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REGULAR ARTICLE

High-growth firms and international trade: evidence from Ecuador

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Abstract

The aim of this article is to open a detailed discussion about the relationship between international trade activities (export, import and trade openness) and the probability of becoming a high-growth firm. International trade has been widely related to a variety of outcomes, but there is no evidence of the relationship to high-growth firms. We study this issue by estimating a two-step probit model to correct the problem of self-selection that usually appears in trade research. Additionally, we use matching techniques as a robustness check to address possible endogeneity problems. We find that international trade is a consistent and robust path for becoming a high-growth firm. Several policy implications are derived from our work.

Keywords Firm age · International trade · High-growth firms · Performance

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1 Introduction

Trade is related to firms' performance through channels such as innovation and technology transfer. As it is important for performance, there might also be a link with the growth of firms, specifically, the group of high-growth firms (HGFs) (Grover Goswami et al. 2019). Therefore, it is relevant to investigate which factors influence the rapid growth of firms. Most of the research done on this topic is based on the role of innovation, productivity and profitability as determinants of HGFs (Bianchini et al. 2017), and they coincide in the fact that most HGFs are small and young firms. However, works like the one done by Robson and Bennett (2000) already mention the importance of export status and the international orientation of firms to become an HGF. However, the approach of internationalization is related to the growth of firms in general and not to HGFs. For instance, Hernández and Nieto (2016) find that performing inward and outward international operations has a positive effect on growth.

Besides the lack of studies that examine the role of trade on the rapid growth of firms, another reason to study this relationship is that trade is an important channel to develop because it contributes to new ways of producing and selling, among others. The knowledge acquired and given through trade could help countries grow, especially developing countries. Therefore, it is relevant to examine all the mechanisms through which trade could improve the economy. One of those mechanisms could be the way it can boost the creation of HGFs, which are known for creating more jobs and improving the performance of firms in general. Hence, it would be relevant to deepen the analysis of the relationship between trade and high-growth firms.

The main objective of this paper is to analyze the role of international trade in high-growth firms. We aim to determine the factors that increase the probability of becoming an HGF, trade variables (exports and imports) among them. Also, we analyze those determinants across the distribution of firms' outputs. To achieve this, we use annual data from the balance sheets and investment reports of private Ecuadorian firms provided by the Superintendencia de Compañias, Valores y Seguros (SCVS). the data is from 2007 to 2018. Ecuador is a relevant case study because it is a small, open and developing economy which has been dollarized since the 2000s. Moreover, there are few studies about HGFs in Ecuador. Recently Simbaña-Taipe et al. (2019) examined the determinants of the rapid growth of firms. Nevertheless, they did not calculate the variable for HGFs according to a specific methodology. They did not consider trade, either, and the period of analysis was between 2010 and 2015. Additionally, our empirical strategy lies in the use of a two-step approach following Heckman (1979) and using a probit model, which corrects the usual problem of self-selection that appears in trade research. In addition, to control for potential sample bias between traders and non-traders, which may be a source of endogeneity, we employ a robustness check by combining two matching techniques.[1]

[1] At this point, we must acknowledge that there might be other sources of endogeneity that we are not able to control for in this paper. However, it is well known in the empirical literature that differences between traders and non-traders is one of the most important sources of endogeneity. We thank an anonymous reviewer comment on this point.

Our contribution to the empirical literature goes on three strands of the economics and business arena. First, in the international trade literature, to our knowledge, this is the first paper that analyzes several international trade activities as determinants of becoming an HGF, whereas previous studies look at research and development, labor mobility, and foreign direct investment, among others. Second, in business economics literature, we contribute by analyzing, again, international trade activities as determinants of firm sales and employment growth. Third, in empirical industrial organization, we study the heterogeneous effect of international trade activities in the manufacturing sector. We divide this sector according to their technological intensity (following the OECD classification) to relax the assumption that all firms operate using a standard technology across all sectors and in a similar competitive environment. Most studies analyze manufacturing and services industries but do not deepen the analysis on the heterogeneity each sector might have. Overall, we find that being in international trade activities increases the probability of becoming an HGF.

The structure of this paper is as follows. Section 2 provides a brief review of the literature. In Section 3, we describe the empirical strategy used to obtain the results in Section 5. Finally, Section 6 describes the main conclusions and policy implications of the results.

2 Literature review

There is an evident importance of high-growth firms in industrial organization literature; however, the connection between trade and high-growth firms (HGFs) has not been studied. There are studies on rapid growth of firms and internationalization (Korsakienė et al. 2019), but none is specialized in high-growth firms. Usually, the literature on this type of firm evaluates the role of innovation or productivity in HGFs, or any other factor that could boost or hinder the rapid growth of firms, but not trade. For instance, Serafinelli (2019) shows that localized knowledge spillovers are one of the most commonly development sources of the productivity advantage of agglomeration, which could lead to an increase in the probability of becoming an HGF. He also finds that labor mobility is one of the most important factors that contributes to creating higher economic growth for start-up businesses (a good example of this is Silicon Valley). R&D investments are another way to achieve high growth, usually in the technology sector, where cutting-edge technology gives a firm an advantage over others.

There are studies that try to examine how internationalization relates to rapid-growth in two ways. One is that rapid-growth firms are more competitive because of greater economies of scale, so they can enter the international market. The other is that firms involved in international transactions are more competitive because of the requirements of the international market, so they can become high-growth firms. In the case of the former, there are studies like Korsakienė et al. (2019) that examine the internationalization of HGFs by investigating the characteristics (attitudes) of owners and professional managers. Their results highlight the importance of the traits and perceptions of owners and managers of HGFs for predicting their internationalization. There is also literature that supports the second approach. For instance,

Keen and Etemad (2012) find that internationalization appeared to have had a positive impact on growth rates and other characteristics. To prove this, they carried out different tests and compared average and median characteristics of local and internationalized firms. Likewise, using a random effects model and lags, Filatotchev and Piesse (2009) find that R&D and export intensities have a positive effect on the sales growth of newly formed firms.

The main mechanism of the relationship between international trade and high-growth firms is that internationalization adds an aggregated value (for instance, increase of quality in production and services and the possibility to acquire technological know-how and therefore improve processes, among other advantages) that could allow the firm to grow faster (Mathews 2006; Petricevic and Teece 2019). An interesting way to analyze that is to prove that trade could increase the sales growth and employment growth of a firm. As mentioned before, there are no studies that mention a direct relationship between trade and HGFs, but we can show the indirect relationship by investigating other studies that mention the direct relationship between trade and the variables that define HGF: sales and employment. It is relevant to mention that firms enter international trade business not only to exploit tangible and intangible resources developed domestically, but also to be able to access resources that are not available in home country markets (Zander et al. 2015). These international resources allow firms to increase their levels of sales (Kuivalainen and Sundqvist 2018), which is related to the rapid growth of a firm.

In addition, in emerging markets, authors mention that entering international trade markets allows firms to open to relatively bigger markets. In these bigger markets the price elasticity of demand is sometimes lower and firms can use their low domestic cost of production to generate a competitive advantage over other firms and obtain higher margins than they could have solely producing at home (Khavul et al. 2010). Besides accessing resources that are not available at home, another advantage of internationalization is that it allows firms to have learning opportunities. For instance, Prange and Verdier (2011) and Khan et al. (2019) find that firms that are related to international firms and markets have a knowledge acquisition that is positively related to the multiple indicators of performance, such as sales, employment, and profits, which could generate a rapid growth of the firm.

Thus, since the analysis of literature has shown that entry into a foreign market could increase the probability that firms improve their levels of sales and employment, thus allowing them to grow faster, we put forward the following hypothesis:

Hypothesis H_1 International trade activities increase the probability of becoming an HGF.

Even though trade activities could initially decrease prospects for firm survival, they can also benefit the firm with opportunities to grow and to learn about how to grow. Sapienza et al. (2006) mention that this growth could occur because internationalization exposes firms to more uncertainty and risks, which influences them to adapt by developing capabilities through structural changes. In sum, they suggest that young firms that enter the international market at the beginning are prone to expand rapidly, looking for growth opportunities by taking advantage of their ability

to innovate. Similarly, Jung et al. (2012) find that there is a relation between early internationalization and the learning process of new firms that are small but grow fast.

Overall, international trade has been stated to be one of the most important factors that improve firms' productivity, being the channel behind the technology transfer from foreign companies to local firms. In terms of imports, there are various studies that discuss the positive impact of importing on productivity (learning-by-importing) (Wagner 2012; Zhang 2017; Kasahara and Rodrigue 2008; Abreha 2019). They can positively contribute to a local firm's productivity performance by incorporating better inputs in their production processes (Camino-Mogro et al. 2020). Also, some argue about the importance of international diffusion of technology, which identifies imports as an important vehicle for knowledge and technology transfer.

Furthermore, firms with higher shares of R&D investment have a higher probability of operating in international markets and also firms that develop innovations new-to-the-market are more prone to become HGFs (Teruel et al. 2021). In this sense, analyzing the intensity of R&D as a moderating effect in becoming a trader and HGF becomes important; however, due to data limitations this is not possible. Although, we approximate this analysis by dividing the manufacturing industry according to their technological intensity (following the OECD classification). Our main assumption is that international trade activities positively affect the probability of being HGF in the most technological intensity industries. In this sense, we consider the following hypothesis:

Hypothesis H_2 International trade activities increase the probability of becoming an HGF more in the most technological intensity industries.

