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TRADE SHOCKS, PRODUCT MIX ADJUSTMENT AND PRODUCTIVITY GROWTH IN ITALIAN MANUFACTURING

by Maria Gabriela Ladu*, Andrea Linarello** and Filippo Oropallo***

Abstract

In this paper we use firm-level data on the universe of Italian manufacturing multi-product exporters to test whether demand shocks in export markets lead multi-product exporters to increase their productivity. The main mechanism behind the documented productivity gains is the reallocation of resources across products within firms (Mayer et al., 2014 and 2016). Intuitively, the increased demand stemming from foreign markets will induce firms to adjust their product-mix by moving inputs from low to high productive/profitable uses. We find that these productivity gains are significant and account for about 30 per cent of aggregate productivity growth in the manufacturing sector.

JEL Classification: D22, F14.
Keywords: Italian manufacturing sector, export, trade shocks, productivity.

Contents

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1. Introduction[1]

The allocation of resources is an important determinant of aggregate productivity growth (Olley and Pakes, 1996; Restuccia and Rogerson, 2008; Hsieh and Klenow, 2010). Until now, the literature has addressed these broad issues by focusing on the entry and exit of firms, as well as on the contribution of reallocation of productive inputs among incumbent firms with different productivity levels (see Hopenhayn, (2014), for a review of the literature). Intuitively, the larger the share of productive inputs deployed in more productive firms and the higher (lower) the productivity level of entering (exiting) firms, the higher the level of aggregate productivity. Motivated by the empirical evidence on US firms about the importance of multi-product firms in terms of output, employment and value added share in manufacturing and the pervasiveness of firm-level adjustments in the product mix (Bernard et al., 2010), recent theoretical and empirical research in the international trade literature has focused on multi-product exporting firms and shows how foreign demand shocks can lead to an increase in these firms' efficiency through the reallocation of resources across different products (Mayer et al., 2014, 2016; henceforth MMO). While very close in spirit to the traditional literature on the positive effect on *aggregate* productivity growth of reallocation across firms, MMO proposes a new channel whereby within-firm reallocation across products can strengthen productivity growth at the *firm level*.

The main intuition behind this novel productivity-enhancing effect is that foreign demand shocks increase the competitive pressures faced by firms in those markets. This feature is common to several models with variable price elasticity of demand (Zhelobodko et al., 2012; Parenti et al. 2017). In these models, an increase in market size leads to an increase in competition in the destinations targeted by the firms. This implies that firms can charge lower markups for each exported product. As a consequence, multi-product exporting firms react by changing their product mix and, in particular, by moving productive inputs from their worst to their best products. In standard models of international trade (Bernard, et al., 2011) the worst and best products are defined in terms of their relative productive efficiency: the best products are those where the firm is most efficient in production and can charge a lower price, reach a larger share of consumers and hence gain higher profit margins in export markets. The ensuing reallocation of resources within firm and across products raises firm productivity.

In this paper we use firm-level data on the universe of Italian multi-product manufacturing exporters between 2001 and 2015 to test this hypothesis that was proposed and already verified on French data by MMO. In particular, our focus is on multi-product exporters which, within the manufacturing sector, account for more than 60 per cent of aggregate employment and about 80 per cent of total output. We accordingly proceed as follows. We first focus on the product mix at firm level. In particular, we rank a firm's exported products according to their shares over the firm's total exports. This allows us to define as best products those with the highest export share. Next we relate the skewness indicator to destination market-specific measures of competition to test the hypothesis that firms facing stronger competitive pressures choose to concentrate more on their sales of best products. Finally, we move to firm-level productivity (measured as real revenue per worker). For

[1] We wish to thank Matteo Bugamelli, Andrea Lamorgese, Francesca Lotti and Paolo Sestito for helpful discussion. The views expressed herein are those of the authors alone and do not necessarily reflect those of the Bank of Italy and of ISTAT. All remaining errors are our own. Corresponding author: andrea.linarello@bancaditalia.it.

each firm, we build a firm-specific trade shock as a weighted average of the changes of total imports of each destination market for each product, where weights are given by the share of that product-market pair over the firm's total exports. When relating this trade shock to firm-level productivity in a regression framework where we control for sector trends and firm-fixed effects, we find that positive trade shocks lead to an increase in firm productivity.

One important drawback of our analysis is that we cannot directly observe how inputs are allocated within firms across exported products and therefore we are unable to provide direct evidence about the mechanisms behind the observed changes in productivity. Nonetheless, we perform some robustness tests to rule out alternative explanations. In particular, we show that the link between trade shocks and productivity growth is absent among single product firms and it is not driven by changes in prices, markups, scale effects and technology. Finally, in the remainder of the paper, we show that the aggregate productivity gains stemming from the reallocation of resources among multi-product manufacturing exporters, are sizeable and account for about 30 percent of aggregate productivity growth in the manufacturing sector.

Our paper is related to the growing literature on the effect of exports on firm productivity growth. While early works have found little evidence of a causal effect of exports on firm productivity growth (Clerides et al., 1998), more recent contributions have consistently documented that exports can improve firm performance (De Loecker, 2007; Voigtländer et al., 2018). More interesting, however, is the debate about the channels through which this can happen. Some works have documented that increases in productivity are driven by technology adoption (Bustos, 2011) or investment (Lileeva et al., 2010). In a series of recent works, Mayer et al., (2014, 2016) propose a novel channel for productivity growth: the reallocation of resources across product lines within firms. Our contribution to this literature is to document those productivity gains for the Italian economy and, in particular, to quantify the overall contribution to aggregate productivity growth.

The remainder of the paper is structured as follows. In section 2 we describe the dataset. Section 3 is devoted to the evidence on the product mix while sections 4 and 5 contain the regression analysis of productivity and trade shocks. In section 6 we quantify the aggregate productivity gains due to trade shocks. Section 7 concludes.

