Growth Welfare Innovation Productivity

Working Paper

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28/2020 September

This project has received funding from the European Union Horizon 2020 Research and Innovation action under grant agreement No 822781

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August 31, 2020

Abstract

In this article we focus on the role of exports in Chinese economic development in the era of WTO accession. We address a series of different, although connected, questions. First, do Chinese exporting and non-exporting firms differ in terms of their productivity performance and paid wages? Second, to what extent exporting and non-exporting firms have contributed to the process of convergence and catching-up? Third, does the productivity-wage pass-through differ between exporting and non-exporting firms? Overall our findings downplay the role of exporting firms as both carriers of labour productivity and wage growth for the Chinese economy. In this respect, "gains from catching-up" outweigh any "gain from trade".

JEL codes: L6, F16, D24, J31

Keywords: Export, Wage, Productivity, Trade, Event studies

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1. Introduction

Trade and economic developments are two intimately related processes as we know at least since Adam Smith. For Smith the gains from trade were unequally appropriated by the country having *absolute* advantage. Conversely, with Ricardo and even more so, with the Heckscher-Ohlin-Samuelson model, *comparative* advantages, different across goods produced by different countries, entail gains from trade for all. Gains from trade stem from internal specialization, given relative factor abundance, and yield exchanges beneficial for all countries in terms of production and consumption, due to exchange with the other countries, each one expanding its own consumption possibility frontier. As a result, the "comparative advantage view" underlies the advocacy for free trade policies, conversely the "absolute advantage view", while not denying in principle the possibility of gains from trade, is more in tune with the notion that development is essentially driven by learning and accumulation of technological and organizational capabilities rather than the exploitation of comparative advantages (Cimoli et al., 2009; Dosi and Soete, 1983).

Indeed, the gain from trade theory has seen a parabola during the last century: free trade has been strongly paddled by international institutions like the World Trade Organization (WTO thereafter) and the IMF advocating both the benefits from intra-industry trade and learning by exporting, until the 2008 crisis. In that year, the fall of the volume of international exchange has been around 10%, while, China has been among the few countries most resilient to such an enormous trade shock. Clearly, the World Factory Economy was at the time still strongly leveraging on the process of internal restructuring and on the adherence to the WTO, in 2001.

After almost twenty years since the adherence of China to the WTO, the international consensus on free trade has been loosing supporters: the big losses in terms of jobs due to international delocalization coupled with wage stagnation and increasing inequality has led the "average white American" to give his support to Donald Trump (Autor et al., 2016), who for the first time after WWII is explicitly implementing protectionist policies of the most rudimentary type, imposing tariffs and restrictions to imports exactly against those Chinese firms considered to be responsible for the huge American occupational loss, because of the effects of import penetrations. Currently, more than ten years after the 2008 crisis, the capitalist economy is facing a yet another recession with the slowing down of US-China (and Germany) trade considered as one of the causes, let alone the effects of the pandemic on international trade.

Given the current macroeconomic picture, it becomes particularly important to understand *on the Chinese side* the impact of trade liberalization which followed the adherence to the WTO. Have there been gains from trade plausibly revealed by a tendency to specialize in the sectors of traditional comparative advantage, and, within sectors, by increasing export premia – in terms of productivity and wages? Or alternatively, is the impressive export record of Chinese manufacturing mainly due to a *generalised catching-up process* involving all sectors and most firms, whether exporting or not? In order to answer, in the following we investigate: first, whether Chinese exporting and non-exporting firms differ in terms of their productivity performance and paid wages, second, the extent to which exporting and non-exporting firms have contributed to the process of convergence and catching-up, and, third, whether the productivity-wage pass-through differ between exporting and non-exporting firms.

Our results show that, first of all, exporting firms do not have any productivity and wage premia in the long-run: if present at the beginning, the premia decrease over time in level, while getting even negative in terms of growth rates. Second, after the access of China to the WTO, exporting firms in the same sector of activity show a pattern of increasing dispersion in labour productivity and wages (i.e., the within-sector/between-firms component), while the dispersion across sectors shrinks (the between-sector component), inside an overall picture of convergence and catching-up. Indeed the access to international trade had implications in terms of both exporting sectors and of their contribution to productivity growth although not of the kind which the conventional wisdom would predict. Against a purported pattern of specialization based on purely cost-competition, after the WTO the share of increasing exporting sectors in China is in technological advanced ones like manufacturing of telecommunication equipments, computers and other electric devices with a steadily decreasing share of the textile sector and other labour-intensive activities. At the same time, inside each sector the between-firm labour productivity and wage heterogeneity of export-starters increased providing evidence against any reallocation effect generated by international trade.

Did exporting firms have a different pattern of gains distribution? According to our analyses, which look at (i) heterogeneous effects along the conditional wage distribution via quantile regression analysis for three distinct populations of firms (always-exporters, never-exporters and export-starters), at (ii) average effects via a difference in difference strategy, and (iii) at timing effects via an event study, we do not find a statistically different pass-through coefficient for exporting vs non-exporting firms. If any anything, in the exporting year, firms reduce the pass-through, which becomes positive only after five years of export activity, and for high-wage firms exclusively. For the rest of exporting firms, the pass-through either remains unaltered or gets persistently negative. Overall, our findings downplay the role of exporting firms as both carriers of labour productivity and wage growth for the Chinese economy. Our study also suggests to go beyond the simple analysis of status-premia captured by a dummy variable, and instead consider the exporting and non-exporting firms as different populations.

The paper is organized as follows: Section 2 discusses the alternative sources of gains generation whether from trade or from catching-up. In Section 3 we present the data structure while in Section 4 we look at the value generation by comparing our methodology of population analysis vis-à-vis the extant analysis performed via dummy variables, showing patterns distinctly characterizing the three populations of firms. Next we perform a shift-and-share decomposition of wages and productivity dispersions to detect the different sources of heterogeneity. Section 5 addresses the firm-level link between wages and productivity by means of quantile regressions to understand how the gains are distributed. Section 6 focuses on the effect of switching status by means of a difference in difference strategy and an event study. Section 7 concludes.

2. Gains from trade and gains from catching-up: the micro perspective

Since the emergence of the "New Trade Theory" back to the eighties, the *gains from trade theory*, which sees in comparative advantage and in heterogeneity in factor endowments the source of international exchanges, has lost momentum. This occurred also due to the increasing importance of intra-industry trade, i.e. international trade occurring within the same sectors possibly due to an increase in the overall product varieties. Product diversification generating temporary monopolistic competition (with declining average costs) allows local (product-specific) economies of scale. Increasing market opportunities, product differentiation and lower prices would have benefited a large fraction of firms (Krugman, 1980, 1981).

In the "New Trade Theory" firms however were all equal. With the access to longitudinal data and the acknowledgement of firm heterogeneity, the "New New Trade Theory" finally takes on board such micro heterogeneity and interprets international exchange also as a process of cleansing: competition in the international market arena will foster reallocation from less efficient toward more efficient firms. As a result, only the best performing ones will gain market shares from international exchanges. Additionally, in this perspective not only more productive but also more innovative firms are the one dominating international trade (Melitz and Trefler, 2012).

Since the seminal contribution by Bernard and Bradford (1999), the pattern of productivity and wage growth has been shown to be only weakly different between exporters and non-exporters on the long run. However, more significant differences emerge when restricting the analysis for shorter term periods (says two-three years). At the same time, the so called theory of learning by exporting does not seem to have a strong empirical support: as the authors argue, better firms, in terms of sales, productivity and employment self-select into the exporting status; conversely being an exporter does not provide a dynamic advantage vis-à-vis non-exporting firms in terms of productivity and wages. Both Clerides et al. (1998) and Bernard and Bradford (1999) do not find evidence supporting the learning by exporting story. Lileeva and Trefler (2010), combining both exporting status and investment activity and looking at the effect of the Canada-US Free Trade Agreement for exporting firms, do find higher productivity gains from exporting for initially low-productive firms. They try to reconcile such evidence with the extant literature suggesting that for initially high-productivity firms sorting into exporting status does not cause increase in productivity growth, but the opposite occurs for low-productivity firms.

The "New New Trade Theory" has the merit to rediscover the role of heterogeneity between firms also in narrowly defined sectors, identified well before in evolutionary perspectives (Dosi, 1988; Nelson, 1991), as a crucial element to better understand the patterns of international trade. However, it basically neglects all sectoral characteristics without any attention toward heterogeneous learning and technological regimes (Pavitt, 1984). So the micro dynamic in computer chips is basically equivalent to that in potato chips (Dosi et al., 2020). And related it also neglects the different role of export at different stages of development: analyses range from the US and Canada, to Mexico, Colombia, Morocco, Brazil. However, the role of exporting activities might be indeed different for catching-up economies.

In this paper, we look exactly at the patterns of value creation and distribution for a country experiencing a dramatic process of catching-up. To analyse value creation we look at the different patterns of labour productivity and wages, in terms of levels and growth rates, characterizing domestic and international firms, and detecting sources of both within- and between-sector heterogeneity. During the period from 1998 to 2007, our window of observation, a part from the adherence to the WTO, as analysed in Yu et al. (2015), China undertook an impressive process of catching-up, characterised by a dramatic growth in labour productivity across the whole manufacturing, driven more by dynamics of *creative restructuring* of State-owned and State-participated firms rather than sheer Schumpeterian patterns of creative destruction. Indeed, the drivers of catching-up in China have been more the State-owned enterprises, and various forms of State-private ventures, than the purely private ones.

This process of catching-up is related to a dramatic increase of the so called *within* component of productivity growth, as the result of both the accumulation of firm level capabilities and the process of creative restructuring which resulted into a recomposition of the industrial structure toward the most innovative sectors and against predefined "comparative advantages". Indeed, China has demonstrated the capability to develop absolute advantages (or reduce absolute disadvantages) nowadays in the most innovative and complex sectors/products. As we shall show, the access of China to the WTO more than favouring reallocation among firms, has favoured a reallocation across sectors in a direction *opposite* to comparative advantages with textile and other labour-intensive industries loosing and ICT gaining export shares.

At the micro level, departing from the extant literature, largely focussing on the probability of becoming an "exporter", we are instead interested in capturing the persistent effects behind the exporting or non-exporting status. We therefore identify three different populations, namely always-exporters, never-exporters and export-starters, in order to follow the time evolution of each of the three categories. We shall look at the patterns pre- and post-WTO accession and characterise the distributions and the dynamics of the attributes of the three populations. To analyse the distribution of the gains generated we estimate the wage-productivity pass-through (Dosi et al., 2020) and we study how it differs among exporting and non-exporting firms.

3. Data and variables description

We draw upon firm level data from the Annual Survey of Industrial Enterprise (ASIE) collected by the National Bureau of Statistics of China (NBSC). The dataset includes all industrial firms with sales above 5 millions of RMB covering the period 1998-2007 and has already been employed in other empirical investigations, among others, Yu et al. (2015).[1] The survey covers approximately 55 to 79 million workers, accounting for about 7.5% to 10.5% of the total Chinese employment. Each firm is assigned to a sector according to the 4-digit Chinese Industry Classification (CIC) system that closely matches the Standard Industrial Classification (SIC) employed by the US Bureau of Census.[2] Out of the comprehensive set of all firms, we focus on manufacturing firms only (CIC 13 - 42).

Table 1 shows their summary statistics. The total number of employees in the manufacturing sector has increased from 50 in 1998 to 68 millions in 2007, after a fall by 5.7 millions from 1998 to 2001. The total output has increased from 5.93 to 35 trillions of RMB in the same period and the number of firms from 148 to 312 thousand units approximately. The total exports has increased from 1.05 in 1998 to 7.29 trillions of RMB in 2007. The percentage of firms involved in exporting activities increased from 23.6% in 1998 to 29.9% in 2004 but dropped to 25.2% in 2007. Their contribution to the overall sales value increased from 18.3% in 1998 to 23.4% in 2004 but dropped to 21.1% in 2007. In the analysis that follows we apply a few cleaning procedures in order to eliminate visible recording errors, yielding what we call "China Micro Manufacturing" (CMM).[3] And we keep firms existing for at least two consecutive years.

Labour productivity (π_{ijt}) is the ratio of value added (at 1998 constant prices) over the number of employees, in logs. It is deflated by the 4-digit output deflator (source: Brandt et al. 2012). Firm's total

[1] Industry is defined to include mining, manufacturing and public utilities, according to NBSC. Five millions of RMB is approximately $US 600,000.

[2] In 2003, the classification system was revised. Some sectors were further disaggregated, while others were merged together. To make the industry code comparable over time, we adopted the harmonized classification proposed in Brandt et al. (2012).

[3] We dropped firms with missing, zero or negative output, value-added, sales, original value of fixed assets, with employment < 8.

Table 1: Summary statistics (total) of the Chinese manufacturing firm-level dataset (before data cleaning)

Year	Number of Firms	%	Value Added	Sales	Output	Emp.	Sales Value	Export	%	Original value of fixed assets	Unemp insurance	Wage	Welfare	Cost of labour
1998	148 664	(23.6)	1.52	5.48	5.94	50.72	5.72	1.05	(18.34)	4.48	49.08	342.94	46.02	0.44
1999	146 078	(23.5)	1.68	5.96	6.37	47.36	6.17	1.12	(18.14)	4.85	50.71	351.01	46.19	0.45
2000	147 249	(25.0)	1.96	7.14	7.48	45.83	7.29	1.42	(19.43)	5.17	54.48	387.11	50.98	0.49
2001	155 665	(26.0)	2.22	7.99	8.40	44.96	8.18	1.59	(19.38)	5.55	32.75	416.44	54.02	0.50
2002	165 801	(27.1)	2.62	9.37	9.79	45.88	9.58	1.97	(20.51)	5.95	30.66	472.03	58.30	0.56
2003	181 013	(27.9)	3.40	12.39	12.72	48.73	12.44	2.65	(21.30)	6.59	29.57	549.62	67.84	0.65
2004	256 448	(29.9)	4.55	17.14	17.49	56.52	17.11	4.00	(23.37)	7.82	29.53	725.55	81.30	0.84
2005	250 975	(29.6)	5.71	21.34	21.74	59.22	21.29	4.71	(22.11)	9.03	34.12	885.23	101.52	1.02
2006	278 667	(28.0)	7.23	26.99	27.40	63.33	26.85	5.99	(22.29)	10.54	38.36	1090.82	123.67	1.25
2007	312 304	(25.2)	9.38	34.70	35.27	68.40	34.57	7.29	(21.08)	12.35	42.86	1415.92	139.65	1.60

Note: all values are denoted in trillions of RMB (total unemployment insurance, wage and welfare are in billions of RMB) and employment in millions of workers. All manufacturing firms are included. Numbers in brackets are the percentage of firms with positive exports and the percentage of export in total sales value. "Cost of Labour" is the sum of unemployment insurance, wage and welfare.