The relationship of exports to increases in firm productivity has also been widely studied. The main theory that supports the effects of this relationship (learning-by-exporting) is the Heterogeneous Firms and Trade model, developed by Bernard and Jensen (1995, 1999) and Melitz (2003). This model describes how exporters can generate higher profits and are able to bear the costs of entering foreign markets, which is accompanied by a general increase in productivity. Innovations in connection with exports are discussed as a mechanism that ensures the growth of firm performance as a result of participation in foreign trade activities (Aw et al. 2007). In addition, Ito and Lechevalier (2010) provide evidence that the relationship between investment in the promotion of export products and investment in innovation creates a sustainable competitive advantage for industrial companies. This means that innovations can be considered a condition of performance growth as a result of the firm's entry into foreign markets.

Hence, the literature suggests that trade can stimulate an increase in various firm outcomes, such as performance.[2] Consequently, we consider the following hypothesis:

[2]For an extensive review of the literature on this topic, see Wagner (2012) and Cassiman and Golovko (2018).

Hypothesis H_3 International trade has a greater effect on the performance of HGF

Although now there is empirical evidence on the links between the international activities of firms, such as exports, imports and foreign direct investment, and their outcomes and performance, such as employment, productivity, wages, and profitability, there are gaps in the analysis. The gap examined in this research is how trade could foster the rapid growth of firms. The main channel of this relationship is that, to enter international markets, there are certain requisites needed to be more competitive, such as more workers, increased sales, or higher salaries (Rahman et al. 2017), which could create a need for firms to hire more employees, increase wages, and increase sales. In this regard, authors like Giovannetti et al. (2011) show that internationalized firms usually face stronger average competition in international markets, which forces them to be efficient. Therefore, early trade activity could act as a catalyst for growth (Sapienza et al. 2006).

3 Data

We use a novel administrative data set provided by the Ecuadorian firms' supervisory and regulatory institution, the Superintendencia de Compañías, Valores y Seguros (SCVS). The data set covers the period 2007 - 2018. This data includes information about the financial statements reported annually by all firms. This SCVS data base has variables such as gross sales, total assets, fixed tangible assets, liabilities, consumption of intermediates (domestic and imported), number of formal employees, wages, consumption of energy, exports, and other accounts. It additionally has geographical information such as the region, province and city where the firm is operating and the six-digit ISIC Rev. 4 industry classification. This data base has several advantages. First, it covers all formal, active, Ecuadorian manufacturing firms. Second, it contains detailed export and import information at the firm level.

We debug our panel data to correct for the inconsistencies that administrative data sets usually have. We follow (Camino-Mogro et al. 2018) process of filtering. First, we select firms only from the manufacturing industry. Second, we exclude firms with zero or negative values of formal employees, total fixed assets, total intermediates and wages. Third, we exclude firms that undergo a merge or acquisition. Fourth, we eliminate the firms that were inactive during the years analyzed. Finally, we only consider formal and private firms because those are the ones that report information to the SCVS. Our final data base is an unbalanced panel data with 28,602 observations and 5,745 formal manufacturing firms.

In this paper, we define an HGF according to the methodology proposed by Eurostat-OECD (2007), but with some modifications.[3] First, firms must start from similar initial conditions, so in the first period, they must have annual gross sales that are four times the GDP per capita of the current year. Second, firms must have a growth of gross sales greater than 20% annually or growth of wages greater than

[3]The modifications made are mainly in the employment variable because of various inconsistencies in the complete data base used to classify HGFs.

30% annually over a period of three years.[4] Our definition is different from that of Segarra and Teruel (2014), Du and Temouri (2015) and other authors, who classify an HGF in terms of sales and employment. In this regard, to identify an HGF, we use the two criteria at the same time. Henrekson and Johansson (2010), in a survey of 19 studies, show that there is no general agreement on the definition of HGFs; nevertheless, the advantage of using the OECD methodology is that the initial population is the same, regardless of whether growth is measured in employment or sales.

Therefore, our final data base has 5,745 formal manufacturing firms, 532 (9.26%) of which are HGFs.[5] Additionally, we categorize the industries of the manufacturing sector according to their technological intensity (following the OECD classification), because it could reveal the different technology transfer channels among firms (Camino-Mogro et al. 2020). Consequently, we group manufacturing firms into low-tech industries, medium-low tech industries and medium-high and high-tech industries. In the Annexes, in Table 10, the classification of each industry is detailed.[6] Medium-high and high-tech industries have the largest participation of HGFs (10.29%), followed by medium-low tech industries (9.59%) and low-tech industries (8.64%).

In Table 1, we present the mean growth rate of industries in the manufacturing sector by deciles and according to their technological intensity. We show that firm growth is faster in terms of sales than in terms of employment in the whole manufacturing sector, but also in their technological intensity classification. Furthermore, the average growth rate is higher for medium-high and high-tech industries than for the other two technological intensity of industries in terms of both sales and employment. Additionally, the dispersion of employment growth rate is higher than the sales growth rate in the whole manufacturing sector, but also when we divide it into according to the technological intensity of industries.[7]

3.1 Variables and some characteristics

In this paper, we consider an HGF our dependent variable. This variable (HGF) is a dummy variable equal to 1 if the firm is an HGF (measured by sales and/or employment); otherwise, it is equal to 0. As we focus on international trade activities, we will consider in a first step firms that are in international trade activities. Thus, we construct the $Trader$ variable, which is a dummy variable that indicates that a firm does exporting and importing activities at the same time.

[4]There are at least three issues that need to be considered when characterizing firm performance: i) the indicator of growth; (ii) the measure of growth; and (iii) the period under study (Reyes 2017; Delmar et al. 2003). The most commonly used indicators in the literature on high-growth firms are sales and number of employees (Daunfeldt et al. 2014).

[5]Similar participation of HGFs in the manufacturing sector are found in Segarra and Teruel (2014), Du and Temouri (2015) and Reyes (2017), among other international empirical evidence.

[6]For this paper, we group the medium-high tech industry and high-tech industry into one, because there are few observations in this latter group, and because the high-tech industry in the OCDE is different from that in Ecuador.

[7]Du and Temouri (2015) argue that employment growth and size patterns have more to do with industrial characteristics than firm performance variations.

Table 1 Mean growth rate in manufacturing industry by deciles (2007–2018)

	All firms		Low-tech		Medium-low tech		Medium-high & High-tech	
Deciles	Sales growth	Employment growth	Sales growth	Employment growth	Sales growth	Employment growth	Sales growth	Employment growth
1	− 39.84	− 58.77	− 35.73	− 55.96	− 49.73	− 69.31	− 35.43	− 55.96
2	− 17.22	− 22.31	− 15.67	− 20.76	− 22.25	− 22.79	− 15.77	− 20.76
3	− 6.75	− 7.25	− 6.04	− 7.27	− 9.31	− 7.41	− 5.65	− 6.89
4	0.00	0.00	0.01	0.00	− 1.07	0.00	1.03	0.00
5	5.60	0.00	5.23	0.00	5.18	0.00	6.95	0.00
6	11.58	4.79	10.68	4.22	12.19	5.00	12.94	5.71
7	19.00	13.40	17.59	12.60	20.73	15.41	20.21	15.01
8	30.23	28.76	27.45	28.77	344.14	31.84	31.83	28.76
9	55.69	69.31	50.78	65.94	63.12	69.31	55.55	69.31
Mean	7.41	2.97	6.89	2.53	7.10	3.26	9.09	3.65
No.Obs.	28,602	28,602	14,226	14,226	8,377	8,377	5,999	5,999

All numbers are in %

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We also consider $GSales$ and $GEmpl$, a group of variables that measures the growth rate of sales and employment, respectively. Moreover, we use $GSales$ as a measure of size, which is adjusted to the Ecuadorian context.[8] Delmar et al. (2003) argue that one drawback of using a sales variable instead of employment is inflation; hence, we deflated all monetary variables using the industry-specific price index. In Table 2, we present the definition of each variable used in this research.

In Table 3, we exhibit the descriptive statistics, divided into HGFs and non-HGFs. We show that HGFs grow faster in terms of sales and employment than non-HGFs. The HGFs in the medium-low tech industries have the largest growth rates compared with HGFs in the other two industries according to their technological intensity. Additionally, HGFs present lower values of average exports, imports, trade openness and capital intensity than their counterparts. Moreover, we show that HGFs are less oriented to international trade activities, since 7.15% of HGFs are two-way traders, whereas the percentage of this type of trader in the group of non-HGFs is higher (8.67%). This result is very similar in two industries according to their technological intensity, but for medium-high and high-tech industries, the participation of HGFs as two-way traders is larger than that of their counterparts. Nevertheless, on average, there are no significant differences between HGFs and non-HGFs.

[8]Firm size is defined in the Organic Code of Production, Trade and Investment of Ecuador: microenterprises, between 1 and 9 workers or revenue less than $100,000; small firms, between 10 and 49 workers or revenue between $100,001 and $1,000,000; medium firms, between 50 and 199 workers or revenue between $1,000,001 and $5,000.000; large firms, more than 200 workers or revenue above $5,000,001. Revenue ranks higher than the number of workers.