2. Data and variable definitions

In our empirical analysis we use firm-level data on the universe of Italian multi-product manufacturing exporters over the period 2001-15. We exclude from our sample intermediaries because, despite their relevance in determining aggregate trade flows (Bernard et al., 2015), we expect the reallocation mechanism across product line to be more relevant among manufacturing firms. The dataset merges two sources: the Business Registry (ASIA) covering the universe of Italian firms that contains information on industry classification (4-digit Nace rev. 2), the number of persons employed and turnover,[2] along with data on all Italian exports disaggregated by exporting

[2] For a detailed description of this part of the dataset see Abbate, Ladu and Linarello (2017) and Linarello and Petrella (2017).

firm, products (classified according to the 6-digit HS combined nomenclature classification) and destination market.[3]

In our empirical analysis we will rely on two different samples of data. In the first one, full sample, we will include the universe of multi-product manufacturing exporters without imposing any further restriction. Notwithstanding the quality and the richness of our data, one key drawback in the full sample is that productivity can only be measured as real sales per worker. Because productivity measures based on real output are sensitive to input substitution (e.g. outsourcing), we will therefore build a restricted sample that includes all firms with balance sheet information. According to Italian law, only incorporated firms must report their account with annual balance sheets. This restriction will allow us to measure labor productivity as real value added per worker and revenue total factor productivity (TFPR),[4] as well as a set of additional controls that we will use to test the robustness of our results, but only on a subsample of firms.

Table 1 reports some descriptive statistics from the universe of manufacturing exporters. On average we observe 70,000 exporting firms per year employing 2.4 million of workers with exports worth some 260 billion of euros. In our empirical analysis we focus on multi-product manufacturing exporters that represent only 40 per cent of manufacturing exporting firms, but account for 90 per cent of total manufacturing exports. Multi-product manufacturing exporters sell on average 10 products to 13 destinations. The fact that multi-product exporters dominate aggregate trade flows in manufacturing is shared with many other countries (see Wagner, 2016, for a review of the empirical literature). Multi-product manufacturing exporters are also prominent in the manufacturing sector as a whole: they may represent a small share of firms (about 16 per cent) but they account for more than 60 per cent of aggregate employment and about 80 per cent of total output.

As already mentioned above, in the full sample we compute revenue productivity at the firm level as real sales per worker. Throughout the period 2001-15, productivity increased on average by 1 per cent per year, recording a negative annual growth rate in the recessionary phases. As shown in figure 1, the productivity growth rate in the sample of multi-product manufacturing exporters used in our empirical analysis is remarkably similar to that of the universe of Italian exporters as a whole. This is partly due to the fact that multi-product manufacturing exporters account for a disproportionate share of real output and employment, but partly also suggests that their productivity dynamic is of particular importance both for Italian manufacturing exporters and for the manufacturing sector as a whole.

[3] For shipments to the EU, detailed product-destination information is available only for firms whose total annual exports exceed €250,000; firms that export below this threshold can choose to report under a simplified scheme without supplying details on product and export destinations. For exports outside the EU, the threshold in terms of annual values goes down to €1,000.

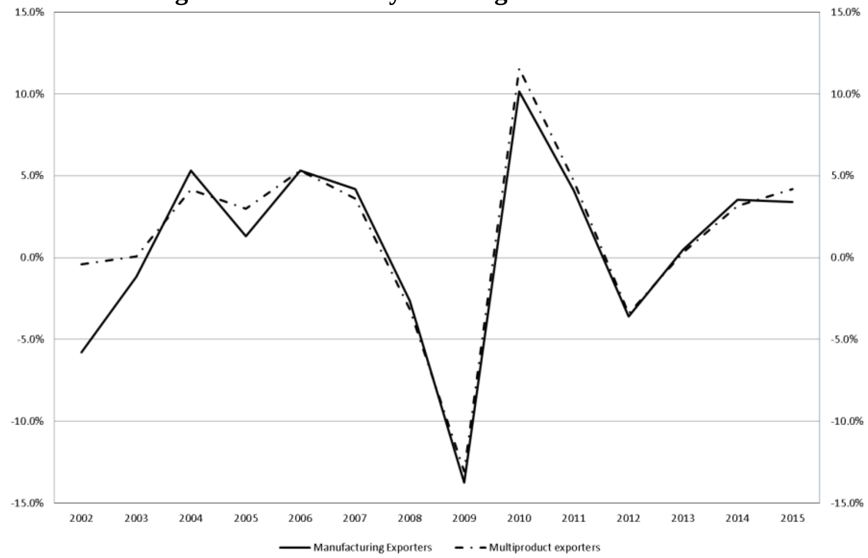
[4] We estimate TFPR as a residual of a Cobb-Douglas value added production function following the Wooldridge (2009) methodology to estimate output elasticities. Capital is measured as the book value of tangible asset. Employment is measured in headcounts. We estimates the production function for each 2-digit sector in the manufacturing sector separately. Because we do not observe firm-specific output and input prices, we follow the literature and call our measure of productivity TFPR, to stress that it can reflect both changes in technical efficiency as well changes in prices and markups.

Table 1. Descriptive statistics: Number of firms, aggregate exports, employment and the importance of multiproduct firms in manufacturing

	Manufacturing Exporters					Manufacturing Multi-product exporters				
	Number of firms	Employment (million)	Exports (billions of euros)	Exports (growth rate)	Productivity (sales per worker)	Share of firms	Share of exports	Share of employment	Number of Products	Number of Destinations
2001	69541	2.5	197.7		233169	40.7%	87.7%	72.7%	10.0	11.6
2002	70838	2.5	198.7	0.5%	240678	45.0%	91.7%	77.5%	10.3	12.0
2003	70057	2.5	195.7	-1.6%	233434	44.4%	92.5%	77.0%	10.4	12.2
2004	68184	2.5	216.2	10.5%	231022	44.7%	91.1%	76.8%	10.4	12.4
2005	65143	2.4	223.5	3.4%	249535	45.2%	91.9%	76.5%	10.5	12.8
2006	66530	2.4	250.2	11.9%	259660	44.4%	92.0%	76.0%	10.6	13.1
2007	64392	2.5	280.1	12.0%	282128	44.9%	91.5%	76.6%	10.7	13.3
2008	64261	2.4	280.5	0.1%	303173	43.2%	90.1%	75.9%	10.6	13.4
2009	61972	2.4	220.0	-21.6%	307183	42.3%	90.1%	74.9%	10.0	13.0
2010	66432	2.4	257.2	16.9%	254905	41.1%	90.4%	74.3%	10.3	13.4
2011	67223	2.4	289.7	12.6%	288788	41.5%	91.2%	74.7%	10.4	13.6
2012	67962	2.4	296.2	2.2%	313421	40.8%	91.6%	74.6%	10.4	13.7
2013	68458	2.3	304.1	2.7%	305445	40.6%	91.1%	75.2%	10.4	13.8
2014	68284	2.3	313.1	3.0%	306147	40.2%	89.8%	74.6%	10.6	14.0
2015	68672	2.3	324.4	3.6%	315863	35.0%	87.7%	70.7%	10.6	14.1