Table 2: Summary statistics (mean) of the dataset after cleaning

Year	Number of Firms	%	Overall				Firms with positive exports				Firms with zero exports			
			L. P.	Wage	Gr. of L. P.	Gr. of Wage	L. P.	Wage	Gr. of L. P.	Gr. of Wage	L. P.	Wage	Gr. of L. P.	Gr. of Wage
1998	108185	(26.7)	43.7	8.5	NA	NA	45.7	10.6	NA	NA	43.0	7.8	NA	NA
1999	125818	(25.5)	47.8	9.0	7.0	7.6	49.4	11.2	8.8	7.8	47.2	8.2	6.4	7.5
2000	125959	(27.1)	53.8	10.2	6.1	7.6	55.8	12.7	7.9	8.7	53.1	9.2	5.4	7.1
2001	138298	(27.7)	59.1	10.4	4.7	−0.8	58.9	12.5	3.8	−0.9	59.1	9.7	5.0	−0.7
2002	149112	(28.6)	68.0	11.0	8.3	6.7	67.4	13.0	8.1	6.8	68.3	10.2	8.4	6.7
2003	162304	(29.6)	76.5	11.9	9.9	6.3	71.1	13.8	8.8	6.4	78.8	11.1	10.4	6.2
2004	220323	(31.5)	82.2	12.6	4.7	9.0	74.6	14.3	1.6	6.8	85.6	11.9	6.5	10.2
2005	238604	(30.3)	97.0	14.4	18.1	15.6	86.5	15.8	18.7	15.2	101.5	13.8	17.8	15.7
2006	265921	(28.6)	114.1	16.6	17.1	15.8	101.9	18.6	14.7	16.0	118.9	15.8	18.2	15.7
2007	248334	(27.7)	137.0	19.2	17.7	14.0	108.0	21.7	13.1	12.5	148.1	18.3	19.5	14.6

Note: labour productivity and wages are at 1998 constant price, in 1000 RMB. Growth rates are calculated as log differences of real values over two consecutive years. Numbers in brackets are the percentage of firms with positive exports. Source: our elaboration on CMM.

labour compensation is composed of wages, unemployment insurance and welfare benefits. Wage (w_{ijt}) is the ratio of firm's total labour compensation (at 1998 constant prices) over the number of employees, in logs. It is deflated by the consumer price index (source: National Bureau of Statistics of China). The growth rate of wage (Δw_{ijt}) and productivity ($\Delta \pi_{ijt}$) is calculated as the log difference of the levels over two consecutive years ($\Delta X_{ijt} = \ln X_{ijt} - \ln X_{ij,t-1}$).

Table 2 shows the summary statistics (mean) of the interested variables for the whole sample, for exporting and non-exporting firms over the whole period. Remarkably, in terms of average productivity levels we do observe exporters dominating non-exporters during 1998-2000, while the opposite occurs during 2001-2007. In terms of wage levels, exporters do show persistently higher salaries, while no distinct pattern emerges in terms of growth rates of both variables.

Figure A.1 in the Appendix shows the fraction of exporters (i.e. exporting firms for at least one year in the panel) for different ownership types. The largest fraction of exporters is represented by HMT-invested (Hong Kong - Macao - Taiwan) and foreign-invested enterprises (FIEs): among those firms more than 60% participated to international trade. At the opposite end, the fraction of exporters in State-owned enterprises (SOEs) has slightly increased from around 14% in 1999 to 18% in 2007, while collective-owned enterprises (COEs) experienced a slightly declining trend since 2005. Both shareholding (SHEs) and private-owned (POEs) enterprises record a stable fraction of exporting firms around 20%.

4. Value creation by domestic and international firms

In order to detect which are the sources of value creation in terms of the generated productivity and paid wages, we conduct a battery of exercises meant to identify how domestic and international firms differ. We first analyse export premia (Subsection 4.1) in line with the standard practice, and we then move to identify three distinct population of firms, presenting a few statistical descriptions of their attributes (Subsection 4.2). Next, we perform a shift-and-share variance decomposition in Subsection 4.3 to understand the roots of their dispersions. Finally, we look at the process of sectoral reallocation (Subsection 4.4) to document the changing sectoral composition of export after the WTO accession.

4.1. Export premia

We start by providing evidence on the performance gap between exporting and non-exporting status by means of a standard analysis of export premia. How much better exporters are at any point in time? Table 3, columns (1)-(5), reports the export premia estimated from a regression of the form:

$$\ln \mathrm{X}_i = \alpha + \beta \, \mathrm{EXPORT}_i + \gamma \, \mathrm{SECTOR}_i + \epsilon_i \tag{1}$$

where X_i indicates one of the firm's attributes – size (proxied by the number of employees), levels of productivity and wages of firm i –; EXPORT_i is a dummy for current export status, and SECTOR_i are dummies for 2-digit (CIC) industry. The export premium, β, shows the average percentage difference between exporters and non-exporters in the same sector. Columns (3) and (5) report premia after adding an additional control for firm's contemporaneous size.

We are also interested in detecting the export premia in the growth rate of labour productivity and wage (whether firm's current exporting status at t is associated with higher productivity and/or wage growth between t and $t+1$) according to the following specification:

$$\Delta \mathrm{X}_{i,+1} = \alpha + \beta \, \mathrm{EXPORT}_i + \gamma \, \mathrm{SECTOR}_i + \epsilon_i \tag{2}$$

where $\Delta \mathrm{X}_{i,+1}$ indicates the annual growth rate of firm's attributes (as from above) in terms of the log difference between two consecutive years ($\Delta \mathrm{X}_{i,+1} = \ln \mathrm{X}_{i,+1} - \ln \mathrm{X}_i$). Table 3, columns (6)-(9), reports the export premia in the growth rate of productivity and wage. Columns (7) and (9) report premia after adding an additional control for firm's contemporaneous size.

The export premia are positive and significant for size and wage levels in all years. Exporters are 65%-70% larger than non-exporters in terms of total employment. The level of wage is 14%-36% higher for exporters, but interestingly the wage premia of exporters *declines* over time until 2005. The productivity premia of exporters declines too and becomes even negative in 2007 (productivity is 11% lower for exporters). No premia is detected in terms of productivity growth and wage growth. On the contrary, the productivity growth is 2%-9% lower for exporters, while the wage growth is 1%-5% lower. It seems therefore that over time there was a change in the composition of firms entering into exporting activity. At the beginning of the period, exporting firms were outperforming non-exporting ones in terms of wages and productivity. Over time the gap reduces and the two populations tend to overlap.

To further exploit the time structure of the dataset, the last two rows of Table 3 show the estimates using the panel data from both OLS (pooling all years and controlling for both industry and year effects) and fixed-effects (FE) (controlling for unobserved and time-invariant heterogeneity, also adding controls for industry and year effects). Pooling all years, exporters are 67% larger than non-exporters in terms of employment. The levels of productivity and wage are 12.5% and 24.3% higher for exporters, while the growth rates of productivity and wage are 6.2% and 3.5% *lower* for exporters. If we look at the within-firm variation only, exporting firms display a positive differential in both productivity (9.9%) and wage levels (5.8%), but a negative one in productivity (6.8%) and wage growth rates (4.6%).

Why are there differences between OLS and FE estimates? The selection bias is a candidate explanation (Angrist and Pischke, 2008). OLS estimates are larger than the FE estimates in all the firm attributes, meaning that firms with higher productivity and wage levels, higher productivity and wage growth rates are more likely to select themselves into exporting status. The fixed effect model partially controls for such bias in so far as it separates out the firm's time invariant unobserved characteristics. Note, however, that all signs (with just one exception) of the premia are preserved.

Table 3: Exporter premia

Year	size (t)	L.P. (t)		Wage (t)		Gr. L.P. (t+1)		Gr. Wage (t+1)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1998	0.663^a	0.174^a	0.353^a	0.319^a	0.355^a	-	-	-	-
1999	0.675^a	0.188^a	0.351^a	0.334^a	0.364^a	0.021^a	-0.022^a	0.005	-0.026^a
2000	0.683^a	0.166^a	0.322^a	0.336^a	0.363^a	0.014^b	-0.027	0.000	-0.029^a
2001	0.650^a	0.099^a	0.243^a	0.294^a	0.327^a	-0.018^a	-0.055^a	-0.008	-0.030^a
2002	0.654^a	0.067^a	0.208^a	0.271^a	0.301^a	-0.003	-0.034^a	-0.005	-0.031^a
2003	0.651^a	0.006	0.136^a	0.253^a	0.279^a	-0.027^a	-0.063^a	-0.006	-0.030^a
2004	0.644^a	-0.075^a	0.054^a	0.188^a	0.209^a	-0.050^a	-0.092^a	-0.042^a	-0.068^a
2005	0.647^a	-0.067^a	0.050^a	0.135^a	0.143^a	-0.028^a	-0.061^a	-0.007^b	-0.027^a
2006	0.692^a	-0.082^a	0.037^a	0.166^a	0.167^a	-0.041^a	-0.065^a	-0.003	-0.015^a
2007	0.706^a	-0.208^a	-0.106^a	0.184^a	0.183^a	-0.059^a	-0.087^a	-0.040^a	-0.051^a
OLS	0.669^a	-0.011^a	0.125^a	0.224^a	0.243^a	-0.028^a	-0.062^a	-0.014^a	-0.035^a
FE	0.135^a	0.014^a	0.099^a	0.029^a	0.058^a	-0.018^a	-0.068^a	-0.014^a	-0.046^a

Note: Numbers in columns (1)-(5) are coefficients of the export dummy in Regression 1. Columns (3) and (5) control firm's size. Numbers in columns (6)-(9) are coefficients of the export dummy in Regression 2. Columns (7) and (9) control for firm's size. All cross-sectional regressions include 2-digit sectoral dummies. OLS pooling all years, including both 2-digit sectoral dummies and year dummies. Fixed effects (FE) include both 2-digit sectoral dummies and year dummies. All regressions are estimated using robust standard errors. a indicates that coefficients are significant at 1% level; b indicates significant at 5% level. Source: our elaboration on CMM.

4.2. Three types of firms: "always-exporters", "never-exporters" and "export-starters"

Although revealing some firms' characteristics, the foregoing analysis mixes up the attributes of very different population of firms, namely those who have always been exporters, those who never did and those who start exporting at any point in time and keep doing it. To better distinguish the attributes of heterogeneous firms, we separate them into three groups based on their exporting behaviours.

We get 6142 firms displaying positive exports for all ten years ("always-exporters"), 10,148 firms displaying zero exports for all ten years ("never-exporters"), and variable numbers of "export-starters" and at different cohorts, from 1999 to 2007. For example, export-starters 1999 cohort captures firms with zero or missing exports in 1998 and positive exports in all the years during 1999-2007; export-starters 2000 cohort captures firms with zero or missing exports in all years during 1998-1999 and positive exports in all years during 2000-2007. Table 4 shows the numbers of always-exporters, never-exporters, the total number of export-starters and export-starters in different cohorts.

Table 4: Number of always-exporters, never-exporters and export-starters in different cohorts

Year	Always-exporter	Never-exporter	Export-starter	Export-starter in Cohort t								
				1999	2000	2001	2002	2003	2004	2005	2006	2007
1998	6142	10148	2021	460	266	177	177	165	262	143	163	208
1999	6142	10148	3582	1571	390	230	242	204	319	182	201	243
2000	6142	10148	5843	1571	1969	394	350	313	436	225	262	323
2001	6142	10148	10524	1571	1969	3495	882	567	738	374	410	518
2002	6142	10148	14282	1571	1969	3495	3527	938	1081	505	513	683
2003	6142	10148	20215	1571	1969	3495	3527	5290	1898	751	738	976
2004	6142	10148	36236	1571	1969	3495	3527	5290	14562	2211	1688	1923
2005	6142	10148	41834	1571	1969	3495	3527	5290	14562	6342	2625	2453
2006	6142	10148	49783	1571	1969	3495	3527	5290	14562	6342	8673	4354
2007	6142	10148	49879	1571	1969	3495	3527	5290	14562	6342	8673	4450

Note: export-starter 1999 cohort captures firms with zero or missing exports in 1998 and positive exports in all the years during 1999-2007; export-starter 2000 cohort captures firms with zero or missing exports in all years during 1998-1999 and positive exports in all years during 2000-2007; similar definitions for export-starter at 2001 - 2007 cohorts. Source: our elaboration on CMM.

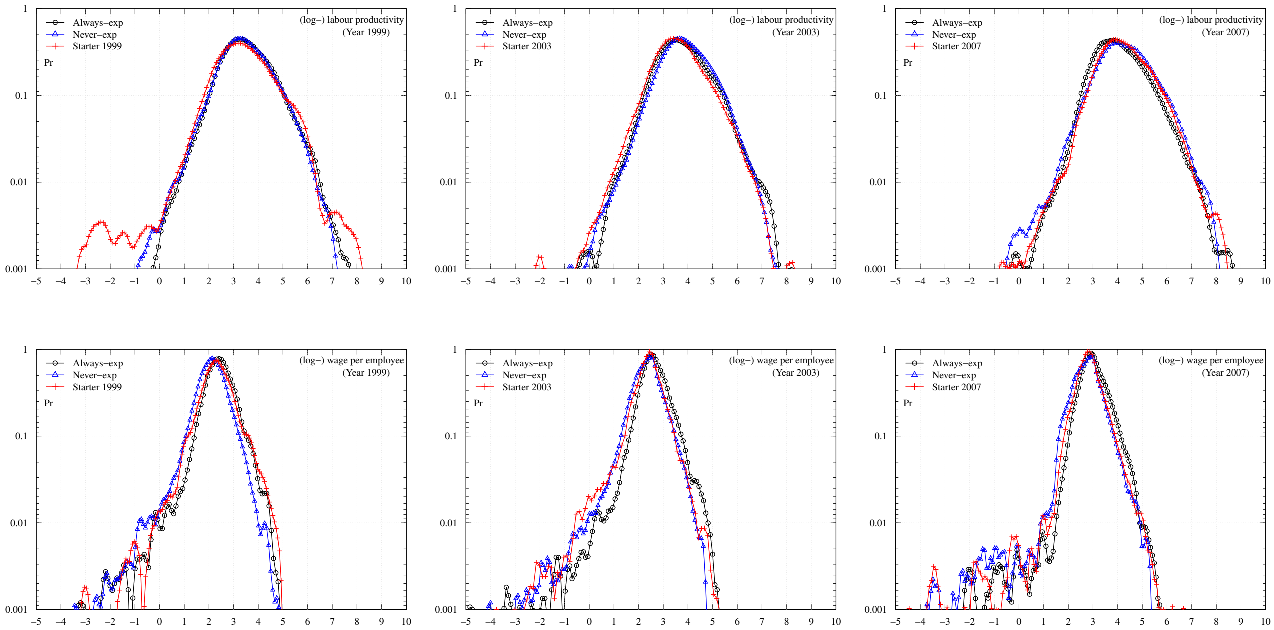
Our classification turns out to be quite important in order to capture persistent patterns in exporting and non-exporting activities and to understand whether over time the attributes of exporting firms change. This is particularly relevant given the accession to the WTO in 2001. Note that in so doing, we depart from the standard way of approaching the export status by means of a dummy variable but instead we focus on the distributional properties of three distinct populations. Table A.1 and Figure A.2 in the Appendix show the distribution across ownership types of the three groups. Interestingly, state-owned, collective-owned, shareholding and private-owned enterprises are largely located in the subgroup of never-exporting firms (around 86% of the population) while HMT and foreign invested firms largely belong to the population of always-exporters (around 60%).

