

PRODUCTIVITY, QUALITY AND EXPORT BEHAVIOUR*

Rosario Crinò and Paolo Epifani

We find a robust negative correlation between Italian firms' productivity and their export share to low-income destinations. To account for this surprising fact, we marry Verhoogen (2008) with Eaton *et al.* (2011), by introducing firm heterogeneity in product quality and country heterogeneity in quality consumption in a framework featuring firm and market-specific shocks in entry costs and demand, and estimate the model's parameters structurally by the simulated method of moments. The estimated preference for quality turns out to be monotonically increasing in foreign destinations' income. The model also predicts a negative correlation between firms' R&D intensity and their export share to low-income destinations, a finding supported by our data. Overall, our results strongly suggest high-quality firms should concentrate their sales in high-income markets.

In this article, we study how the interplay between firm and foreign market characteristics affects key aspects of export behaviour. Our contribution is motivated by some new and perhaps surprising facts in the light of the recent heterogeneous-firms literature. In particular, using a representative sample of Italian manufacturing firms, drawn from a reliable dataset also used in other studies,¹ we find a strong and robust negative correlation between firms' productivity and their share of total exports to low-income destinations. This fact seems at odds with the common wisdom, positing that only the most productive firms are profitable enough to break into harder-to-reach destinations.

In line with a recent literature pointing to the crucial role of quality in international trade, we argue that this and other empirical regularities can arise from the interplay between endogenous, cross-firm heterogeneity in product quality and cross-country heterogeneity in quality consumption. Specifically, we conjecture that more productive firms tend to concentrate their sales in high-income markets because they produce higher-quality products, for which relative demand is higher in high-income destinations. This conjecture is indeed supported by our data.

* Corresponding author: Paolo Epifani, Department of Economics, Università Commerciale Luigi Bocconi, Via Röntgen 1, 20136, Milano, Italy. Email: paolo.epifani@unibocconi.it.

The article has benefited enormously from the comments of three anonymous referees. We also thank Francisco Alcalá, Carlo Altomonte, Elisa Borghi, Bruno Cassiman, Davide Castellani, Luca De Benedictis, Anna Falzoni, Samuel Kortum, Crt Kostevc, Marco Leonardi, Marc Muendler, Marcella Nicolini, Fabrizio Onida, Gianmarco Ottaviano, Luca Sala, Daniel Treffer, Jaume Ventura, Eric Verhoogen, Frederic Warzynski and seminar participants at many venues for comments and discussions. All errors are our own. We gratefully acknowledge financial support from Unicredit Banca, Centro Studi Luca d'Agliano, Paolo Baffi Centre on Central Banking and Financial Regulation, the FIRB project 'International Fragmentation of Italian Firms. New Organizational Models and the Role of Information Technologies' (Italian Ministry of Education, University and Research) and the EFIGE project (European Commission FP7, N. 225551). Rosario Crinò gratefully acknowledges also the support of the Barcelona Graduate School of Economics, the Government of Catalonia, and the Spanish Ministry of Science and Innovation (Project ECO 2009-07958).

¹ For instance, Parisi *et al.* (2006), Benfratello *et al.* (2009) and Angelini and Generale (2008) use the same dataset to investigate, respectively, the impact of firms' innovation strategies on the growth of TFP, the relationship between financial development and innovation, and the relationship between financial constraints and firm size distribution. Moreover, using older releases of our dataset, Castellani (2002) shows evidence that exporters are generally more productive than non-exporters and that productivity increases after exporting (learning-by-exporting).

We start, in Section 1, by illustrating the main patterns in our data. We first show that it replicates the empirical regularities recently unveiled by (Eaton *et al.*, 2011, henceforth EKK) using French data. Next, we show some new facts. In particular, we provide extensive evidence on a negative cross-firm correlation between productivity (revenue-TFP or value added per unit of factor cost, as in EKK) and the export share to low-income destinations. The negative correlation holds independent of sample size (i.e., it is equally strong for the sample of all exporters and for that of exporters to both high-income and low-income destinations) and is not affected by outliers, estimation method and specification details.

In Section 2, building on Verhoogen (2008), we start by formulating a stripped-down heterogeneous-firms model that clarifies the main insight behind our interpretation of the evidence, and discuss its implications in the light of the received literature. The crucial assumptions for the results are that consumers choose quality consumption based on their income and firms product quality based on their productivity.² The baseline model can nicely explain a negative correlation between productivity and the export share to low-income destinations but only conditional on firms entering both high-income and low-income destinations. Yet, in our data the negative correlation also holds strong unconditionally, i.e. across all exporters. Moreover, in the baseline model firms enter foreign markets according to an exact hierarchy, whereas there is no strict sorting of exporters in our data. Therefore, following EKK, we extend the model to allow for firm and market-specific heterogeneity in entry costs and demand, and estimate its deep parameters by the simulated method of moments. Consistent with our theory, estimated parameters imply the preference for quality to be monotonically increasing in per capita income of the destinations: on average, it is almost three times higher in high-income destinations; in the richest destination (North America) it is roughly 20 times as high as in the poorest destination (Africa). Moreover, with the estimated set of parameters, the model matches our data well and correctly predicts a negative unconditional (as well as conditional) correlation between exporters' productivity and their export share to low-income destinations.

The model also predicts a strong negative correlation between firms' R&D intensity and their export share to low-income destinations, with or without controlling for productivity. These implications are successfully tested in Section 3. More generally, in our model high-productivity firms produce higher-quality products because they invest more in R&D and related activities. Hence the model suggests, in line with the empirical literature on quality differentiation (Sutton, 1998, and more recently Kugler and Verhoogen, 2012), that firms' innovation activities are close proxies for product quality. Exploiting a quasi-unique feature of our dataset, we therefore extract the principal component from a number of firm-level variables measuring innovation activities and treat it as a synthetic quality proxy.³ Consistent with our theory, we find

² In Verhoogen (2008), which uses a different model, these two ingredients prove crucial to explain the link between trade and skill upgrading in Mexico.

³ We are aware of only one dataset, for a developing country, with broadly similar information on innovation activities (Bustos, 2011). We view our approach to estimating product quality as complementary to the standard practice of using unit values as, e.g., in the recent firm-level studies by Manova and Zhang (2012) and Bastos and Silva (2010). Its main advantage is that it does not require a one-to-one relationship between quality and prices; see Hallak (2006) and Khandelwal (2010) on this point. For an alternative approach to estimating quality, based on producer ratings from wine guides, see Crozet *et al.* (2012).

this variable to be strongly negatively correlated with the export share to low-income destinations. Finally, the model predicts the correlations between the export share to an individual destination and productivity, R&D intensity or product quality to be all increasing in the destination's per capita income. We find strong support for these predictions using a panel of firms' export shares to all of the destinations for which we have data.

Our article is related to various strands of the literature. First, it is related to the empirical literature on quality and trade. Based on industry and product-level data, studies in this area suggest quality consumption to be strongly increasing in per capita income and cross-country heterogeneity in product quality to be crucial to explain international specialisation.⁴ In this respect, our results can be interpreted as the micro-level counterpart, in the presence of heterogeneous firms, of the Linder hypothesis, positing that richer countries tend to import more from countries producing higher-quality goods.⁵

Second, our article is related to a number of recent contributions introducing quality into a heterogeneous-firms framework.⁶ With the notable exception of Verhoogen (2008), these studies do not posit a role for both product quality and quality consumption. Our main contribution to this growing literature is to show how these ingredients can help to explain some important aspects of export behaviour.

Finally, and probably more importantly, our article is closely related to EKK, which develops and estimates a heterogeneous-firms model *à la* Melitz (2003) with firm-specific shocks and endogenous entry costs *à la* Arkolakis (2010). Their work represents the most demanding and successful attempt so far to explain export behaviour across destinations, yet it cannot easily accommodate our empirical regularities. Our contribution is to show how embedding Verhoogen's (2008) insight on product quality and quality consumption into an EKK-like framework may help one to understand what we view as key features of export behaviour.

1. Empirical Regularities

In this Section, we illustrate our data and the main patterns in them.

1.1. Data

Our data come from the 9th survey 'Indagine sulle Imprese Manifatturiere', administered by the Italian Commercial Bank *Unicredit*. The survey is based on a questionnaire sent to a sample of 4,289 manufacturing firms and contains information for the period 2001–3. Answers to the survey questions are complemented by balance sheet data. The sample is stratified by size class, geographical area and industry to be representative of the population of Italian manufacturing firms with more than 10

⁴ As for trade and quality consumption see, in particular, Bils and Klenow (2001), Hummels and Skiba (2004), Brooks (2006), Hallak (2006, 2010) and Choi *et al.* (2009). As for product quality and trade, see Schott (2004), Hummels and Klenow (2005) and Hallak and Schott (2011).

⁵ See, in particular, Hallak (2006, 2010), for empirical evidence on the Linder hypothesis using bilateral, industry-level data.

⁶ See, in particular, Manasse and Turrini (2001), Alcalà (2007), Hallak and Sivadasan (2009), Baldwin and Harrigan (2011), Johnson (2012) and Kugler and Verhoogen (2012).

employees. We drop roughly 100 firms reporting negative values for sales, capital stock or material purchases, or for which the various categories of employees (by educational level or occupation) do not add up to the reported total employment. Out of the remaining firms, 3,365 have complete information on TFP and sales to individual destinations; we use these firms in most of the empirical analysis and the simulations.

The dataset contains information on firms' exports in the year 2003 to the following destinations: EU15, New EU Members, Other European countries, North America, Latin America, China, Other Asian countries, Africa and Oceania. To show our main empirical regularities, we aggregate them into two groups of high-income and low-income destinations. In particular, the former group includes North America, EU15 and Oceania (*NA*, *EU15*, *OCE*), whereas the latter includes Africa, China, Latin America and New EU Members (*AFR*, *CHN*, *LAT*, *EU10*). We exclude Other Europe and Other Asia from the two groups, because these destinations include countries that are very heterogeneous in terms of per capita income.⁷ Based on data from the World Development Indicators, average PPP per capita income in 2003 equals 27,000 US\$ in the group of high-income destinations and 4500 US\$ in the group of low-income destinations.⁸

Table 1 reports statistics on firms' entry and exports across destinations. The total number of exporters for which we have complete information on TFP and sales to individual destinations is 2,507, roughly 75% of the total number of firms;⁹ among them, 2,428 sell to high-income destinations and 1,315 to low-income destinations. As for individual destinations, EU15 is the most popular one, with 2,357 exporters and an average export share of 70%. Conversely, the least popular destination is China, with 321 exporters and an average export share of 2%.

1.2. *EKK-Type Patterns*

Following EKK, in Table 2 we report the number of exporters to the strings of the seven foreign destinations that obey a hierarchy in terms of popularity. If firms entered markets according to an exact hierarchy, exporters to the $(n + 1)$ th most popular destination would also sell in the n th most popular destination. As shown in column (1), only 54% of the exporters enter markets according to an exact hierarchy.¹⁰ In Column (2), we use marginal probabilities of entry in each destination, drawn from column (2) of Table 1, to predict how many exporters would enter each string under independence, namely, under the assumption that selling in a destination is independent of selling in any other destination. Note that only 38% of exporters would enter strings according to an exact hierarchy under independence. These patterns are

⁷ Both areas include the richest and poorest countries in the world. For instance, Other Asia comprises Japan and Afghanistan, whereas Other Europe comprises Switzerland and Norway, as well as Russia and the Balkans. Our main results are however robust to including these areas among either the low-income or the high-income destinations.

⁸ As for individual destinations, PPP per capita income (in US\$) is: 29,000 (*NA*), 27,000 (*EU15*), 20,000 (*OCE*), 13,000 (*EU10*), 7,000 (*LAT*), 5,000 (*CHN*), 2,000 (*AFR*).

⁹ This figure is very close to that reported in other studies based on micro-level data collected by the Italian Statistical Office, e.g., Castellani *et al.* (2010).

¹⁰ The issue of non-hierarchical destinations becomes less relevant if we focus on two aggregate destinations (high-income and low-income), as most exporters to low-income destinations also export to high-income destinations (1236 out of 1315).

Table 1
Firms' Entry and Exports Across Destination

	Number of Exporters	Share of Total Exporters	Export Share
	(1)	(2)	(3)
<i>Aggregate Destinations</i>			
High-Income	2,428	0.97	0.83
Low-Income	1,315	0.52	0.17
<i>Individual Destinations</i>			
EU15	2,357	0.94	0.70
North America	1,104	0.44	0.12
New EU Members	865	0.35	0.08
Africa	562	0.22	0.04
Latin America	494	0.20	0.03
Oceania	350	0.14	0.01
China	321	0.13	0.02
Total	2,507		

Notes. High-income destinations include North America, EU15 and Oceania. Low-income destinations include Africa, China, Latin America and New EU Members. All variables are computed for the year 2003. Source: Unicredit.

Table 2
Firms Selling to Strings of Foreign Destinations

	Number of Exporters	Under Independence
	(1)	(2)
<i>Export Strings</i>		
EU15	759	404
EU15 – NA	332	318
EU15 – NA – EU10	99	167
EU15 – NA – EU10 – AFR	35	48
EU15 – NA – EU10 – AFR – LAT	31	12
EU15 – NA – EU10 – AFR – LAT – OCE	38	2
EU15 – NA – EU10 – AFR – LAT – OCE – CHN	55	0
Total	1,349	951
% of Total	0.54	0.38

Notes. The string “EU15” means selling in EU15 but not in the other destinations, “EU15 - NA” means selling in EU15 and North America but not in the other destinations, etc.. Column (1) shows how many exporters sell to each string in the data. Column (2) shows how many exporters would sell to each string under the assumption that selling in a destination is independent of selling in any other destination; these numbers are computed using data in column (2) of Table 1.

broadly consistent with those reported by EKK using more detailed export destination data.¹¹ They suggest that, although firms do not enter foreign markets according to an exact hierarchy, entry does not seem to be a random process.

More generally our data replicate, all the main empirical regularities unveiled by EKK for French firms on a smaller scale. In particular, in the Appendix we show that:

¹¹ EKK find that 27% of exporters enter the seven most popular destinations according to an exact hierarchy (*versus* 13% under independence).

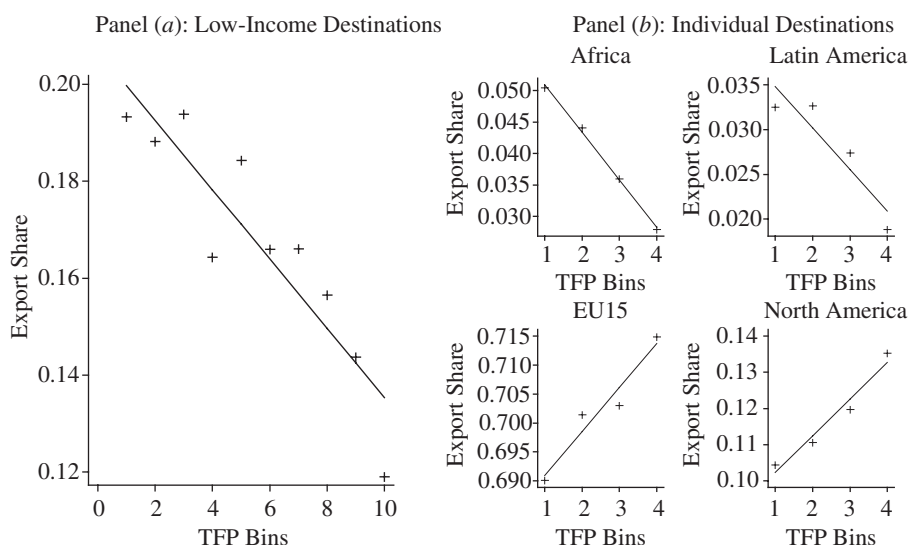


Fig. 1. *Productivity and Export Shares: Non-Parametric Evidence*

Notes. To construct each graph, the exporters' TFP distribution is split into bins of equal size and the average export share is computed across all exporters in each bin. Results are based on the augmented Olley and Pakes TFP estimate (see Table 3).