Notes. Table 1 displays descriptive statistics of our final sample of data. Column 1 reports the number of manufacturing exporters, i.e. firms with detailed information on the products and destination of exports. Column 2 displays total employment. Columns 3 and 4 show total exports and growth rates. Column 5 reports aggregate productivity, measured as total revenues over total employment. Columns 6, 7 and 8 show the share of multi-product manufacturing exporting firms and their share of exports and employment computed over the corresponding figure for the manufacturing exporters as a whole. The last two columns report the average number of products sold and the average number of destinations reached by multi-product manufacturing exporters.

Figure 1. Productivity annual growth rate 2001-15



Notes: The solid line shows the productivity growth rate computed for the universe of manufacturing exporters; the dashed line shows the productivity growth rate for the sample of multi-product manufacturing exporters used in the analysis.

To identify a relationship between trade shocks and firm productivity we build a firm-specific trade shock faced by firms in foreign markets exploiting the information on products and the destination of trade flows at the firm level. In particular, consider a firm *i* which exports a product *p* to destination *d* and the first year t_0 it appears in our dataset. We define a firm-specific trade shock as the growth of total imports (excluding Italy) of product *p* by the destination country *d* for all product-destination pairs where the firm recorded exports at t_0. We exclude Italy to ensure that changes in imports in destination countries are not driven by supply factors driven in turn by changes in the Italian manufacturing firms. Let $\Delta \log M_{pdt}$ indicates the changes in imports into *d* of product *p* from the world excluding Italy. Our trade shock can be written:

$$\Delta Trade\ shock_{it} = \sum_{p,d} \frac{x_{ipdt_0}}{x_{it_0}} \Delta \log M_{pdt}$$

Where the weights $\frac{x_{ipdt_0}}{x_{it_0}}$ represent firms' initial shares of export of product *p* to destination *d* over total exports. We keep the weights constant at the beginning of the period to make sure that changes in trade shocks do not reflect product mix adjustment. This shock aggregates only across export markets and it does not reflect the degree of exposure to foreign demand shocks; therefore we rescale it using export intensity:

$$\Delta Trade\ shock_{it} = \frac{x_{it_0}}{x_{it_0} + d_{it_0}} \sum_{p,d} \frac{x_{ipdt_0}}{x_{it_0}} \Delta \log M_{pdt} \qquad (1)$$

where $\frac{x_{it_0}}{x_{it_0} + d_{it_0}}$ is the ratio between exports and total revenues, given by the sum of export sales (x_{it_0}) and domestic revenues (d_{it_0}), to obtain an overall measure of exposure to foreign trade shock at firm level.

3. Skewness of exported product mix

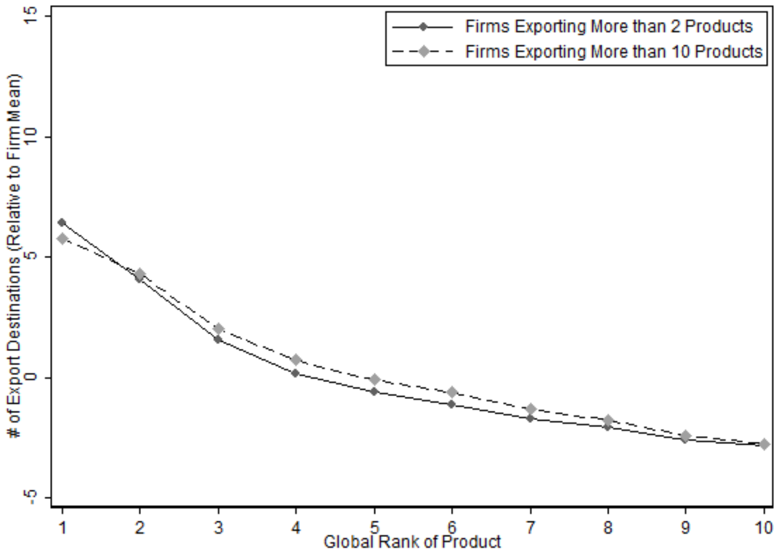
As a first step we investigate whether firms have best performing products that are sold in many markets. In order to do that, we need a measure of a firm's product ladder. In theoretical models of multi-product firms, best performing products are defined in terms of productivity (or production costs), which is unobservable in our data at the product level.[5] As an alternative observable characteristic, following MMO we define the best performing products in terms of export shares. We build two product rankings: a global rank of all the products exported by a firm; and a local rank of the products sold in each destination. These rankings are computed annually for each firm in our sample.

By definition, global rankings do not vary across destinations but local rankings can do. The Spearman rank correlation between a firm's local and global rankings, in each export market destination, is 0.62. We computed the rank correlation for different samples where we gradually restrict to firms that export many products to many markets. The rank correlation remains remarkably stable and high across the different cuts of the data, even if we find that it slightly decreases when we restrict the sample to firms exporting more than 50 products to more than 50 destinations (0.57). In figure 2 we provide further evidence that best performing products are exported to many markets. For each product, sorted on the horizontal axis according to its global ranking, we plot the ratio between the average number of destinations reached by that product and the average number of destination reached by the firm computed across all products. Suppose, for example, that a firm sell its best performing product to 10 destinations and on average it reaches 2 markets. The ratio will be equal to 5 (=10/2) and it would imply that the best performing product is sold to a number of destinations 5 times larger than the average product. As expected, products with lower global rankings are exported to fewer destinations; on average, the best performing product is exported to around five more destinations relative to firm mean.