In order to grasp the degree of heterogeneity and the properties of non-Gaussianity and fat-taildness of our sample, we start by comparing the kernel density distributions of wage and labour productivities for always-exporters, never-exporters and export-starters (cohort t), shown in Figure 1, and the companion productivity and wage growth rates in Figure 2. With reference to the dynamics in levels, the distributional analysis confirms that if in 1998 there was a premium for exporting starters (red right-tail), the latter disappears over time. Additionally we do not detect any systematic difference in terms of either labour productivity or wages in terms of both the overall support and its movement over time. However, when looking at the distribution of growth rates, while always- and never-exporters tend to overlap, exporter-starters do present more granular and bumpy growth rates particularly in the upper tail.[4]

Moving from the distributional analysis toward the time series one, a surprising result is shown in Figure 3 presenting the evolution of the mean of productivity levels. Although, wages and productivity levels of the three populations largely overlap over time, the productivity premium, if any,

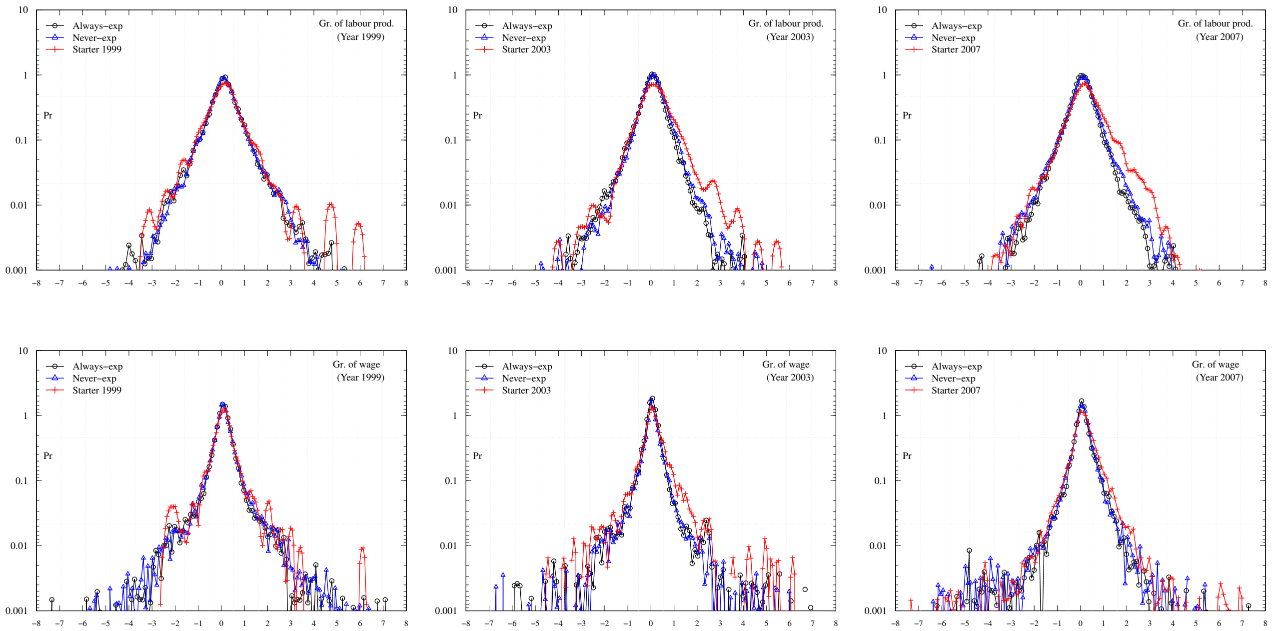
[4]The Asymmetric Exponential Power estimates of the underlying parameters are available upon request.

Figure 1: Always-exporters vs. Never-exporters vs. Export-starters cohort t. Distribution of (log) labour productivities (first row) and (log) wage per employee (second row) in years 1999, 2003 and 2007 (at 1998 constant price).



Note: Export-starters in the three plots are from different cohorts. Pooling all firms in manufacturing. Source: our elaboration on CMM.

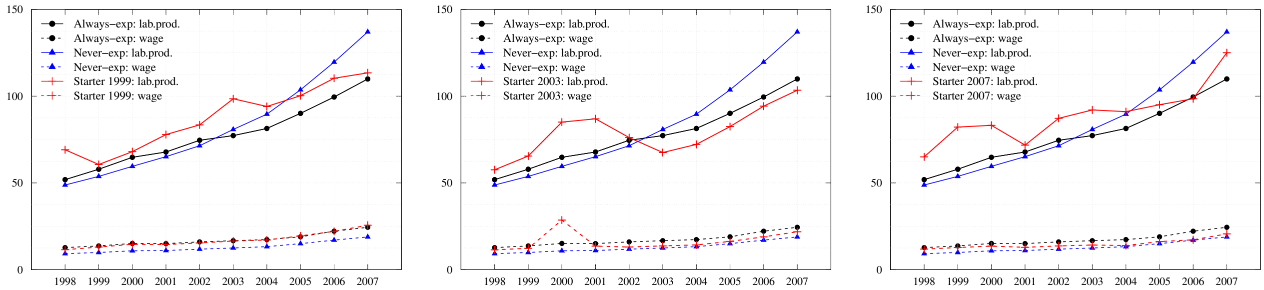
Figure 2: Always-exporters vs. Never-exporters vs. Export-starters cohort t. Distribution of growth rates of labour productivities (first row) and wage (second row) in years 1999, 2003 and 2007 (at 1998 constant price).



Note: Export-starters in the three plots are from different cohorts. Pooling all firms in manufacturing. Source: our elaboration on CMM.

is present in non-exporting firms. This result is due to the ownership composition. In fact, analyses available upon request show that for the majority of each ownership types labour productivity of never-exporter is higher (or equal in the case of SHEs) than those participating in international trade, the exception are State-owned enterprises which show export premia in productivity and wage levels, and in productivity growth. Those few SOEs engaging in export experience higher productivity than their non-exporting counterpart. The opposite occurs for the rest, including also those firms most inclined to export activities such as HMTs and FIEs. Figure 4 shows that also in terms of growth rates of productivity, never-exporting firms outperform always-exporters in most of the periods.

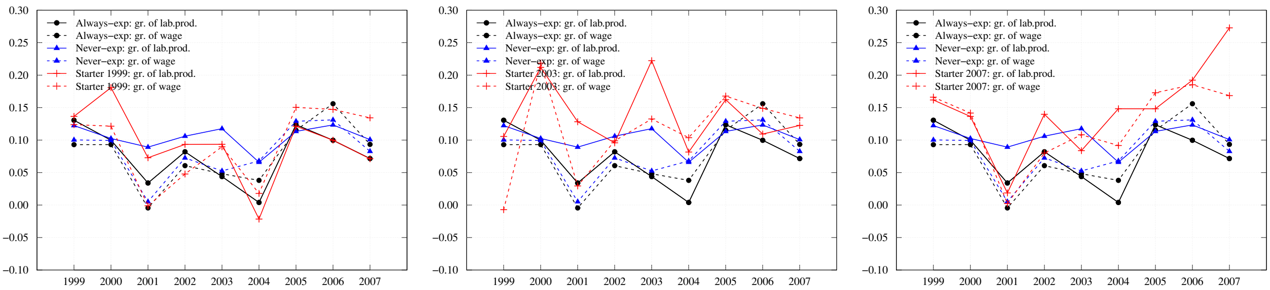
Figure 3: Mean of wages and labour productivities levels for always-exporters, never-exporters and export-starter at cohort t.



Note: mean values across always-exporters, never-exporters or export-starter at cohort t. Source: our elaboration on CMM.

Moving a step further into the analysis of the inter-firm heterogeneity, let us consider alternative measures of dispersion for productivity and wages within narrowly defined sectors and/or ownership types. The 90-10 wage (productivity) ratio is defined as the ratio of the $90th$ percentile to the $10th$ percentile of the wage (productivity) distribution. Figure 5 shows the 90-10 ratio for the three population of firms, with export-starters at different cohorts. As already documented in Dosi et al. (2020) both wages and productivity exhibit a process of convergence. This is broadly confirmed also by our three sub-populations, with never-exporting firms presenting the highest ratio for the wage levels and always-exporting the lowest. Conversely, the interdecile ratios for productivity are almost

Figure 4: Mean of growth rates of wages and labour productivities for always-exporters, never-exporters and export-starter at cohort t.

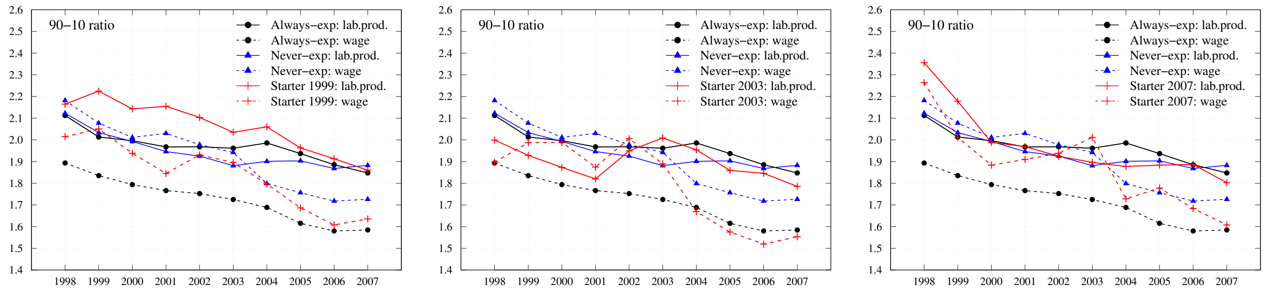


Note: mean values across always-exporters, never-exporters or export-starter at cohort t. Source: our elaboration on CMM.

overlapping.

In order to understand the statistical drivers of convergence, we split the 90-10 ratio in two components. The 90-50 wage (productivity) ratio is defined as the ratio of the $90th$ percentile to the $50th$ percentile (the median) of the wage (productivity) distribution. It captures dispersion in the upper tail of the distribution. Symmetrically, the 50-10 wage (productivity) ratio is the ratio of the $50th$ percentile to the $10th$ percentile of the wage (productivity) distribution, capturing the dispersion in the bottom tail of the distribution. Figures 6 and Figure 7 show the 90-50 and 50-10 ratios for wages and productivity distributions respectively for export-starters in different cohorts. In both variables, the process of convergence, if any, has been driven by those firms located at the bottom of the distribution. This is particularly true for wages of never-exporters in the bottom deciles and for export-starters which present the highest rate of convergence. But the pattern is similar, although less steep, for wages of exporting firms in the bottom deciles. Productivity presents a smoother trend with never-exporting firms presenting the lowest heterogeneity in the top part of the distribution.

Figure 5: Wage/productivity 90-10 ratio by year, always-exporters, never-exporters and export-starters at cohorts 1999, 2003 and 2007.



Note: equal weights. Source: our elaboration on CMM.

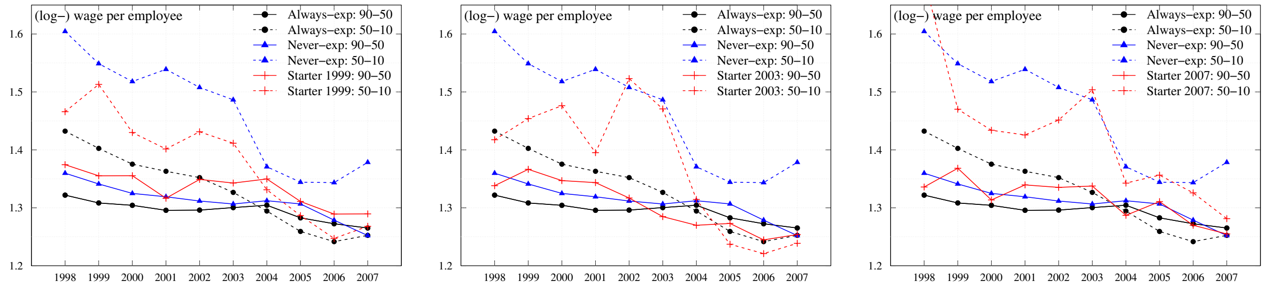
4.3. Decomposition of wage/productivity variance

Having detected some convergence processes in the distribution of both wages and productivity driven by the bottom part of the distribution, let us investigate by means of a shift and share decomposition the relative contribution of the *within* and *between* sectoral components. The (labour-weighted) variance of wage ($Var\ w_{ijt}$)/ productivity ($Var\ \pi_{ijt}$) is decomposed into a within-sector component and a between-sector one, according to:

$$\underbrace{\sum_i \frac{L_{ijt}}{L_t}(w_{ijt} - \overline{w}_t)^2}_{\text{Var } w_{ijt}} \equiv \underbrace{\sum_j \frac{L_{jt}}{L_t} \sum_{i \in j} \frac{L_{ijt}}{L_{jt}}(w_{ijt} - \overline{w}_{jt})^2}_{\text{within}} + \underbrace{\sum_j \frac{L_{jt}}{L_t}(\overline{w}_{jt} - \overline{w}_t)^2}_{\text{between}} \qquad (3)$$

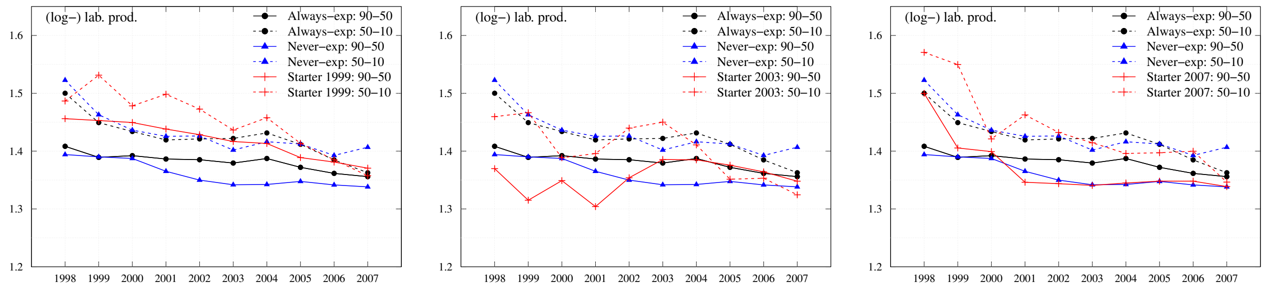
where L_{ijt} is the number of employees of firm i in sector j at time t; L_{jt} is the total number of employees of sector j at time t; L_t is the total number of employees at time t; $\overline{w}_t = \sum_i \sum_j \frac{L_{ijt}}{L_t} w_{ijt}$ is the grand (labour) weighted mean of wages; $\overline{w}_{jt} = \sum_{i \in j} \frac{L_{ijt}}{L_{jt}} w_{ijt}$ is the sectoral (labour) weighted mean of wages. The decomposition is done by pooling all firms in manufacturing. And, identically, we decompose

Figure 6: Wage at the top (90-50 ratio) versus bottom (50-10 ratio) of the distribution by year, always-exporter, never-exporters and export-starters at cohorts 1999, 2003 and 2007.



Note: equal weights. Source: our elaboration on CMM.

Figure 7: Productivity at the top (90-50 ratio) versus bottom (50-10 ratio) of the distribution by year, always-exporters, never-exporters and export-starters at cohorts 1999, 2003 and 2007.



Note: equal weights. Source: our elaboration on CMM.

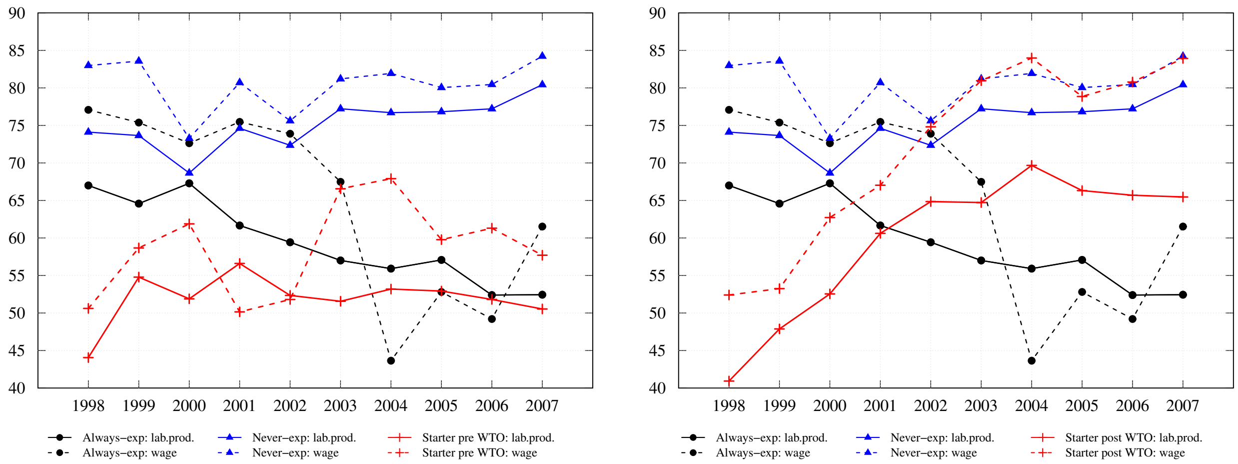
the variance in productivity.[5]

Figure 8 presents the graphical summary of the decomposition distinguishing the pre- and post-WTO export-starters: the within component accounts for the largest share of the variability for always- and never-exporters, meaning that the difference between-firms of the same sector rather than between-sectors accounts more for the overall dispersion. However, the temporal pattern clearly differs between the two groups: while for non-exporting firms the degree of within-sector heterogeneity presents a mild increasing trend, the between-firm heterogeneity markedly goes down for both wages and productivity for always-exporters. Looking at export-starters the picture changes. First of all the between-sector heterogeneity accounts for almost 50% of total variance at the beginning of the time-span. Additionally, the heterogeneity between export-starters after the WTO accession tends to increase. This evidence challenges the reallocation prediction according to which the access to international trade reduces between-firm heterogeneity inside narrowly defined sectors. Moreover, sector-specific factors, not identified here, seem to yield a relatively higher variability in entry rates and entry types.