- (i) the number of exporters (normalised by Italy's market share in a destination) and their sales to a destination are increasing in the destination's market size;
- (ii) firms entering a greater number of foreign destinations and firms entering harder-to-reach destinations, sell more in Italy;
- (iii) firms' normalised export intensity (i.e., sales to a destination over domestic sales, both normalised by average sales in the respective market) is higher in more popular destinations.

1.3. *Productivity and the Export Share to Low-Income Destinations*

Having shown that the patterns in our data are consistent with those in EKK, we now document a new fact, namely, a strong and robust negative correlation between productivity and the export share to low-income destinations (the ratio of exports to these areas over total exports, henceforth ES_i). To begin with, we split the exporters' TFP distribution into 10 bins of equal size and compute the average value of ES_i across all exporters in each bin.¹² The results are reported in Figure 1 (a), showing that the relationship between ES_i and TFP is strongly decreasing across bins. In panel (b), we repeat the exercise for selected destinations using four TFP bins. Note that the correlation is strongly negative for Africa and Latin America (two low-income destinations) and strongly positive for EU15 and North America (two high-income destinations).

Next, we turn to parametric estimates to perform statistical inference. In particular, we run cross-sectional OLS regressions of the following form:

¹² Unless otherwise stated, the TFP measure we refer to is the augmented Olley and Pakes (1996) estimate proposed by De Loecker (2011), see footnote 14.

$$ES_{ij} = \chi_0 + \chi_1 \ln TFP_j + \chi_i + e_j, \quad (1)$$

where j indexes firms, χ_i are 3-digit industry fixed effects¹³ and e is an error term. Our coefficient of interest, χ_1 , reflects the correlation between TFP and the export share to low-income destinations. The baseline results are reported in Table 3, where each column refers to a different TFP estimate. In particular, TFP is based on: cross-sectional estimates of a Cobb-Douglas production function in columns (1)–(4) and of a translog production function in columns (5)–(8) (as in Amiti and Konings, 2007); semiparametric Cobb-Douglas panel estimates in columns (9)–(11), as in Olley and Pakes (1996); Levinsohn and Petrin (2003); De Loecker (2011); cross-sectional OLS Cobb-Douglas estimates at the 2-digit industry level in column (12), as in Bernard and Jensen (1999) and Kugler and Verhoogen (2009).¹⁴ Given that our main regressor is estimated, we report bootstrapped standard errors based on 500 replications (in brackets), as well as, for comparison, heteroscedasticity-robust analytical standard errors (in parenthesis).

In panel (a), we estimate (1) for all exporters. Note that χ_1 is always negative and significantly different from zero beyond the 1% level, using either type of standard errors. Point estimates imply that a doubling of TFP is associated with a fall in the export share to low-income destinations of roughly 8% points. In panel (b), we estimate (1) on the subsample of exporters to both high-income and low-income destinations. Note that the negative correlation between ES_i and TFP is slightly larger and still precisely estimated across the board.¹⁵

Finally, in Table 4 we show that the TFP elasticity of export revenue is increasing in the destination's per capita income.¹⁶ In panels (a–c) we regress, respectively, log exports to low-income destinations (r_l), log exports to high-income destinations (r_h) and log total exports ($r_h + r_l$) on TFP and 3-digit industry dummies. Note that the export-TFP elasticity is positive and precisely estimated in all cases, and that in

¹³ Industries are classified according to the ATECO system, the standard industrial classification in Italy, equivalent to the NACE classification.

¹⁴ All production functions are estimated using a revenue-based measure of output and four inputs (high-skill labour, low-skill labour, materials and physical capital). Log TFP is defined as $\ln Y_j - \sum_{\varrho} \xi_{\varrho} \ln \varrho_j$, where Y is output, ϱ is one of the four inputs and ξ_{ϱ} is one of the twelve estimates of its output elasticity. By using a battery of TFP estimates (whose correlation equals 0.84 on average and ranges from a minimum of 0.40 to a maximum of 0.99), we tackle the main issues involved in the estimation of production function parameters, namely: (i) choice of appropriate specification and sectorial aggregation of the production function; (ii) choice of appropriate estimators to address attenuation and simultaneity biases. As we do not observe firm-level prices, our revenue-TFP estimates may also reflect price differences across firms (Foster *et al.*, 2008). A first-order source of price differences, namely, markup heterogeneity due to asymmetries in market power in a context of horizontal product differentiation (omitted price variable bias, Klette and Griliches, 1996), is addressed by the augmented Olley and Pakes estimator proposed by De Loecker (2011), which we use in column (11). We implement this estimator by augmenting the production function with log average output ($\ln Q_j$) in the 3-digit industry of each firm, and then compute log TFP as $[1/(1 - \chi_Q)](\ln Y_j - \sum_{\varrho} \xi_{\varrho} \ln \varrho_j - \chi_Q \ln Q_j)$, where χ_Q is the coefficient on $\ln Q_j$. Revenue-TFP may also capture quality heterogeneity across firms, which may lead to both upward and downward biases, with ambiguous net effects (Katayama *et al.*, 2009; Kugler and Verhoogen, 2012). Guided by our theoretical model, we control for quality heterogeneity by adding R&D intensity in most of the TFP estimates. In the next Section we discuss, in the light of our structural estimates, the possible impact of measurement error in TFP on our results.

¹⁵ As we showed in a previous version of the article, Crinò and Epifani (2010), an equally strong pattern of correlations obtains when normalising exports to low-income destinations by total sales (rather than total exports).

¹⁶ From here onwards, to save space, we report bootstrapped standard errors only and focus on the augmented Olley and Pakes TFP estimate. Our main results are robust across the twelve TFP measures and are available upon request.

Table 3
Productivity and Export Behaviour: TFP

Cobb-Douglas Production Functions				Translog Production Functions				Panel Regressions				CD+Controls (2-Digit Ind.)
Baseline	Adding Controls	Prod/ Non-Prod	2SLS	Baseline	Adding Controls	Prod/ Non-Prod	2SLS	Lev./ Pet.	Olley/ Pakes	Olley/ Pakes	Augmented	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	
<i>(a) All Exporters</i>												
In TFP	-0.080*** [0.024]	-0.078*** [0.021]	-0.087*** [0.024]	-0.098*** [0.027]	-0.098*** [0.026]	-0.085*** [0.023]	-0.102*** [0.027]	-0.079*** [0.021]	-0.079*** [0.021]	-0.077*** [0.021]	-0.075*** [0.024]	
Obs.	2,185	2,507	2,185	2,185	2,185	2,507	2,185	2,507	2,507	2,507	2,185	
R-squared	0.11	0.10	0.12	0.12	0.12	0.10	0.12	0.10	0.10	0.10	0.11	
<i>(b) Exporters to Both High-Income and Low-Income Destinations</i>												
In TFP	-0.097** [0.038]	-0.095** [0.038]	-0.086*** [0.033]	-0.124*** [0.037]	-0.121*** [0.038]	-0.103*** [0.034]	-0.135*** [0.036]	-0.099*** [0.034]	-0.090*** [0.033]	-0.090*** [0.033]	-0.096*** [0.037]	
Obs.	1,077	1,077	1,236	1,077	1,077	1,236	1,077	1,236	1,236	1,236	1,077	
R-squared	0.14	0.14	0.12	0.14	0.14	0.13	0.14	0.13	0.13	0.13	0.14	

Notes. OLS regressions with robust standard errors in parenthesis and bootstrapped standard errors based on 500 replications in brackets. The dependent variable is the export share to low-income destinations (ES). ***, **, * = significant at 1, 5 and 10% level, respectively. All specifications include a full set of industry dummies, defined at the 3-digit level of the ATECO classification. Each column in the Table refers to a different TFP estimate. All production functions are estimated using a revenue-based measure of output and four inputs: high-skill labour, low-skill labour, materials and physical capital. Revenue-based output is the sum of sales, capitalised costs and change in final goods inventories; material inputs are the difference between purchases and change in inventories of intermediate goods; capital stock is the book value of capital. Skills are proxied by occupations (production *versus* non-production workers) in columns (3), (7) and (9)–(11); otherwise, they are proxied by educational attainment (workers with at least a high school degree *versus* other workers). The production functions are estimated on the cross-section of firms for the year 2003 in columns (1)–(8) and (12) and on the three-year panel for 2001–3 in columns (9)–(11). Estimation is performed by: OLS in columns (1)–(3), (5)–(7) and (12); Two-Stage Least Squares (using inputs in 2001 and 2002 as instruments for their level in 2003) in columns (4) and (8); semiparametric methods (respectively, Olley and Pakes, 1996; Levinsohn and Petrin, 2003; De Loecker, 2011) in columns (9)–(11). In columns (2)–(4) and (6)–(12), the production functions include the following controls: R&D intensity, the share of part-time workers in total employment, a dummy for firms quoted on the stock market, three dummies for ownership structure and full sets of dummies for Italian administrative regions and 3-digit industries. In columns (9)–(11), they also include time dummies.

Table 4
TFP Elasticity of Foreign Sales

	(a) Log Exports to Low-Income Destinations (η_l)	(b) Log Exports to High-Income Destinations (η_h)	(c) Log Total Exports ($\eta_h + \eta_l$)
ln TFP	0.447* [0.246]	1.087*** [0.183]	0.991*** [0.164]
Obs.	1,315	2,428	2,507
R-squared	0.12	0.11	0.12
<i>Exporters to Both Destinations</i>	(d) Log Exports to Low-Income Destinations (η_l)	(e) Log Exports to High-Income Destinations (η_h)	(f) Log Total Exports ($\eta_h + \eta_l$)
ln TFP	0.526* [0.278]	1.091*** [0.296]	0.936*** [0.270]
Obs.	1,236	1,236	1,236
R-squared	0.12	0.16	0.15

Notes. The dependent variables are indicated in panels' headings. TFP is based on the augmented Olley and Pakes estimate. All specifications include a full set of 3-digit industry dummies and standard errors are bootstrapped (500 replications). See also notes to previous Tables.

high-income destinations it is roughly twice as large as in low-income destinations. In panels (d–f), we control for sample size by rerunning the same regressions on exporters to both destinations and find very similar results.

1.4. *Robustness Checks*

We start by checking that the negative correlation between ES_i and TFP is not driven by outliers. The results are in panel (a) of Table 5. In columns (1)–(2) we winsorise and trim, respectively, the distributions of TFP and ES_i at the 5th and 95th percentiles, whereas in column (3) we estimate (1) using an outlier-robust procedure.¹⁷ In all cases, the results are similar to those reported in Table 3 (a). In column (4), we regress ES_i on three dummy variables for firms in the second, third and fourth quartile of the TFP distribution: the estimated coefficients are negative, statistically significant and increasing in absolute value, confirming that outliers play no role for our results.

In panel (b), we check the robustness of our results with respect to the estimation strategy. To begin with, note that our TFP estimates build on the implicit assumption that firms share the same production function and that all heterogeneity is concentrated in the TFP term. We now allow for the possibility that exporters to low-income destinations use different technologies. To this purpose, we estimate TFP separately on exporters to low-income destinations and all other firms, and then rerun (1) using the new estimate. The results in column (5) show that the negative correlation between ES_i and TFP is now even stronger.

Next, note that so far we have relied on a two-step approach, in which TFP is estimated first, and then ES_i is regressed on it. An alternative strategy is to estimate the

¹⁷ As for winsorising, we replace the observations in the tails of the distributions of ES_i and TFP with the 5th and 95th percentiles. As for the outlier-robust procedure, we use the `rreg` command in Stata.

Table 5
TFP and Export Behaviour: Robustness Checks

	(a) Outliers			(b) Estimation Method				(c) Specification			
	Winsorising	Trimming	Robust Estimation	TFP Bins	Sample Split	One-Step Approach	One-Step Approach	Tornqvist Index of TFP	General Controls	Trade Controls	Exp. MKT Dummies
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
											(12)
<i>ln TFP</i>	-0.083*** [0.023]	-0.101*** [0.035]	-0.077*** [0.022]		-0.269*** [0.024]			-0.069*** [0.026]	-0.066*** [0.022]	-0.079*** [0.021]	-0.029** [0.013]
<i>ES_i</i>						-0.071*** [0.020]	-0.062*** [0.022]				
<i>ln TFP</i> (2nd Quartile)				-0.026* [0.016]							
<i>ln TFP</i> (3rd Quartile)				-0.031* [0.016]							
<i>ln TFP</i> (4th Quartile)				-0.053*** [0.015]							
<i>FDI</i>											
<i>IMP/INT</i>										0.667 [0.963]	
<i>SERV</i>										0.043 [0.040]	
<i>INSH</i>										0.016 [0.013]	
										-0.008 [0.019]	
Obs.	2,507	1,116	2,507	2,507	2,507	2,185	2,185	2,115	2,473	2,507	2,507
R-squared	0.11	0.12	0.10	0.10	0.17	0.96	0.97	0.11	0.12	0.10	0.60

Notes. The dependent variable is the export share to low-income destinations (*ES_i*), except in columns (6) and (7) where it is log output (*Y_i*). The observations in the tails of the distributions of *ES_i* and *TFP* are replaced by the 5th and 95th percentiles in column (1) and excluded in column (2). The results in column (3) are obtained using the *reg* command in Stata. In column (4), the explanatory variables are dummies taking a value of 1 for firms in the second, third and fourth quartile of the *TFP* distribution; the reference group is given by firms in the first *TFP* quartile. In column (5), *TFP* is estimated separately on exporters to low-income destinations and all other firms. In columns (6) and (7), the Cobb-Douglas production function is augmented by *ES_i*; inputs enter linearly in the former column and interacted with 3-digit industry dummies in the latter. In column (8), *TFP* is computed rather than estimated, using the formula for the Tornqvist index illustrated in the text. In column (9), *general controls* are: the share of part-time workers in total employment, a dummy for firms quoted on the stock market, three dummies for ownership structure and a full set of dummies for Italian administrative regions. In column (10), *FDI* is the ratio of outward FDI to sales over the period 2001–3, *IMP/INT* is the share of imported inputs in total input purchases, *SERV* is a dummy variable equal to 1 for importers of services, and *INSH* is the share of sales subcontracted from abroad. In column (11), *export market dummies* are seven dummies each taking a value of 1 for firms exporting to a given destination. Column (12) also includes interactions between export market dummies and 2-digit industry dummies. All specifications include a full set of 3-digit industry dummies. See also notes to previous Tables.

correlation between TFP and ES_i jointly with the production function parameters, so as to allow for the export decision in the first stage. Following Amity and Konings (2007), we implement this one-step approach by adding ES_i as an explanatory variable in a Cobb-Douglas specification. The results are in column (6). Note that the coefficient on ES_i is negative, very precisely estimated and similar in size to those in Table 3 (a). In column (7), we repeat the exercise by interacting each input with 3-digit industry dummies, thereby further relaxing the assumption of equal technologies across industries. The estimated correlations are largely unchanged, confirming that one-step and two-step approaches yield similar results. In column (8), we revert to the two-step approach and allow for fully flexible (i.e., firm-specific) technologies, by using a Tornqvist index of TFP. The latter is constructed as $(\ln Y_j - \overline{\ln Y}) - 0.5[\sum_q (sh_{qj} + \overline{sh_q}) \cdot (\ln q_j - \overline{\ln q})]$, where Y is output, sh_q is the cost share of input q (i.e., labour, capital and materials) and a bar over a variable denotes its sample mean.¹⁸ Importantly, the coefficient on the TFP index is negative, significant at the 1% level and similar in size to those obtained in Table 3 (a) using estimated TFP measures.¹⁹

In panel (c), we finally show that our stylised fact is unlikely to be driven by omitted variables correlated with TFP and ES_i . We start, in column (9), by showing that the results are little affected when adding to the baseline regression a large battery of controls: a full set of dummies for Italian administrative regions, the share of part-time workers in total employment, a dummy variable for firms quoted on the stock market and a set of three dummy variables controlling for ownership structure. In column (10), we control instead for other forms of firm participation in foreign markets, and in particular for foreign direct investment (*FDI*), material and service offshoring (*IMPINT* and *SERV*) and inshoring (*INSH*).²⁰ Note that the export share is weakly positively correlated with most of these variables and that our coefficient of interest is unaffected.