As discussed above, the theoretical literature predicts that the increased competitive pressures generated by demand shocks faced by firms in foreign markets should trigger the reallocation of resources across products within firms. We start by analyzing if in the cross section in more competitive markets export sales are more concentrated in best performing products. We use firm's global and local product rank to construct measures of its destination-specific skewness of sales as the ratio of a firm's export sales to every destination for its best performing product relative to its next best performing product (globally and locally).

[5] Productivity at the product level is rarely measured due to data limitations, in particular, the unavailability of inputs usage at product level makes the estimation of multi-product production function cumbersome. The few exceptions to this rule include De Loecker et al., (2016) on Indian data, Garcia-Marin and Voigtländer (2019) and Lamorgese et al., (2014) on Chilean data; moreover, even when physical productivity can be measured at product level, it is difficult to build rankings across products due to differences in units of measurement.

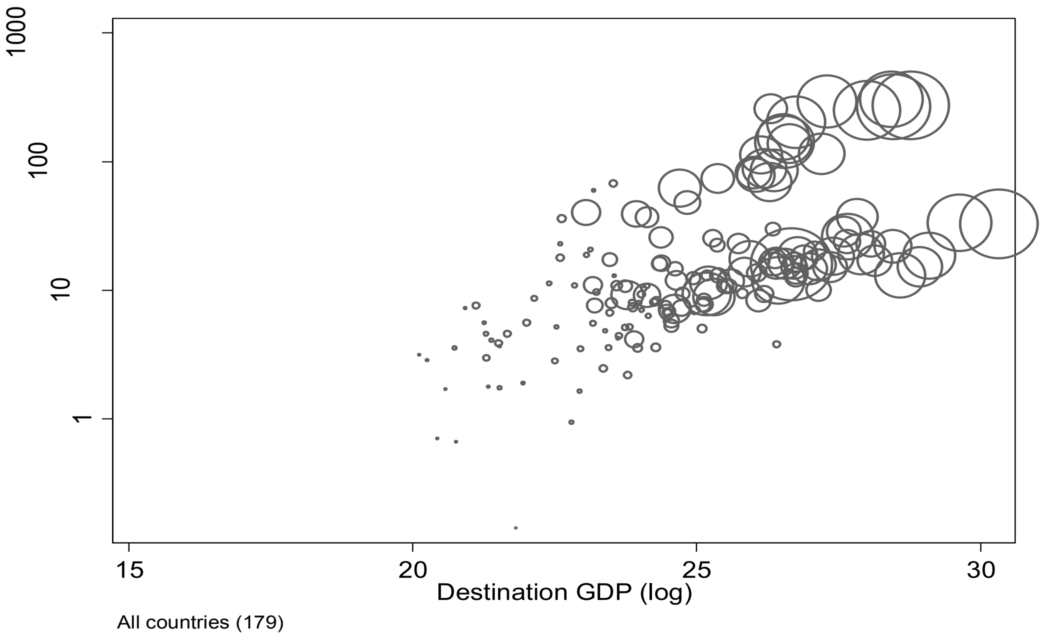
Figure 2. Number of export destinations as a function of a product's global rank



Notes. Figure 2 plots the average number of export destinations for a product as a function of its global ranking. The number of destinations is measured relative to the firm-mean number of destinations (across products).

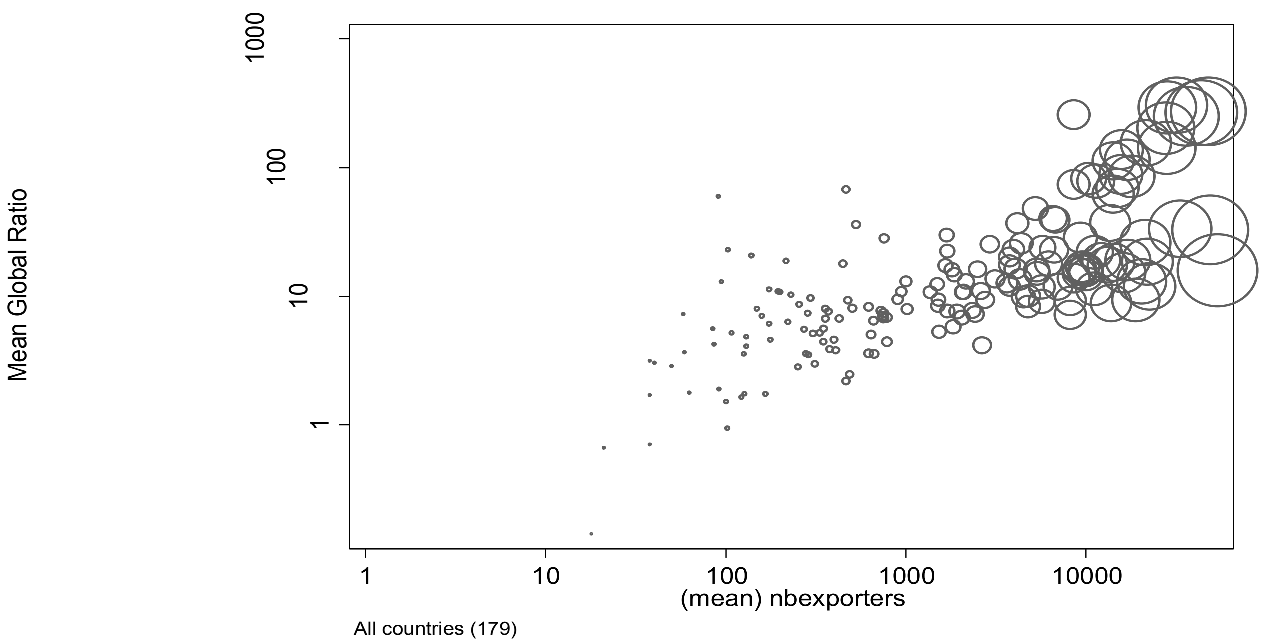
Figures 3 and 4 show the relation between the average global ratio across firms in a given destination and the GDP and the number of Italian exporters in that destination. As we can see, there is a very strong positive correlation between the concentration of export sales in the best performing product in a given destination and the measures of market size and the number of competitors in that destination.