Table 2 Definition of variables

Variable	Code	Definition
Gross revenue	Y	Total income from sales = revenues from sales of ordinary activities of the company (income from extraordinary activities is excluded from the business of each company, for example, sale of land, machinery, etc.). This variable is deflated using the industry-specific price index obtained from the Ecuadorian National Institute of Statistics.
Workers	L	Number of legally registered employees.
Capital stock	K	Net tangible assets = the sum of the real dollar value of buildings, machinery, and vehicles, assuming a depreciation of 5, 10, and 20 percent, respectively. We measure the capital stock with the gross investment in equipment in year t (I_{it}), net fixed assets in real value (physical capital in year $t-1$) (k_{it-1}), a depreciation rate (d_{it}) and the price index for equipment at the industry level (P_t) obtained from the Ecuadorian National Institute of Statistics.
Size	y	Natural log of gross revenue (Y).
Growth sales	GSales	Annual growth rate calculated by taking log differences of gross revenue (Y)
Growth Employment	GEmpl	Annual growth rate calculated by taking log differences of workers (L).
Export	ExpOnly	Dummy variable which indicates whether the firm exports but does not import.
Import	ImpOnly	Dummy variable which indicates whether the firm imports but does not export.
Two-way trader	Trader	Dummy variable which indicates whether the firm imports and exports.
Export intensity	EI	Export intensity measured as the logarithm of the amount of exports per gross revenue.
Import intensity	II	Import intensity measured as the logarithm of the amount of imports per gross revenue.
Trade openness intensity	TOI	Trade openness measured as the logarithm of the amount of exports and imports per gross revenue.
Capital intensity	KI	Natural log of capital stock (K) per gross revenue (Y). This variable is deflated by a price index.
High-growth firm	HGF	Dummy variable equal to 1 if the firm is an HGF; otherwise, it is equal to 0.
TFP	TFP	Total factor productivity estimated by the Levinsohn and Petrin (2003) estimator and using the command implemented by Rovigatti and Mollisi (2018).
Foreign Direct Investment	FDI	Dummy variable equal to 1 if the firm receives foreign direct investment; otherwise, it is equal to 0.
Age	age	Measured as the difference between the current year and the year the firm registered in the country's mercantile register to start business.
Year dummies		Time dummies to control for common macroeconomic effects.
Sectoral dummies		Sectoral dummies to control for common shocks at the industrial level (two-digit ISIC).
City dummies		City dummies to control for common shocks of the firm's geographical localization.

The authors, based on data provided by the Superintendencia de Compañías, Valores y Seguros

Table 3 Descriptive statistics: average values (2007–2018)

	All firms		Low-tech		Medium-low tech		Medium-high & High-tech	
Statistic	HGFs	Non-HGFs	HGFs	Non-HGFs	HGFs	Non-HGFs	HGFs	Non-HGFs
GSales (%)	31.96	4.46	30.43	4.26	35.11	3.62	30.94	6.15
GEmpl (%)	16.36	1.37	16.52	0.95	19.48	1.25	11.97	2.54
OTI	− 0.452	− 0.454	− 0.476	− 0.444	− 0.335	− 0.382	− 0.556	− 0.579
EI	− 0.291	− 0.341	− 0.310	− 0.338	− 0.201	− 0.315	− 0.371	− 0.388
II	− 0.491	− 0.478	− 0.505	− 0.479	− 0.350	− 0.395	− 0.648	− 0.589
KI	− 2.307	− 1.946	− 2.231	− 1.809	− 2.208	− 1.985	− 2.588	− 2.223
TFP	9.325	9.281	8.300	8.236	8.843	8.838	9.274	9.213
age	2.245	2.367	2.267	2.378	2.192	2.334	2.273	2.387
Trader (%)	7.15	8.67	7.69	8.88	4.63	8.03	9.36	9.05
ExpOnly (%)	7.81	5.83	11.63	7.82	4.53	3.67	4.49	4.06
ImpOnly (%)	15.71	14.91	13.19	13.14	14.79	14.62	21.92	19.55
Mult (%)	0.09	0.38	0.19	0.21	0.00	0.46	0.00	0.71
No.Obs.	3,341	32,720	1,547	16,361	1,014	9,556	780	6,803

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We find similar results when we compare the participation of HGFs and non-HGFs in exports or imports. The descriptive statistics suggest that there are more exporting and importing firms as HGFs than their counterparts. However, there are no significant differences between HGFs and non-HGFs. Finally, we show that there is no participation of new firms as HGFs in any of the industries. Similar results are found for multinational firms, where the percentage of multinational firms is lower among HGFs than it is among their counterparts. Finally, we show that there are no substantial differences in total factor productivity (TFP) between HGFs and non-HGFs.

4 Empirical framework

To analyze the relationship between international trade activities and HGFs, we take a two-step approach. In the first step, we follow Lopez-Garcia and Puente (2012) and Segarra and Teruel (2014) to establish the main determinants of the probability of being an HGF by using a probit model. Our latent variable is HGF, which is a binary variable that takes the value of 1 if firm i is an HGF at time t, and takes the value of 0 otherwise. Since we analyze the impact of international trade activities on the probability of becoming an HGF, our latent variable is observed only if the firm is in the international market, so the estimation will be biased towards those firms.

In this regard, we apply the methodology proposed by Heckman (1979), using a probit model that corrects by sample selection (Van de Ven and Van Praag 1981).[9] Our selection equation considers the probability that a firm is in international trade activities depending on a set of determinants, but also we include sectoral, city and time dummies to correct for unobservable microeconomic and macroeconomic characteristics. Our selection equation is as follows:

$$P(Trader = 1)_{it} = \chi' Z_{1it-1} + \upsilon_j + \nu_r + \eta_t + \epsilon_{1it} \quad (1)$$

where χ' corresponds to the vector of parameters to be estimated, and Z_{1it-1} is a vector that captures a set of control variables that are important determinants for becoming an HGF. These variables include $size$, measured by the log of gross revenue (y), and TFP, which is the total factor productivity at the firm level, estimated by the Levinsohn and Petrin (2003) estimator for the whole manufacturing sector and for industries according to their technological intensity (following the OECD classification).[10] Capital intensity (KI) controls for firms that use more capital. Acs and Audretsch (1987, 1990) argue that the level of small firm growth is negatively related to industry capital intensity. Hence, HGFs could be negatively induced to use more capital to grow because it would represent more costs.

Moreover, FDI is a binary variable that takes the value of one if the firm receives foreign direct investment, zero otherwise. FDI is our variable of exclusion in the main equation because we argue that FDI is correlated with the probability of becoming a trader but not with being an HGF. Specifically, a firm that receives FDI would benefit from technology diffusion because it could import intermediates from multinationals, some of which are their owners, but it would also benefit from the networks of the multinational firm and would export its goods.[11] However, Coad and Tamvada (2012) argue that knowledge from foreign sources has no clear beneficial effect on growth, because firms that receive FDI may not have enough absorptive capacity. (Reyes 2017) mentions that the low absorptive capacity of the average firm (in developing countries) prevents it from capturing more FDI benefits. Moreover, Girma (2005) and Crespo and Fontoura (2007) mention that it is also important to understand the quality and characteristics of the FDI (for example, country of origin, mergers, technological transfer, greenfield investments, etc.), because the effect of FDI depends on its characteristics.[12,13]

[9] We use the command $heckprobit$ implemented in STATA by Miranda and Rabe-Hesketh (2006).

[10] We perform our estimations using the prodest command of Stata, developed by Rovigatti and Mollisi (2018). As a robustness check, we also estimate the TFP using the (Wooldridge 2009) estimator. Results of these estimations are available upon request.

[11] For an extensive review of the literature about this topic, see Keller (2010).

[12] According to the Central Bank of Ecuador, the manufacturing sector has in recent years received around 14% of the total FDI, and the main countries that have invested in this sector are the USA, Peru, England, Uruguay, New Zealand, Panama, Chile, Colombia, Costa Rica and Mexico.

[13] In Table 11 in the Annexes, we show the correlation matrix between our variables of interest. Specifically, we show that FDI is not correlated with being an HGFs

On the other hand, there is little evidence that suggest that multinational firms (or firms that receive FDI) perform better and grow faster than domestic firms (see, for example, Castellani et al. 2006, 2018; Cruz et al. 2020; Dunning and Lundan 2008; Mata and Portugal 2004; Xu 2000).

Additionally, age is a continuous variable measured as the difference between the current year and the year the firm started the business. Authors like Farinas and Moreno (2000), Yasuda (2005), Geroski and Gugler (2004), Coad et al. (2013), and Coad et al. (2013) mention that firm performance deteriorates with age. Finally, to control for heterogeneity, we include a two-digit industry-specific component (υ_j), a city-specific component (ν_r), a time-specific component (η_t) fixed effects, and the idiosyncratic error term is ϵ_{it}.