In column (11), we add to our baseline specification a full set of export market dummies for firms selling in each of the seven destinations. This should help to control, among other things, for price differences across markets that are constant across firms; see also De Loecker (2007) on this point.²¹ Note that the main results are qualitatively similar. Finally, in column (12) we add a full set of interaction terms between export market dummies and 2-digit industry dummies, so as to allow for industry-specific price differences across markets. This specification now includes roughly 300 variables, with a dramatic loss of degrees of freedom. Strikingly, however, the export share to low-income destinations remains strongly negatively correlated with TFP.

¹⁸ See, e.g., Aw *et al.* (2001). Unlike in the other TFP estimates, here we use overall labour rather than high-skill and low-skill labour, because we do not observe wages by skill group.

¹⁹ Note that the TFP index nicely complements the one-step approach, because a computed measure of TFP is less likely to be affected by the bias due to abstracting from the export decision in the first step. However, the TFP index builds on stronger assumptions and cannot accommodate measurement error (Van Biesebroeck, 2007).

²⁰ *FDI* is the ratio of investment over total sales for the period 2001–3. *IMPINT* is the share of imported inputs in total input purchases in 2003. *SERV* is a dummy variable equal to 1 if a firm purchased services from abroad in 2003. *INSH* is the share of sales arising from productions subcontracted by foreign firms in 2003.

²¹ If, *ceteris paribus*, exporters systematically charge lower prices in low-income destinations, their revenue-TFP may be underestimated and its negative correlation with ES_i overstated (Demidova *et al.*, 2006; Corcos *et al.*, forthcoming).

Table 6
Productivity and Export Behaviour: Value Added per Unit of Factor Cost

	(a) Main Specifications		(b) Robustness Checks		
	All Exporters	Exporters to Both High-Income and Low-Income Destinations	Winsorising	General Controls	Trade Controls
	(1)	(2)	(3)	(4)	(5)
ln VA_{FC}	−0.036*** [0.011]	−0.029** [0.015]	−0.035*** [0.012]	−0.031*** [0.011]	−0.036*** [0.011]
Obs.	2,494	1,227	2,494	2,460	2,450
R-squared	0.11	0.12	0.11	0.12	0.11

Notes. The dependent variable is the export share to low-income destinations (ES_L). VA_{FC} is value added per unit of factor cost. Value added equals revenue minus intermediate spending and factor cost equals total wage bill plus the cost of capital. The cost of capital is computed as the capital stock multiplied by the real interest rate (3%) plus the depreciation rate (12%). All specifications include a full set of 3-digit industry dummies and standard errors are robust to heteroscedasticity. See also notes to previous Tables.

1.5. Value Added Per Unit of Factor Cost

So far, we have relied on the TFP-based productivity measures most commonly used in the empirical trade literature. We now show the results obtained with an alternative productivity measure recently proposed by EKK. Specifically, we define productivity as value added per unit of factor cost (VA_{FC}), where value added equals revenue minus intermediate spending and factor cost equals total wage bill plus the cost of capital.²² Then, we re-estimate the main regressions for the export share to low-income destinations using the new productivity measure instead of TFP. As shown in Table 6, the results are similar, confirming that our evidence is not crucially affected by the way productivity is defined and measured.

2. Theory and Structural Estimation

In this Section, we first formulate a simple model illustrating the key ingredients behind our interpretation of the above empirical regularities, and discuss its implications in the light of the heterogeneous-firms literature. Then, following EKK, we develop a structural model, estimate its deep parameters by the simulated method of moments and study its implications.

2.1. Baseline Model

The representative consumer in destination z is characterised by the following preferences:

$$U_z = \left[\int_{v \in V_z} \lambda(v)^{i(y_z)(1-\rho)} d(v)^\rho \right]^{\frac{1}{\rho}} \quad 0 < \rho < 1, \tag{2}$$

²² The cost of capital is computed as the capital stock multiplied by the real interest rate (3%) plus the depreciation rate (12%).

where $v \in V_z$ indexes goods available for consumption in destination z , $d(v)$ is consumption and $\lambda(v) \geq 1$ is the quality of good v . Our first key assumption is that the preference for quality, reflected by the parameter $\iota(y_z) > 0$, is non-homothetic with respect to per capita income, y_z .²³ Specifically, we assume that $\iota(y_h) > \iota(y_l)$ for $y_h > y_l$. Maximisation of (2) subject to a budget constraint yields the demand for good v in destination z :

$$d_z(v) = \lambda_z(v)^{\iota(y_z)} \frac{p_z(v)^{-\sigma} R_z}{P_z^{1-\sigma}}, \quad (3)$$

where R_z is total expenditure, $p_z(v)$ is the price of good v in destination z , $\sigma = (1 - \rho)^{-1} > 1$ is the constant elasticity of substitution between any two goods and P_z is the ideal price index associated to (2). Equation (3) implies that the relative demand for high-quality products is *ceteris paribus* higher in high-income destinations.²⁴

Firms produce differentiated goods under monopolistic competition and are heterogeneous in terms of efficiency, φ , and product quality, λ . Home (Italian) firms are indexed by j . We assume that the marginal cost of producing good j for market z , $MC_z(j)$, is decreasing in firms j 's efficiency and increasing in product quality:²⁵

$$MC_z(j) = c_z(j) \lambda_z(j)^\delta, \quad c_z(j) = \frac{w \tau_z}{\varphi(j)}, \quad (4)$$

where w is the unit price of the bundle of inputs used to produce final output, $\tau_z > 1$ is an iceberg trade cost and $\delta \geq 0$ is the elasticity of marginal cost to product quality; $c_z(j)$ can be interpreted as a measure of the marginal cost per unit of quality.

The profit maximising price is a constant markup $(1/\rho)$ over marginal cost:²⁶

$$p_z(j) = \frac{1}{\rho} c_z(j) \lambda_z(j)^\delta. \quad (5)$$

Using (3) and (5) yields firm j 's revenue in destination z :

$$r_z(j) = \lambda_z(j)^{\tilde{\iota}(y_z)} R_z (\rho P_z)^{\sigma-1} c_z(j)^{1-\sigma}, \quad (6)$$

where $\tilde{\iota}(y_z) = \iota(y_z) - \delta(\sigma - 1)$ is the elasticity of revenue with respect to product quality. Note, from (4) and (6), that the term $\varphi(j)^{\sigma-1}$ captures how efficiency gets translated into revenue for given quality; henceforth, we will refer to it as productivity.

²³ Some recent contributions provide interesting microfoundations for the non-homotheticity of the demand for quality. In Fajgelbaum *et al.* (2011), it is the outcome of discrete choices by consumers and complementarity in preferences between the quality of differentiated goods and the quantity of homogeneous goods. In Alcalà (2009), it arises instead from the fact that consumption requires time, leisure time is decreasing in per capita income and higher-quality goods provide higher satisfaction per unit of time. See also Markusen (1986), Hunter (1991), Matsuyama (2000) and Fielor (2011) on the role of non-homothetic preferences in international trade with representative firms, and Falvey and Kierzkowski (1987), Flam and Helpman (1987), Stokey (1991) and Murphy and Shleifer (1997) on product quality in international trade.

²⁴ Note that, in a poor country, the elasticity of aggregate demand with respect to product quality may look like that of a rich country if income distribution is extremely unequal. The structural estimation results reported in the next subsection seem to suggest, however, that this is not the case in our data.

²⁵ Marginal cost may be increasing in product quality if, for instance, higher-quality products require higher-quality inputs, see, e.g., Verhoogen (2008), Johnson (2012) and Kugler and Verhoogen (2012).

²⁶ For an alternative approach in which quality is embedded into a framework *à la* Melitz and Ottaviano (2008) featuring variable markups see, for instance, Kneller and Yu (2008).

Our second key assumption is that producing higher-quality products requires higher fixed costs in terms of R&D and other innovation activities.²⁷ Specifically, we assume that producing a variety of quality λ_z for destination z requires a fixed cost $RD_z = b\lambda_z^\gamma$, where $b > 0$ is a constant and $\gamma > 0$ is the elasticity of the fixed cost with respect to product quality. Note that λ is indexed by z because we assume that firms sell goods of different quality in different markets.²⁸

Firm j 's profits in market z are given by:

$$\pi_z(j) = \frac{1}{\sigma} r_z(j) - E_z - b\lambda_z(j)^\gamma, \quad (7)$$

where E_z is a destination-specific exogenous entry cost. Firm j chooses λ_z to maximise profits in z ; provided that $\tilde{I}(y_z) > 0$, the first-order condition for a maximum can be written as:

$$RD_z(j) = b\lambda_z(j)^\gamma = \frac{\tilde{I}(y_z)}{\gamma\sigma} r_z(j), \quad (8)$$

which implies that the fixed cost of quality upgrading is proportional to firm j 's revenue in destination z .²⁹ Solving for $\lambda_z(j)$ and using (6) yields optimal product quality:

$$\lambda_z(j) = \left[\frac{\tilde{I}(y_z) R_z(\rho P_z)^{\sigma-1} c_z(j)^{1-\sigma}}{b\gamma\sigma} \right]^{\frac{1}{\gamma-\tilde{I}(y_z)}}, \quad (9)$$

where $\gamma - \tilde{I}(y_z) > 0$ by the second-order condition for a maximum. Note that more productive firms produce higher-quality products for all the destinations they sell to, because they can spread the higher fixed costs of quality upgrading over a greater revenue. Using (9) in (6), revenue can be written as:

$$r_z(j) = \left[\frac{\tilde{I}(y_z)}{b\gamma\sigma} \right]^{\frac{\tilde{I}(y_z)}{\gamma-\tilde{I}(y_z)}} \left[R_z(\rho P_z)^{\sigma-1} c_z(j)^{1-\sigma} \right]^{\frac{\gamma}{\gamma-\tilde{I}(y_z)}}. \quad (10)$$

Firm j enters destination z if $\pi_z(j) > 0$; using (8) in (7) yields the zero-profit revenue cutoff:

$$\bar{r}_z = \frac{\gamma\sigma E_z}{\gamma - \tilde{I}(y_z)}. \quad (11)$$

Equating (10) to (11) yields the zero-profit cost cutoff:

²⁷ See, e.g., Sutton (1991, 1998) and more recent applications to a heterogeneous-firms framework by Hallak and Sivadasan (2009), Johnson (2012) and Kugler and Verhoogen (2012). For instance, in a variant of the model in the latter article, fixed costs are complementary to input quality in producing output quality.

²⁸ See Verhoogen (2008) for an interesting case study consistent with this assumption. See also Bastos and Silva (2010) for evidence on within-firm-product variation in unit values across export destinations. In the Appendix we show, however, that similar results hold under the alternative assumption that firms target their global market in choosing quality.

²⁹ If $\tilde{I}(y_z) \leq 0$, revenue is non-increasing in product quality. In this case, firms maximise profits by setting $\lambda_z = 1$, i.e., they sell standardised products in destination z . See also the discussion in the Appendix.

$$\bar{c}_z = \left[\frac{\gamma - \tilde{t}(y_z)}{\gamma \sigma E_z} \right]^{\frac{\gamma - \tilde{t}(y_z)}{\gamma(\sigma-1)}} \left[\frac{\tilde{t}(y_z)}{b\gamma\sigma} \right]^{\frac{\tilde{t}(y_z)}{\gamma(\sigma-1)}} R_z^{\frac{1}{\sigma-1}} \rho P_z. \quad (12)$$

Finally, using (12) in (9) and (10) we can write the expressions for product quality and revenue in destination z (conditional on entry) as functions of zero-profit cutoffs:

$$\lambda_z(j) = \left[\frac{\tilde{t}(y_z) E_z / b}{\gamma - \tilde{t}(y_z)} \right]^{\frac{1}{\gamma}} \left[\frac{c_z(j)}{\bar{c}_z(j)} \right]^{\frac{(1-\sigma)}{\gamma - \tilde{t}(y_z)}}, \quad (13)$$

$$r_z(j) = \frac{\gamma \sigma E_z}{\gamma - \tilde{t}(y_z)} \left[\frac{c_z(j)}{\bar{c}_z} \right]^{\frac{(1-\sigma)\gamma}{\gamma - \tilde{t}(y_z)}} = \frac{\gamma \sigma E_z}{\gamma - \tilde{t}(y_z)} \left[\frac{\varphi(j)}{\bar{\varphi}_z} \right]^{\frac{(\sigma-1)\gamma}{\gamma - \tilde{t}(y_z)}}, \quad (14)$$

where $\bar{\varphi}_z = w\tau_z/\bar{c}_z$ is the zero-profit productivity cutoff in destination z . Note, from (14), that the elasticity of revenue with respect to productivity is increasing in per capita income of destination z .

Consider now two foreign destinations, indexed by h and l , with $y_h > y_l$. Firm j 's export share to the low-income destination is:

$$ES_l(j) = \frac{r_l(j)}{r_l(j) + r_h(j)} = \frac{r_l(j)/r_h(j)}{r_l(j)/r_h(j) + 1}. \quad (15)$$

Evidently, $ES_l(j)$ is monotonically increasing in relative exports, $r_l(j)/r_h(j)$. Using (14), taking the log of $r_l(j)/r_h(j)$ and differentiating yields:

$$\frac{d \ln r_l(j)/r_h(j)}{d \ln \varphi(j)^{\sigma-1}} = - \left[\frac{\tilde{t}(y_h)}{\gamma - \tilde{t}(y_h)} - \frac{\tilde{t}(y_l)}{\gamma - \tilde{t}(y_l)} \right] < 0. \quad (16)$$

Hence, for firms exporting to both destinations, the model naturally delivers a negative relationship between productivity and the export share to the low-income destination.³⁰

2.2. Discussion

This stripped-down model captures the basic idea behind our interpretation of the evidence, namely, that the empirical correlations between productivity and exports arise from the interaction between non-homothetic preferences and firm heterogeneity in product quality. Before extending the model and estimating its deep parameters, we pause to discuss its implications in the light of the heterogeneous-firms literature with homogeneous quality.