Figure 3. Mean global ratio and destination country GDP in 2005



Notes. Figure 3 shows the correlation between the global ratio and destination country GDP. The global ratio is constructed as the ratio of a firm's export sales to every destination for its best performing product relative to its next best performing product.

Figure 4. Mean global ratio and number of Italian exporters in destination Country in 2005



Notes. Figure 4 shows the correlation between the global ratio and a combined measure of the toughness of competition constructed by using the number of Italian exporters to a destination. It clearly shows the existence of a strong relationship between the global ratio and this measure of competition.

As a second step in our analysis, we investigate whether an increase in competition faced by firms in destination markets leads to an increase in the sales of the best performing product and a decrease of the sales of the other products, thus leading to an increase in the skewness of sales towards best performing products. We test this correlation in a regression framework using the following model:

$$\Delta \ln Skewness_{it} = \alpha + \beta \cdot \Delta\, Trade\ shock_{\mathrm{it}} + \delta_{jt} + \varepsilon_{it} \qquad (2)$$

The dependent variable is a firm specific measure of skewness and the main explanatory variables are the firm specific trade shocks (see eq. 1). All regressions include industry*time fixed effects (δ_{jt}). We use three different measures of skewness. In the first column we use the log change in the Theil index. An increase in the Theil index implies that the distribution of exports become more concentrated. In the second column we use the change in the export share of the core product. Finally, in the third column, we use the log change in the sales ratio of the first relative to the second best performing product. For each firm we first measure the skewness by destinations and, second, we aggregate them at firm level using destination specific time-invariant export shares measured at the beginning of the period. Table 2 reports the results.

Consistent with the theoretical prediction of the MMO model and the cross-sectional evidence provided before, the results show that an increase in competition faced by firms in foreign markets lead to an increase in the concentration of export sales into the best performing products. The results are robust to the different measures of export skewness.

Table 2 : Skewness and trade shocks

	$\Delta \log Theil_{it}$	Δ *share core products*	$\Delta \log(\frac{Export(1)}{Export(2)})$
$\Delta Trade\ shock_{it}$	0.553***	0.00620*	0.0978***
	[0.0698]	[0.00361]	[0.0252]
Observations	331212	331772	331544
R-squared	0.013	0.012	0.011

Notes: Table 2 displays the correlation between the change in the average Theil index (column 1), the change in the average export share of core products (column 2), and the change in the average local ratio – export of core products relative to the second best performing products. Averages across destinations at firm levels are calculated using destination export shares at the beginning of the period. All regressions also include industry-year fixed effects. Robust standard errors in parentheses are clustered at the firm level. Significance *** p<0.01, ** p<0.05, * p<0.1

4. Trade shocks and productivity

In the previous sections we provided some evidence that (i) multi-product firms have best performing products sold in many markets, (ii) the concentration of exports in best performing products is higher in larger and more competitive markets and (iii) an increase in competition faced by firms in foreign markets leads to an increase in the concentration of sales in top products. We now analyze the effect of an increase in competition on productivity. As discussed above, we will rely on two different samples; in the full sample our measure of productivity is real revenue per worker; in the restricted sample we will measure productivity as real value added per worker.

Figure 5. Productivity growth and trade shocks (averages 2001-15)

Notes. Figure 5 shows the relationship between firm-level productivity growth and a trade shock. On the horizontal axis we categorize firms according to the distribution of a trade shock conditional on industry*year fixed effects. Productivity growth (on the vertical axis) is measured as the log difference in real revenue per worker, again conditional on industry*year fixed effects.

Figure 5 shows the relationship between firm-level productivity growth and trade shock. We plot productivity gains against the trade shock by regressing them on industry–year pair fixed effects plotting the residuals. Productivity growth (on the vertical axis) is measured as the log difference in revenue per worker. We find a very strong positive response of firm productivity to changes in trade shock in foreign markets.

In Table 3 we generalize this result by running the following regression:

$$\Delta \ln PROD_{it} = \alpha + \beta \cdot \Delta\, Trade\ shock_{\text{it}} + \delta_{jt} + \delta_i + \varepsilon_{it} \qquad (3)$$

where the dependent variable is the log difference of measures of firm productivity and the main explanatory variable is the firm-specific trade shock (see eq. 1); we also add to the regression industry-time fixed effects (δ_{jt}) to account for common demand and supply shocks that can affect productivity, and firm-fixed effects (δ_i) to account for unobservable time-invariant firm heterogeneity. In the first three columns we report the results for the full sample of multi-product manufacturing exporters. An increase in trade shock leads to an increase in firm productivity, in all columns the coefficients are positive and statistically significant. In the first column we add industry and time-fixed effects separately, in the second column we add industry*time fixed effects, while in the third column we include also firm fixed effects. In the second and third columns, even though the point estimates are halved, they remains highly significant. A one-standard-deviation increase in the trade shock raises firm productivity by 0.5 per cent per year.

In the last three columns of table 3 we run our regression on the restricted sample; in column 4 we use as dependent variable real output per worker and in the following two columns we use real value added per worker and TFPR. In both cases the results are confirmed and we find a positive and significant effect of trade shocks on firms' productivity. Interestingly, the effect of trade shocks on real output per worker are remarkably similar to the one estimated in column 2, suggesting the selection bias should not be a major concern when working on the restricted sample.