Moreover, as we are interested in the determinants of becoming an HGF, our main equation is the probability that a firm becomes an HGF. Consequently, we introduce the Mill's ratio parameter, previously estimated in Eq. 1. Finally, the main equation we estimate is the following:

$$P(HGF = 1)_{it} = \beta' Z_{2it-1} + h(Z_{2it-1}, \gamma_0) + \upsilon_j + \nu_r + \eta_t + \epsilon_{2it} \qquad (2)$$

where β' are the parameter vector, of explanatory variables (Z_{2it-1}) for becoming an HGF, and h($\cdot$) is the inverse of Mill's ratio, which controls for sample selection. The explanatory variables included in Eq. 2 are $size$, TFP, KI, age, $ExpOnly$ (a dummy variable equal to one if the firm exports but does not import), and $ImpOnly$ (a dummy variable equal to one if the firm imports but does not export). Additionally, we add TOI, which is the trade openness intensity measured as the log of exports and imports per gross revenue. Cruz et al. (2020) assert that high-growth status is more prevalent among small and young firms, and also firms that export or import because imports and exports are relevant for determining productivity (Camino-Mogro and López 2021)[14]. We lagged estimation Eq. 2 by one year ($t-1$) to mitigate potential endogeneity issues. Moreover, we corrected heteroskedastic standard errors by clustering at the individual firm level (Du and Temouri 2015).

In the second step, we use a quantile regression model to address the possible heteroskedasticity of growth rate distributions. This type of regression is used not to restrict the error terms ϵ_{it} and make the estimation method semi-parametric. One of the benefits of using quantile regressions approach is that it is robust to extreme observations on the dependent variable (Coad et al. 2016). Similar to Coad and Rao (2008), Segarra and Teruel (2014) and Du and Temouri (2015), we adopt the quantile regression approach to analyze the role of international trade activities as determinants of becoming an HGF along the growth rates distribution. Koenker and Bassett (1978) introduce the conditional quantile regressions (CQR). Nevertheless, we apply the unconditional quantile regression (UQR) approach of Firpo et al. (2009) because we are interested in the quantiles (q_τ) of the marginal distribution of the outcome variable Y. The advantage of the UQR model is that the quantiles are defined pre-regression.

[14]There is a large body of empirical evidence that suggests that firms engaged in international trade activities grow faster than domestic firms (see, for example, Bernard et al. 2007; Cassiman and Golovko 2018; Wagner 2012).

Therefore, the model is not influenced by any right-hand side variable (Killewald and Bearak 2014). In UQR we could include, for example, high-dimensional fixed effects to adjust for selection bias without redefining the quantiles, cluster–robust standard errors and bootstrapped standard errors.[15,16]

This methodology consists of two steps. The first step is to obtain the recentered influence function (RIF). The second step is to include this RIF as an outcome variable in a regression along with the right-hand side variables. In this regard, RIF is defined as:

$$RIF(Y; q_\tau, F_Y) = q_\tau + \frac{\tau - \mathbb{1}\{Y \leq q_\tau\}}{f_Y(q_\tau)} \tag{3}$$

where q_τ is the value of the outcome variable, Y, at the quantile τ. F_Y is the cumulative distribution function of Y, and $f_Y(q_\tau)$ is the density of Y at q_τ. The indicator function $\mathbb{1}\{Y \leq q_\tau\}$ identifies whether the value of the outcome variable, Y, for the individual is below q_τ. To identify the RIF for each quantile, one needs to 1) estimate the value of the outcome variable, Y, at each quantile q_τ; 2) estimate the density $f_Y(q_\tau)$ at q_τ using, for instance, kernel methods; and 3) generate a dummy variable, $\mathbb{1}\{Y \leq q_\tau\}$, which indicates whether the value of the outcome variable is above or below the value of Y at each quantile. The resulting RIF is a dummy variable and could serve as the outcome variable in an OLS model (linear probability model), a so-called RIF-OLS (Firpo et al. 2009). In addition, the distributional statistics of the outcome are represented as the conditional expectation of the RIF given the set covariates:

$$q_\tau = E[RIF(Y; q_\tau)|Z] \tag{4}$$

Similar to Agyire-Tettey et al. (2018), we assume the law of iterated expectation. Then, the distributional statistics of growth rates are defined in terms of the conditional expectation, and the unconditional or marginal quantile is given as:

$$q_\tau = \int E[RIF(Y; q_\tau)|Z]dF(Z) \tag{5}$$

Now, we can represent the conditional expectation as a linear function of observable independent variables, $E[RIF(Y; q_\tau)|Z] = \beta' Z + \epsilon$. Nevertheless, the expected value of the error term is approximated to zero, which makes it easier, simple and meaningful to employ OLS techniques in estimating the RIF (Agyire-Tettey et al. 2018). In this regression, our outcomes are $Gsales$ and $GEmpl$, and the explanatory variables are the same used in the first step, but we include EI, II and TOI, which represent the international market intensity of each firm.

[15]This modification is implemented by Borgen (2016) in the *Stata* command *xtrifreg* for fixed effects panel data quantile regressions.

[16]Porter (2015) mentions two reasons to prefer (UQR) over (CQR). First, the transformed outcome variable (the RIF) is defined pre-regression. Thus, unlike CQR, including control variables does not change the definition of the quantile. Second, the transformed outcome variable (the RIF) depends heavily on the estimated density, $f_Y(q_\tau)$.

5 Results

The determinants of being an HGF are reported in Table 4 for the whole manufacturing sector and for industries according to their technological intensity (following the OECD classification). We reported the estimated parameters discussed in the previous section as determinants that could affect the probability of becoming a trader, and in the second stage, the probability of becoming an HGF.

First, Table 4 shows the determinants that affect the probability of becoming a trader. We find that receiving FDI has a positive effect on becoming a $trader$ in the whole manufacturing sector and in each of the OECD technological intensity classification. Moreover, we show that the effect is larger in medium-high & high-tech industries. Keller and Yeaple (2009) argue that FDI spillovers are particularly strong in high-tech sectors, whereas they are largely absent in low-tech sectors. We also find that firm size, measured as sales growth, shows a positive effect on the probability of becoming a $trader$. This result is expected since large firms are more engaged in international markets than smaller firms because they can assume the sunk costs related to international activities (see, for example, Alessandria and Choi 2007; Kasahara and Lapham 2013). However, this evidence is significant only for firms that operate in low-tech and medium-low tech industries. We also find that TFP shows a significant effect of becoming a trader in the whole manufacturing sector and in all three OECD industry classifications. This result is in concordance with empirical literature since it is well known that firms with previous higher TFP self-select to enter in international markets. Additionally, we show that firms with more capital intensity (KI) are more prone to become a $trader$. This result agrees with the idea that if the firm has more capital, it has more capacity to produce and supply other markets. Finally, firm age shows a positive probability of becoming a $trader$. The main argument is that firms gain expertise when they enter new foreign markets, which lowers the fixed costs of entry in any further new market over the following years (see, for example, Sheard 2014; Wagner 2015). In general, the results are very similar in each industry according to technological intensity; nevertheless, we show that the effects are greater in high-tech industries. This might be because high-tech firms are more engaged in international markets.

Following our main equation, we find different results in the whole manufacturing sector and industries according to their technological intensity (following the OECD classification), which proves hypothesis H_1 and H_2. First, in the manufacturing sector, we find that being only an exporter ($ExpOnly$), only an importer ($ImpOnly$) and trade openness intensity (TOI) have a positive impact on the probability of becoming an HGF. This result is expected because it is well known that HGFs are involved in international trade activities (see, for example, Dwyer and Kotey 2016; Golovko and Valentini 2011; Hessels and van Stel 2011). Additionally, we find that firm $size$ shows a significant negative impact on the probability of becoming an HGF, which suggests that HGFs are on average small in this sector. Similar results are found in Segarra and Teruel (2014) and Du and Temouri (2015). Moreover, TFP shows a negative but insignificant effect (at standard levels) on the probability of becoming an HGF. This result is unexpected; nevertheless, this could happen if firms do not have enough absorptive capacity to grow with more productivity. Furthermore,

Table 4 Probability of becoming an HGF

Variable	All firms	Low-tech	Medium-low tech	Medium-high & High-tech
Probability of becoming an HGF				
Determinants of international trade activities				
TOI	0.156***	0.084	0.104	0.168***
	(0.035)	(0.059)	(0.085)	(0.042)
$ExpOnly$	0.536***	0.048	0.928***	0.978***
	(0.191)	(0.292)	(0.318)	(0.309)
$ImpOnly$	0.494***	0.178	0.952***	0.914***
	(0.154)	(0.245)	(0.256)	(0.107)
Control variables				
$Size$	− 0.210***	− 0.179*	− 0.238*	− 0.188***
	(0.066)	(0.104)	(0.135)	(0.109)
TFP	− 0.200	0.266	− 0.466	− 0.252
	(0.184)	(0.234)	(0.333)	(0.227)
KI	− 0.066**	− 0.091	0.055	− 0.028
	(0.031)	(0.057)	(0.064)	(0.035)
age	− 0.170***	− 0.148**	− 0.128*	− 0.284***
	(0.039)	(0.061)	(0.069)	(0.063)
$Constant$	2.704	0.357	3.902	2.105***
	(1.883)	(2.192)	(2.464)	(1.405)
rho	− 0.529***	0.108	− 0.742**	− 0.766*
	(0.202)	(0.265)	(0.363)	(0.446)
Probability of becoming a trader				
FDI	0.248***	0.251**	0.242*	0.260**
	(0.066)	(0.090)	(0.127)	(0.132)
$Size$	0.031	0.112***	0.124***	0.018
	(0.023)	(0.033)	(0.041)	(0.042)
TFP	0.120**	0.144**	0.521***	0.356***
	(0.055)	(0.070)	(0.108)	(0.127)
KI	0.147***	0.162***	0.084***	0.085***
	(0.010)	(0.016)	(0.012)	(0.020)
age	0.167***	0.161***	0.149***	0.219***
	(0.019)	(0.016)	(0.040)	(0.044)
$Constant$	− 3.438***	− 1.201**	− 4.329***	− 5.238***
	(0.494)	(0.521)	(0.917)	(0.984)
No. Obs.	27,931	13,867	8,182	5,877
Selected Obs.	2,636	1,366	691	576
Non-selected Obs.	25,295	12,501	7,491	5,301

Standard errors clustered at the firm level in parentheses. We control for sector, time and city dummies. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Probit estimation and Probit corrected for sample selection (Industries according to their technological intensity)

age shows a significant negative effect on the probability of being an HGF, which suggests that small and young firms are more prone to be HGFs. This evidence is similar to previous empirical evidence of determinants and stylized facts of HGFs (see, for example, Coad 2009; Cruz et al. 2020; Moreno and Coad 2015).