2.2.1. Melitz

In the simplest case in which product quality plays no role (i.e., $\lambda_z(j) = 1$ for all j and z), we are back in the Melitz (2003) model and firm j 's revenue can be written as:

³⁰ Note that $ES_l = 0$ for $\varphi < \bar{\varphi}_l$, implying an ambiguous unconditional correlation between ES_l and productivity (more on this below).

$$r_z(j) = \sigma E_z \left[\frac{\varphi(j)}{\bar{\varphi}_z} \right]^{\sigma-1},$$

where $\bar{\varphi}_z^{\sigma-1} = \sigma E_z / [R_z(\rho P_z / w \tau_z)^{\sigma-1}]$. Conditional on firms selling in both destinations, the export share to the low-income destination is therefore unrelated to productivity:

$$\frac{r_l(j)}{r_h(j)} = \frac{E_l}{E_h} \left(\frac{\bar{\varphi}_h}{\bar{\varphi}_l} \right)^{\sigma-1}.$$

Unconditionally, i.e. across all exporters, the model predicts instead a positive correlation between ES_l and productivity, as $ES_l = 0$ for $\bar{\varphi}_h < \varphi < \bar{\varphi}_l$. Hence, the simplest version of the Melitz model cannot explain our empirical regularities.³¹

2.2.2. Export versus FDI

Next, consider the export *versus* FDI decision. As argued by Helpman *et al.* (2004), the FDI option is relatively more profitable for more productive firms. This suggests that, by reducing exports of more productive firms, FDI may induce a negative correlation between exports and productivity. However, given that a (horizontal) FDI may be a better substitute for exports to similar-income destinations (Markusen, 1995), it may lead more productive Italian firms to export relatively less to other high-income markets, thereby inducing a positive (rather than a negative) correlation between productivity and the export share to low-income destinations. Therefore, FDI does not seem to provide an obvious alternative explanation for our key empirical regularity. Moreover, as already shown in Table 5, controlling for FDI (and other variables broadly related to it) does not weaken the negative correlation between ES_l and productivity.

2.2.3. Endogenous market penetration costs

Consider now endogenous market penetration costs *à la* Arkolakis (2010). In this case, firm j 's entry costs in destination z are given by:

$$E_z(j) = E_z \frac{1 - [1 - f_z(j)]^{1-\beta}}{1 - \beta}, \quad (17)$$

where $\beta > 0$ and $f_z(j)$ is the share of consumers reached by firm j in destination z . Equation (17) reflects the assumption that entry costs (i.e. marketing costs) are increasing and convex in the degree of market penetration. According to (17), the marginal cost of market penetration equals $E_z[1 - f_z(j)]^{-\beta}$; firm j 's revenue now equals instead $r_z(j) = \sigma f_z(j) E_z[\varphi(j)/\bar{\varphi}_z]^{\sigma-1}$, and profit maximisation yields the following expression for optimal market penetration: $f_z(j) = 1 - [\bar{\varphi}_z/\varphi(j)]^{(\sigma-1)/\beta}$. Note that $f_z(j)$ is decreasing in $\bar{\varphi}_z$, i.e. firms reach a larger share of consumers in more popular destinations. It follows that the export share to the low-income destination is now increasing in productivity also conditional on firms entering both destinations:

³¹ Our empirical regularities are not implied, either, by the models in Bernard *et al.* (2003), Bernard *et al.* (2007) and Melitz and Ottaviano (2008).

$$\begin{aligned}
 \frac{r_l(j)}{r_h(j)} &= \frac{1 - \left[\frac{\bar{\varphi}_l}{\varphi(j)} \right]^{(\sigma-1)/\beta}}{1 - \left[\frac{\bar{\varphi}_h}{\varphi(j)} \right]^{(\sigma-1)/\beta}} \frac{E_l \left(\frac{\bar{\varphi}_h}{\bar{\varphi}_l} \right)^{\sigma-1}}{E_h} \\
 &\Rightarrow \frac{d \ln[r_l(j)/r_h(j)]}{d \ln \varphi(j)^{\sigma-1}} = \frac{1}{\beta \varphi(j)} \frac{f_h(j) - f_l(j)}{f_l(j) f_h(j)} > 0.
 \end{aligned} \tag{18}$$

Hence, convex entry costs *à la* Arkolakis do not seem to help explain our empirical regularities, as they lead more productive firms to sell to relatively more consumers in harder-to-reach destinations.³²

2.2.4. Firm-specific heterogeneity in entry costs and demand

Our baseline model can nicely explain a negative correlation between productivity and the export share to low-income destinations but only conditional on firms exporting to both destinations. Yet, our evidence shows that the negative correlation holds strong also across all exporters. Moreover, in the baseline model firms enter foreign destinations according to an exact hierarchy dictated by their efficiency; yet, as shown in Section 1, there is no strict sorting of exporters in our data.

To account for these facts, following EKK, in the next subsection we generalise our model by introducing firm and market-specific heterogeneity in entry costs and demand. To provide context, we start by discussing how the presence of firm-specific shocks is likely to affect the unconditional correlation between ES_l and φ . Note, first, that a standard selection effect implies that low-productivity firms are less likely to export to less popular destinations. This leads to a higher frequency of zero export shares ($ES_l = 0$) among low-productivity exporters and induces, *ceteris paribus*, a positive correlation between ES_l and φ . Second, low-productivity firms hit by a positive entry shock in a low-income destination are likely to export only there. This implies a higher frequency of export shares equal to one ($ES_l = 1$) among low-productivity exporters and leads, *ceteris paribus*, to a negative correlation between ES_l and φ . Hence, the two effects push in opposite directions and are stronger among low-productivity exporters, as high-productivity firms are more likely to export to both destinations.

To have a sense of how these forces affect the relationship between ES_l and φ in EKK, we have simulated their model using our data.³³ Specifically, we have run 50 simulated regressions of $ES_l(j)$ on $\ln[\varphi(j)^{\sigma-1}]$ for 2,507 artificial exporters, so as to mimic the regression results reported in Table 3. The average simulated regression coefficient (standard error) is 0.076 (0.013) unconditionally and 0.127 (0.013) conditional on firms entering both high-income and low-income destinations, thereby suggesting that the EKK model cannot easily accommodate our key empirical regularities.

³² In Arkolakis (2010) and EKK, endogenous entry costs are useful to accommodate the presence of small exporters. In our model, a similar role is played by the endogenous, market-specific fixed costs of quality upgrading, as they lead more productive firms to bear higher overall fixed costs in each of the destinations they sell to.

³³ See the next subsection for more details on the simulation algorithm.

2.3. Structural Model

Following the tractable and elegant approach proposed by EKK, we now add more structure to the baseline model, in order to estimate its deep parameters and test its predictions in the presence of firm and market-specific heterogeneity in entry costs and demand.

2.3.1. Additional assumptions

We assume that entry costs to destination z equal $E_z(j) = \varepsilon_z(j)E_z$, where $\varepsilon_z(j)$ is a fixed-cost shock specific to firm j in destination z . Similarly, we denote by $\alpha_z(j)$ an exogenous demand shock specific to firm j in destination z . Finally, we assume that $\alpha_z(j)$ and $\eta_z(j) = \alpha_z(j)/\varepsilon_z(j)$ (where η can be interpreted as an entry shock) are drawn from a joint density $g(\alpha, \eta)$ that is the same across destinations and independent of $c_z(j)$.

Next, we assume that the measure of firms in country $m \in \{1, 2, \dots, \bar{m}\}$ with efficiency greater than φ equals $\mu^m(\varphi) = T^m \varphi^{-\theta}$, where $\theta > 0$ and $T^m > 0$. Using (4), the measure of firms with a unit cost of serving destination z less than c is therefore $\mu_z^m(c) = \Phi_z^m c^\theta$, where $\Phi_z^m = T^m (w^m \tau_z^m)^{-\theta}$. Under these assumptions, the expressions for \bar{c}_z , $\lambda_z(j)$ and $r_z(j)$ in (12)–(14) generalise as follows:³⁴

$$\bar{c}_z(j) = \left[\frac{\gamma - \tilde{t}(y_z)}{\gamma \sigma E_z} \frac{\eta_z(j)}{\alpha_z(j)} \right]^{\frac{\gamma - \tilde{t}(y_z)}{\gamma(\sigma - 1)}} \left[\frac{\tilde{t}(y_z)}{b \gamma \sigma} \right]^{\frac{\tilde{t}(y_z)}{\gamma(\sigma - 1)}} [\alpha_z(j) R_z]^{\frac{1}{\sigma - 1}} \rho P_z, \quad (19)$$

$$\lambda_z(j) = \left[\frac{\alpha_z(j) \tilde{t}(y_z) E_z / b}{\eta_z(j) \gamma - \tilde{t}(y_z)} \right]^{\frac{1}{\gamma}} \left[\frac{c_z(j)}{\bar{c}_z(j)} \right]^{\frac{(1 - \sigma)}{\gamma - \tilde{t}(y_z)}}, \quad (20)$$

$$r_z(j) = \frac{\alpha_z(j)}{\eta_z(j)} \frac{\gamma \sigma E_z}{\gamma - \tilde{t}(y_z)} \left[\frac{c_z(j)}{\bar{c}_z(j)} \right]^{\frac{(1 - \sigma)\gamma}{\gamma - \tilde{t}(y_z)}}. \quad (21)$$

2.3.2. Price index

The price index faced by the representative consumer in destination z is:

$$P_z = \frac{1}{\rho} \left\{ \int \int \left[\sum_{m=1}^{\bar{m}} \int_0^{\bar{c}_z^m(\alpha, \eta)} \alpha \lambda_z^m(c) \tilde{t}(y_z) c^{1 - \sigma} d\mu_z^m(c) \right] g(\alpha, \eta) d\alpha d\eta \right\}^{-\frac{1}{\sigma - 1}},$$

where the inner integral represents the price index in destination z of the bundle of goods imported from country m for a given realisation of the shocks. Using (19) and (20), and following the same steps as in EKK, yields:

$$P_z = \frac{1}{\rho} R_z^{-\frac{\theta - (\sigma - 1)}{(\sigma - 1)\theta}} \left(\frac{q_z}{b\sigma} \right)^{-\frac{q_z}{\sigma - 1}} (1 - q_z)^{\frac{1}{\theta} - \frac{1 - q_z}{\sigma - 1}} (\kappa_{1z} \psi_z)^{-\frac{1}{\theta}}, \quad (22)$$

³⁴ To save on notation, in the following we omit the country superscript when we refer to Home variables.

where:

$$\begin{aligned} q_z &= \frac{\tilde{t}(y_z)}{\gamma} < 1 - \frac{1}{\tilde{\theta}}, \tilde{\theta} = \frac{\theta}{\sigma - 1}, \\ \psi_z &= \sum_m \Phi_z^m (\sigma E_z^m)^{-(1-q_z)\tilde{\theta}+1}, \\ \kappa_{1z} &= \kappa_{0z} \int \int \alpha^{q_z\tilde{\theta}+1} \eta^{(1-q_z)\tilde{\theta}-1} g(\alpha, \eta) d\alpha d\eta, \\ \kappa_{0z} &= \frac{(1-q_z)\tilde{\theta}}{(1-q_z)\tilde{\theta}-1}. \end{aligned}$$

Note that q_z is the elasticity of revenue with respect to product quality divided by the elasticity of fixed costs with respect to product quality. We may refer to it as the normalised preference for quality. In this framework, it parsimoniously summarises the impact of product quality and quality consumption on export behaviour.³⁵

Substituting (22) into (19) yields the following expression for the cost cutoff $\bar{c}_z(j)$:

$$\bar{c}_z(j) = \alpha_z(j)^{\frac{q_z}{(\sigma-1)}} \eta_z(j)^{\frac{1-q_z}{(\sigma-1)}} (\sigma E_z)^{-\frac{1-q_z}{(\sigma-1)}} \left[\frac{R_z(1-q_z)}{\kappa_{1z}\psi_z} \right]^{\frac{1}{\tilde{\theta}}}. \quad (23)$$

2.3.3. Entry and sales

The measure N_z of domestic firms selling in destination z is obtained by integrating the measure $\mu_z(\bar{c}_z(\alpha, \eta))$ of firms passing the entry hurdle over the joint density $g(\alpha, \eta)$:

$$N_z = \int \int \Phi_z \bar{c}_z^\theta(\alpha, \eta) g(\alpha, \eta) d\alpha d\eta = \frac{\kappa_{2z} \Pi_z R_z (1-q_z)}{\kappa_{1z} \sigma E_z}, \quad (24)$$

where:

$$\begin{aligned} \Pi_z &= \frac{\Phi_z}{\psi_z} (\sigma E_z)^{1-\frac{1-q_z}{(\sigma-1)}}, \\ \kappa_{2z} &= \int \int \alpha^{\tilde{\theta}q_z} \eta^{\tilde{\theta}(1-q_z)} g(\alpha, \eta) d\alpha d\eta. \end{aligned}$$

For a given realisation of the shocks, total sales $X_z(\alpha, \eta)$ of domestic firms in destination z are obtained by substituting (23) into (21) and integrating revenue over the measure of costs $\mu_z(c)$:

$$X_z(\alpha, \eta) = \frac{\alpha_z(j) \sigma E_z}{\eta_z(j) (1-q_z)} \int_0^{\bar{c}_z(\alpha, \eta)} \left(\frac{c}{\bar{c}_z} \right)^{\frac{1-\sigma}{1-q_z}} \theta \Phi_z c^{\theta-1} dc = \frac{\kappa_{0z}}{\kappa_{1z}} \Pi_z R_z \alpha^{\tilde{\theta}q_z+1} \eta^{\tilde{\theta}(1-q_z)-1}.$$

Total sales are then obtained by integrating $X_z(\alpha, \eta)$ over the joint density $g(\alpha, \eta)$:

³⁵ The restriction $q_z < 1 - 1/\tilde{\theta}$ follows from our assumption of a positive and finite P_z . Note that this restriction ensures that the second-order condition for optimal product quality $(\gamma - \tilde{t}(y_z)) > 0 \iff q_z < 1$ is also satisfied.

$$X_z = \frac{\Pi_z R_z}{\kappa_{1z}} \kappa_{0z} \int \int \alpha^{\tilde{\theta} q_z + 1} \eta^{\tilde{\theta}(1-q_z) - 1} g(\alpha, \eta) d\alpha d\eta = \Pi_z R_z. \quad (25)$$

Using (25) and (24) yields average sales \bar{X}_z of domestic exporters in destination z , which in turn allows us to write market entry costs in terms of \bar{X}_z :

$$\bar{X}_z = \frac{X_z}{N_z} = \frac{\kappa_{1z}}{\kappa_{2z}} \frac{\sigma E_z}{1 - q_z} \Rightarrow \frac{\sigma E_z}{1 - q_z} = \frac{\kappa_{2z}}{\kappa_{1z}} \bar{X}_z. \quad (26)$$

2.3.4. Standardised unit costs

Following EKK, we define a new variable, the standardised unit cost $u(j)$, obtained as a transformation of firm j 's efficiency:

$$u(j) = T\varphi(j)^{-\theta} \Rightarrow \varphi(j) = \left[\frac{T}{u(j)} \right]^{\frac{1}{\theta}}.$$

The above transformation implies that the measure of firms with standardised unit cost below u equals the measure of firms with efficiency greater than $(T/u)^{1/\theta}$, and therefore we have: $\mu[(T/u)^{1/\theta}] = T[(T/u)^{1/\theta}]^{-\theta} = u$. It follows that standardised unit costs have a uniform measure that does not depend on any parameter.³⁶ Next, we write $c_z(j)$ and $\bar{c}_z(j)$ in terms of $u(j)$ and $\bar{u}_z(j)$:

$$c_z(j) = \frac{w\tau_z}{\varphi(j)} = \left[\frac{u(j)}{\Phi_z} \right]^{\frac{1}{\theta}} \Rightarrow \bar{c}_z(j) = \left[\frac{\bar{u}_z(j)}{\Phi_z} \right]^{\frac{1}{\theta}}. \quad (27)$$

Using (23) and (24) in (27) yields an expression for $\bar{u}_z(j)$ in terms of N_z :

$$\bar{u}_z(j) = \Phi_z \bar{c}_z(j)^\theta = \alpha_z(j)^{\tilde{\theta} q_z} \eta_z(j)^{\tilde{\theta}(1-q_z)} \frac{\Pi_z R_z (1 - q_z)}{\sigma E_z \kappa_{1z}} = \frac{N_z}{\kappa_{2z}} \alpha_z(j)^{\tilde{\theta} q_z} \eta_z(j)^{\tilde{\theta}(1-q_z)}. \quad (28)$$

Substituting (26)–(28) into (21), firm j 's revenue can finally be written as:

$$r_z(j) = \frac{\kappa_{2z} \alpha_z(j) \bar{X}_z}{\kappa_{1z} \eta_z(j)} v(j)^{-1/\tilde{\theta}(1-q_z)}, \quad (29)$$

where $v(j) = u(j)/\bar{u}_z(j)$ has a uniform distribution on the unit interval conditional on entry into market z .