The distinction among the three populations of firms also allows to grasp the increasing role played by sectoral reallocation after the WTO accession. Does it stand for a tendency toward specialization, as dynamics driven by comparative advantages would imply?

[5]Note: deviation from the labour-weighted 4-digit wage mean.

Figure 8: The share of between-firm/within-sector wage/labour productivity dispersion, always-exporters, never-exporters and export-starters at cohorts pre-WTO and post-WTO.



Note: pooling all firms in manufacturing sector, deviation from the 4-digit sectoral labour-weighted mean. Source: our elaboration on CMM.

4.4. Between sectors reallocation

In fact, one observes the opposite with *shrinking* sectoral heterogeneity after the WTO accession. First of all, Table 5 documents an increasing number of 4-digit sectors significantly entering the exporting status over-time. The increasing number of sectors is of course associated with an increasing number of firms accessing to international markets. However, the sectoral distribution of export shares reveals an underlying anti-specialization tendency against pre-existing comparative advantages.

First of all, did the structural composition of export-starters change post-WTO? Figure 9 and Table 6 show the rank distribution of the share in exports of export-starters (top 10 4-digit sectors) distinguishing the pre- and post-WTO accession. Manufacturing of textile clothing (CIC 1810) is the top export-starter sector during 1998-2002. However in the post-WTO period it moves down in the rank, reducing its share in exports to less than 6%. In contrast, several 4-digit sectors in manufacturing of telecommunication equipments, computers and other electric devices (CIC 40) overtake the traditional textile clothing manufacturing sectors since 2003 as top exporting starters. For example, computer integrated manufacturing (CIC 4041) shows a rising contribution from around 3% in 2001 to less than 9% in 2007.

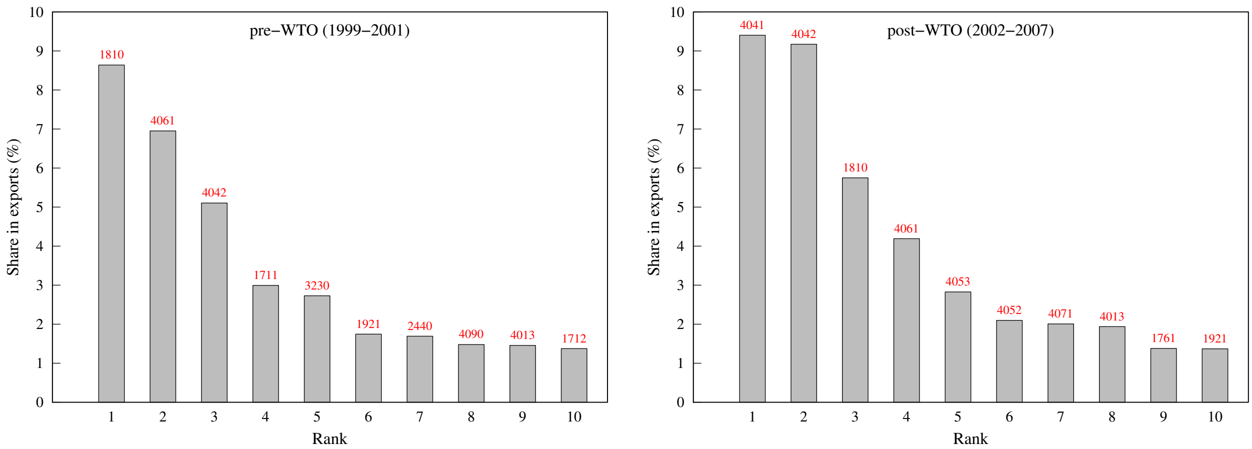
If we look at the overall sectoral ranking, neglecting for a while export-starters, Figure 10 compares the top 10 sectors in terms of export shares before and after China's WTO accession. Again, it confirms the disproportionate pattern of growth in telecommunication equipments, computers and other electronic devices (CIC 40) with conversely traditional sectors with "expected" comparative advantages (like Manufacturing of leather shoes (1921) and Manufacturing of toys (2440)) disappearing from the list of top exporters post-WTO (Table 7).

It is interesting to compare the changing sectoral composition of export activity with the sectoral dynamics of productivity. The contribution of 4-digit sectors to aggregate productivity growth is calculated based on van Ark and Timmer (2003) shift-share method (see subsection B in the Appendix) accounting for the *intra-sectoral productivity growth (i.e. intra-effect)* and the *sectoral reallocation of labour*

Table 5: Number of 4-digit sectors that export-starters are entering in each year. Source: our elaboration on CMM.

Export-starters in cohort t	Number of sectors
1999	281
2000	293
2001	325
2002	339
2003	358
2004	398
2005	379
2006	382
2007	376

Figure 9: Rank distribution of the 4-digit sectoral share in exports of export-starters, top 10 sectors in manufacturing, pre-WTO and post-WTO accession.



Note: numbers in the vertical axis are in percentages. The group of export-starters in the year they start exporting. The sectors are labelled by their CIC codes. Source: our elaboration on CMM.

(i.e. shift-effect).

Figure 11 shows the rank distribution of the contribution of 4-digit sectors to aggregate productivity growth in manufacturing. The distribution is more skewed in the post-WTO period based on the Kolmogorov-Smirnov test. Are the top contributing sectors to productivity growth also the ones which participated the most to international trade? Looking at the contribution of the top 10 sectors to aggregate productivity growth (Figure 12 and Table 8) we see that this is not the case.

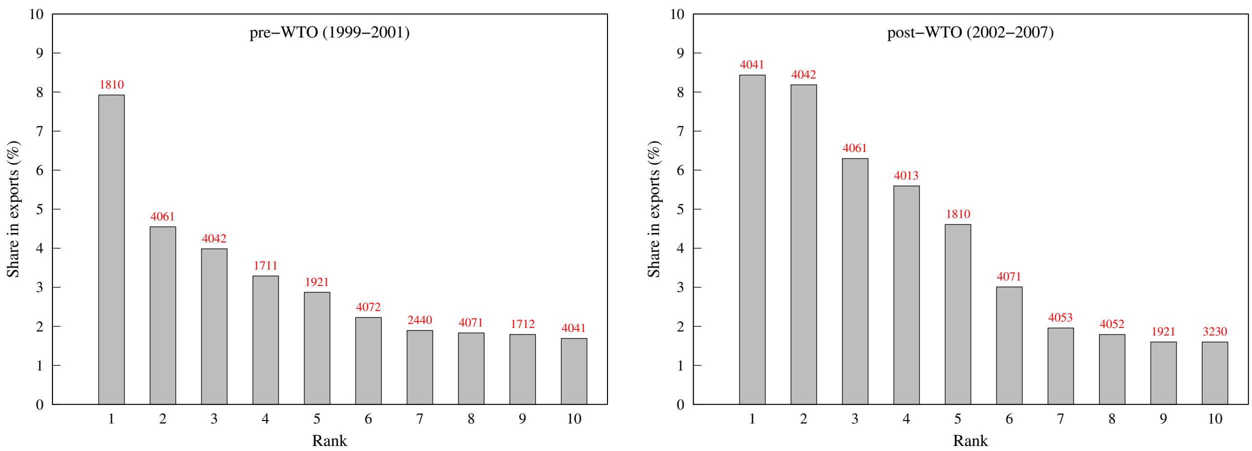
When looking at the relationship between the percentage contribution to aggregate productivity growth in the pre-WTO (1998-2001) and in the post-WTO (2001-2007), and the rank of the sectoral contribution to exports for the top 20 exporting sectors, we do not find any strong correlation (Figure 13). This evidence again contradicts the purported reallocation effect due to access to international trade: although there was a process of restructuring in terms of the composition of exporting sectors, those sectors which contributed the most to productivity growth in the manufacturing are not the ones contributing the most to export. This is true for both the pre- and post-WTO growth phases. Table 9

Table 6: Name of the top 10 sectors in terms of the sectoral share in exports of export-starters in manufacturing, corresponding to the CIC codes above the bars in Figure 9.

Rank	Sector (Pre-WTO, 1999-2001)	Sector (Post-WTO, 2001-2007)
1	Manuf. of textile clothing (1810)	Computer integrated manuf. (4041)
2	Electronic components and sets manuf. (4061)	Computer network equipment manuf. (4042)
	Printed circuit boards manuf. (4062)	Computer peripherals manuf. (4043)
3	Computer network equipment manuf. (4042)	Manuf. of textile clothing (1810)
	Computer peripherals manuf. (4043)	
4	Processing of cotton and chemical fiber textile (1711)	Electronic components and sets manuf. (4061)
		Printed circuit boards manuf. (4062)
5	Steel calendering (3230)	Integrated circuit manuf. (4053)
6	Manuf. of leather shoes (1921)	Semiconductor discrete devices manuf. (4052)
		Photoelectron parts and other electronic parts manuf. (4059)
7	Manuf. of toys (2440)	Home video equipment manuf. (4071)
8	Other electronic equipment manuf. (4090)	Communications terminal equipment manuf. (4013)
		Mobile communications and terminal equipment manuf. (4014)
9	Communications terminal equipment manuf. (4013)	Knitgoods and knitworks manuf. of cotton and
	Mobile communications and terminal equipment manuf. (4014)	chemical fiber (1761)
10	Dyeing and finishing of wool textile (1712)	Manuf. of leather shoes (1921)

Note: the CIC codes in Figure 12 follow the harmonized classification. The CIC codes in this table follow the CIC GB/T 4754-2002 standard.

Figure 10: Rank distribution of the 4-digit sectoral share in exports, top 10 sectors in manufacturing, pre-WTO and post-WTO accession.



Note: numbers in the vertical axis are in percentages. The sectors are labelled by their CIC codes. Source: our elaboration on CMM.

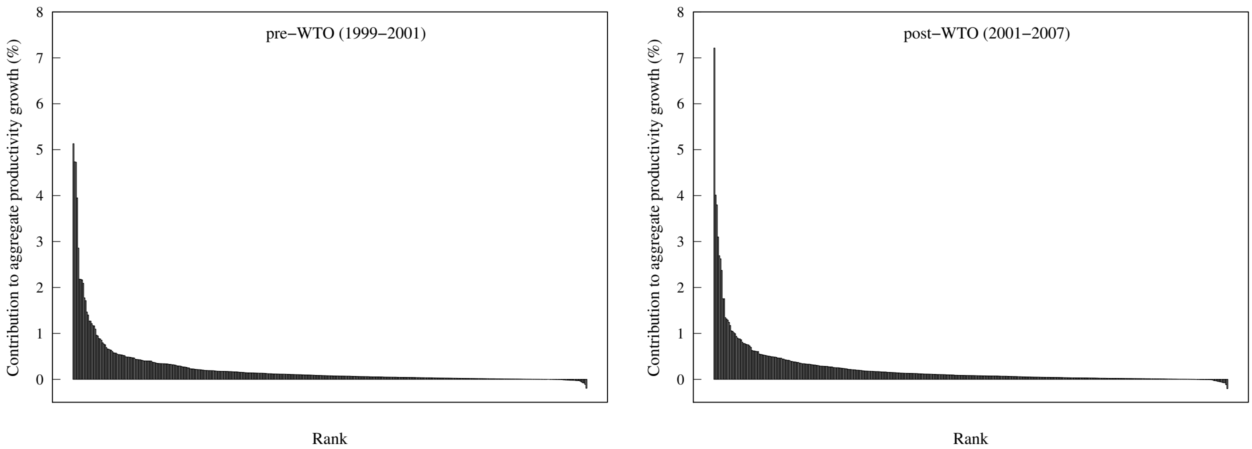
lists the names of the top 20 4-digit sectors in terms of their contributions to the share in exports in 1999 and 2007, that correspond to the CIC codes above the bars in Figure 13, top-left and bottom-right panels. If the access to international trade would have exerted an impact on the growth process, one should have seen a more correlated pattern after the WTO accession, instead the sectoral contribution to productivity growth and to export participation remain uncorrelated also in 2007.

Table 7: Name of the top 10 sectors in terms of the sectoral share in exports in manufacturing, corresponding to the CIC codes above the bars in Figure 10.

Rank	Sector (Pre-WTO, 1999-2001)	Sector (Post-WTO, 2001-2007)
1	Manuf. of textile clothing (1810)	Computer integrated manuf. (4041)
2	Electronic components and sets manuf. (4061)	Computer network equipment manuf. (4042)
	Printed circuit boards manuf. (4062)	Computer peripherals manuf. (4043)
3	Computer network equipment manuf. (4042)	Electronic components and sets manuf. (4061)
		Printed circuit boards manuf. (4062)
4	Processing of cotton and chemical fiber textile (1711)	Communications terminal equipment manuf. (4013)
		Mobile communications and terminal equipment manuf. (4014)
5	Manuf. of leather shoes (1921)	Manuf. of textile clothing (1810)
6	Home audio equipment manuf.	Home video equipment manuf. (4071)
7	Manuf. of toys (2440)	Integrated circuit manuf. (4053)
8	Home video equipment manuf. (4071)	Semiconductor discrete devices manuf. (4052)
		Photoelectron parts and other electronic parts manuf. (4059)
9	Dyeing and finishing of wool textile (1712)	Manuf. of leather shoes (1921)
10	Computer integrated manuf. (4041)	Steel calendering (3230)

Note: the CIC codes in Figure 12 follow the harmonized classification. The CIC codes in this table follow the CIC GB/T 4754-2002 standard.

Figure 11: Rank distribution of the sectoral contribution to aggregate productivity growth in manufacturing (rank all 4-digit sectors). Left panel: aggregate productivity growth during pre-WTO period (1998-2001). Right panel: aggregate productivity growth during post-WTO period (2001-2007).



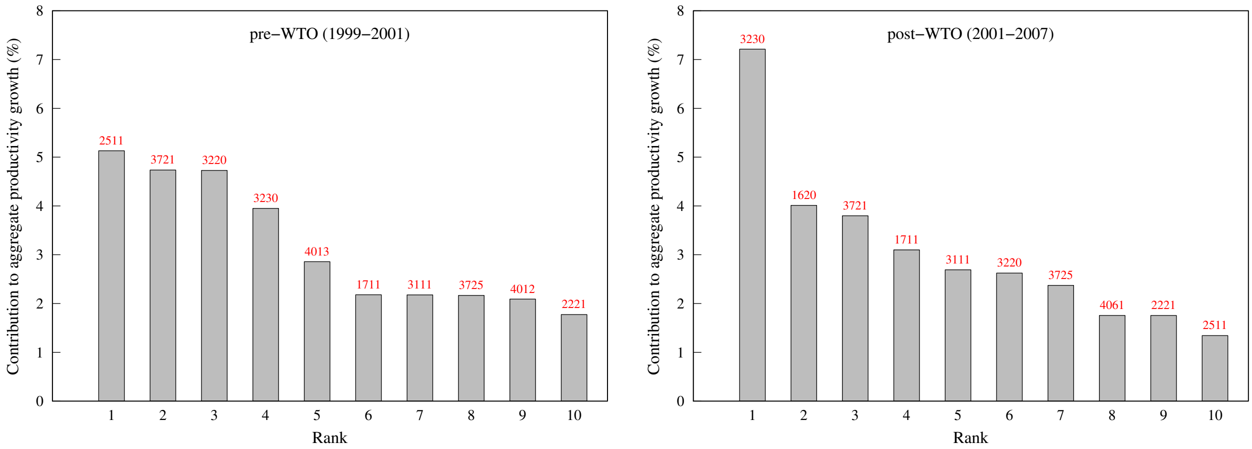
Note: numbers in the vertical axis are in percentages. The sectors are labelled by their CIC codes. Shift-share method from van Ark and Timmer (2003) are adopted for calculating the contribution of each 4-digit sector to aggregate productivity growth. Source: our elaboration on CMM.