Second, when we divide the manufacturing sector into industries according to their technological intensity, we find that, in the low-tech industries, the variables of international trade activities have a positive effect on the probability of becoming an HGF; however, this effect is not statistically significant at standard levels. We only find, for this industry, that size and age have a negative impact on the probability of becoming an HGF. This reinforces the idea that small and young firms are more prone to be HGFs in this industry. Furthermore, in the medium-low tech industries, being an exporter only ($ExpOnly$) and being an importer only ($ImpOnly$) have a positive impact on the probability of becoming an HGF, and firm *size* and *age* show a negative impact. Finally, we show that, in the medium-high and high-tech industries, all of the variables of international trade activities have a significant effect on becoming an HGF. This finding is expected because firms in high-tech industries have higher growth rates than firms in low-tech industries. Again, firm *size* and *age* have a significant, negative impact on the probability of becoming an HGF, which suggests in this kind of industry that small and young firms are more prone to be HGFs.

Overall, we show that, depending on the industry analyzed, export, import and intensity of trade openness affect the probability of becoming an HGF. It could happen since exports and imports are complements in firm production and productivity (Camino-Mogro and López 2021). Moreover, in all the industries, we find evidence that supports the fact that small and young firms are more prone to be a HGFs. Finally, the results of Table 4 support H_1 and H_2, except in low-tech industries.

5.1 Determinants of firm growth

Tables 5, 6, 7 and 8 show the results of the determinants of firm growth measured in sales and employment for the whole manufacturing sector and for industries according to their technological intensity (following the OECD classification). We find that being in international trade activities influences the performance (growth) of firms, proving hypothesis H_3.

First, we show that, in the manufacturing sector, sales growth (Panel A in Table 5) is positively associated with international trade activities, since in the OLS estimation, we show that the three variables of international trade activities are positive and significant at the 1% level. However, we provide information about the determinants of growth distribution and how its effect varies in low to upper quantiles. In this regard, we find that being a *trader* has a U-shaped effect on sales growth, and in particular, this effect is larger and significant in quantiles superior to 0.75. According to the export only activity, we find a positive association with sales growth in quantile 0.25. Moreover, the import only activity has a U-shaped effect on sales growth, which is positive and significant in lower and upper quantiles but not significant at the median and in quantile 0.75. In terms of firm *size*, this variable has a negative and significant effect on sales growth in all the quantiles. This again suggests that

Table 5 Bootstrapped quantile regressions of the determinants of firm sales and employment growth

	(1) OLS	(2) Q5	(3) Q10	(4) Q25	(5) Q50	(6) Q75	(7) Q90	(8) Q95
Panel A: Sales growth								
$Trader_{t-1}$	0.102***	0.081	0.100**	0.030	0.020	0.058***	0.082**	0.096
	(0.015)	(0.071)	(0.040)	(0.019)	(0.013)	(0.018)	(0.040)	(0.074)
$ExpOnly_{t-1}$	0.063***	− 0.026	0.009	0.031*	0.005	0.001	0.016	0.052
	(0.021)	(0.089)	(0.051)	(0.018)	(0.013)	(0.020)	(0.053)	(0.105)
$ImpOnly_{t-1}$	0.054***	0.082	0.066**	0.023*	0.010	0.014	0.053*	0.045
	(0.011)	(0.062)	(0.032)	(0.014)	(0.010)	(0.013)	(0.030)	(0.060)
$Size_{t-1}$	− 0.126***	− 0.510***	− 0.323***	− 0.151***	− 0.119***	− 0.243***	− 0.845***	− 1.860***
	(0.011)	(0.045)	(0.025)	(0.010)	(0.007)	(0.014)	(0.065)	(0.139)
KI_{t-1}	0.041***	0.041**	0.016**	0.003	− 0.002	− 0.005	− 0.005	0.010
	(0.004)	(0.017)	(0.008)	(0.003)	(0.002)	(0.003)	(0.010)	(0.020)
FDI_{t-1}	0.199***	0.013	− 0.027	0.007	0.026**	− 0.002	0.080*	0.400***
	(0.023)	(0.057)	(0.035)	(0.018)	(0.013)	(0.016)	(0.045)	(0.087)
TFP_{t-1}	0.339***	0.225*	0.053	0.011	− 0.038***	− 0.099***	0.069	0.561***
	(0.034)	(0.129)	(0.059)	(0.023)	(0.015)	(0.026)	(0.080)	(0.155)
age_t	− 0.118***	0.063	0.042	0.012	0.011	− 0.146***	− 0.886***	− 1.688***
	(0.006)	(0.069)	(0.036)	(0.013)	(0.009)	(0.016)	(0.067)	(0.159)
$R^2/PseudoR^2$	0.109	0.032	0.053	0.096	0.147	0.194	0.261	0.288

Table 5 (continued)

	(1) OLS	(2) Q5	(3) Q10	(4) Q25	(5) Q50	(6) Q75	(7) Q90	(8) Q95
Panel B: Employment growth								
$Trader_{t-1}$	0.024	0.148	0.103	− 0.011	− 0.008	0.002	− 0.083**	− 0.286
	(0.017)	(0.248)	(0.113)	(0.026)	(0.007)	(0.025)	(0.035)	(0.295)
$ExpOnly_{t-1}$	− 0.008	0.043	− 0.047	− 0.019	− 0.002	− 0.032	− 0.099***	− 0.522*
	(0.018)	(0.273)	(0.118)	(0.027)	(0.006)	(0.029)	(0.038)	(0.317)
$ImpOnly_{t-1}$	0.009	− 0.057	0.092	0.019	0.004	− 0.011	− 0.047*	− 0.139
	(0.012)	(0.185)	(0.084)	(0.020)	(0.005)	(0.021)	(0.028)	(0.207)
$Size_{t-1}$	− 0.008**	− 0.100	− 0.048	− 0.023***	− 0.011***	− 0.059***	− 0.088***	− 0.279**
	(0.003)	(0.083)	(0.039)	(0.008)	(0.002)	(0.010)	(0.016)	(0.109)
KI_{t-1}	− 0.000	− 0.002	− 0.016	− 0.003	− 0.002***	− 0.017***	− 0.018***	− 0.018
	(0.002)	(0.041)	(0.017)	(0.004)	(0.001)	(0.004)	(0.006)	(0.038)
FDI_{t-1}	0.058*	0.142	0.227**	0.085***	0.023***	0.021	0.004	− 0.080
	(0.031)	(0.245)	(0.108)	(0.025)	(0.006)	(0.028)	(0.035)	(0.243)
TFP_{t-1}	0.021	0.208	0.012	− 0.001	− 0.012*	− 0.099***	− 0.107**	− 0.420
	(0.014)	(0.309)	(0.135)	(0.028)	(0.006)	(0.029)	(0.043)	(0.313)
age_t	− 0.041***	− 0.044	0.029	− 0.010	0.004	− 0.090***	− 0.116***	− 0.360*
	(0.004)	(0.165)	(0.092)	(0.019)	(0.004)	(0.022)	(0.030)	(0.216)
$R^2/PseudoR^2$	0.029	0.017	0.011	0.012	0.025	0.028	0.032	0.030
Observations	28,602	28,602	28,602	28,602	28,602	28,602	28,602	28,602

Year, city and sectoral dummies are included. Standard errors in parentheses (300 bootstrap replications). * p<0.10, ** p<0.05, *** p<0.01

Table 6 Bootstrapped quantile regressions of the determinants of firm sales and employment growth. (Low-tech industries)