Table 3. Impact of trade shock on firm productivity

	(1)	(2)	(3)	(4)	(5)	(6)
		Full sample			Restricted sample	
Dep. Var.	$\Delta \ln PROD_{it}$	$\Delta \ln PROD_{it}$	$\Delta \ln PROD_{it}$	$\Delta \ln PROD_{it}$	$\Delta \ln VA\ PROD_{it}$	$\Delta \ln TFPR_{it}$
$\Delta Trade\ shock_{it}$	0.147***	0.0793***	0.0968***	0.114***	0.107***	0.102***
	[0.00832]	[0.00836]	[0.00931]	[0.00980]	[0.0135]	[0.0140]
Year FE	*YES*					
Industry FE	*YES*					
*Industry*year FE*		*YES*	*YES*	*YES*	*YES*	*YES*
Firm FE			*YES*	*YES*	*YES*	*YES*
Observations	345000	345000	345000	260114	260114	244953
R-squared	0.052	0.078	0.206	0.214	0.169	0.169

Notes. Table 3 displays the correlation between the change in productivity and the change in trade shocks. Columns 1, 2, and 3 report the regressions using the whole sample of multi-product manufacturing exporting firms. The last 3 columns report the regressions using the sample of multi-product manufacturing exporting firms with balance sheet information. In columns 1 to 4, productivity is measured as real sales per worker. Column 5 uses real value added per worker as a measure of productivity, while column 6 uses TFPR. Robust standard errors are in parentheses (clustered at the firm level): *** p<0.01, ** p<0.05, * p<0.1

5. Robustness and additional results

Given our crude measure of productivity and our trade shock the interpretation of our results merits some discussion. An increase in measured productivity, i.e. real output per worker, could reflect both an increase in productivity due to the more efficient allocation of resources across products within the firm, but also to changes in sales, prices and markup simply driven by an increase in the potential demand for exports faced by firms in the foreign market as measured by our trade shock. These alternative stories can be problematic because they cast doubt on the interpretation of our results in light of the reallocation mechanism discussed above. Unfortunately, due to data limitation, we are unable to assess to what extent firms allocate more resources to their best performing products, because we do not observe directly how inputs are allocated to different product lines. Nonetheless in the remainder of this section, we provide some evidence that will exclude alternative mechanisms that could lead to an increase in productivity at firm level following a trade shock.

We begin by showing that the baseline results do not hold consistently among single product firms. If the underlying mechanism driving the growth of productivity was the reallocation of resources across products within firms, we would expect those gains to be absent among single product firms. In the first two columns of table 4 we replicate our baseline regression on the full sample of single product exporters. In the first column, where we control for time and industry-fixed effects separately, the estimated coefficient is positive and significant. In the second column, where we add time*industry fixed effects the point estimates almost halved and lost significance. In the last two columns we run our baseline regression on the restricted sample, using both real output and real value added productivity measures. Again, we do not find strong evidence of an increase in productivity among single product firms. While these results support the idea that reallocation within the firm can be an important channel at work, it does not exclude, however, that other mechanisms could be at play.

Table 4. Single product firms

	(1)	(2)	(3)	(4)
	Full sample		Restricted sample	
Dep. Var.	$\Delta \ln PROD_{it}$	$\Delta \ln PROD_{it}$	$\Delta \ln PROD_{it}$	$\Delta \ln VA\ PROD_{it}$
$\Delta Trade\ shock_{it}$	0.0737***	0.0352	0.0768**	-0.00964
	[0.0280]	[0.0281]	[0.0316]	[0.0430]
Year FE	*YES*			
Industry FE	*YES*			
*Industry*year FE*		*YES*	*YES*	*YES*
Observations	68411	68195	36007	36007
R-squared	0.025	0.071	0.120	0.116

Notes. Table 4 displays the correlation between productivity and trade shock for the subsample of single product firms. Columns 1 and 2 report the regression using the whole sample of manufacturing single product exporting firms. Columns 3 and 4 report the regression using the sample of manufacturing single product exporting firms with balance sheet information. The last column uses as a measure of productivity real value added per worker. Robust standard errors are in parentheses (clustered at the firm level): *** p<0.01, ** p<0.05, * p<0.1

One possible concern about our results is that changes in productivity could reflect changes in prices and markups, rather than changes in how efficiently resources are allocated within the firm.

An increase in foreign demand in fact could lead firms to charge higher markups and prices (Chatterjee et al. 2013, Caselli et al. 2017). In table 5 we try to address these concerns. Using detailed export data by product and destination, we build for each firm in our sample an *export price index:*

$$\Delta \ln P_{it}^{x} = \sum_{p,d} \frac{x_{ipdt-1}}{x_{it-1}} \Delta \ln P_{pdt}$$

where $\Delta \ln P_{pdt}$ are log changes in unit values (measured as the ratio between export revenues and quantity) of exported products (p), to destination (d) between two consecutive years, and the weights are the export shares computed at the beginning of the period. If the documented changes in productivity were mainly driven by changes in export prices, when including this proxy in our regression we would expect to find a positive correlation between prices and productivity and a more limited role of the trade shock. As shown in table 5 when we include the export price index to our regressions the point estimates on the trade shock variable are remarkably stable and remain highly significant.

Table 5. Controlling for changes in export prices and markups

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	$\Delta \ln PROD_{it}$	$\Delta \ln PROD_{it}$	$\Delta \ln PROD_{it}$	$\Delta \ln PROD_{it}$	$\Delta \ln VA\ PROD_{it}$	$\Delta \ln TFPR_{it}$
$\Delta Trade\ shock_{it}$	0.114***	0.110***	0.111***	0.107***	0.101***	0.0981***
	[0.00980]	[0.00980]	[0.0102]	[0.0102]	[0.0137]	[0.0141]
$\Delta \ln P_{it}^{x}$		0.0359***		0.0326***	0.0606***	0.0615***
		[0.00349]		[0.00361]	[0.00475]	[0.00484]
$\Delta Markup_{it}$			0.0525***	0.0545***	0.231***	0.190***
			[0.00973]	[0.0101]	[0.0496]	[0.0478]
*Industry*year FE*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Firm FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Observations	260114	250028	244968	242464	236046	228937
R-squared	0.214	0.216	0.220	0.221	0.176	0.174

Notes. Table 5 displays the correlation between productivity and trade shock. Column 1 reports the baseline result of column 3 in table 3 for reference. In column 1 to 4 the dependent variable is the change in log real output per worker. In column 5 we measure productivity as real value added per worker. In the last column we use the log change of TFPR. All regressions include industry*time and firm fixed effect. Robust standard errors in parentheses (clustered at the firm level): *** p<0.01, ** p<0.05, * p<0.1

One could argue that changes in export prices are not a good proxy for the overall pricing behavior of the firms, moreover changes in prices do not necessarily reflect the underlying changes in markups, because firms can reduce prices and yet increase their markups in response to an increase in competitive pressure faced in international markets. We tackle this issue by computing firm-level markups for each firm in our sample using the methodology developed in De Loecker and Warzynski (2012).[6] When we add the changes in markup to our regression, we find a positive correlation between changes in markups and changes in measured productivity and the impact of trade shocks remains positive and significant.