2.3.5. Parametrisation of the shocks

Finally, as in EKK, we assume that $\ln \alpha$ and $\ln \eta$ are normally distributed with zero mean, variance σ_α^2 and σ_η^2 and correlation $\rho_{\alpha\eta}$. Under these assumptions, κ_{1z} and κ_{2z} can be written as:

³⁶ This result proves useful in simulations, as it allows one to isolate the stochastic elements of the model from its parameters. See Eaton and Kortum (2010, ch. 4) for an illustration.

$$\begin{aligned}
\kappa_{1z} &= \frac{\tilde{\theta}(1-q_z)}{\tilde{\theta}(1-q_z)-1} \times \exp\left(\frac{1}{2}\left\{\sigma_\alpha^2(\tilde{\theta}q_z+1)^2\right.\right. \\
&\quad \left.\left.+ 2\rho_{\alpha\eta}\sigma_\alpha\sigma_\eta(\tilde{\theta}q_z+1)\left[\tilde{\theta}(1-q_z)-1\right] + \sigma_\eta^2\left[\tilde{\theta}(1-q_z)-1\right]^2\right\}\right), \\
\kappa_{2z} &= \exp\left(\frac{1}{2}\left\{\sigma_\alpha^2(\tilde{\theta}q_z)^2 + 2\rho_{\alpha\eta}\sigma_\alpha\sigma_\eta\tilde{\theta}^2q_z(1-q_z) + \sigma_\eta^2\left[\tilde{\theta}(1-q_z)\right]^2\right\}\right).
\end{aligned} \tag{30}$$

By comparing the expressions in (28)–(30) for entry hurdles, revenue, κ_{1z} and κ_{2z} with the equivalent expressions in EKK, note that our model boils down to theirs for $q_z = 0$ (under the assumption of exogenous entry costs). As illustrated below, we can therefore easily adapt the EKK algorithm to simulate our model's behaviour.

2.4. Simulation, Estimation and Model Fit

In this subsection, we simulate a set of artificial Italian firms selling in at least one out of seven foreign destinations, three high-income and four low-income destinations. We use these artificial data to compute a set of artificial moments, which will then be compared with moments from the actual data to estimate the model's parameters and study its implications.

2.4.1. Simulation algorithm

We simulate a set of S artificial firms, indexed by S . This requires assigning a cost draw $u(s)$ and a value of the destination-specific shocks $\ln\alpha_z(s)$ and $\ln\eta_z(s)$ to each of them. As for the shocks, we first draw $S \times 7$ realisations of $a_z(s)$ and $h_z(s)$ independently from the standard normal distribution $N(0,1)$ and then construct the realisations of $\ln\alpha_z(s)$ and $\ln\eta_z(s)$ as:

$$\begin{bmatrix} \ln\alpha_z(s) \\ \ln\eta_z(s) \end{bmatrix} = \begin{bmatrix} \sigma_\alpha\sqrt{1-\rho_{\alpha\eta}^2} & \sigma_\alpha\rho_{\alpha\eta} \\ 0 & \sigma_\eta \end{bmatrix} \begin{bmatrix} a_z(s) \\ h_z(s) \end{bmatrix}. \tag{31}$$

As for the cost draws, we first draw S realisations of $v(s)$ independently from the uniform distribution $U[0,1]$. Then, we use (28) to construct $S \times 7$ entry hurdles $\bar{u}_z(s)$. To this purpose, we use (30) to calculate κ_{1z} and κ_{2z} in each destination, and we replace N_z with the actual integer number of Italian firms selling in each destination. This allows us to construct the cost draws as $u(s) = v(s)\bar{u}^X(s)$, where $\bar{u}^X(s) = \max_z\{\bar{u}_z(s)\}$. This ensures that $u(s)$ is a realisation from the uniform distribution over the interval $[0, \bar{u}^X(s)]$ and is therefore consistent with firm s selling in at least one foreign destination. Next, using (29) we calculate sales in destination z as:

$$r_z(s) = \delta_z(s) \frac{\kappa_{2z} \alpha_z(s) \bar{X}_z}{\kappa_{1z} \eta_z(s)} \left[\frac{u(s)}{\bar{u}_z(s)} \right]^{-1/\tilde{\theta}(1-q_z)}, \tag{32}$$

where $\delta_z(s)$ is an indicator variable equal to one for $u(s) \leq \bar{u}_z(s)$, namely, for firms selling in destination z . Moreover, we replace \bar{X}_z with actual average sales of Italian firms entering destination z . Finally, we use (15) to compute the export share to

low-income destinations as $ES_l(s) = r_l(s)/[r_l(s) + r_h(s)]$, where $r_l(s)$ are the overall sales to the four low-income destinations and $r_h(s)$ are the overall sales to the three high-income destinations.

2.4.2. Estimation

We use the above algorithm to estimate the following vector of parameters: $\beta = \sigma_z, \sigma_\eta, \rho_{z\eta}, \tilde{\theta}, q_z$, where z is one of the seven export destinations. To estimate β , we simulate 50,000 artificial firms and use this data to compute a vector of moments $\hat{\phi}(\beta)$. We choose the set of moments to exploit information on the distribution of exporters' sales across destinations. Specifically, we compute the q th percentile (for $q = 5, 10, \dots, 90$) of normalised sales (i.e., divided by average sales) for each destination (r_z), for low-income and high-income destinations (r_l and r_h), and for total exports ($r_h + r_l$). This gives us a 180-element vector of artificial moments to be matched with the equivalent vector ϕ of moments from the actual data. We therefore compute $\Delta(\beta) = \phi - \hat{\phi}(\beta)$, the vector of deviations between actual and artificial moments, and search for a $\hat{\beta}$ such that $\hat{\beta} = \arg \min_{\beta} \{\Delta(\beta)' W \Delta(\beta)\}$, where W is a 180×180 identity matrix.³⁷ The best fit is achieved at the following parameter values (with bootstrapped standard errors in parenthesis):³⁸

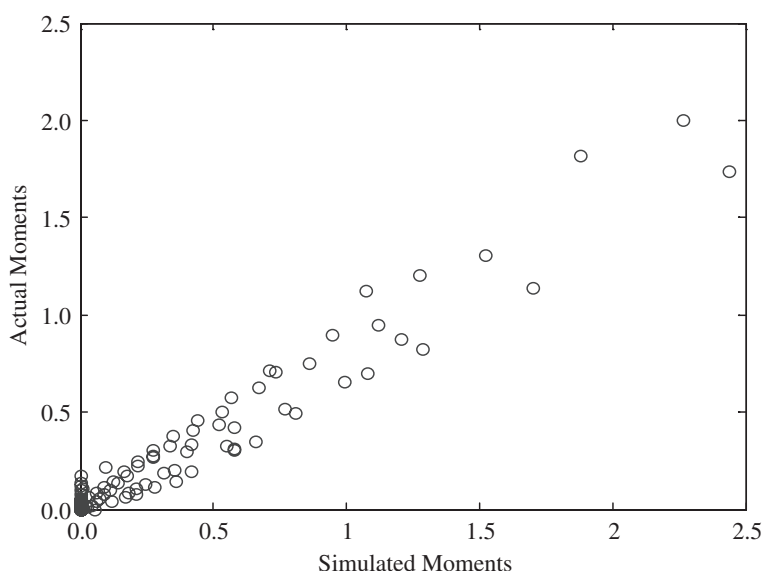
σ_z	σ_η	$\rho_{z\eta}$	$\tilde{\theta}$			
0.096	1.080	-0.916	2.607			
(0.004)	(0.166)	(0.040)	(0.452)			
q_{NA}	q_{EU15}	q_{OCE}	q_{EU10}	q_{LAT}	q_{CHN}	q_{AFR}
0.310	0.265	0.173	0.157	0.132	0.061	0.013
(0.020)	(0.025)	(0.017)	(0.007)	(0.006)	(0.003)	(0.001)

Although our estimates cannot be directly compared with those in EKK, who rely on more disaggregated data, it is nonetheless interesting to note that our estimate of σ_z (0.09 *versus* 1.69 in EKK) implies a much lower (by an order of magnitude) idiosyncratic variation in firms' sales across destinations, whereas our estimate of σ_η (1.08 *versus* 0.34 in EKK) implies a higher idiosyncratic variation in firms' entry costs across destinations.

More importantly our estimates imply that, consistent with our theory, the normalised preference for quality is monotonically increasing in the destination's per capita income. Cross-destination differences in q_z are also large and little affected by simulation error. For instance, the estimated preference for quality in the poorer destina-

³⁷ Following EKK, we also computed $W = \Omega^{-1}$, where Ω is the estimated variance-covariance matrix of the data moments. Specifically, we first drew with replacement 2,000 random samples of 2,382 exporters, i.e., 95% of all exporting firms in our data set (using 90% or 99% random samples would yield the same conclusions). Then, for each resampling bs , we computed the 180-element vector of moments ϕ^{bs} . Finally, we calculated $\Omega = \frac{1}{2000} \sum_{bs=1}^{2000} (\phi^{bs} - \phi)(\phi^{bs} - \phi)'$. It turned out that Ω is singular, as many of its elements are zero to working precision, thereby precluding invertibility. Taking the generalised inverse of Ω (as in EKK, where however Ω is singular not because of small sample variation but because, by construction, some moments are linear combinations of the others) would imply losing critical information to the identification of the model's parameters. Moreover, the small-sample performance of estimators based on singular or quasi-singular estimates of Ω is generally very poor (Deaton, 1986; Altonji and Segal, 1996). Hence, following a standard practice in these cases, we used the consistent estimator based on the identity matrix.

³⁸ Bootstrapped standard errors are based on 25 replications of the minimisation procedure, implemented in MATLAB using the simplex algorithm.

Fig. 2. *Model Fit*

tion, Africa, is less than one-20th that in the richest destination, North America. Such asymmetries suggest quality to play a prominent role for the direction and intensity of international trade.³⁹

2.4.3 *Model fit*

To get a broad picture of the model fit, Figure 2 plots the vector ϕ of actual moments on the y -axis against the vector $\hat{\phi}$ of simulated moments on the x -axis. A regression of ϕ on $\hat{\phi}$ yields an R -squared of 0.95, suggesting that, with the estimated set of parameters, the model does a good job of matching moments of Italian data.

Next, we check whether the model is able to predict our key stylised fact. To this purpose, we run 50 simulated regressions of $ES_i(j)$ on $\ln[\varphi(j)^{\sigma-1}]$ for a set of 2507 artificial exporters.⁴⁰ The average simulated regression coefficient (standard error) equals -0.051 (0.012) for all exporters and -0.063 (0.011) for firms entering both high-income and low-income destinations. By comparing simulated results with actual regression results in panels (a) and (b) of Table 3, note that the model correctly predicts the pattern of correlations and broadly matches their size. Simulated coefficients are however smaller than actual ones in absolute value.

In comparing simulated and actual regression results, we are abstracting from measurement error in TFP. Guided by our structural estimates, which are independent of TFP estimates, we can have a sense of how mis-measurement of TFP may affect our empirical regularities. In particular, simulated regressions yield revenue-productivity elasticities equal to 1.85 (high-income destinations), 1.35 (low-income destinations) and 1.70 (total exports). The actual elasticities reported in Table 4 are therefore

³⁹ For instance, they may help to explain why rich countries still trade so little with African countries in manufacturing. See also Sutton (2007) on this point.

⁴⁰ In the simulations, cross-firm variation in log productivity is captured by the term $-(1/\bar{\theta})\ln u(s)$.

downward biased according to the model, consistent with measurement error in TFP. However, the estimates in panels (a) and (c) of Table 4 also imply an ES_t -TFP elasticity of $0.45 - 0.99 = -0.54$, *versus* an implied simulated elasticity of $1.35 - 1.70 = -0.35$. Hence, these back-of-the-envelope calculations suggest attenuation bias due to mis-measured TFP to be largely netted out in the regressions for the export shares and potentially to account for all of the discrepancy between simulated and actual regressions in Table 3.

2.5. Value Added per Unit of Factor Cost

We now test whether the model is able to predict a negative correlation also between $ES_t(j)$ and value added per unit of factor cost, $VA_{FC}(j)$. To this purpose, we define firm j 's value added as $VA(j) = r(j) - I(j)$, where $r(j) = \sum_{z \in Z} r_z(j)$ is total revenue and $I(j)$ is intermediate spending, computed as:⁴¹

$$I(j) = (1 - \beta_V) \frac{\sigma - 1}{\sigma} r(j) + (1 - \beta_E) E(j) + (1 - \beta_{RD}) RD(j),$$

where β_V , β_E and β_{RD} reflect, respectively, the share of factor cost in: variable cost, $[(\sigma - 1)/\sigma]r(j)$, fixed entry costs, $E(j) = \sum_{z \in Z} E_z(j)$, and R&D costs, $RD(j) = \sum_{z \in Z} b\lambda_z^\gamma(j)$.

Computing intermediate spending and factor cost requires an estimate of the elasticity of substitution σ and of the share of factor cost in the three cost components. In the spirit of EKK, we calibrate these parameters to match actual data on value added per unit of factor cost. Specifically, we choose as moments the 5th to 90th percentiles of the distribution of VA_{FC} (18 moments overall), thereby obtaining the following parameter estimates: $\sigma = 1.58$, $\beta_V = 0.12$, $\beta_E = 0.37$ and $\beta_{RD} = 0.03$.

Using the above estimates, we simulate the behaviour of 3,365 artificial firms (with 50 draws), so as to match the actual number of firms in our dataset (i.e., including non-exporters). The model predicts, on average, 2,687 exporters (*versus* 2,507 in our data). Then, we run simulated regressions of $ES_t(j)$ on $\ln[VA_{FC}(j)]$ to replicate the results in columns (1) and (2) of Table 6. The average simulated regression coefficient (standard error) equals -0.095 (0.019) for all exporters and -0.061 (0.017) for firms entering both high-income and low-income destinations. Note that the model correctly predicts the pattern of correlations, although it overpredicts their size.

2.6. R&D Intensity and Export Behaviour

We now use the simulated model to draw implications for the relationship between firms' R&D intensity and their export behaviour. From (8), we have:

$$RD(j) = \sum_{z \in Z} b\lambda_z^\gamma(j) = \frac{1}{\sigma} \sum_{z \in Z} q_z r_z(j). \quad (33)$$

⁴¹ Note that the set of destinations z now includes also the domestic market. This requires modifying the simulation algorithm to include non-exporters. Specifically, in $u(s) = v(s)\bar{u}^X(s)$, we replace $\bar{u}^X(s)$ with $\bar{u}(s) = \max_{z \in Z} \{\bar{u}_z(s)\}$. Moreover, it requires choosing a value of q_z for the domestic market, which we set equal to the average for high-income destinations.