5. Distribution of the gains

The analyses so far suggest that the spectacular increase in value creation by Chinese manufacturing firms is basically due to fast and broad patterns of learning and catching-up, rather than exploitation of sectoral comparative advantages. But, how are these gains distributed? In the following, by means of a quantile regression exercise, we intend to capture the patterns of value distribution by studying the wage-productivity pass-through.

Recall Figure 1. Looking at levels, both wages and productivity distributions display skewness and fat tails. All this evidence on deep heterogeneity and lack of Gaussian features militates in

Figure 12: Rank distribution of the sectoral contribution to aggregate productivity growth in manufacturing, top 10 sectors. Left panel: aggregate productivity growth during pre-WTO period (1998-2001). Right panel: aggregate productivity growth during post-WTO period (2001-2007).



Note: the sectors are labelled by their CIC codes. Source: our elaboration on CMM. Note: numbers in the vertical axis are in percentages.

Table 8: Name of the top 10 4-digit sectors in terms of the sectoral contribution to aggregate productivity growth in manufacturing, corresponding to the CIC codes above the bars in Figure 12.

Rank	Sector (Growth pre-WTO, 1999-2001)	Sector (Growth post-WTO, 2001-2007)
1	Processing of crude oil & manuf. of petroleum products (2511)	Steel calendering (3230)
2	Manuf. of the complete automobile (3721)	Tobacco manuf. (1620)
3	Steel-making (3220)	Manuf. of the complete automobile (3721)
4	Steel calendering (3230)	Processing of cotton and chemical fiber textile (1711)
5	Communications terminal equipment manuf. (4013)	Manuf. of cement (3111)
	Mobile communications and terminal equipment manuf. (4014)	
6	Processing of cotton and chemical fiber textile (1711)	Steel-making (3220)
7	Manuf. of cement (3111)	Manuf. of parts and accessories of the automobile (3725)
8	Manuf. of parts and accessories of the automobile (3725)	Electronic components and sets manuf. (4061)
		Printed circuit boards manuf. (4062)
9	Communications exchange equipment manuf. (4012)	Manuf. of machine-made paper and cardboards (2221)
10	Manuf. of machine-made paper and cardboards (2221)	Processing of crude oil & manuf. of petroleum products (2511)

Note: the CIC codes in Figure 12 follow the harmonized classification. The CIC codes in this table follow the CIC GB/T 4754-2002 standard.

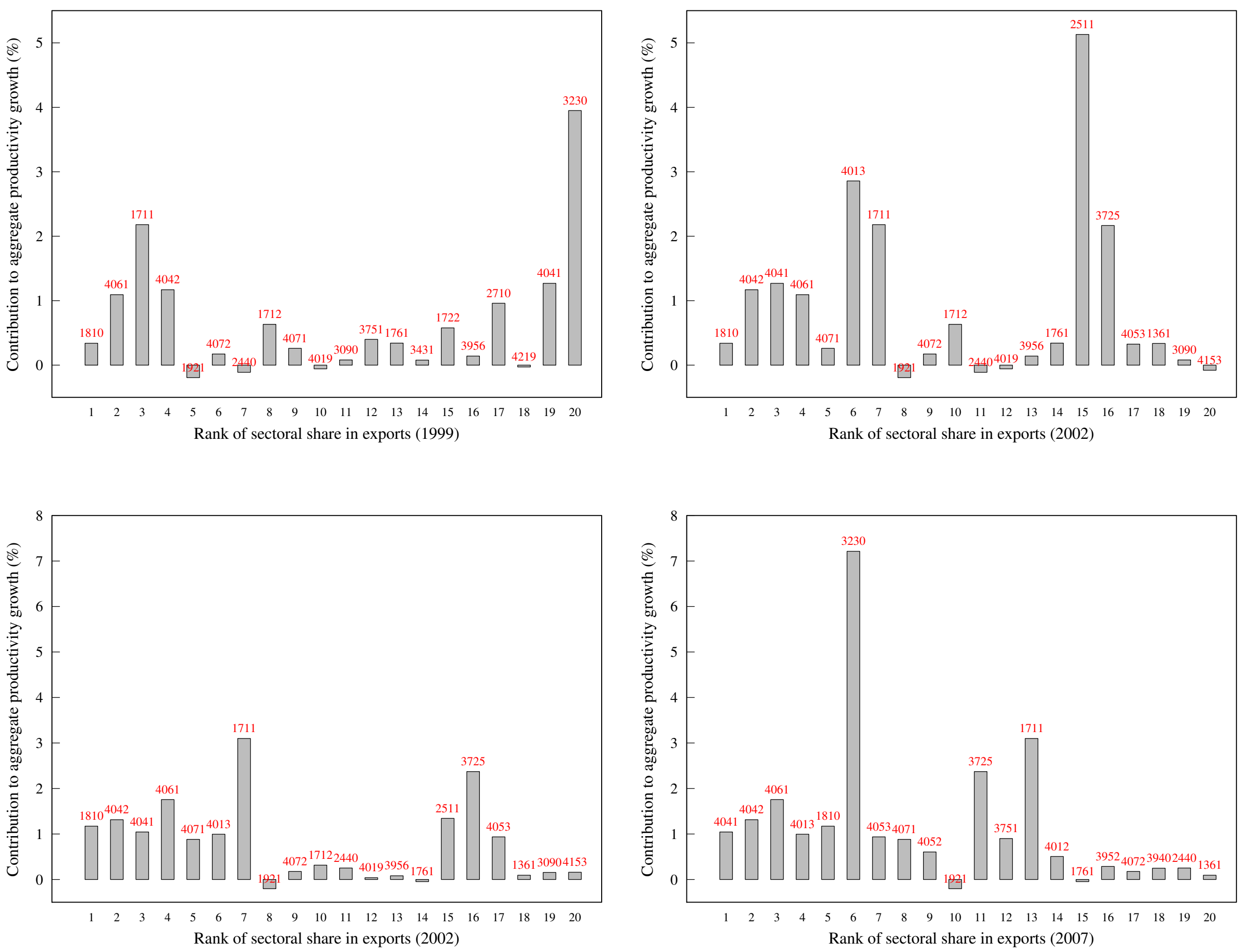
favour of the use of quantile regression analysis which allows to capture the different intensities of the productivity-wage pass-through along the conditional quantile of the wage distribution. The quantile regression model (Koenker and Bassett Jr, 1978) reads as:

$$y_{it} = x'_{it}\beta_\tau + u_{\tau it} \quad \text{with} \quad \mathrm{Q}_\tau(y_{it}|x_{it}) = x'_{it}\beta_\tau \tag{4}$$

where y_{it} is the dependent variable, x is a set of regressors, β is the vector of parameters to be estimated, and u is a vector of residuals. $\mathrm{Q}_\tau(y_{it}|x_{it})$ stands for the τ^{th} conditional quantile of y_{it} given x_{it}. The τ^{th} conditional quantile solves the minimization problem:

$$\beta_\tau \equiv \underset{b}{\text{argmin}}\ E[\rho_\tau(y_{it} - x'_{it}b)] \tag{5}$$

Figure 13: Pre-WTO (1998-2001) and post-WTO period (2001-2007), top 20 sectors. Contribution to aggregate productivity growth in manufacturing vs. rank of contribution to exports (sectoral share in exports), all sectors, year 1999, 2002 and 2007.



Note: numbers in the vertical axis are in percentages; pre-WTO (first row) and post-WTO (second row) periods. Source: our elaboration on CMM.

where $\rho(u) = 1(u > 0) \cdot \tau|u| + 1(u \leq 0) \cdot (1-\tau)|u|$ is called the "check function". If $\tau = 0.5$, this turns out in terms of least absolute deviations. In this case, $Q_\tau(y_{it}|x_{it})$ is the conditional median since the conditional median minimizes absolute deviations. Otherwise, the check function weights positive and negative terms asymmetrically. The quantile regression estimator, $\hat{\beta}_\tau$ is the sample analogy of Equation 5. This minimization procedure involves the solution of a linear programming problem. As one increases τ from 0 to 1, one traces the entire conditional distribution of y_{it}, conditional on x_{it}.

We mean to detect the relationship between the level of productivity and the level of wages. The model, estimated at the 2-digit sectoral-level of disaggregation and at the 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95 quantiles of the conditional wage distribution, reads as:

$$w_{it} = \alpha + \beta_\tau \pi_{it} + y_t + \epsilon_{\tau it} \tag{6}$$

where w_{it}, the dependent variable, is the (log) real wage per employee for firm i at time t and π_{it} the (log) labour productivity level. We also control for common macroeconomic shocks by including year

Table 9: Name of the top 20 sectors in terms of the sectoral share in exports in 1999 and 2007, corresponding to the CIC codes above the bars in Figure 13.

Rank	1999	2007
1	Manuf. of textile. clothing (1810)	Computer integrated manuf. (4041)
2	Electronic components and sets manuf. (4061)	Computer network equipment manuf. (4042)
	Printed circuit boards manuf. (4062)	Computer peripherals manuf. (4043)
3	Processing of cotton and chemical fiber textile (1711)	Electronic components and sets manuf. (4061)
		Printed circuit boards manuf. (4062)
4	Computer network equipment manuf. (4042)	Communications terminal equipment manuf. (4013)
	Computer peripherals manuf. (4043)	Mobile communications and terminal equipment manuf. (4014)
5	Manuf. of leather shoes (1921)	Manuf. of textile. clothing (1810)
6	Home audio equipment manuf. (4072)	Steel calendering (3230)
7	Manuf. of toys (2440)	Integrated circuit manuf. (4053)
8	Dyeing and finishing of cotton and chemical fiber textile (1712)	Home video equipment manuf. (4071)
9	Home video equipment manuf. (4071)	Semiconductor discrete devices manuf. (4052)
		Photoelectron parts and other electronic parts manuf. (4059)
10	Other communications equipment manuf. (4019)	Manuf. of leather shoes (1921)
11	Manuf. of other plastic products (3090)	Manuf. of parts and accessories of the automobile (3725)
12	Manuf. of mental ships (3751)	Manuf. of mental ships (3751)
13	Knitgoods and knitworks manuf. of cotton and chemical fiber (1761)	Processing of cotton and chemical fiber textile (1711)
14	Manuf. of containers (3431)	Communications exchange equipment manuf. (4012)
15	Wool manuf. (1722)	Knitgoods and knitworks manuf. of cotton and chemical fiber (1761)
16	Manuf. of household hairdressing and health caring electrical appliances (3956)	Manuf. of household air-conditioning electrical appliances (3952)
	Manuf. of special fitting of household electrical appliances (3957)	
	Manuf. of other household electrical appliances (3959)	
17	Manuf. of the original drug of chemicals (2710)	Home audio equipment manuf. (4072)
18	Other arts and crafts manuf. (4219)	Manuf. of batteries (3940)
19	Computer integrated manuf. (4041)	Manuf. of toys (2440)
20	Steel calendering (3230)	Freezing and processing of aquatic products (1361)

Note: the CIC codes (in Figure 13) follow the harmonized classification. The CIC codes in this table follow the CIC GB/T 4754-2002 standard.

dummies y_t. The violin plot in Figure 14 presents the median, the interquartile ranges, and the kernel density distribution of the coefficient estimates for each quantile of the conditional wage distribution.

The always-exporters (left panel), never-exporters (the middle-panel) and export-starters pooling all cohorts (right panel) present a monotonic increasing pattern, meaning that the wage-productivity pass-through increases along the conditional wage distribution.[6] On average, non-exporting firms have a lower degree of pass-through but the range of variation is quite similar for the three types going from [0.1-0.3]. The difference in the intensity of the pass-through remains always significant, although less pronounced for the upper part of the wage distribution. From this last battery of results we cannot detect any systematic different wage bargaining process among the three types of firms: the pass-through increases along the conditional wage distribution independently from being or not an exporter. This pattern was already highlighted in Dosi et al. (2020).

To identify any changing pattern due to the WTO accession, we distinguish export-starters into two cohorts, pre-WTO (aggregating cohorts 1998, 1999 and 2000) and post-WTO (aggregating cohorts 2001-2007). The intensity of the wage-productivity pass-through for export-starters pre-WTO cohorts is even slightly higher than that of the post-WTO cohorts (Figure 15).

In order to check the robustness of our findings we add a series of control variables estimating Equation 7:

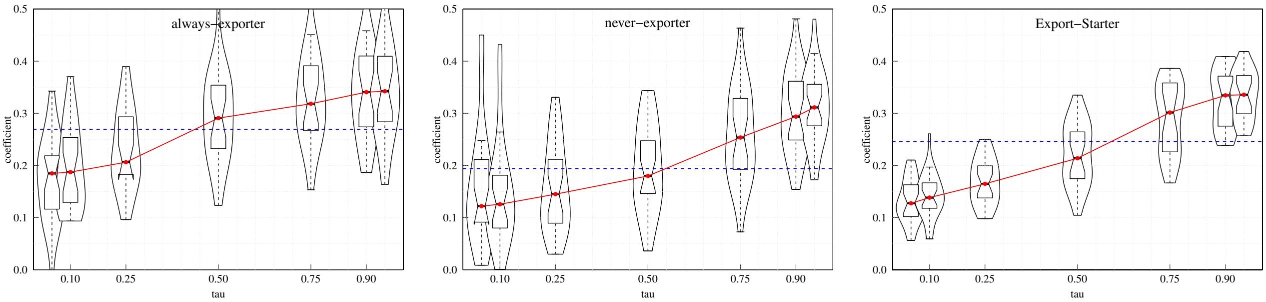
$$w_{it} = \alpha + \beta_{1\tau}\pi_{it} + \beta_{2\tau}\text{size}_{it} + \beta_{3\tau}\text{age}_{it} + \beta_{4\tau}\text{ownership}_{it} + \beta_{5\tau}\text{geo}_{i} + y_t + \epsilon_{\tau it} \tag{7}$$

with size_{it} being the (log-) number of employees of firm i in year t, age being the age of firm, ownership being ownership dummies, geo regional dummies, y_t year dummies, ϵ error term.

Figure 16 shows the quantile regression estimation for equation 7 while Figure 17 distinguishes

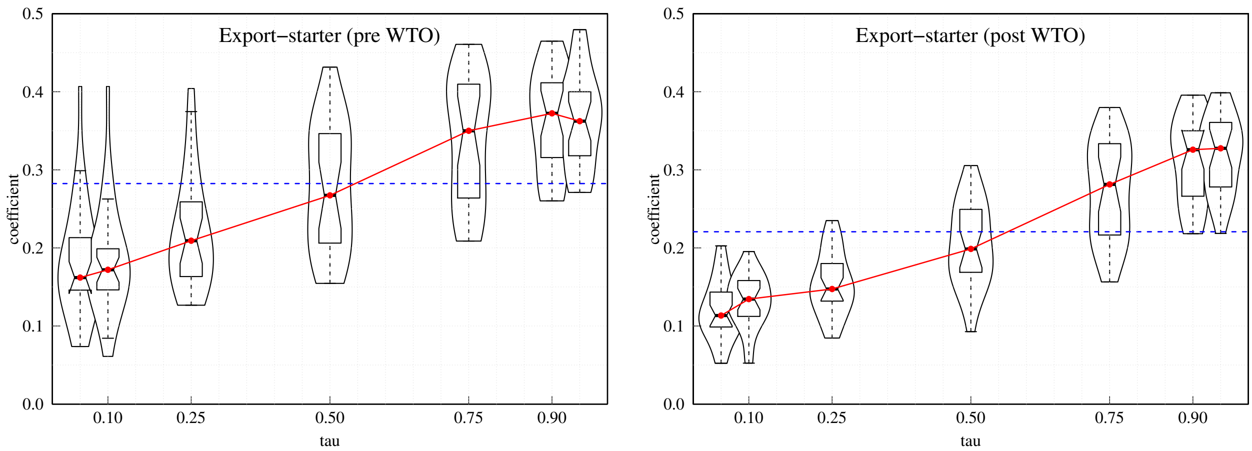
[6] The observed monotonic increasing pattern is robust to higher levels of aggregation with estimates of Equation (6) pooling all manufacturing firms and including 2-digit sectoral dummies. Results are available upon request.