	(1) OLS	(2) Q5	(3) Q10	(4) Q25	(5) Q50	(6) Q75	(7) Q90	(8) Q95
Panel A: Sales growth								
$Trader_{t-1}$	0.104***	0.115	0.120**	0.040*	0.031**	0.077***	0.058	0.107
	(0.019)	(0.082)	(0.049)	(0.022)	(0.015)	(0.023)	(0.052)	(0.118)
$ExpOnly_{t-1}$	0.053**	0.085	0.075	0.053**	0.016	− 0.000	0.044	0.123
	(0.024)	(0.112)	(0.059)	(0.021)	(0.014)	(0.024)	(0.058)	(0.135)
$ImpOnly_{t-1}$	0.065***	0.081	0.079**	0.006	0.004	0.012	0.043	− 0.001
	(0.014)	(0.073)	(0.037)	(0.017)	(0.012)	(0.017)	(0.041)	(0.086)
$Size_{t-1}$	− 0.116***	− 0.285***	− 0.208***	− 0.112***	− 0.103***	− 0.216***	− 0.761***	− 2.085***
	(0.015)	(0.061)	(0.028)	(0.010)	(0.007)	(0.015)	(0.066)	(0.202)
KI_{t-1}	0.039***	0.043**	0.021**	0.006*	− 0.001	− 0.007	− 0.002	0.047
	(0.005)	(0.018)	(0.010)	(0.004)	(0.002)	(0.004)	(0.012)	(0.030)
FDI_{t-1}	0.183***	0.080	0.032	0.008	0.020	− 0.011	0.082	0.594***
	(0.030)	(0.072)	(0.039)	(0.020)	(0.015)	(0.021)	(0.054)	(0.143)
TFP_{t-1}	0.299***	− 0.035	− 0.004	0.022	− 0.008	− 0.104***	0.063	0.713***
	(0.042)	(0.138)	(0.070)	(0.023)	(0.017)	(0.030)	(0.093)	(0.217)
age_t	− 0.124***	− 0.105	− 0.006	− 0.014	− 0.003	− 0.115***	− 0.810***	− 1.783***
	(0.008)	(0.082)	(0.039)	(0.018)	(0.011)	(0.019)	(0.084)	(0.220)
$R^2/PseudoR^2$	0.103	0.023	0.042	0.095	0.144	0.197	0.276	0.305

Table 6 (continued)

	(1) OLS	(2) Q5	(3) Q10	(4) Q25	(5) Q50	(6) Q75	(7) Q90	(8) Q95
Panel B: Employment growth								
$Trader_{t-1}$	0.046*	0.026	0.029	0.033	− 0.011	0.009	− 0.186	− 0.440
	(0.026)	(0.394)	(0.128)	(0.035)	(0.010)	(0.037)	(0.126)	(0.409)
$ExpOnly_{t-1}$	0.019	− 0.015	− 0.061	− 0.001	− 0.006	− 0.028	− 0.147	− 0.230
	(0.023)	(0.320)	(0.133)	(0.032)	(0.009)	(0.033)	(0.114)	(0.378)
$ImpOnly_{t-1}$	0.012	− 0.094	0.086	0.018	− 0.004	− 0.040	− 0.108	− 0.427
	(0.018)	(0.253)	(0.102)	(0.026)	(0.007)	(0.027)	(0.080)	(0.290)
$Size_{t-1}$	− 0.005	− 0.031	− 0.020	− 0.024**	− 0.012***	− 0.049***	− 0.140**	− 0.394**
	(0.005)	(0.107)	(0.048)	(0.011)	(0.003)	(0.014)	(0.068)	(0.192)
KI_{t-1}	− 0.004*	0.021	− 0.008	− 0.004	− 0.002**	− 0.018***	− 0.033	− 0.029
	(0.003)	(0.047)	(0.019)	(0.005)	(0.001)	(0.006)	(0.021)	(0.057)
FDI_{t-1}	0.066	0.336	0.280***	0.096***	0.027***	0.044	− 0.073	− 0.109
	(0.044)	(0.321)	(0.105)	(0.031)	(0.009)	(0.037)	(0.106)	(0.354)
TFP_{t-1}	0.014	0.669*	0.168	0.050	− 0.001	− 0.102***	− 0.249	− 0.587
	(0.018)	(0.388)	(0.135)	(0.033)	(0.008)	(0.038)	(0.156)	(0.443)
age_t	− 0.044***	− 0.237	− 0.009	− 0.019	0.001	− 0.076***	− 0.110	− 0.079
	(0.005)	(0.225)	(0.099)	(0.026)	(0.007)	(0.029)	(0.099)	(0.290)
$R^2/PseudoR^2$	0.028	0.019	0.013	0.015	0.028	0.027	0.030	0.026
Observations	14,225	14,225	14,225	14,225	14,225	14,225	14,225	14,225

Year, city and sectoral dummies are included. Standard errors in parentheses (300 bootstrap replications). * p<0.10, ** p<0.05, *** p<0.01

Table 7 Bootstrapped quantile regressions of the determinants of firm sales and employment growth. (medium-low tech industries)

	(1) OLS	(2) Q5	(3) Q10	(4) Q25	(5) Q50	(6) Q75	(7) Q90	(8) Q95
Panel A: Sales growth								
$Trader_{t-1}$	0.121***	0.100	0.099	0.009	− 0.017	0.094**	0.211**	− 0.025
	(0.031)	(0.094)	(0.086)	(0.045)	(0.030)	(0.042)	(0.104)	(0.159)
$ExpOnly_{t-1}$	0.121**	− 0.110	0.034	− 0.058	− 0.015	0.009	− 0.016	− 0.275
	(0.053)	(0.170)	(0.123)	(0.047)	(0.031)	(0.051)	(0.122)	(0.185)
$ImpOnly_{t-1}$	0.057***	0.080	0.050	0.032	0.017	0.016	0.113	0.016
	(0.022)	(0.089)	(0.070)	(0.035)	(0.022)	(0.029)	(0.076)	(0.115)
$Size_{t-1}$	− 0.184***	− 0.549***	− 0.454***	− 0.200***	− 0.148***	− 0.290***	− 0.912***	− 1.872***
	(0.030)	(0.093)	(0.068)	(0.026)	(0.018)	(0.037)	(0.110)	(0.279)
KI_{t-1}	0.032***	0.035	0.022	− 0.000	− 0.002	− 0.006	− 0.023	− 0.052
	(0.008)	(0.027)	(0.018)	(0.006)	(0.004)	(0.007)	(0.018)	(0.038)
FDI_{t-1}	0.173***	− 0.049	− 0.113	− 0.004	0.030	− 0.017	0.015	0.137
	(0.041)	(0.118)	(0.079)	(0.032)	(0.027)	(0.038)	(0.093)	(0.157)
TFP_{t-1}	0.457***	0.377*	0.114	− 0.005	− 0.070*	− 0.138**	− 0.058	0.259
	(0.084)	(0.196)	(0.139)	(0.057)	(0.039)	(0.070)	(0.182)	(0.362)
age_t	− 0.108***	0.172	0.138	0.035	0.036*	− 0.150***	− 0.885***	− 1.707***
	(0.012)	(0.122)	(0.088)	(0.031)	(0.022)	(0.041)	(0.130)	(0.312)
$R^2/PseudoR^2$	0.125	0.047	0.070	0.106	0.159	0.206	0.254	0.282

Table 7 (continued)

	(1) OLS	(2) Q5	(3) Q10	(4) Q25	(5) Q50	(6) Q75	(7) Q90	(8) Q95
Panel B: Employment growth								
$Trader_{t-1}$	0.009	0.518	0.143	− 0.042	0.011	0.005	− 0.098	− 0.139
	(0.032)	(0.441)	(0.133)	(0.062)	(0.018)	(0.057)	(0.103)	(0.311)
$ExpOnly_{t-1}$	− 0.055	0.501	0.069	− 0.095	− 0.008	− 0.123*	− 0.149	− 0.475
	(0.037)	(0.496)	(0.136)	(0.070)	(0.019)	(0.068)	(0.118)	(0.358)
$ImpOnly_{t-1}$	0.010	− 0.119	− 0.001	0.025	0.020*	0.030	− 0.011	0.117
	(0.023)	(0.324)	(0.086)	(0.044)	(0.011)	(0.042)	(0.073)	(0.228)
$Size_{t-1}$	− 0.016*	− 0.152	− 0.030	− 0.028*	− 0.014***	− 0.053***	− 0.125***	− 0.118
	(0.008)	(0.120)	(0.036)	(0.016)	(0.004)	(0.019)	(0.042)	(0.101)
KI_{t-1}	− 0.000	− 0.048	− 0.010	0.000	− 0.002	− 0.015*	− 0.034**	− 0.020
	(0.004)	(0.061)	(0.015)	(0.008)	(0.002)	(0.009)	(0.017)	(0.038)
FDI_{t-1}	0.021	0.031	0.062	0.007	0.016	− 0.043	0.067	0.136
	(0.062)	(0.342)	(0.087)	(0.051)	(0.016)	(0.052)	(0.093)	(0.249)
TFP_{t-1}	0.048	0.054	− 0.058	− 0.052	− 0.025	− 0.070	− 0.139	− 0.249
	(0.032)	(0.466)	(0.125)	(0.062)	(0.017)	(0.068)	(0.120)	(0.345)
age_t	− 0.037***	0.208	− 0.067	− 0.022	0.007	− 0.102**	− 0.158*	− 0.201
	(0.008)	(0.283)	(0.082)	(0.039)	(0.011)	(0.043)	(0.084)	(0.251)
$R^2/PseudoR^2$	0.036	0.019	0.017	0.016	0.027	0.030	0.037	0.035
Observations	8,376	8,376	8,376	8,376	8,376	8,376	8,376	8,376

Year, city and sectoral dummies are included. Standard errors in parentheses (300 bootstrap replications). * p<0.10, ** p<0.05, *** p<0.01