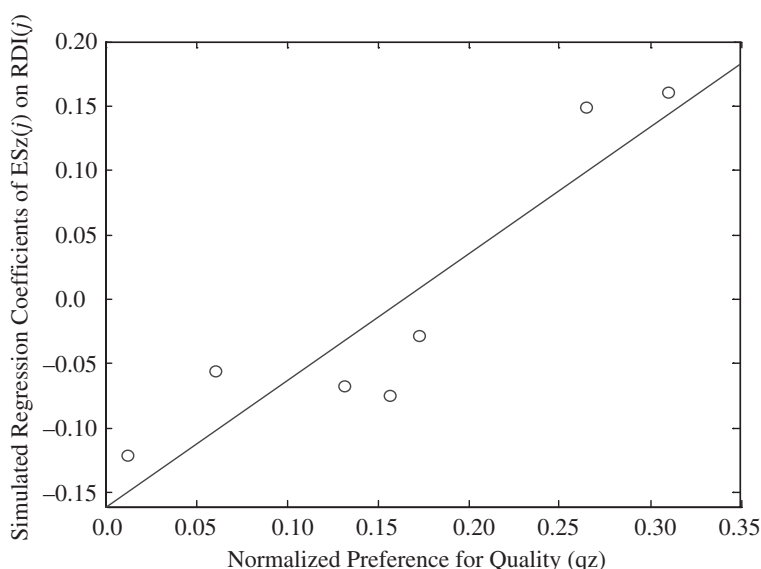


Fig. 3. *R&D Intensity and Export Shares across Destinations*

Hence, R&D spending equals a sort of weighted average of firms' revenues in the destinations they sell to, with weights proportional to per capita income of the destinations (recall that q_z is increasing in y_z). The model therefore implies that firms' R&D intensity is closely related to their sales distribution across destinations. In particular, simulated regressions imply a strong negative correlation between $ES_l(j)$ and $RDI(j) = RD(j)/r(j)$, with or without controlling for $\ln[\varphi(j)^{\sigma-1}]$, whose correlation with the export share is also significantly negative.⁴² Finally, simulated regression results imply that the correlation between $RDI(j)$ and the export share to individual destinations, $ES_z(j) = r_z(j)/\sum_{z \neq d} r_z(j)$, is strongly increasing in q_z , as shown in Figure 3.⁴³

3. Evidence on Innovation, Quality and Export Behaviour

In this Section, we test the above-mentioned qualitative implications. To this purpose, we exploit some unique information in our dataset on firms' innovation activities. We focus, in particular, on the following variables: R&D intensity (R&D spending over total sales, RDI), the share of sales from innovative products, and a dummy variable equal to one for firms that invested in process innovation in the previous 3 years. We start by

⁴² Specifically, simulated regressions of $ES_l(j)$ on $RDI(j)$ and $\ln[\varphi(j)^{\sigma-1}]$ yield average coefficients (standard errors) of -0.325 (0.005) and -0.013 (0.004), where the former coefficient is essentially identical also without controlling for productivity. The intuition for why productivity may affect the export share also conditional on R&D intensity (and, therefore, also conditional on quality) is that our model features more dimensions of heterogeneity, due to firm-specific shocks in entry costs and demand. This breaks the simple, deterministic relationship between productivity and other endogenous firm-level variables, which characterises models with one dimension of heterogeneity. See also Hallak and Sivadasan (2009) on this point. They formulate a model with two dimensions of firm heterogeneity, in order to explain their robust finding that exporters' premia remain positive and statistically significant conditional on firm size.

⁴³ The model also implies the correlation between $ES_z(j)$ and productivity to be increasing in q_z .

Table 7
Innovation, Quality and Export Behaviour

	Baseline			Controlling for TFP				Controlling for Firm Size				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
R&D Intensity (<i>RDI</i>)	-0.020*** [0.007]				-0.019*** [0.007]				-0.019*** [0.007]			
Share of Sales from Innovative Products		-0.051*** [0.014]				-0.050*** [0.015]				-0.050*** [0.015]		
Dummy for Process Innovation			-0.172 [0.123]				-0.144 [0.137]				-0.145 [0.136]	
<i>Quality</i>				-0.041*** [0.014]				-0.041*** [0.014]				-0.041*** [0.014]
<i>ln TFP</i>					-0.078*** [0.024]	-0.089*** [0.026]	-0.084*** [0.023]	-0.081*** [0.027]	-0.079*** [0.024]	-0.089*** [0.026]	-0.084*** [0.023]	-0.082*** [0.027]
<i>ln Employment</i>									0.012 [0.023]	0.015 [0.023]	0.003 [0.022]	0.017 [0.025]
Obs.	2,415	2,515	2,754	2,186	2,341	2,272	2,486	2,115	2,341	2,272	2,486	2,115
R-squared	0.10	0.10	0.10	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11

Notes. The dependent variable is the export share to low-income destinations (*ES_l*). *Quality* is the principal component of the first three variables, extracted through factor analysis. All specifications include a full set of 3-digit industry dummies and standard errors are robust to heteroskedasticity. See also notes to previous Tables.

Table 8
Innovation, Quality and Export Behaviour: Robustness Checks

Control Variables:	General Controls	Trade Controls	Exp. MKT Dummies	General Controls	Trade Controls	Exp. MKT Dummies	General Controls	Trade Controls	Exp. MKT Dummies
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>(a) Using R&D Intensity</i>									
<i>RDI</i>	-0.020*** [0.007]	-0.022*** [0.008]	-0.015** [0.006]	-0.018*** [0.007]	-0.020*** [0.008]	-0.014** [0.006]	-0.019*** [0.007]	-0.020*** [0.007]	-0.013** [0.006]
<i>ln TFP</i>				-0.067*** [0.025]	-0.080*** [0.025]	-0.029* [0.016]	-0.068*** [0.025]	-0.080*** [0.025]	-0.027* [0.016]
<i>ln Employment</i>							0.010 [0.028]	0.000 [0.025]	-0.061*** [0.017]
Obs.	2,380	2,334	2,415	2,309	2,305	2,341	2,309	2,305	2,341
R-squared	0.12	0.10	0.60	0.12	0.11	0.60	0.12	0.11	0.60
<i>(b) Using Quality</i>									
<i>Quality</i>	-0.039*** [0.014]	-0.047*** [0.014]	-0.019* [0.011]	-0.041*** [0.014]	-0.045*** [0.014]	-0.019* [0.011]	-0.041*** [0.014]	-0.045*** [0.014]	-0.019* [0.011]
<i>ln TFP</i>				-0.071** [0.028]	-0.082*** [0.027]	-0.031* [0.018]	-0.071** [0.028]	-0.082*** [0.028]	-0.029* [0.018]
<i>ln Employment</i>							0.013 [0.029]	0.006 [0.026]	-0.059*** [0.018]
Obs.	2,155	2,114	2,186	2,087	2,086	2,115	2,087	2,086	2,115
R-squared	0.13	0.11	0.60	0.13	0.11	0.59	0.13	0.11	0.60

Notes. The dependent variable is the export share to low-income destinations (*ES*). *General controls* in columns (1), (4) and (7) are the share of part-time workers in total employment, a dummy for firms quoted on the stock market, three dummies for ownership structure and a full set of dummies for Italian administrative regions. *Trade controls* in columns (2), (5) and (8) are the ratio of outward FDI to sales over the period 2001–3, the share of imported inputs in total input purchases, a dummy variable equal to 1 for importers of services and the share of sales subcontracted from abroad. *Export market dummies* in columns (3), (6) and (9) are seven dummies each taking a value of 1 for firms exporting to a given destination. All specifications include a full set of 3-digit industry dummies and standard errors are robust to heteroskedasticity. See also notes to previous Tables.

testing whether these variables are inversely correlated with the export share to low-income destinations. As shown in columns (1)–(3) of Table 7, the correlation is always negative and, except for the dummy variable, very precisely estimated. In columns (5)–(7), we control for TFP. As predicted by the model, the coefficient on *RDI* (and related proxies) is unaffected, and the coefficient on TFP is also negative and precisely estimated. Finally, as a further robustness check, in columns (9)–(11) we also control for firm size using the log number of employees. The main results are unchanged and the coefficient on firm size is insignificantly different from zero.

Next we construct a new variable, dubbed *Quality*, obtained by extracting the principal component from the above proxies for firms' innovation activities. In the light of our model, this variable can be given two complementary interpretations. First, it can be interpreted as a synthetic proxy for the intensity of firms' innovation activities. Second, and probably more interestingly, it can be treated as a proxy for product quality. The reason is that, as suggested by (33), high-productivity firms produce higher-quality products because they invest more in R&D and related activities.⁴⁴ In columns (4), (8) and (12) of Table 7, we therefore use the new proxy instead of the individual proxies for

⁴⁴ This interpretation is also consistent with the classic and more recent literature on quality differentiation (Sutton, 1998; Kugler and Verhoogen, 2012), which suggests the scope for quality upgrading to be associated with the intensity of R&D and other activities aimed at producing new products or processes.

innovation intensity. Note that ES_i is strongly negatively correlated with *Quality*, with or without controlling for productivity and firm size.

In Table 8, we perform additional robustness checks, using *RDI* in panel (a) and *Quality* in panel (b). Specifically, we add to the baseline specification the same controls used in Table 5: general controls in column (1), trade controls in column (2) and export market dummies in column (3). In columns (4)–(6), we add TFP to the above specifications, and in columns (7)–(9) we also control for firm size. In all cases, the export share to low-income destinations is strongly negatively correlated with both *RDI* and *Quality*.

Finally, we study how the correlation between ES_i and *Quality* depends on industry characteristics. It is easy to conjecture that a multi-sector extension of our model would predict industries characterised by a greater scope for quality differentiation to deliver a stronger negative correlation between the two variables. This is because a given heterogeneity in efficiency would translate into higher quality heterogeneity in these industries. To test this conjecture, following Kugler and Verhoogen (2012), we construct a variable, *Quality Differentiation*, equal to the median R&D intensity across all firms in each 3-digit industry. The results are reported in Table 9, with standard errors corrected for clustering within 3-digit industries. In column (1), we regress ES_i on *Quality*, *Quality Differentiation* and their interaction: as expected, the coefficients on *Quality* and its interaction with *Quality Differentiation* are negative and very precisely estimated. In column (2), we add TFP and its interaction with *Quality Differentiation*: the coefficient on the latter interaction term is insignificantly different from zero and our

Table 9
Industry Characteristics, Quality and Export Behaviour

	Baseline	Controlling for TFP	Controlling for Firm Size	Controlling for Horizontal Differentiation
	(1)	(2)	(3)	(4)
<i>Quality</i>	−0.044*** [0.012]	−0.045*** [0.012]	−0.045*** [0.012]	−0.031 [0.027]
<i>Quality</i> × <i>Quality Differentiation</i>	−0.049*** [0.017]	−0.045** [0.018]	−0.045** [0.018]	−0.044** [0.018]
ln <i>TFP</i>		−0.100*** [0.029]	−0.100*** [0.030]	−0.100*** [0.030]
ln <i>TFP</i> × <i>Quality Differentiation</i>		−0.005 [0.034]	−0.005 [0.034]	−0.005 [0.034]
ln <i>Employment</i>			0.003 [0.021]	0.004 [0.022]
ln <i>Employment</i> × <i>Quality Differentiation</i>			0.001 [0.035]	0.001 [0.035]
<i>Quality</i> × <i>Horizontal Differentiation</i>				−0.019 [0.033]
<i>Quality Differentiation</i>	0.150*** [0.047]	0.138*** [0.048]	0.137*** [0.052]	0.137*** [0.052]
Obs.	2,186	2,115	2,115	2,115
R-squared	0.01	0.02	0.02	0.02

Notes. The dependent variable is the export share to low-income destinations (ES_i). *Quality differentiation* is the median R&D intensity across all firms in each 3-digit industry. *Horizontal differentiation* is a dummy for differentiated (3-digit) industries, identified using the Rauch (1999) classification. Standard errors are corrected for clustering within 3-digit industries. See also notes to previous Tables.

coefficients of interest are little affected. In column (3), we add firm size and its interaction with *Quality Differentiation*, and find that the results are unchanged. Finally, in column (4) we also interact *Quality* with a dummy for differentiated (3-digit) industries, identified using the Rauch (1999) classification. Consistent with this variable being a proxy for horizontal rather than vertical differentiation, the coefficient on the new interaction term is insignificantly different from zero and the other results are qualitatively unchanged.

3.1. Panel Evidence

Our model predicts that the correlations between productivity, R&D intensity or product quality and the export share to a destination are increasing in the destination's per capita income. To test these predictions, we construct a panel of export shares to each of the seven destinations and estimate regressions of the form:

$$ES_{zj} = \chi_z + \chi_{zi} + \chi_1 \Omega_j + \chi_2 (\Omega_j y_z) + e_{zj}, \quad (34)$$

where ES_{zj} is firm j 's export share to destination z , χ_z are destination fixed effects, χ_{zi} are destination-industry fixed effects, y_z is destination z 's per capita income⁴⁵ and Ω is one of the following three variables: productivity (TFP or VA_{FC}), *RDI* or *Quality*. Note that the term $\Omega_j y_z$ captures the impact of foreign income on the correlation between ES_z and Ω : the expected sign of χ_2 is therefore positive. The results are reported in Table 10, with standard errors corrected for clustering at the firm level. To begin with, in columns (1) and (2) we estimate (34) with $\Omega = \text{productivity}$. As expected, the coefficient χ_2 is always positive and statistically significant beyond the 1% level.

Next, we set $\Omega = RDI$ in columns (3)–(7) and $\Omega = Quality$ in columns (8)–(12). In particular, in columns (3) and (8) we estimate the baseline specification, in columns (4) and (9) we control for TFP and its interaction with foreign income and in columns (5) and (10) we add firm size and its interaction with foreign income. Note that χ_2 is positive and precisely estimated across the board. Finally, in columns (6)–(7) and (11)–(12) we sequentially add distance and population of the foreign destination interacted with all the above firm characteristics, so as to check that our main results are not spuriously driven by the correlation of distance and market size with per capita income.⁴⁶ Strikingly, the coefficient χ_2 is very precisely estimated also in these very demanding specifications.⁴⁷

⁴⁵ We measure y_z using data on per capita GDP in PPP for the year 2003 (sourced from the World Development Indicators) and normalise it by Italy's per capita income.

⁴⁶ We compute distances as the number of kilometers between Rome and the capital city of Italy's main trading partner within destination z (Corcos *et al.*, forthcoming, for a discussion of alternative distance measures). We use data from CEPII and normalise individual distances by the average across all destinations. For a given destination, the main trading partner is the country with the highest share in Italy's trade, retrieved from CEPII's data on bilateral trade flows for the year 2003. In particular, the main trading partners are: Germany (*EU15*), United States (*NA*), Australia (*OCE*), Poland (*EU10*), Brazil (*LAT*), Tunisia (*AFR*) and China (*CHN*). Population figures are sourced from the WDI for the year 2003 and normalised by Italy's population.