Figure 14: Distributions of quantile regression coefficients across 28 2-digit sectors (only sectors with the number of observations larger than 160).



Note: quantile regression estimation of equation (6) for each 2-digit sector, the coefficient of log- labour productivity reported for the 0.05, 0.10, 0.25, 0.50, 0.75, 0.90 and 0.95 quantiles. Each violin reports a box plot and a kernel density to each side of the box plot. The median of Pseudo R^2 are 0.1649 (always-exporters), 0.1289 (never-exporters) and 0.1452 (export-starters) for quantile regression. The dashed line is the median of the distribution of OLS estimates (for export-starter, pooling all cohorts and controlling for export status timing.) Upon the Dunn test which compares the distributions of the coefficients (median) across the three groups of firms at each of the seven quantiles (in the figure), the coefficients of always-exporters are significantly higher than that of never-exporters at quantiles 0.10, 0.25, 0.50 and 0.75 at 0.01 significance level. Always-exporters and export-starters are significantly different at the median at 0.01 significance level. Source: our elaboration on CMM.

Figure 15: Distributions of quantile regression coefficients across 27 (pre-WTO) and 28 (post-WTO) 2-digit sectors (only sectors with the number of observations larger than 160).

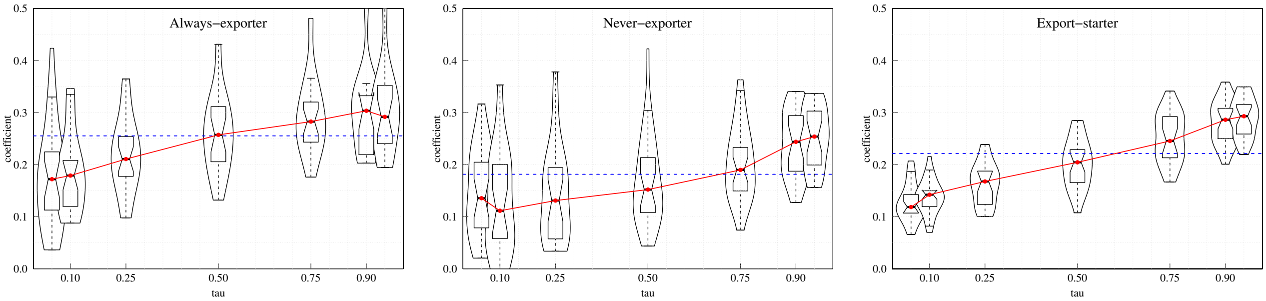


Note: quantile regression estimation of equation (6) for each 2-digit sector, the coefficient of log- labour productivity reported for the 0.05, 0.10, 0.25, 0.50, 0.75, 0.90 and 0.95 quantiles. Each violin reports a box plot and a kernel density to each side of the box plot. The median of Pseudo R^2 is 0.1730 (pre-WTO) and 0.1326 (post-WTO) for quantile regression. The dashed line is the median of the distribution of OLS estimates (for export-starters controlling for export status timing). Upon the Dunn test, the coefficients for pre-WTO period are significantly higher than post-WTO period for all quantiles at 0.01 significance level. Source: our elaboration on CMM.

export-starters into pre-WTO and post-WTO cohorts. Controlling for this ensemble of covariates leaves our estimates basically unchanged.

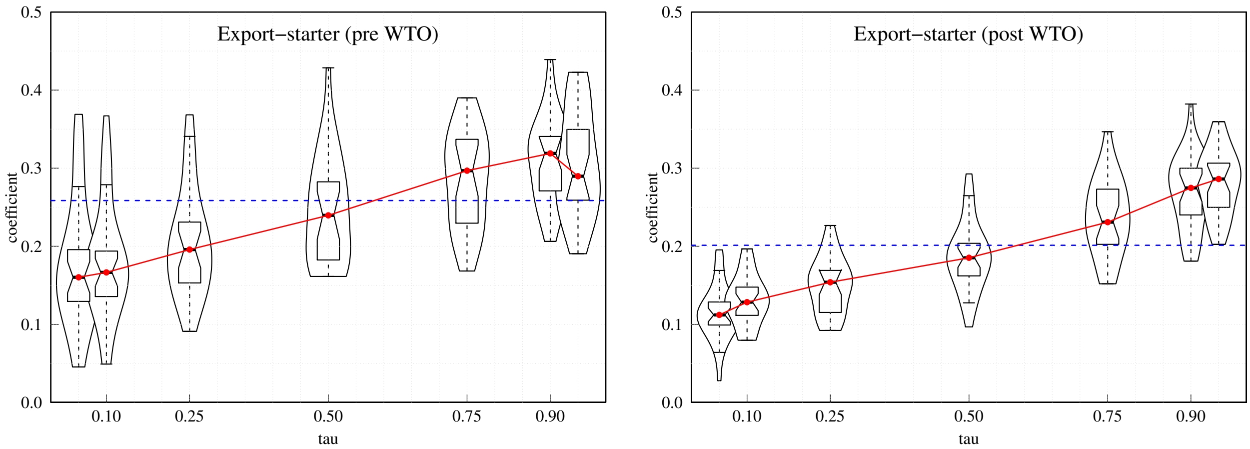
Let us next replicate our analysis employing the panel dimension of the data to control for unobserved heterogeneity, therefore linking quantile regression and dynamic panel techniques. In par-

Figure 16: (Model with controls) Distributions of quantile regression coefficients across 28 2-digit sectors (only sectors with the number of observations larger than 160).



Note: quantile regression estimation of equation (7) for each 2-digit sector, the coefficient of log- labour productivity reported for the 0.05, 0.10, 0.25, 0.50, 0.75, 0.90 and 0.95 quantiles. Each violin reports a box plot and a kernel density to each side of the box plot. The median of Pseudo R^2 is 0.2324 (always-exporters), 0.2065 (never-exporters), and 0.1761 (export-starters) for quantile regression. The dashed line is the median of the distribution of OLS estimates (for export-starters controlling for export status timing). Upon the Dunn test, the coefficients of always-exporters are significantly higher than that of never-exporters at quantiles 0.25, 0.50, 0.75 and 0.90 at 0.01 significance level. Source: our elaboration on CMM.

Figure 17: (Model with controls) Distributions of quantile regression coefficients across 28 2-digit sectors (only sectors with the number of observations larger than 160).



Note: quantile regression estimation of equation (7) for each 2-digit sector, the coefficient of log- labour productivity reported for the 0.05, 0.10, 0.25, 0.50, 0.75, 0.90 and 0.95 quantiles. Each violin reports a box plot and a kernel density to each side of the box plot. The median of Pseudo R^2 is 0.2259 (pre-WTO) and 0.1702 (post-WTO) for quantile regression. The dashed line is the median of the distribution of OLS estimates. Upon the Dunn test, the coefficients of pre-WTO period are significantly higher than that of the post WTO period at all quantiles (except 0.95) at 0.01 significance level. Source: our elaboration on CMM.

ticular, we shall present the results of the correlated random effect model. Following Abrevaya and Dahl (2008) we link the quantile regression estimation with correlated random effects using Chamberlain (1982) and Chamberlain (1984) approach (only for balanced panel).[7] According to the correlated

[7]The pooled quantile regression employed the panel structure of the data only for computing standard errors. Since each firm appears at least once in the data, the clustered sampling bootstrap is used. Being present dependence within firm's indicators over years, the standard asymptotic-variance formula (Koenker and Bassett Jr, 1978) and the standard bootstrap approach, both based upon independent observations, should not be applied. Hence, instead, a given bootstrap sample is

random effect model, y_{it} is generated by:

$$y_{it} = x'_{it}\beta + c_i + u_{it} \tag{8}$$

where the time invariant idiosyncratic component c_i behaves according to:

$$c_i = \phi(x_i) + v_i, \quad E(v_i|x_i) = 0 \tag{9}$$

For any $\tau \in [0, 1]$, the conditional quantile function of y_{it} is:

$$Q_\tau(y_{it}|x_i) = x'_{it}\beta + Q_\tau(v_i + u_{it}|x_{it}) + \phi(x_i) \tag{10}$$

assuming that v_i is orthogonal to x_i and allowing for the heteroschedasticity of x_i, that is $Q_\tau(u_{it}|x_i, v_i) = Q_\tau(u_{it}|x_{it})$ we have the final specification for the quantile regression with a correlated random effect estimation:

$$\mathrm{Q}_\tau(y_{it}|x_{it}) = x'_{it}\beta_\tau + \phi(x_i) \tag{11}$$

where:

$$x'_{it}\beta_\tau = x'_{it}\beta + Q_\tau(v_i + u_{it}|x_{it}) \tag{12}$$

with $\phi(x_i)$, in the case of balanced panel, being:

$$\phi(x_i) = \psi^t_\tau + x'_{i1}\lambda^1_\tau + ... + x'_{iT}\lambda^T_\tau \tag{13}$$

or alternatively for an unbalanced panel we have $\phi(x_i) = \psi^t_\tau + \overline{x'_i}\lambda_\tau$ (Mundlak, 1978). In the following, we estimate a wage level - productivity level quantile regression with a correlated random effect, according to such an approach, as our panel is not balanced.

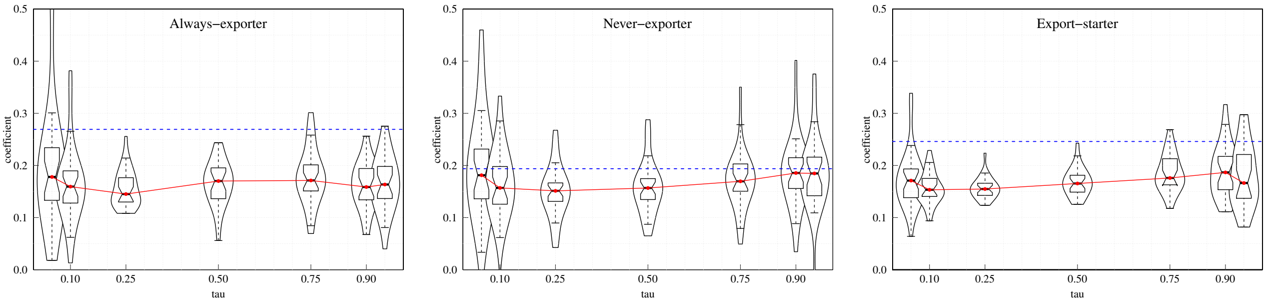
Figure 18 shows the results using the correlated random effects quantile regression (CREM thereafter), accounting for the dynamic evolution of idiosyncratic productivity over time. Distinguishing export-starters into pre-WTO and post-WTO cohorts, Figure 19 shows the corresponding results using CREM. The monotonic increasing pattern of the pass-through disappeared such as the previously marginally higher intensity for always-exporters. In the estimates of the wage-productivity pass-through, the coefficients do not show any significant difference among quantiles when taking into account the micro dynamics of productivity. Conditioning on the productivity gains the pass-through is completely flat. Table 10 summarizes the quantile regression estimates for the three groups of firms using the baseline model, model with controls and the correlated random effects model. The CREM model, accounting for the overall dynamics of firm-level productivity, highlights how the distribution of the gains to wages is basically equal across the conditional distribution for the three types of firms.

6. The effects of switching status on gains creation and distribution

In order to further grasp any hidden effect of the exporting event we focus on the impact of switching status for export-starters. Export-starters can be distinguished into different cohorts based on the year they start it (see Table 4). To investigate the transition effect – any change in firm characteristics

created by repeatedly drawing (with replacement) a firm from the sample of M firms and including all its measures (over years), where the draws continue until the desired bootstrap sample size is reached.

Figure 18: (CREM) Distributions of quantile regression coefficients across 28 2-digit sectors (only sectors with the number of observations larger than 160).



Note: quantile regression estimation of equation (6) for each 2-digit sector, the coefficient of log- labour productivity reported for the 0.05, 0.10, 0.25, 0.50, 0.75, 0.90 and 0.95 quantiles. Each violin reports a box plot and a kernel density to each side of the box plot. The median of Pseudo R^2 is 0.1725 (always-exporters), 0.1364 (never-exporters) and 0.1353 (export-starters) for quantile regression. The dashed line is the median of the distribution of OLS estimates. Upon the Dunn test, the coefficients of the three groups are not statistically different at any quantiles. Source: our elaboration on CMM.

Table 10: Coefficients of quantile regressions. Median of the distribution of coefficients at each of the seven quantiles. Source: our elaboration on CMM.

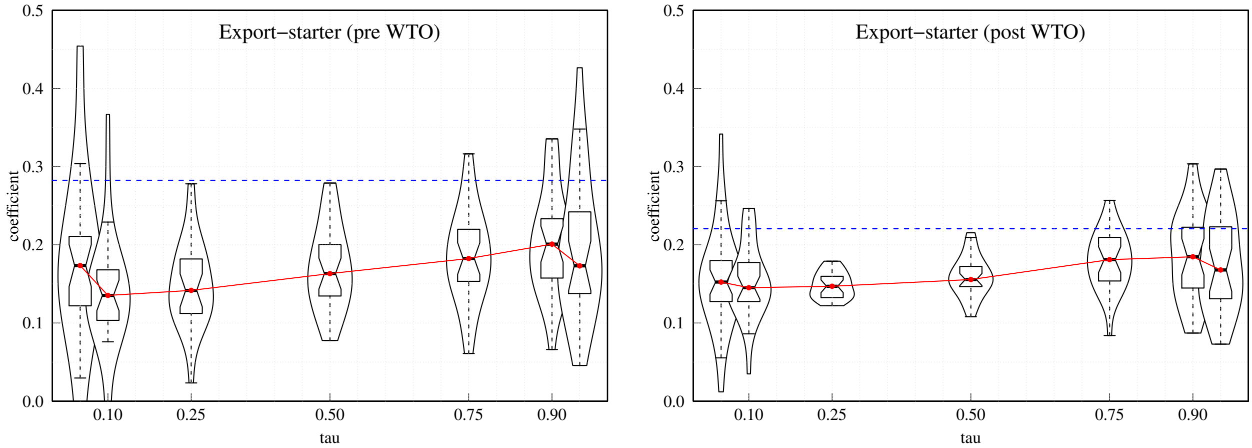
		Quantiles							
Model	Group	0.05	0.10	0.25	0.50	0.75	0.90	0.95	OLS
Baseline model	Always-exporter	0.1847	0.1872	0.2062	0.2908	0.3184	0.3406	0.3423	0.2692
	Never-exporter	0.1220	0.1256	0.1449	0.1798	0.2536	0.2938	0.3113	0.1938
	Export-starter	0.1274	0.1383	0.1647	0.2138	0.3015	0.3344	0.3357	0.2460
Model with controls	Always-exporter	0.1722	0.1791	0.2108	0.2573	0.2828	0.3038	0.2919	0.2553
	Never-exporter	0.1356	0.1115	0.1311	0.1521	0.1899	0.2439	0.2540	0.1816
	Export-starter	0.1186	0.1423	0.1677	0.2045	0.2455	0.2863	0.2931	0.2213
CREM	Always-exporter	0.1780	0.1594	0.1452	0.1701	0.1712	0.1587	0.1635	0.2692
	Never-exporter	0.1813	0.1569	0.1513	0.1568	0.1696	0.1855	0.1847	0.1938
	Export-starter	0.1710	0.1534	0.1548	0.1654	0.1760	0.1867	0.1663	0.2460

and changes in the magnitude of the pass-through associated with a switch in status from being non-exporter to exporter – we examine the sample of first-time exporters who began as non-exporters, become exporters and remain so until the end of our sample period.

We use a regression framework to analyse changes occurred before and after exporting (estimating firm fixed effects) and examine the difference-in-difference effects relative to other firms (i.e. using never-exporters as control group) in the industry (including firm and industry-year fixed effects). We supplement these analyses with an event-study approach that attempts a more fine-grained exploration of the timing of these effects. We define the first time a firm exports as an event and examine the timing in which eventual changes in firm attributes and in the ensuing pass-through did occur (Balasubramanian and Sivadasan, 2011).