[6] Markups are measured by dividing output elasticities (see section 2 for a description of production function estimation) by the share of expenditure in intermediate inputs.

Another mechanism that could lead to an increase in productivity is technological upgrading. Following a positive trade shock, the increase in market size and the resulting increase in competition could provide firms with the incentive to invest in new machinery and adopt better technology. If that were the case, then the observed increase in productivity could be the result of the increase in the capital labor ratio (our proxy for technological upgrading) rather than the reallocation of resources across different product lines. In Table 6 we add as a control to our baseline regression a control for the change in capital labor ratios. This robustness is performed only on the restricted sample because our measure of capital – the book value of capital – is available only for those firms for which we have balance sheet information. The results show that an increase in the capital labor ratio is associated with an increase in firms' productivity. Nonetheless, the inclusion of this additional control does not change the point estimates of the trade shock, which remain highly significant.

Table 6. Controlling for changes in capital labor ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	$\Delta \ln PROD_{it}$	$\Delta \ln PROD_{it}$	$\Delta \ln VA\ PROD_{it}$	$\Delta \ln VA\ PROD_{it}$	$\Delta \ln TFPR_{it}$	$\Delta \ln TFPR_{it}$
$\Delta Trade\ shock_{it}$	0.114***	0.114***	0.107***	0.108***	0.102***	0.102***
	[0.00980]	[0.00973]	[0.0135]	[0.0135]	[0.0140]	[0.0140]
$\Delta \log(K/L)_{it}$		0.081***		0.085***		-0.013***
		[0.00172]		[0.00245]		[0.00253]
*Industry*year FE*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Firm FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Observations	252504	252504	252504	252504	237334	237334
R-squared	0.214	0.230	0.169	0.178	0.169	0.169

Notes. Table 6 displays the correlation between the change in productivity and the change in trade shocks. Columns 1 and 2 report the regression using real output productivity. Columns 3 and 4 report the regression using real value added productivity. Columns 5 and 6 use TFPR. All regressions include industry*time and firm fixed effects. Robust standard errors are in parentheses (clustered at the firm level): *** p<0.01, ** p<0.05, * p<0.1

As an additional robustness exercise, we try to rule out the fact that an increase in revenue per worker could simply reflect changes in input intensities or the existence of economies of scale. Suppose, for example, that in response to an increase in competition a firm becomes bigger, in the presence of economies of scale this would lead to an increase in measured productivity driven by the reduction in production costs due to scale economy rather than the reallocation of resources across products. In the first 3 columns of Table 7 we control for these effects. We divide our firms into three subsamples according to the distribution of observed employment growth over the period under investigation: increasing, stable or decreasing. If the increase in productivity were mostly driven by scale effects, one would expect the increase in productivity to be concentrated among firms with positive employment dynamics. The results show that the effect of a trade shock on firm productivity is strong in all subsamples and is not driven by firms increasing employment. Moreover, as reported in column 2, we find that productivity increases also among firms with a stable employment dynamic, i.e. among firms that employ the same amount of labor input.

Another potential confounder in our analysis is offshoring. Thanks to the advances in ICT and the reduction in trade costs, firms have reorganized their production processes across different countries. Offshoring could be problematic in the context of our analysis because it will allow firms to produce the same amount of output and value added using less labor input. To address this issue, we divide firms into three groups according to their share of imported intermediate inputs, a measure that proxy for offshoring. In the first group we classify firms that import less than 1% of their intermediate inputs, in the second group firms that import between 1% and 25%, while in the third group we include firms that buy abroad more than 25% of their inputs. The last 3 columns of Table 7 show that trade shocks increase productivity and that there is no systematic differences across firms with different share of imported inputs, suggesting that offshoring is not the main forces behind the documented productivity gains.

Table 7: Controlling for Scale Effects and Offshoring

	Changes in Employment			Import shares		
	decrease	stable	increase	Low	Medium	High
$\Delta Trade\ shock_{it}$	0.109***	0.102***	0.0852***	0.118***	0.0953***	0.136***
	[0.0239]	[0.0124]	[0.0190]	[0.0271]	[0.0149]	[0.0161]
*Industry*year FE*	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Observations	70889	159987	93784	47820	116916	77172
R-squared	0.406	0.311	0.378	0.302	0.255	0.275

Notes. Table 7 controls for scale economies and offshoring. The dependent variable is the log change in real sales per workers. We divide our firms into three subsamples according to the dynamic of employment, decreasing (first column), stable (second column) or increasing (third column), over the period 2001-15. Each firm is assigned to a column according to the observed distribution of employment growth: in the first column we include the bottom 25 percentile of firms with employment growth lower than -1.7 per cent; in the second column we include firms with employment growth between -1.7 and 1.7 per cent, corresponding to 50 per cent of firms in our sample; finally, in the last column we include firms in the top quartile of the employment growth distribution, that is with employment growth above 1.7 per cent. All regressions include industry*year and firm fixed effect. Standard errors are in parentheses (clustered at the firm level): *** p<0.01, ** p<0.05, * p<0.1

As documented in Bernard et al. (2019) many manufacturing firms engage in exporting of products that they do not produce themselves. They show that three quarters of exported products and thirty percent of export value from Belgian manufacturers are in goods that are not produced by the firm, they label this phenomenon Carry-Along Trade (CAT, henceforth). In the presence of CAT, increase in real output per worker could be due to an expansion in products sold in foreign markets but that are not produced by the exporting firm. Because CAT products are exported in small quantities, this would be compatible with both an increase in skewness and measured productivity. As documented by Bernard et al. (2018), the extent of CAT is increasing in firms productivity. In table 8 we divide firms in our sample according to their productivity level, that is, within each 4-digit industry we split firms into four quartile of the productivity distribution. If productivity gains were due to CAT exporting, we would expect to document productivity growth only among the most productive firms. Our results, instead, suggest the trade shocks increase productivity among all firms, independently of their productivity levels. It is important to notice, that while CAT could be responsible for productivity gains at the firm level, our results suggest that this is not systematically correlated with our trade shock.