⁴⁷ Although the coefficients are imprecisely estimated, our results are broadly consistent with the correlation between export shares and quality/marginal cost being increasing in distance. They are therefore consistent with the Hummels and Skiba (2004) 'good apples' story and with a by now large literature showing that export unit values are higher in more distant markets; see, in particular, Bastos and Silva (2010); Martin (2010); Baldwin and Harrigan (2011); Johnson (2012); Manova and Zhang (2012).

Table 10
Productivity, Quality and Export Behaviour: Panel Regressions

	Ω = Productivity			Ω = RDI			Ω = Quality								
	TFP	VA _{FC}	(2)	Baseline	(3)	(4)	Adding Firm Size	Adding Distance	Adding Population	Baseline	TFP	(9)	Adding Firm Size	Adding Distance	Adding Population
ln Productivity	-0.032*** [0.008]	-0.014*** [0.004]				-0.028*** [0.008]	-0.029*** [0.008]	-0.028*** [0.008]	-0.053*** [0.020]			-0.030*** [0.009]	-0.030*** [0.009]	-0.026*** [0.009]	-0.048*** [0.022]
ln Productivity × Income	0.058*** [0.015]	0.025*** [0.008]				0.051*** [0.015]	0.051*** [0.015]	0.051*** [0.015]	0.070*** [0.021]			0.053*** [0.017]	0.053*** [0.017]	0.055*** [0.017]	0.070*** [0.024]
RDI				-0.007*** [0.003]		-0.007*** [0.003]	-0.007*** [0.003]	-0.007*** [0.004]	-0.019*** [0.010]						
RDI × Income				0.013*** [0.005]		0.012*** [0.005]	0.012*** [0.005]	0.012*** [0.005]	0.020*** [0.008]						
Quality															
Quality × Income															
ln Employment							0.003 [0.008]	-0.011 [0.008]	-0.018 [0.017]						
ln Employment × Income							-0.006 [0.015]	-0.011 [0.016]	-0.006 [0.020]						
ln Productivity × Distance								-0.001 [0.005]	-0.000 [0.005]						
RDI × Distance								0.001 [0.003]	0.001 [0.003]						
Quality × Distance															
ln Employment × Distance															
ln Productivity × Population															
RDI × Population															

Table 10
(Continued)

	Ω = Productivity			Ω = RDI				Ω = Quality					
		VA_{PC}		Baseline	Adding TFP	Adding Firm Size	Adding Distance	Adding Population	Baseline	Adding TFP	Adding Firm Size	Adding Distance	Adding Population
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	
$Quality \times Population$													0.002***
$\ln Employment \times Population$													[0.001]
							0.000						0.000
							[0.001]						[0.001]
Obs.	17,549	17,458	16,905	16,387	16,387	16,387	16,387	15,302	14,805	14,805	14,805	14,805	14,805
R-squared	0.67	0.68	0.67	0.67	0.67	0.67	0.67	0.67	0.68	0.68	0.68	0.68	0.68

Notes. The dependent variable is the export share to destination z ($ES_{z,j}$). The panel is obtained by pooling data on firms' export shares to the following destinations: EU15, New EU Members, North America, China, Latin America, Africa and Oceania. *Income* is the average PPP per capita GDP of each destination, relative to Italy's. *Distance* is the number of kilometers between Rome and the capital city of the main trading partner within each destination, relative to the average distance across all destinations. *Population* is the size of each destination's population relative to Italy's. All regressions control for destination and destination-industry fixed effects. Standard errors are corrected for clustering at the firm level. See also notes to previous Tables.

4. Conclusion

In this article, we have documented new empirical regularities in the pattern of firms' exports across destinations. Using firm-level data for Italy we have shown, in particular, that a number of productivity measures are strongly negatively correlated with the export share to low-income destinations. We have argued that this fact cannot be easily accommodated by the existing heterogeneous-firms literature. We have therefore formulated a simple model in which, in the spirit of Verhoogen (2008), high-productivity firms endogenously choose higher-quality products and high-income countries have a stronger preference for high-quality goods. The model naturally delivered the main patterns in our data and was amenable to the structural estimation of its parameters along the lines recently suggested by Eaton *et al.* (2011).

With the estimated set of parameters, the model fitted our data well. The estimated parameters imply the preference for quality is monotonically increasing in per capita income of the foreign destinations and suggest cross-destination heterogeneity in quality consumption to be large. The estimated model also delivered testable predictions concerning the relationship between R&D intensity, product quality and export behaviour. Exploiting some unique information in our dataset, we tested these predictions and found that they are supported by our data. In particular, we found that a number of proxies for firms' involvement in innovation activities are strongly negatively correlated with their export share to low-income destinations.

Our results bear some potentially relevant implications. In particular, they suggest that what firms produce, and how they produce it, seems to be closely related to where they sell it. This implies, for instance, that quality upgrading may be a prerequisite for effective access to richer countries' markets. Moreover, our results suggest that North-South trade liberalisation may have not too disruptive effects on rich countries' industrial structure, because the trade-reducing effect of non-homothetic preferences may be exacerbated in the presence of firm heterogeneity in productivity and quality.

Although in recent years we have dramatically improved our understanding of firms' export behaviour, the determinants of the popularity of foreign destinations from the standpoint of domestic exporters are not yet fully understood. We hope that, by showing how firms' exports may depend on the interplay between productivity, product quality and quality consumption, our contribution can shed light on this important issue. We still do not know, however, whether the empirical regularities documented in this article, although strong and plausible, hold elsewhere. Testing whether our results extend beyond Italian manufacturing is therefore a promising avenue for future research.

Appendix A. EKK-Type Patterns

We now show that the Italian data broadly replicate all the main patterns unveiled by EKK using French data (see Section 2 of that article).

In Figure A1, we show how firms' entry and sales to each of the seven foreign destinations depend on market size. Panel (a) plots the number of Italian exporters to each destination (normalised by Italy's market share in the destination) against the destination's total manufacturing absorption.⁴⁸ Note that the normalised number of exporters is strongly increasing in the destination's market size. Panel (b) plots the 50th and 90th percentiles of exporters' sales in each destination against total manufacturing absorption. With one exception (*EU10*), sales are strongly increasing in the destination's market size.

In Figure A2, we show the relationship between firms' export participation and sales in Italy. To begin with, we group firms according to the minimum number k of foreign destinations in which they sell, with k ranging from 1 to 7 in our data. In panel (a), we plot the 90th percentile sales in Italy of firms exporting to at least k destinations, with k on the horizontal axis. Note that sales in Italy are almost monotonically increasing in k . In panel (b), we plot sales in Italy against the number of exporters to at least k destinations. The relationship is almost monotonically decreasing. In panel (c), we plot sales in Italy against the number of exporters to each destination. With the exception of China, firms selling to more popular destinations have lower sales in Italy.

Finally, we show how the normalised export intensity varies with the number of exporters to a destination; the former variable is defined as the ratio of sales to a destination over domestic sales, both divided by average sales in the respective market. In Figure A3, we plot the mean and 95th percentile export intensity against the number of exporters to each destination. Note that the normalised export intensity is strongly increasing in the popularity of a destination.

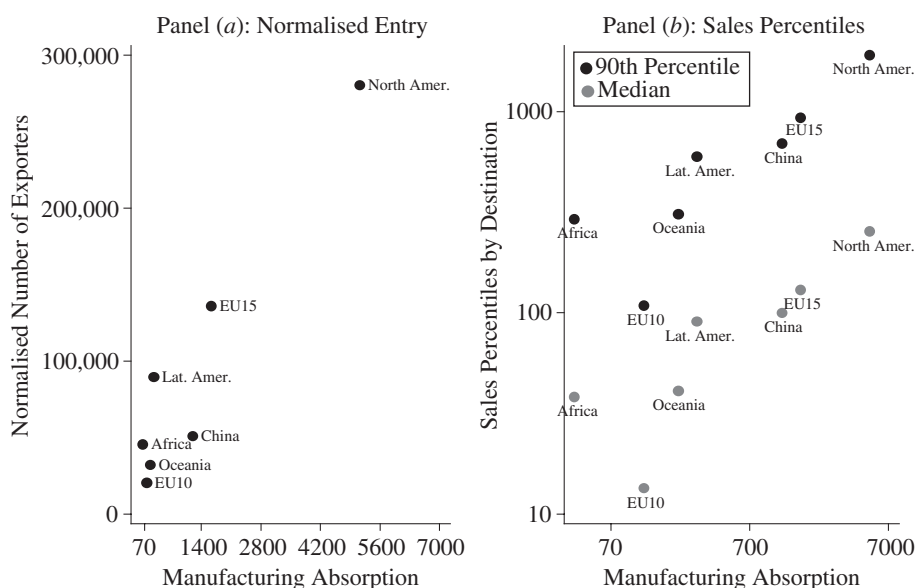


Fig. A1. *Entry and Sales by Market Size*

Notes. Manufacturing absorption is defined as production plus imports minus exports and is expressed in billions of euro.

⁴⁸ Italy's market share in each destination and total manufacturing absorption of the destinations, are constructed using data from Dekle *et al.* (2007), available for the year 2004. We use data on Italy's main trading partner within each destination. Market shares are defined as Italy's exports over total expenditure in the destinations; manufacturing absorption is defined instead as production plus imports minus exports in each destination. Data are converted from US\$ to euro using exchange rates from the European Central Bank.

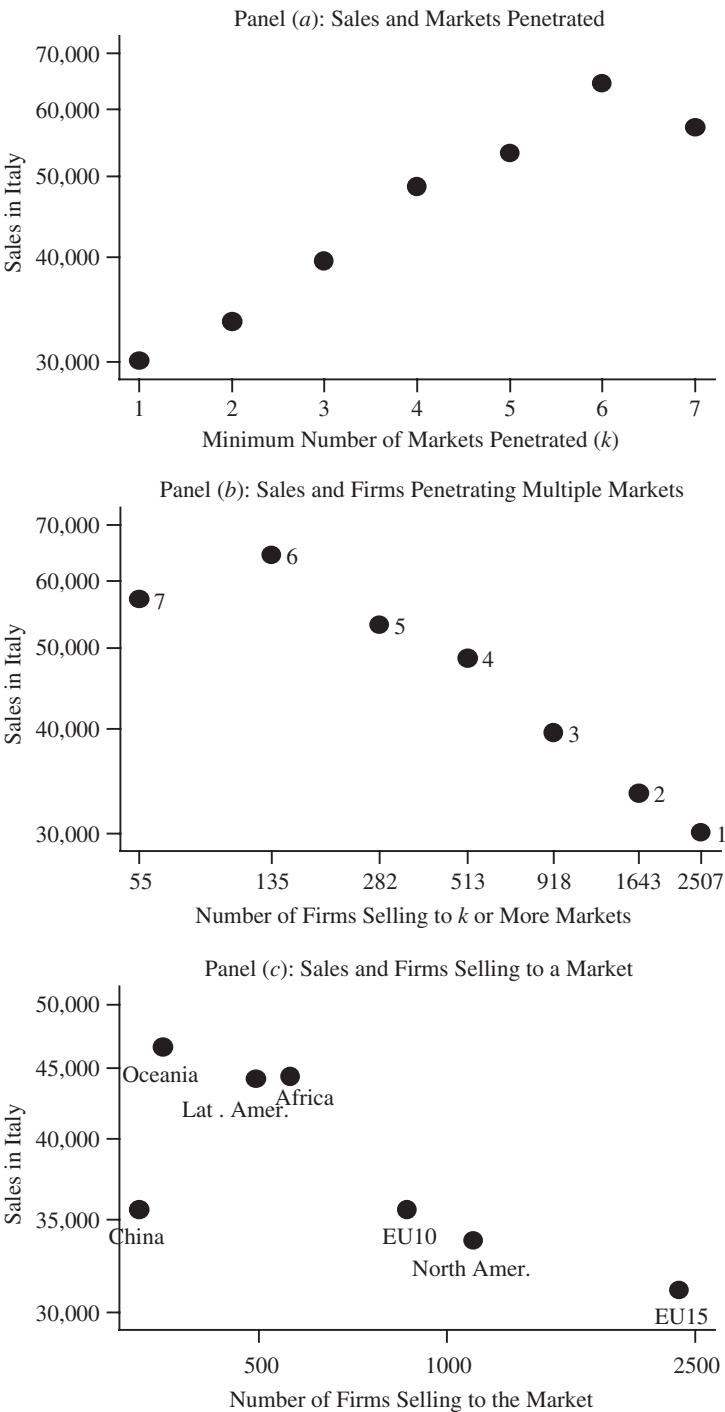


Fig. A2. Domestic Sales and Export Participation

Notes. The vertical axis of each graph reports the 90th percentile of sales in Italy (in thousands of euro) for the corresponding group of exporting firms.

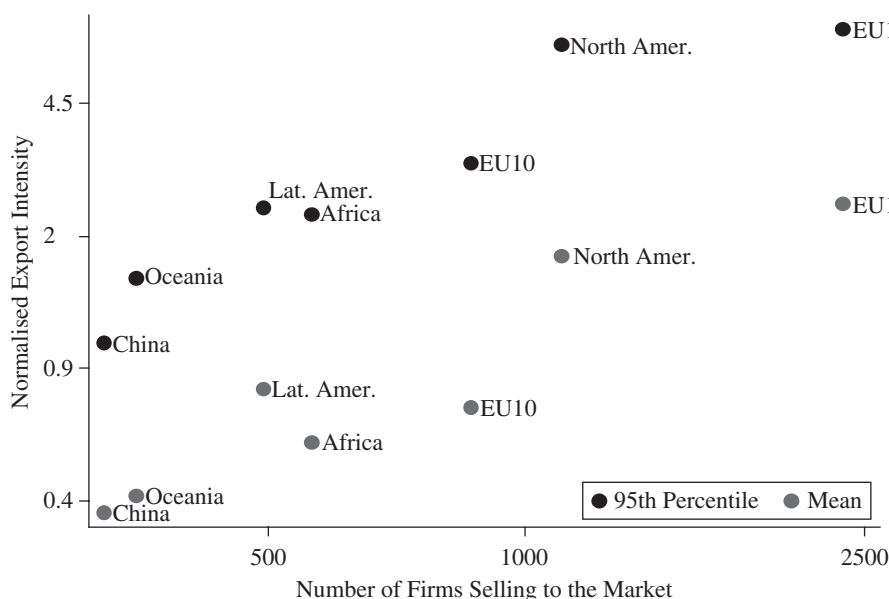


Fig. A3. *Export Intensity by Destination*

Notes. Normalised export intensity is defined as the ratio of sales to a destination over domestic sales, both divided by average sales in the respective market.

To conclude our data nicely replicate, on a smaller scale, EKK-type patterns, and hence do not seem to be special in this respect.⁴⁹ By the same token, the new patterns shown in our article, not studied by EKK, may perhaps hold true in their (and other) datasets as well.