Let us start by exploring whether the transition of status does impact in any respect upon firm properties in terms of levels and growth rates of wages and productivity. In order to address this question we run the following regression analysis using pooled OLS and FE estimators:

Figure 19: (CREM) Distributions of quantile regression coefficients across 28 2-digit sectors (only sectors with the number of observations larger than 160).



Note: quantile regression estimation of equation (6) for each 2-digit sector, the coefficient of log- labour productivity reported for the 0.05, 0.10, 0.25, 0.50, 0.75, 0.90 and 0.95 quantiles. Each violin reports a box plot and a kernel density to each side of the box plot. The median of Pseudo R^2 is 0.1699 (pre-WTO) and 0.1276 (post-WTO) for quantile regression. The dashed line is the median of the distribution of OLS estimates. Upon the Dunn test, the coefficients of the two groups are not statistically different at any quantiles. Source: our elaboration on CMM.

$$\text{Level} : \ln \mathrm{X}_{ijt} = a + b\,\mathrm{D}_{ijt} + \mu_{jt} + \epsilon_{ijt} \tag{14}$$

$$\text{Growth} : \Delta\,\mathrm{X}_{ijt} = a + b\,\mathrm{D}_{ij,t-1} + \mu_{jt} + \epsilon_{ijt} \tag{15}$$

where X_{ijt} is one of firm's attributes in levels, labour productivity or wages; $\Delta\,\mathrm{X}_{ijt}$ is the growth rate of labour productivity or of wages; D_{ijt} is a dummy variable that equals to 1 if the firm started exporting in a given year and keeps to be equal to 1 for the subsequent years, and 0 before the first exporting year; μ_{jt} denotes industry and year dummies; ϵ_{ijt} is the residual error term. The coefficient b provides a simple estimate of the changes that accompany the exporting event. For this analysis the sample is restricted to firms that switch exporting status during our sample period (export-starters only).

Table 11, sections A1 and A2, shows the estimation results using the panel structure of export-starters: both OLS estimators and fixed-effects ones with different specifications (i.e., different sets of controls) are presented. Pooling all years (see model 3 in panel A1), export-starters are 4.8% lower in productivity level, 6.9% lower in productivity growth and 4.3% lower in wage growth rate, but 4.7% higher in wage level compared to their non-exporting status. However, the fixed-effects (FE) estimators, measuring the *within-firm* elasticity of firm characteristics to changes in exporting status (see model 6 in panel A2), show that switching from non-exporting to exporting status is associated with 14.5% increase in productivity level, 8% increase in wage level, but 8% slowing down in productivity growth and 6.2% slowing down in wage growth. These results are in line with our initial investigation presented in Table 3. In order to begin to export, a lot of firms appear to undergo some important organizational and technological transitions involving both productivity and wage "jumps". Most likely, this is the domain of detailed firm-level studies by business economics and management of organizations. However, such "jumps" do not bear long-lasting effects, and new exporters appear to move even slower in the productivity and wage dimensions than non-exporting equivalents.

Table 11: Before-and-after export effects on firm's attributes (labour productivity, wage, growth of labour productivity, growth of wages). The table reports the coefficients of the dummy variable D_{ijt} from equation (14) to (17). Each column is one of the four characteristics.

Model	Specifications	L. P.	Wage	Gr. L.P.	Gr. Wage
	A1. Export-starters only (cross section estimates)				
(1)	OLS	$-0.0571^a(0.0099)$	$0.1002^a(0.0065)$	$-0.0601^a(0.0045)$	$-0.0316^a(0.0039)$
(2)	OLS (control size)	-0.0057 (0.0098)	$0.1091^a(0.0065)$	$-0.0761^a(0.0046)$	$-0.0433^a(0.0039)$
(3)	OLS (control size, age, region, ownership)	$-0.0477^a(0.0096)$	$0.0470^a(0.0062)$	$-0.0691^a(0.0046)$	$-0.0426^a(0.0040)$
	Number of Observations	234,199	231,498	183,067	179,449
	A2. Export-starters only (control for firm's unobserved time-invariant effect)				
(4)	FE	$0.0931^a(0.0072)$	$0.0565^a(0.0059)$	$-0.0384^a(0.0089)$	$-0.0350^a(0.0082)$
(5)	FE (control size)	$0.1454^a(0.0071)$	$0.0803^a(0.0059)$	$-0.0795^a(0.0090)$	$-0.0613^a(0.0083)$
(6)	FE (control size, age, region, ownership)	$0.1448^a(0.0071)$	$0.0805^a(0.0059)$	$-0.0798^a(0.0090)$	$-0.0616^a(0.0083)$
	Number of Observations	234,199	231,498	183,067	179,449
	B. Export-starters and never-exporters (difference-in-difference effects)				
(7)	FE	$0.0786^a(0.0072)$	$0.0651^a(0.0057)$	$-0.0530^a(0.0081)$	$-0.0335^a(0.0074)$
(8)	FE (control size)	$0.1761^a(0.0072)$	$0.1073^a(0.0058)$	$-0.1299^a(0.0082)$	$-0.0854^a(0.0076)$
(9)	FE (control size, age, region, ownership)	$0.1763^a(0.0072)$	$0.1061^a(0.0058)$	$-0.1284^a(0.0082)$	$-0.0848^a(0.0076)$
	Number of Observations	335,679	331,488	274,399	268,424

Note: all regressions include 2-digit sectoral dummies and year dummies. Numbers in parentheses are robust standard errors clustered at the firm level. a indicates that coefficients are significant at 1% level; b indicates significant at 5% level. Panel A1 and A2: the samples are restricted to export-starters only. Panel B: the samples are restricted to export-starters and never-exporters. Source: our elaboration on CMM.

Thus, since we are interested in the change of firm characteristics associated with switching into exporting status *relative to never-exporters*, now we use the sample including both export-starters and never-exporters. We control for firm-fixed effects and compare within-firm changes between export-starters and never-exporters, then obtain a difference-in-difference estimate as in the following specification:

$$\text{Level}: \ln \mathrm{X}_{ijt} = a + b_{DID}\,\mathrm{D}_{ijt} + \mu_{jt} + \eta_i + \epsilon_{ijt} \tag{16}$$

$$\text{Growth}: \Delta\,\mathrm{X}_{ijt} = a + b_{DID}\,\mathrm{D}_{ij,t-1} + \mu_{jt} + \eta_i + \epsilon_{ijt} \tag{17}$$

where η_i is the firm-fixed effect. The coefficient b_{DID} captures the change in export-starter characteristics relative to changes in never-exporter characteristics conditional on different set of control variables. Results, presented in Table 11, panel B, confirms the findings from panel A2. Those firms switching into export experience a 17.6% increase in productivity level, 10.6% increase in wage level, but -12.8% slowing down in productivity growth and -8.5% slowing down in wage growth when compared to never-exporters.

Given the different effects on productivity and wages, let us now look at the impact of switching export status on the wage-productivity pass-through in order to capture any change associated with the access to international trade:

$$\text{OLS}: w_{ijt} = \alpha + \beta\,\pi_{ijt} + \gamma\,\pi_{ijt}\mathrm{D}_{ijt} + \sigma\,\mathrm{D}_{ijt} + \mu_{jt} + \epsilon_{ijt} \tag{18}$$

$$\text{FE}: w_{ijt} = \alpha + \beta\,\pi_{ijt} + \gamma\,\pi_{ijt}\text{D}_{ijt} + \sigma\,\text{D}_{ijt} + \mu_{jt} + \eta_i + \epsilon_{ijt} \tag{19}$$

where the coefficient γ provides a simple estimate of the changes in the pass-through that accompany the exporting event. Table 12 (panel A1 and A2) shows the OLS and FE coefficient estimates from six different specifications. Pooling all years (see panel A1 model 3), the exporting status is associated with a 1.8% lower wage-productivity pass-through. However, if we look at the within-firm variation (see panel A2 model 3), switching from non-exporting to exporting status is associated with a 0.6% lower wage-productivity pass-through, but it is not statistically significant. The fact that OLS estimates of the coefficient of export dummy (σ) are higher than fixed effects may indicate that, conditional on the same productivity level (and the same size, age, ownership and region), firms with higher wage levels are more likely to self select into export.

Table 12: The wage-productivity pass-through in switching firms. The table reports the coefficients of the dummy variable D_{ijt} from equation (18) to (20).

Variables	(1)	(2)	(3)
Panel A1: export-starters only (cross section OLS)			
log- L.P.	$0.2531^a\,(0.0062)$	$0.2545^a\,(0.0062)$	$0.2367^a\,(0.0059)$
log- L.P. × Export Dummy	$-0.0225^a\,(0.0063)$	$-0.0226^a\,(0.0063)$	$-0.0184^a\,(0.0061)$
Export Dummy	$0.1998^a\,(0.0233)$	$0.1972^a\,(0.0233)$	$0.1285^a\,(0.0225)$
Size		$0.0078^a\,(0.0020)$	$0.0009\ \ (0.0021)$
Age			$0.0027^a\,(0.0003)$
Region dummies			yes
Ownership dummies			yes
R^2	0.2180	0.2181	0.2486
Number of obs.	231,498	231,498	231,493
Panel A2: export-starters only (control for unobserved firm-fixed effects FE)			
log- L.P.	$0.1784^a\,(0.0058)$	$0.1569^a\,(0.0058)$	$0.1569^a\,(0.0058)$
log- L.P. × Export Dummy	$-0.0108\ \ (0.0057)$	$-0.0057\ \ (0.0057)$	$-0.0057\ \ (0.0057)$
Export Dummy	$0.0817^a\,(0.0221)$	$0.0797^a\,(0.0220)$	$0.0801^a\,(0.0221)$
Size		$-0.1162^a\,(0.0049)$	$-0.1165^a\,(0.0049)$
Age			$0.1059^a\,(0.0030)$
Region dummies			yes
Ownership dummies			yes
R^2			
Number of obs.	231,498	231,498	231,493
Panel B: export-starters and never-exporters (difference-in-difference effects FE)			
log- L.P.	$0.1720^a\,(0.0033)$	$0.1528^a\,(0.0033)$	$0.1534^a\,(0.0033)$
log- L.P. × Export Dummy	$-0.0015\ \ (0.0040)$	$0.0051\ \ (0.0040)$	$0.0042\ \ (0.0039)$
Export Dummy	$0.0573^a\,(0.0162)$	$0.0595^a\,(0.0161)$	$0.0620^a\,(0.0161)$
Size		$-0.1065^a\,(0.0040)$	$-0.1080^a\,(0.0040)$
Age			$0.0970^a\,(0.0027)$
Region dummies			yes
Ownership dummies			yes
R^2			
Number of obs.	331,480	331,480	331,459

Note: all regressions include 2-digit sectoral dummies and year dummies. Numbers in parentheses are robust standard errors clustered at the firm level. a indicates that coefficients are significant at 1% level; b indicates significant at 5% level. Panel A1 and A2: the samples are restricted to export-starters only. Panel B: the samples are restricted to export-starters and never-exporters. Source: our elaboration on CMM.

As above, let us estimate the coefficient of the change in the wage-productivity pass-through of switching firms compared to never-exporters based on the sample including both export-starters and never-exporters, using the following specification:

$$w_{ijt} = \alpha + \beta\, \pi_{ijt} + \gamma_{DID}\, \pi_{ijt}\mathrm{D}_{ijt} + \sigma\, \mathrm{D}_{ijt} + \mu_{jt} + \eta_i + \epsilon_{ijt} \tag{20}$$

where the coefficient γ_{DID} provides a simple estimate of the changes in the pass-through that accompany the exporting event now relative to the changes in the pass-through in never-exporters. Results in Table 12, panel B, confirm the findings for panel A2. Switching into export status does not have significant impacts on the magnitude of the wage-productivity pass-through when compared to never-exporters.

The above regressions and the coefficient of the interaction show the change of the *average* wage-productivity pass-through between non-exporting and exporting status. Does switching from non-exporting to exporting unevenly affect the wage-productivity pass-through along the quantiles of the conditional wage distribution? The above model is now estimated using quantile regression at the 2-digit sectoral-level:

$$w_{ijt} = \alpha + \beta\, \pi_{ijt} + \gamma\, \pi_{ijt}\mathrm{D}_{ijt} + \sigma\, \mathrm{D}_{ijt} + y_t + \epsilon_{ijt} \tag{21}$$

with y_t year dummies. Figure 20 shows the coefficient estimates along the conditional wage distribution. The picture now changes. The first plot shows the distribution of the coefficients of the exporting status. Exporting status positively affects the wage level but only for those firms located at the lower quantiles of the wage distribution (left panel).[8] Looking at the interaction between productivity and the change in status (right panel), exporting leads to a decrease of the wage-productivity pass-through at the lower tail of the wage distribution while has no impact upon the median and upper tails. Indeed, the average analysis conducted before did not allow to capture the negative interaction at the lower tail of the conditional wage distribution.[9]

Figure D.3 in the Appendix shows the coefficients γ and σ for each ownership type. The exporting status is associated with higher wage levels declining along the conditional wage distribution (except for COEs) in line with the aggregate analysis. However, when looking at the coefficient of the interaction between productivity and exporting status the latter is not significantly different from zero for SOEs and COEs, while is significantly negative at the lower-tail and at the median of the conditional wage distribution for FIEs, HMT-invested and POEs. Regarding shareholding enterprises, the coefficient of the interaction term is significantly negative only at the very lower tail, around 0.05 quantile. Therefore exporting significantly reduces the wage-productivity pass-through at the low and medium part of the conditional wage distribution particularly for foreign-invested enterprises. State-owned, collective-owned and shareholding enterprises are instead resilient to the change of status. The above evidence has been confirmed with the CREM method.

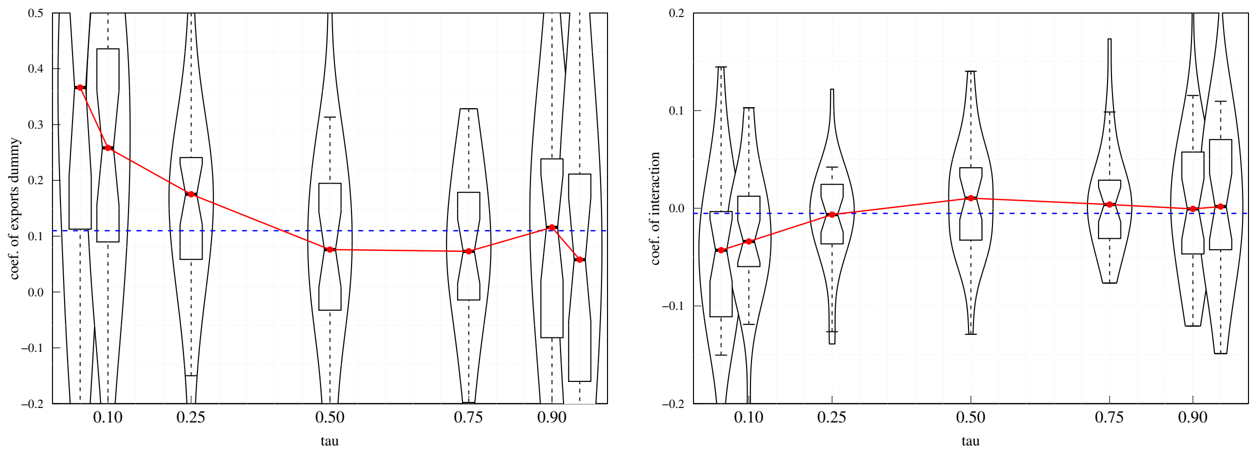
6.1. Timing effects: event study analysis of export-starters

We conclude our empirical analysis by conducting a fine-grained investigation of the timing of the effects (if any) associated with a change in exporting status by means of an event-study approach. In

[8] Based on Wilcoxon signed-rank test, the median of the coefficient distribution at quantile 0.05 is significantly higher than zero, and based on Dunn test, the distribution of the coefficient at quantile 0.05 are significantly different from the distribution of coefficients at higher quantiles 0.50, 0.75 and 0.95 at 0.01 significance level.