Table 8 Bootstrapped quantile regressions of the determinants of firm sales and employment growth. (medium-high and high-tech industries)

	(1) OLS	(2) Q5	(3) Q10	(4) Q25	(5) Q50	(6) Q75	(7) Q90	(8) Q95
Panel A: Sales growth								
$Trader_{t-1}$	0.060*	− 0.040	0.019	− 0.019	0.015	0.008	0.114	0.200
	(0.030)	(0.160)	(0.088)	(0.037)	(0.029)	(0.040)	(0.083)	(0.162)
$ExpOnly_{t-1}$	0.028	− 0.200	− 0.137	− 0.010	− 0.025	0.005	− 0.039	0.114
	(0.060)	(0.209)	(0.120)	(0.044)	(0.030)	(0.049)	(0.116)	(0.218)
$ImpOnly_{t-1}$	0.025	0.108	0.106	0.029	0.023	0.019	0.084	0.075
	(0.023)	(0.127)	(0.067)	(0.026)	(0.020)	(0.030)	(0.065)	(0.133)
$Size_{t-1}$	− 0.114***	− 0.551***	− 0.330***	− 0.149***	− 0.117***	− 0.235***	− 0.716***	− 1.983***
	(0.019)	(0.113)	(0.055)	(0.020)	(0.014)	(0.024)	(0.091)	(0.363)
KI_{t-1}	0.028***	0.038	0.014	0.004	0.007	0.006	0.004	− 0.003
	(0.006)	(0.027)	(0.016)	(0.008)	(0.006)	(0.007)	(0.014)	(0.042)
FDI_{t-1}	0.273***	0.043	− 0.027	0.035	0.026	0.019	0.096	0.484**
	(0.061)	(0.092)	(0.080)	(0.041)	(0.026)	(0.040)	(0.085)	(0.242)
TFP_{t-1}	0.281***	0.229	0.040	− 0.026	− 0.108**	− 0.059	0.099	0.762**
	(0.060)	(0.307)	(0.133)	(0.058)	(0.045)	(0.053)	(0.143)	(0.367)
age_t	− 0.111***	0.150	0.044	0.041	0.017	− 0.206***	− 0.819***	− 1.736***
	(0.012)	(0.137)	(0.076)	(0.027)	(0.020)	(0.032)	(0.128)	(0.380)
$R^2/PseudoR^2$	0.115	0.042	0.058	0.101	0.145	0.183	0.236	0.263

Table 8 (continued)

	(1) OLS	(2) Q5	(3) Q10	(4) Q25	(5) Q50	(6) Q75	(7) Q90	(8) Q95
Panel B: Employment growth								
$Trader_{t-1}$	− 0.004	0.086	0.105	− 0.065	− 0.029	− 0.029	− 0.043	0.041
	(0.031)	(0.302)	(0.209)	(0.052)	(0.018)	(0.054)	(0.114)	(0.465)
$ExpOnly_{t-1}$	− 0.061	0.068	0.024	− 0.029	0.014	− 0.053	− 0.148	− 0.651
	(0.046)	(0.373)	(0.260)	(0.056)	(0.018)	(0.062)	(0.121)	(0.511)
$ImpOnly_{t-1}$	0.002	0.059	0.074	0.008	0.008	0.015	− 0.052	− 0.175
	(0.023)	(0.271)	(0.145)	(0.038)	(0.012)	(0.043)	(0.096)	(0.373)
$Size_{t-1}$	− 0.001	− 0.050	− 0.015	− 0.008	− 0.009	− 0.055***	− 0.073	− 0.021
	(0.007)	(0.125)	(0.080)	(0.019)	(0.006)	(0.021)	(0.057)	(0.174)
KI_{t-1}	0.009*	− 0.006	0.008	0.000	− 0.002	− 0.002	0.009	0.077
	(0.005)	(0.058)	(0.032)	(0.009)	(0.003)	(0.008)	(0.018)	(0.083)
FDI_{t-1}	0.085	0.129	0.163	0.086	0.034*	0.020	0.035	− 0.447
	(0.057)	(0.326)	(0.197)	(0.053)	(0.018)	(0.052)	(0.103)	(0.417)
TFP_{t-1}	− 0.014	− 0.157	− 0.177	− 0.057	− 0.029	− 0.111*	− 0.027	− 0.316
	(0.031)	(0.426)	(0.278)	(0.073)	(0.021)	(0.065)	(0.141)	(0.664)
age_t	− 0.041***	0.038	0.125	0.023	0.014	− 0.104**	− 0.307**	− 1.110**
	(0.008)	(0.267)	(0.163)	(0.037)	(0.011)	(0.045)	(0.135)	(0.462)
$R^2/PseudoR^2$	0.027	0.012	0.006	0.008	0.020	0.028	0.031	0.027
Observations	5,996	5,996	5,996	5,996	5,996	5,996	5,996	5,996

Year, city and sectoral dummies are included. Standard errors in parentheses (300 bootstrap replications). * p<0.10, ** p<0.05, *** p<0.01

Table 9 Impact of being in international trade activities on being an HGF: propensity score matching

	(1) Nearest neighbor	(2) Kernel	(3) Radius
Panel A: ExpOnly vs. Non-ExpOnly			
ExpOnly Vs. Non-ExpOnly	0.059***	0.070***	0.093***
	(0.022)	(0.019)	(0.014)
No. of obs.	3,373	3,373	3,373
Panel B: ImpOnly vs. Non-ImpOnly			
ImpOnly Vs. Non-ImpOnly	0.022*	0.020*	0.004
	(0.012)	(0.010)	(0.007)
No. of obs.	9,113	9,113	9,113
Panel C: Traders vs. Non-Traders			
Traders Vs. Non-Traders	0.074***	0.076***	0.104***
	(0.017)	(0.017)	(0.009)
No. of obs.	4,690	4,690	4,690

Year, city and sectoral dummies are included. Standard errors in parentheses. All PSM are estimates after using the CEM. * p<0.10, ** p<0.05, *** p<0.01

small firms have larger sales growth than larger firms. The KI variable has a positive effect on sales growth in lower quantiles, and FDI has a positive effect on sales growth in upper quantiles. TFP is positively related to sales growth, specifically at quantiles 0.05 and 0.95; nevertheless, firms at the median and quantile 0.75 show a negative effect. The variable age shows a negative effect in upper quantiles to 0.75. This evidence suggests that, in general, HGFs are positively affected by being a two-way trader, TFP and FDI, but negatively affected by size and age. These results are in line with previous results found in this paper.

According to the measure of employment growth (Panel B in Table 5), we find that FDI is a positive determinant of employment growth. However, firm $size$ and age are negative determinants. More specifically, when we analyze the quantiles, we find that our three measures of international trade activities have a negative and significant effect on employment growth in upper quantiles (0.90). This result shows that HGFs in terms of employment are negatively affected by international trade activities, which may be because the spillover effects of international trade activities are less common in employment measures. Again, the idea that young and small firms are more prone to be HGFs is found when we analyze employment growth.

In Table 6, we present the results of the determinants of sales and employment growth in the low-tech industries. In terms of sales growth (Panel A in Table 6), we find that the three international trade activities are positive determinants of sales growth. Also, KI, FDI and TFP are positively related to $GSales$, but $size$ and age are negative determinants. However, when we analyze the effect in the entire growth distribution, our results suggest that being a $trader$ has a positive effect in quantiles lower than 0.90. Export only activity is positively related to sales growth at

quantile 0.25, and import only is positively related to sales growth at quantile 0.10. Firm $size$ has a significant, negative sign in the whole distribution but is larger in upper quantiles. Similar results are found with the variable age. Furthermore, KI as it relates to sales growth is only positive and significant at quantiles inferior to 0.25. Additionaly, FDI has a significant, positive sign in quantile 0.95. Finally, TFP is positively related to sales growth in quantile 0.95, but negatively related in quantile 0.75. In terms of employment growth (Panel B in Table 6), we find that, on average, only $trader$, KI and age are determinants of employment growth. On the other hand, $size$ has a significant negative effect on employment growth in quantiles larger than 0.25, KI has a negative effect on $GEmpl$ at the median and quantile 0.75, and FDI shows a positive effect in quantiles larger than the median. Finally, TFP and age are negative and significant as they relate to employment growth in quantile 0.75.

In this industry, we show that HGFs are negatively affected by size and age, and not statistically affected by international trade activities. This outcome may occur because firms in low-tech industries produce outputs with low value added and their markups are lower than firms with high-tech process and output.[17]

Again, in Tables 7 and 8 of medium-low and medium-high and high-tech industries, the results are very similar. Our evidence suggests that, in medium-low tech industries, HGFs are positively affected by being a two-way $trader$ but negatively affected by firm $size$[18] and age in terms of sales growth. This pattern is similar in the determinants of employment growth but with the inclusion of KI as a negative determinant. In medium-high and high-tech industries, our results are similar in the determinants of sales growth. We find that HGFs are positively affected by TFP and FDI, but negatively affected by firm $size$ and age. However, in terms of employment growth, only age is a negative determinant in upper quantiles.