Appendix B. Global Quality Upgrading

Finally, we show that similar results hold when firms target their global market (rather than individual destinations) in choosing quality. In this case, they solve the following problem:

$$\max_{\lambda} \left\{ \varphi(j)^{\sigma-1} \sum_{z \in \{d, h, l\}} \delta_z(j) \left[M_z \lambda^{\tilde{l}(y_z)} - E_z \right] - b \lambda^{\gamma} \right\}, \quad (\text{B.1})$$

where a subscript d indexes domestic variables, $M_z = R_z(\rho P_z / w \tau_z)^{\sigma-1}$ and $\delta_z(j)$ is an indicator variable equal to one if firm j sells in market z (i.e., $\delta_z(j) = 1$ for $\varphi(j) > \bar{\varphi}_z$). The first-order condition for this problem can be written as:

$$\gamma b \lambda^{\gamma} = \varphi(j)^{\sigma-1} \sum_{z \in \{d, h, l\}} \delta_z(j) \tilde{l}(y_z) M_z \lambda^{\tilde{l}(y_z)}, \quad (\text{B.2})$$

where both the LHS and the RHS are increasing in λ and, by the second-order condition for a maximum, the LHS is steeper than the RHS. Note, first, that a higher value of φ shifts the RHS upwards, implying a higher equilibrium value of λ for given δ_z . Second, starting from $\delta_d = 1$ and $\delta_h = \delta_l = 0$, the RHS shifts upwards for $\delta_h = 1$ and for $\delta_h = \delta_l = 1$, implying

⁴⁹ Although explaining the above empirical regularities was clearly not the focus of this article, our model is able to replicate their qualitative pattern with the estimated set of parameters. The results are available upon request.

that firms exporting to a larger number of markets choose a higher value of λ . Moreover, for $\bar{\varphi}_l > \bar{\varphi}_h > \bar{\varphi}_d$, the latter firms are more productive. Hence, as in the baseline model, high-productivity firms produce higher-quality products: they enter more destinations (extensive margin) and sell more in each of them (intensive margin), hence they can spread the higher fixed costs of quality upgrading over a greater revenue. By applying the implicit function theorem to (B.2), we can write a general expression for the elasticity of product quality to productivity:

$$\epsilon \equiv \frac{d \ln \lambda(j)}{d \ln \varphi(j)^{\sigma-1}} = \frac{\sum_{z \in \{d, h, l\}} \delta_z(j) \tilde{t}(y_z) M_z \lambda(j)^{\tilde{t}(y_z)}}{\sum_{z \in \{d, h, l\}} \delta_z(j) [\gamma - \tilde{t}(y_z)] \tilde{t}(y_z) M_z \lambda(j)^{\tilde{t}(y_z)}} > 0,$$

where the inequality follows from the second-order condition for optimal product quality. Hence we have:

$$\frac{r_l(j)}{r_h(j)} = \lambda(j)^{\tilde{t}(y_l) - \tilde{t}(y_h)} \frac{M_l}{M_h} \Rightarrow \frac{d \ln [r_l(j)/r_h(j)]}{d \ln \varphi(j)^{\sigma-1}} = \epsilon [\tilde{t}(y_l) - \tilde{t}(y_h)] < 0. \quad (\text{B.3})$$

A special case is of interest because it may lead to quality differentiation across destinations (as in the baseline model) even when firms choose quality to solve (B.3). To see this assume, for simplicity, that $y_d = y_h$. More importantly, assume that y_l is so low that revenue is decreasing in quality in destination l , i.e., $\tilde{t}(y_l) = t(y_l) - \delta(\sigma - 1) < 0$. In this case, firms maximise profits by selling standardised products in the low-income destination (i.e., they set $\lambda_l(j) = 1$), and otherwise choose quality based only on the size of high-income countries.⁵⁰ In this case, it is straightforward to show that:

$$\frac{d \ln (r_l(j)/r_h(j))}{d \ln \varphi(j)^{\sigma-1}} = - \frac{\tilde{t}(y_h)}{\gamma - \tilde{t}(y_h)} < 0.$$

University of Brescia

Bocconi University

Submitted: 13 May 2010

Accepted: 16 February 2012

References

- Alcalà, F. (2007). 'Product, quality and trade', mimeo, University of Murcia.
- Alcalà, F. (2009). 'Time, quality and growth', Working Paper No. 07, Departamento de Fundamentos del Análisis Económico, University of Murcia.
- Altonji, J.G. and Segal, L.M. (1996). 'Small-sample bias in GMM estimation of covariance structures', *Journal of Business and Economic Statistics*, vol. 14(3), pp. 353–66.
- Amiti, M. and Konings, J. (2007). 'Trade liberalization, intermediate inputs, and productivity: evidence from Indonesia', *American Economic Review*, vol. 97(5), pp. 1611–38.
- Angelini, P. and Generale, A. (2008). 'On the evolution of firm size distributions', *American Economic Review*, vol. 98(1), pp. 426–38.
- Arkolakis, K. (2010). 'Market penetration costs and the new consumers margin in international trade', *Journal of Political Economy*, vol. 118(6), pp. 1151–99.

⁵⁰ Note, in passing, that the model provides a possible microfoundation for the assumption, standard in the literature on endogenous technological change (Gancia and Zilibotti, 2009), that firms target their innovations based on the size of high-income markets only.

- Aw, B.Y., Chen, X. and Roberts, M.J. (2001). 'Firm-level evidence on productivity differentials and turnover in Taiwanese manufacturing', *Journal of Development Economics*, vol. 66(1), pp. 51–86.
- Baldwin, R.E. and Harrigan, J. (2011). 'Zeros, quality and space: trade theory and trade evidence', *American Economic Journal: Microeconomics*, vol. 3(2), pp. 60–88.
- Bastos, P. and Silva, J. (2010). 'The quality of a firm's exports: where you export to matters', *Journal of International Economics*, vol. 82(2), pp. 99–111.
- Benfratello, L., Schiantarelli, F. and Sembenelli, A. (2009). 'Banks and innovation: microeconomic evidence on Italian firms', *Journal of Financial Economics*, vol. 90(2), pp. 197–217.
- Bernard, A.B., Eaton, J., Jensen, J.B. and Kortum, S. (2003). 'Plants and productivity in international trade', *American Economic Review*, vol. 93(4), pp. 1268–90.
- Bernard, A. B. and Jensen, J.B. (1999). 'Exceptional exporter performance: cause, effect or both?', *Journal of International Economics*, vol. 47(1), pp. 1–25.
- Bernard, A.B., Redding, S.J. and Schott, P.K. (2007). 'Comparative advantage and heterogeneous firms', *Review of Economic Studies*, vol. 74(1), pp. 31–66.
- Bils, M. and Klenow, P. (2001). 'Quantifying quality growth', *American Economic Review*, vol. 91(4), pp. 1006–30.
- Brooks, E.L. (2006). 'Why don't firms export more? Product quality and Colombian plants', *Journal of Development Economics*, vol. 80(1), pp. 160–78.
- Bustos, P. (2011). 'Trade liberalization, exports, and technology upgrading: evidence on the impact of MERCOSUR on Argentinean firms', *American Economic Review*, vol. 101(1), pp. 304–40.
- Castellani, D. (2002). 'Export behavior and productivity growth: evidence from Italian manufacturing firms', *Weltwirtschaftliches Archiv/Review of World Economics*, vol. 138(4), pp. 605–28.
- Castellani, D., Serti, F. and Tomasi, C. (2010). 'Firms in international trade: importers' and exporters' heterogeneity in the Italian manufacturing industry', *World Economy*, vol. 33(3), pp. 424–57.
- Choi, Y.C., Hummels, D. and Xiang, C. (2009). 'Explaining import quality: the role of the income distribution', *Journal of International Economics*, vol. 77(2), pp. 265–75.
- Corcos, G., Del Gatto, M., Mion, G. and Ottaviano, G. (forthcoming). 'Productivity and firm selection: quantifying the "new" gains from trade', *ECONOMIC JOURNAL*.
- Crinò, R. and Epifani, P. (2010). 'Productivity, quality, and export intensities', Working Paper No. 824.10, UFAE&IAE.
- Crozet, M., Head, K. and Mayer, T. (2012). 'Quality sorting and trade: firm-level evidence for French wine', *Review of Economic Studies*, vol. 79(2), pp. 609–44.
- Deaton, A. (1986). 'Demand analysis', in (Z. Griliches and M.D. Intriligator, eds.), *Handbook of Econometrics III*, pp. 1767–834, Amsterdam: Elsevier Science Publishers.
- Dekle, R., Eaton, J. and Kortum, S. (2007). 'Unbalanced trade', *American Economic Review: Papers and Proceedings*, vol. 97(2), pp. 351–5.
- De Loecker, J. (2007). 'Do exports generate higher productivity? Evidence from Slovenia', *Journal of International Economics*, vol. 73(1), pp. 69–98.
- De Loecker, J. (2011). 'Product differentiation, multi-product firms and estimating the impact of trade liberalization on productivity', *Econometrica*, vol. 79(5), pp. 1407–51.
- Demidova, S., Looi Kee, H. and Krishna, K. (2006). 'Do trade policy differences induce sorting? Theory and evidence from Bangladeshi apparel exporters', Working Paper No. 12725, NBER.
- Eaton, J. and Kortum, S. (2010). 'Technology in the global economy a framework for quantitative analysis', mimeo: University of Chicago.
- Eaton, J., Kortum, S. and Kramarz, F. (2011). 'An anatomy of international trade: evidence from French firms', *Econometrica*, vol. 79(5), pp. 1453–98.
- Fajgelbaum, P., Grossman, G. and Helpman, E. (2011). 'Income distribution, product quality, and international trade', *Journal of Political Economy*, vol. 119(4), pp. 721–65.
- Falvey, R. and Kierzkowski, H. (1987). 'Product quality, intra-industry trade and (im)perfect competition', in (H. Kierzkowski, ed.), *Protection and Competition in International Trade*, pp. 495–511, Oxford: Basil Blackwell.
- Fieler, A.C. (2011). 'Nonhomotheticity and bilateral trade: evidence and a quantitative explanation', *Econometrica*, vol. 79(4), pp. 1069–101.
- Flam, H. and Helpman, E. (1987). 'Vertical product differentiation and North–South trade', *American Economic Review*, vol. 77(5), pp. 810–22.
- Foster, L., Haltiwanger, J. and Syverson, C. (2008). 'Reallocation, firm turnover, and efficiency: selection on productivity or profitability?', *American Economic Review*, vol. 98(1), pp. 394–425.
- Gancia, G. and Zilibotti, F. (2009). 'Technological change and the wealth of nations', *Annual Review of Economics*, vol. 1, pp. 93–120.
- Hallak, J.C. (2006). 'Product quality and the direction of trade', *Journal of International Economics*, vol. 68(1), pp. 238–65.
- Hallak, J. C. (2010). 'A product-quality view of the Linder hypothesis', *Review of Economics and Statistics*, vol. 92(3), pp. 453–66.
- Hallak, J.C. and Schott, P.K. (2011). 'Estimating cross-country differences in product quality', *Quarterly Journal of Economics*, vol. 126(1), pp. 417–74.

- Hallak, J.C. and Sivadasan, J. (2009). 'Firms' exporting behavior under quality constraints', Working Paper No. 14928, NBER.
- Helpman, E., Melitz, M.J. and Yeaple, S.R. (2004). 'Export versus FDI with heterogeneous firms', *American Economic Review*, vol. 94(1), pp. 300–16.
- Hummels, D. and Klenow, P. (2005). 'The variety and quality of a nation's exports', *American Economic Review*, vol. 95(3), pp. 704–23.
- Hummels, D. and Skiba, A. (2004). 'Shipping the good apples out? An empirical confirmation of the Alchian-Allen conjecture', *Journal of Political Economy*, vol. 112(6), pp. 1384–402.
- Hunter, L. (1991). 'The contribution of non-homothetic preferences to trade', *Journal of International Economics*, vol. 30(3–4), pp. 345–58.
- Johnson, R.C. (2012). 'Trade and prices with heterogeneous firms', *Journal of International Economics*, vol. 86(1), pp. 43–56.
- Katayama, H., Lu, S. and Tybout, J. (2009). 'Firm-level productivity studies: illusions and a solution', *International Journal of Industrial Organization*, vol. 27(3), pp. 403–13.
- Khandelwal, A.K. (2010). 'The long and short (of) quality ladders', *Review of Economic Studies*, vol. 77(4), pp. 1450–76.
- Klette, T.J. and Griliches, Z. (1996). 'The inconsistency of common scale estimators when output prices are unobserved and endogenous', *Journal of Applied Econometrics*, vol. 11(4), pp. 343–61.
- Kneller, R.A. and Yu, Z. (2008). 'Quality selection, Chinese exports and theories of heterogeneous firm trade', Discussion Paper 08/44, GEP, University of Nottingham.
- Kugler, M. and Verhoogen, E. (2009). 'Plants and imported inputs: new facts and an interpretation', *American Economic Review: Papers and Proceedings*, vol. 99(2), pp. 501–7.
- Kugler, M. and Verhoogen, E. (2012). 'Prices, plant size, and product quality', *Review of Economic Studies*, vol. 79(1), pp. 307–39.
- Levinsohn, J. and Petrin, A. (2003). 'Estimating production functions using inputs to control for unobservables', *Review of Economic Studies*, vol. 70(2), pp. 317–42.
- Manasse, P. and Turrini, A. (2001). 'Trade, wages and superstars', *Journal of International Economics*, vol. 54(1), pp. 97–117.
- Manova, K. and Zhang, Z. (2012). 'Export prices across firms and destinations', *Quarterly Journal of Economics*, vol. 127(1), pp. 379–436.
- Markusen, J.R. (1986). 'Explaining the volume of trade: an eclectic approach', *American Economic Review*, vol. 76(5), pp. 1002–11.
- Markusen, J.R. (1995). 'The boundaries of multinational enterprises and the theory of international trade', *Journal of Economic Perspectives*, vol. 9(2), pp. 169–89.
- Martin, J. (2010). 'Mark-ups, quality and transport costs', Working Paper No. 2010–17, CREST.
- Matsuyama, K. (2000). 'A Ricardian model with a continuum of goods under non-homothetic preferences: demand complementarities, income distribution, and North–South trade', *Journal of Political Economy*, vol. 108(6), pp. 1093–120.
- Melitz, M.J. (2003). 'The impact of trade on intra-industry reallocations and aggregate industry productivity', *Econometrica*, vol. 71(6), pp. 1695–725.
- Melitz, M.J. and Ottaviano, G. (2008). 'Market size, trade, and productivity', *Review of Economic Studies*, vol. 75(1), pp. 295–316.
- Murphy, K.M. and Shleifer, A. (1997). 'Quality and trade', *Journal of Development Economics*, vol. 53(1), pp. 1–15.
- Olley, G.S. and Pakes, A. (1996). 'The dynamics of productivity in the telecommunications equipment industry', *Econometrica*, vol. 64(6), pp. 1263–97.
- Parisi, M.L., Schiantarelli, F. and Sembenelli, A. (2006). 'Productivity, innovation and R&D: micro evidence for Italy', *European Economic Review*, vol. 50(8), pp. 2037–61.
- Rauch, J.E. (1999). 'Networks versus markets in international trade', *Journal of International Economics*, vol. 48(1), pp. 7–35.
- Schott, P.K. (2004). 'Across-product versus within-product specialization in international trade', *Quarterly Journal of Economics*, vol. 119(2), pp. 647–78.
- Stokey, N. (1991). 'The volume and composition of trade between rich and poor countries', *Review of Economic Studies*, vol. 58(1), pp. 63–80.
- Sutton, J. (1991). *Sunk Costs and Market Structure: Price Competition, Advertising, and the Evolution of Concentration*, Cambridge, MA: MIT Press.
- Sutton, J. (1998). *Technology and Market Structure: Theory and History*, Cambridge, MA: MIT Press.
- Sutton, J. (2007). 'Quality, trade and the moving window: the globalisation process', *ECONOMIC JOURNAL*, vol. 117(524), pp. F469–98.
- Van Biesebroeck, J. (2007). 'Robustness of productivity estimates', *Journal of Industrial Economics*, vol. 3(55), pp. 529–69.
- Verhoogen, E. (2008). 'Trade, quality upgrading and wage inequality in the Mexican manufacturing sector', *Quarterly Journal of Economics*, vol. 123(2), pp. 489–530.