-seeking behaviors such as monopoly pricing. Further redefining the margins in terms of the total number of market destinations and the number of market destinations by product, our results show a positive effect of robotization on both margins.

The relationships between robotization and export value, and the intensive and extensive margins of exports observed in this paper implies that the adoption of robots in the industrial processes create markets and/or sustains export positions for, and/or expands the competitiveness of a country's exports. These give credence for trade, industrial and innovation policies that target and encourage robot adoption and application in the bid to advance a country's production processes. However, the accumulation and application of robots may be biased and skewed towards specific industries. Future research could focus on the industry-specific effects of robotization on export.

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