In general, we find heterogeneous determinants depending on industries according to their technological intensity in which firms operate. However, we find strong evidence that suggest that firm $size$ and age negatively affect sales growth and employment growth in upper quantiles (HGF). Our evidence of the effect of international trade activities on industries according to their technological intensity is mixed, depending on the measure of growth and also on the industry.

5.2 Robustness check

The empirical literature has raised concerns regarding endogeneity issues in the decision to be in international markets (export, import and two-way traders) (see, for example, Camino-Mogro and López 2021; De Loecker 2013; Kasahara and Rodrique 2008). In particular, firms that are in international trade activities have certain characteristics which may make them more probable to grow faster compared with their counterparts. In this sense, one may be concerned that endogeneity might represent a major issue in our setting. To rule out this threat, we follow the strategy performed by Afcha and García-quevedo (2016) and combine two matching techniques in order

[17] In general, HGFs are located in quantiles 0.90 and 0.95 (Segarra and Teruel 2014).

[18] Similar to Teruel (2010), we suggest that manufacturing firms are achieving a minimum efficient size.

to ensure the maximum degree of similarity between firms that are in international markets and firms that only operates in the domestic market.[19]

The first matching technique is the coarsened exact matching (CEM) proposed by Blackwell et al. (2009). The CEM is particularly useful when some independent variables are subject to an endogeneity problem. Moreover, Iacus et al. (2011) show that the CEM dominates commonly used existing matching methods in its ability to reduce imbalance, model dependence, estimation error, bias, variance, mean square error and other criteria. The second matching technique is the propensity score matching (PSM) as proposed initially by Rosenbaum and Rubin (1983). Using CEM before the implementation of the subsequent matching technique is suggested as an appropriate procedure that improves the quality of matching and the inferences drawn after PSM (Afcha and García-quevedo 2016; Blackwell et al. 2009; Iacus et al. 2011).

In addition, Afcha and García-quevedo (2016) mention that, in order to guarantee the similarity between treated (firms that are in international markets) and control (firms that only operates in the domestic market) groups, the first method used is the CEM, which allows covariates to be matched exactly. This allows us to improve the estimation of causal effects and reduces differences between treated and control groups. By combining CEM with other matching methods, it is possible to improve the estimates in several ways, such as reducing variance or removing heterogeneity. Furthermore, CEM has two main benefits. It meets the congruence principle and it restricts the matched data to areas of common empirical support (Iacus et al. 2011). To do so, we estimate an equation of the form:

$$p(X) \equiv P(D = 1|X) = E(D|X) \tag{6}$$

where D is a dummy variable, that indicates whether the firm is only an exporter, only an importer or a two-way trader, taking values $D = (0, 1)$, independently. X is a vector of covariates such as FDI, TFP, size, KI and age, lagged one period. We also include industry, city and year fixed effects. Then, ATT is formulated as follows:

$$\tau = p(X)|D = 1[E[Y(1)|D = 1, P(X)] - E[Y(0)|D = 0, P(X)]] \tag{7}$$

where Y(1) shows the expected outcome (being an HGF) for firms that only export, only import, or do both at same time (two-way trader), independently. Y(0) represents the outcome (not being an HGF) for firms that are not only exporters, only importers or two-way traders, independently.

Table 9 shows the results of this exercise. We get the expected signs and statistically significant results for the three specifications. This supports our identification strategy and is in line with our baseline results, which means that, after working with the matched sample, the effect is not washed out.

[19] Also, we use these two methodologies to control for potential sample bias between traders and non-traders. However, the nature of the problem of the endogeneity between variables is indeed still not totally controlled, but considerably reduced.

6 Conclusions

Using a large Ecuadorian firm-level panel data set from 2007-2018, this paper analyzes the determinants of becoming an HGF, and the determinants of international trade activities on firm growth. The analysis categorizes the manufacturing sector according to their technological intensity (following the OECD classification).

Our main conclusions based on the preceding analysis are the following. First, the Ecuadorian manufacturing firms most likely to become HGFs are small and young firms. This pattern is similar when we analyze different manufacturing industries according to their technological intensity. With respect to international trade activities, we find that firms that only export demonstrate a greater probability of becoming an HGF in the whole manufacturing industry. However, the results are heterogeneous when we analyze the manufacturing industries according to their technological intensity. In particular, we find that international trade activities do not have an effect on the probability of becoming an HGF for firms that operate in low-tech industries. On the other hand, being only an exporter or an importer positively affects the probability of becoming an HGF in medium-low and medium-high and high-tech industries. Second, we apply an unconditional quantile regression approach to analyze the different determinants of firm growth in the entire distribution. We conclude that, in the whole manufacturing sector, being a two-way trader has a U-shaped effect on sales growth, and, specifically, this effect is larger, significant and positive in quantiles superior to 0.75. As for export only activity, we show a positive association with sales growth only in quantile 0.25. For import only activity, we show a U-shaped effect on sales growth, which is positive and significant in lower and upper quantiles but not significant at the median or in quantile 0.75. In general, HGFs are positively affected by being a two-way trader, TFP and FDI in terms of sales growth. Nevertheless, in terms of employment growth, we find that our three measures of international trade activities have a negative effect in upper quantiles (0.90). In all the cases, size and age are negative determinants of firm growth. Third, by combining two matching techniques in order to ensure the maximum degree of similarity between firms that are in international markets and firms that only operates in the domestic market, we find robust evidence that supports our identification strategy and is in line with our baseline results, which means that, after working with the matched sample, the effect is not washed out.

Our results suggest that the effect of international trade activities on firm growth is heterogeneous across manufacturing industries according to their technological intensity and also across quantiles. We show that HGFs in low-tech industries are negatively affected by size and age, and are not affected by international trade activities. Meanwhile, in the medium-low tech industries, HGFs are positively affected by being a two-way trader, but negatively affected by firm size and age in firm growth. Finally, in the medium-high and high-tech industries, HGFs are positively affected by TFP and FDI, but negatively affected by firm size and age.

Our results are important from different perspectives. First, for policy makers, we show that the Ecuadorian government should focus its promotion to enter international markets on young and small firms in order to create employment and growth in this kind of firm. Also, it is necessary to reduce credit constraints for this kind

of firm to reduce the high sunk costs associated with being in international markets. Second, for managerial strategies, firms need to open their equity and attract FDI. These are some policy ideas that needs to do for an internationalization process and the government should support these initiative by providing public solid institutions, with low levels of corruption and with clear laws. Moreover, the government could apply tax breaks to fresh FDI in small and young manufacturing firms.

Future research is needed to analyze international trade activities as determinants of becoming an HGF. In particular, it might be interesting to know whether export or import to/from developed or developing countries has a different effect on the probability of becoming an HGF. Also, analyzing this effect by country regions might show clearer effects of this issue. Finally, it is also necessary to research the factors associated with international trade that cause firms to cease being HGFs. Due to limitations of our data set, these questions are still open.

Appendix

Table 10 Correspondence between ISIC codes and industries according to technological intensity

Industry	Subsectors	ISIC Codes
Low-tech industry	Food, beverages and tobacco	10 + 11 + 12
	Textile and clothing	13 + 14 + 15
	Wood products	16
	Paper manufacturing	17
	Editing and printing	18
	Furniture and other manufacturing industries	31 + 32
Medium-low tech industry	Coke manufacturing and oil refining	19
	Manufacture of rubber and plastic products	22
	Manufacture of other non-metallic mineral products	23
	Mineral-based products	24
	Metal products	25
	Repair and installation of machinery and equipment	33
Medium-high and	Chemical industry	20
High tech industry	Machinery and electrical equipment	27
	Agricultural and industrial machines	28
	Motor vehicles	29
	Other transport material	30
	Pharmaceutical products	21
	Manufacture of computer, electronic, and optical products	26

Eurostat indicators on high-tech industry and knowledge; Superintendencia de Compañías, Valores y Seguros

Table 11 Matrix of Pearson correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	HGF	1.000										
(2)	$GSales$	0.037*	1.000									
(3)	$GEmpl$	0.015*	0.104*	1.000								
(4)	$Size_{t-1}$	0.093*	− 0.185*	− 0.019*	1.000							
(5)	$ExpOnly_{t-1}$	0.052*	− 0.010	− 0.005	0.130*	1.000						
(6)	$ImpOnly_{t-1}$	0.021*	− 0.021*	− 0.009	0.239*	− 0.110*	1.000					
(7)	TOI_{t-1}	− 0.025*	0.021*	0.011	− 0.284*	− 0.278*	− 0.483*	1.000				
(8)	FDI_{t-1}	− 0.007	0.043*	0.009	0.210*	0.041*	0.025*	− 0.073*	1.000			
(9)	TFP_{t-1}	0.038*	− 0.057*	− 0.014*	0.817*	0.089*	0.266*	− 0.251*	0.241*	1.000		
(10)	KI_{t-1}	− 0.027*	0.131*	0.001	− 0.047*	0.003	0.053*	− 0.035*	0.038*	0.027*	1.000	
(11)	age	− 0.016*	− 0.091*	− 0.035*	0.383*	0.032*	0.185*	− 0.184*	0.091*	0.389*	0.082*	1.000

Superintendencia de Compañías, Valores y Seguros. * Significant at 5%

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Declarations

Ethics approval This article does not contain any studies with human participants or animals performed by any of the authors.

Conflict of Interests The authors declare that they have no conflict of interests.

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