Table 8. Productivity gains by productivity quartile

	(1) q # 1	(2) q # 2	(3) q# 3	(4) q# 4
Dep. Var.	$\Delta \ln PROD_{it}$			
$\Delta Trade\ shock_{it}$	0.0748*** [0.0257]	0.110*** [0.0209]	0.0911*** [0.0202]	0.0947*** [0.0187]
*Industry*year FE*	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	45542	52153	57123	62536
R-squared	0.354	0.392	0.377	0.296

Notes. Table 8 shows regression results of productivity on the trade shock by quartile of productivity distribution (reported at the top of the columns). All regressions include industry*year and firm fixed effect. Standard errors in parentheses (clustered at the firm level): *** p<0.01, ** p<0.05, * p<0.1

Finally, if the underlying mechanism of product mix adjustment in the export market is the main determinant of the observed increase in productivity, we would expect the positive effect of competition shock to be stronger among firms with higher exposure in export markets. In table 9 we estimate our regression for the different quartiles of firm export intensity (measured as exports over total sales within each 4-digit industry). Our results show that we find evidence of the existence of the trade-productivity link for firms in all quartiles, but this correlation is increasing in firm export intensity.

Table 9. Productivity gains by export intensity

	q # 1	q # 2	q# 3	q# 4
Dep. Var.	$\Delta \ln PROD_{it}$			
$\Delta Trade\ shock_{it}$	0.0444*** [0.00910]	0.0555*** [0.00974]	0.0718*** [0.0105]	0.0955*** [0.0117]
*Industry*year FE*	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	56684	67003	71620	73820
R-squared	0.317	0.330	0.331	0.265

Notes. Table 9 shows regression results of productivity on the trade shock by quartile of export intensity (reported at the top of the columns). All regressions include industry*year and firm fixed effect. Standard errors are in parentheses (clustered at the firm level): *** p<0.01, ** p<0.05, * p<0.1

6. Aggregate productivity gains

In table 10 we quantify the size of productivity gains, that is we use the micro estimates to drawn implications for aggregate productivity growth. In the first row we report average aggregate productivity growth among multi-product exporters, both for real output per worker (first column) and real value added per worker (second column) between 2001 and 2015. Following Olley and Pakes (1996), changes in aggregate productivity can be decomposed into productivity growth within firms (‘*within*’) and reallocation of resources among firms (‘*between*’). In order to quantify the aggregate effects of trade shocks we make two simplifying assumptions: first, we assume that the trade shocks are the only source of within-firm productivity growth; second, we assume that there is no reallocation, that is we keep employment shares constant at the beginning of the period.

We shut down the reallocation component because it is not possible to build a counterfactual, that is, it is not possible to predict the employment shares what would have been if within firm productivity growth changed only in response to the trade shock. For this reason, the comparison between the actual productivity growth and our counterfactual should be interpreted with all these caveats in mind.

With these two assumptions we can build a counterfactual aggregate productivity growth useful for our back-of-the-envelope quantification. For each firm in our sample we compute a predicted productivity growth by multiplying the firm level trade shock by the estimated coefficients of table 7 (that is we use different elasticities among firms with different export intensities):

$$\Delta \ln \widehat{PROD}_{it} = \hat{\beta} \cdot \Delta\, Trade\ shock_{it}$$

We then aggregate the estimated productivity gains using employment shares at the beginning of the period:

$$\Delta \ln \widehat{PROD}_{t} = \sum_{i} \Delta \ln \widehat{PROD}_{it} \cdot \frac{l_{it-1}}{L_{t-1}}$$

The second row of table 9 reports the counterfactual productivity gains; the last row reports the share of actual productivity growth explained by the trade shock. Real output per worker increased between 2001 and 2015 by almost 1 percent per year; the counterfactual productivity growth due to the firm specific trade shock is 0.4 per cent, therefore the share explained by the trade shock is about 40 per cent (=0.41/0.96).

Table 10 . Aggregate productivity gains

	Output	Value added
Aggregate productivity growth in the sample	0.96	1.29
Counterfactual productivity growth	0.41	0.40
Share of aggregate productivity growth	42.7%	31.0%

The picture for real value added productivity is slightly different: while productivity growth has been about 1.3 percent per year, the predicted productivity growth is again 0.4 per cent, therefore the share explained by the trade shock is about 30 per cent (=0.40/1.29). All in all, in our simple back-of-the-envelope calculation, among multi-product exporters the share of aggregate productivity growth explained by the trade shock is non-negligible, about 30 per cent.

7. Conclusion

In this paper we study the relation between trade shock and productivity growth. Using high quality data for Italian manufacturing exporters between 2001 and 2015, we show that positive trade shocks – measured as the increase in imports in destination countries – increase firm productivity. A one-standard deviation increases in the trade shock leads to firm productivity growth of between 0.5 and 0.7 percent per year. The main underlying mechanism behind the documented productivity growth is the reallocation of resources within the firm across product lines. Following the recent contribution by Mayer et al. (2014, 2016), we show that positive trade shocks are associated with an increase in the concentration of sales in best performing exported products. Moreover, in a series of robustness checks we show that the productivity gains are not driven by alternative mechanism that could take place when firms are hit by trade shocks (technology adoption and scale economies) and are not present among single product firms. Finally, in order to gauge the aggregate implications of our findings, we build a counterfactual productivity growth and show that trade shocks can explain a substantial share, about 30 per cent, of aggregate productivity growth.

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