[9] Based on Dunn test, the coefficient distribution at quantile 0.10 is significantly different from the coefficient distributions at the other upper quantiles (0.50, 0.75 and 0.95) at 0.05 significance level. Based on Wilcoxon signed-rank test, the median of the coefficient distribution at quantile 0.05 is significantly lower than zero. Both patterns are confirmed under CREM estimation.

Figure 20: Distributions of quantile regression coefficients γ (left-hand side) and σ (right-hand side) across 28 2-digit sectors (only sectors with the number of observations larger than 160).



Note: quantile regression estimation of equation (21) for each 2-digit sector showing the coefficients of export status dummy and the interaction (between log- labour productivity and export status dummy) reported for the 0.05, 0.10, 0.25, 0.50, 0.75, 0.90 and 0.95 quantiles. Each violin reports a box plot and a kernel density to each side of the box plot. The median of Pseudo R^2 is 0.1364 for quantile regression. The dashed line is the median of the distribution of OLS estimates.

doing so, we try to detect, once the change occurred, its impact over time.

For each firm switching status we define an $index$ as the difference between the current and the first exporting year. Thus, the $index$ takes negative integer values for the years before exporting, zero in the first year of exporting, and positive integer values after the first year. Since the number of observations for extreme values of the index is small, we censored at -6 on the lower end and at +6 on the upper end. We then perform the following OLS regression:

$$\text{Level:} \;\; \ln \mathrm{X}_{ijt} = \alpha + \sum_{k=-6}^{+6} \beta_k \mathrm{D}_{kit} + \mu_{jt} + \epsilon_{ijt} \tag{22}$$

$$\text{Growth:} \;\; \Delta\, \mathrm{X}_{ijt} = \alpha + \sum_{k=-6}^{+6} \beta_k \mathrm{D}_{ki,t-1} + \mu_{jt} + \epsilon_{ijt} \tag{23}$$

where X_{ijt} is one of the firm's characteristics (labour productivity or wage); $\Delta \mathrm{X}_{ijt}$ is the growth rate of the variable thereof; dummy $\mathrm{D}_{kit} = 1$ if $index = k$ for firm i in year t. We then plot the β_k coefficients against the $index$ to detect how the dependent variable changes before and after exporting.

We first estimate equations 22 and 23 for the export-starters sample only. Figure 21 compares the coefficient estimates for the timing before and after exporting for the firm attributes and performances. The dummy's coefficient is normalized to zero at the year before starting to export ($t = -1$). In line with the previous analysis, labour productivity levels are positively and persistently affected by the switching status as shown by the OLS and FE estimations, with the latter far higher. The level of productivity persistently increases in the post switching years and reaches the peak after four years. When looking at the wage level however OLS and FE estimations present more controversial results. While OLS show a positive increasing time effect, FE estimation gives an inverted U pattern, with a peak of the effect at the third year and then a declining impact. Conversely, results are neater for the growth variables: as already detected the impact of switching status is persistently negative over time, with milder negative impacts with FE estimators. Overall, this analysis reveals that if any impact of switching status is detected, it appears quite immediately but in some cases it tends to disappear over time.

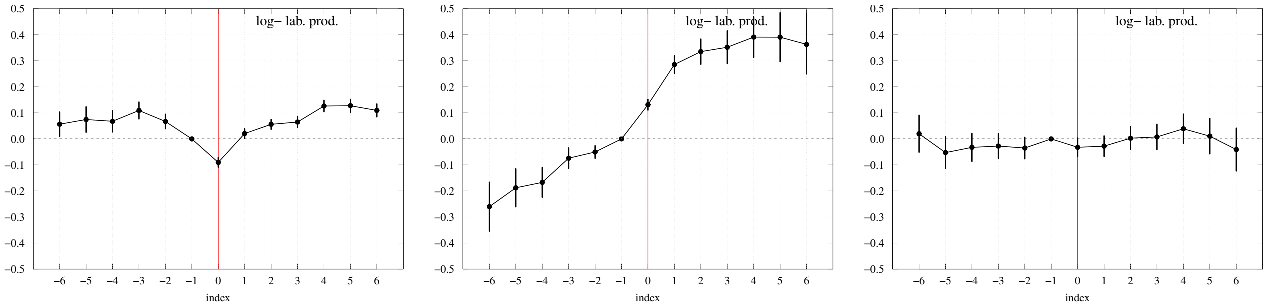
The third column in figure 22 shows the results from DID method, to control for potential selection bias (i.e. some firm unobserved heterogeneity may contribute to firms self selecting into exporting status, and affect the outcome variable - the level/growth of productivity/wage). We undertake a difference-in-difference approach relative to a matched nearest neighbor. Each export-starter (in the treatment group) is matched with a never-exporter (in the control group). Specification 22 is estimated with cell and year fixed effects using the one-on-one matched sample.[10] A striking evidence is that switching into exporting does not have any significant impact on productivity level and that the nil impact is persistent over time when compared to non-exporting firms. This DID estimation result is very different from FE estimates (the second column). Consistent with OLS and FE estimates, DID results report a persistent positive impact on wage level, and a persistent negative impact on productivity and wage growth rates.[11]

[10]The matched control firm is chosen from never-exporters in the same CIC 4-digit sector, of the same age as the switching firm, and with the closest employment size to the switching firm in the data year prior to exporting. The timing index dummies for control firms are all set to zero.

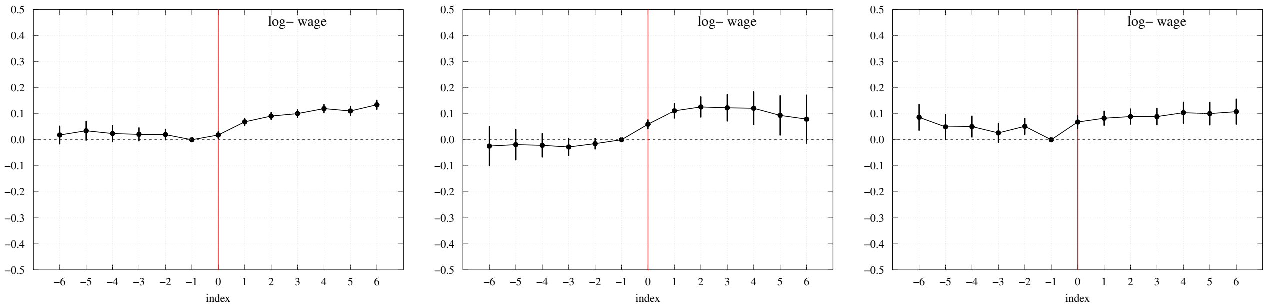
[11]We also estimate the models only controlling for industry and year dummies, and controlling for size. These specifications yield very similar results which are available upon request.

Figure 21: Regression coefficients of the timing before and after exporting for each of the firm attributes for equation 22 and 23. Different model specifications for each attribute: the first column shows OLS estimates; the second column shows FE estimates; the third column shows DID estimates.

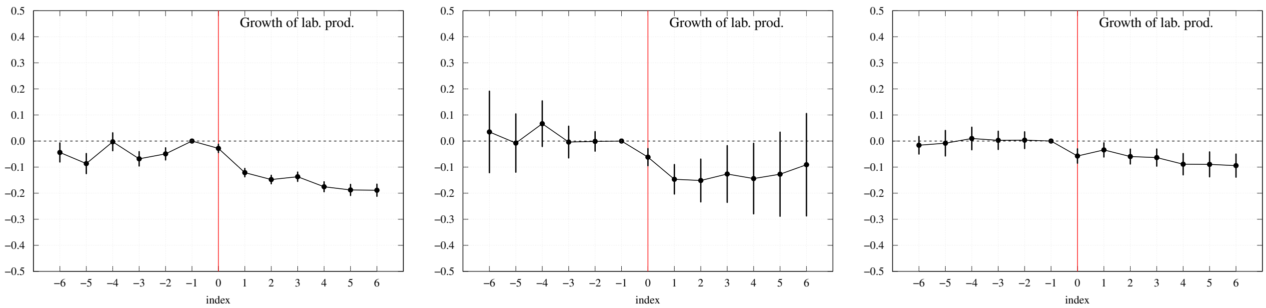
(a) (log) labour productivity



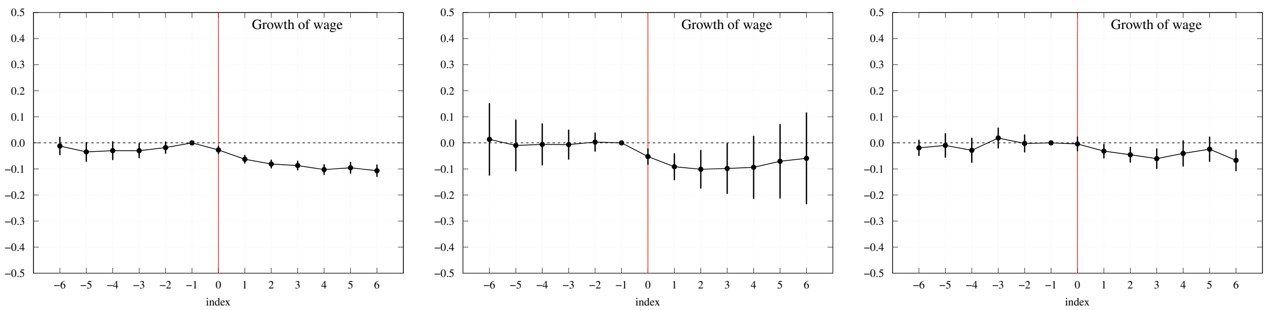
(b) (log) wage per employee



(c) Growth of labour productivity



(d) Growth of wage



Note: all models include 2-digit sectoral and year dummies, and control for size, age, ownership and regional dummies. The vertical bars indicate 95% confidence interval. All regressions with robust standard errors. All variables normalized to zero for index = -1. The red vertical line denotes the first year of exporting ($timing = 0$). The first and second plot are based on export-starters only sample; the third DID plot is estimated using the one-on-one matched sample. Source: our elaboration on CMM.

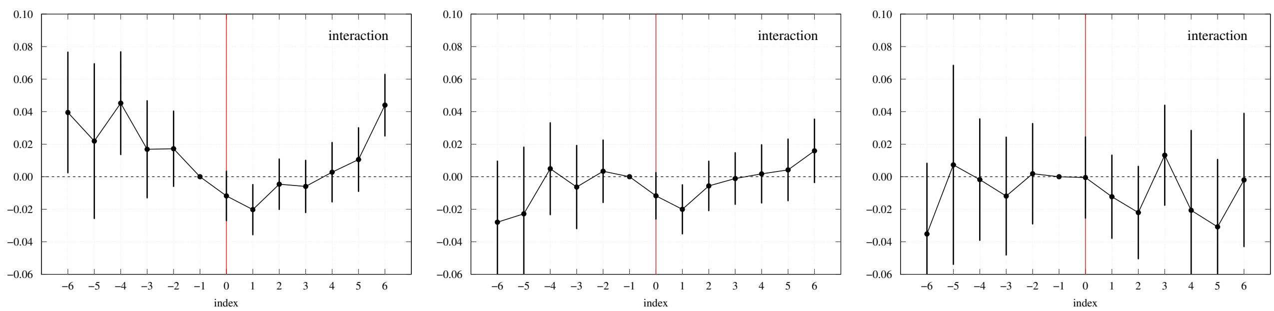
We now turn to estimate the time effect for the wage-productivity pass-through according to the following specification:

$$w_{ijt} = \alpha + \beta\pi_{ijt} + \sum_{k=-6}^{+6} \gamma_k \, \pi_{ijt}\mathrm{D}_{kit} + \sum_{k=-6}^{+6} \sigma_k \mathrm{D}_{kit} + \mu_{jt} + \epsilon_{ijt} \tag{24}$$

The coefficient γ_k provides an estimate of the dynamics of the changes in the pass-through that accompany the exporting event.

Figure 22 shows the OLS, FE and DID coefficient estimates of interactions at different timing before and after exporting. The coefficient of the interaction is normalized to zero at the year before starting to export ($t = -1$). For all specifications, the coefficient of $t = 0$ and $t = 1$ are negative (in particular $t = 1$). Both OLS and FE estimations present a similar pattern: in the year of switching to export and for the consecutive one the wage-productivity pass-through turns out to be lower. It smooths down to a zero impact for the subsequent three years and some positive impacts are revealed after five years from exporting. Differently from the effects on the pure characteristics, the patterns of the gains distribution appear to be more sticky and negatively affected by entering into export. DID estimates, although more volatile, do not show any significant change in the pass-through when comparing export starters with similar non-exporting firms.[12]

Figure 22: Regression coefficients of the interaction term (γ, between productivity and export timing dummies) in equation 24. Compare OLS (first plot), FE (second plot) and DID (third plot) models.



Note: all models include 2-digit sectoral and year dummies, control for size, age, ownership and region. Pooling all firms in manufacturing. The vertical bars indicate 95% confidence interval. All regressions with robust standard errors. All variables normalized to zero for index = -1. The red vertical line denotes the first year of exporting ($timing = 0$). The first and second plot are based on export-starters only sample; the third DID plot is estimated using the one-on-one matched sample. Source: our elaboration on CMM.

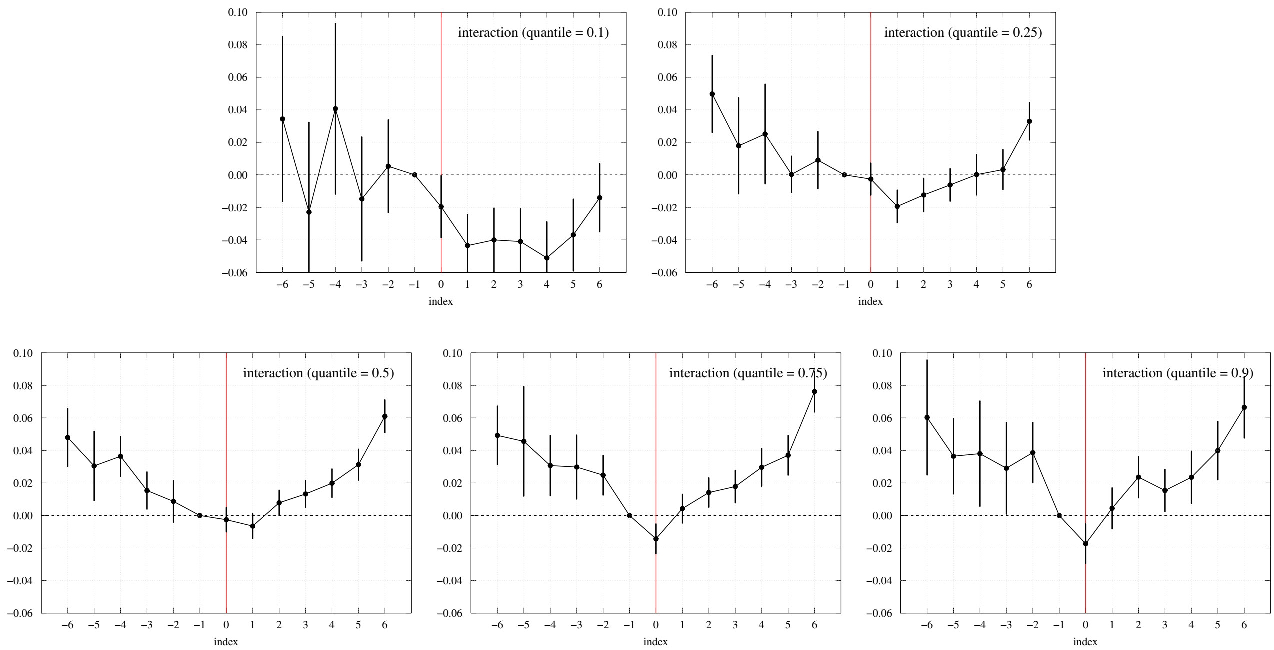
Given that previously we detected overall a nil impact of the switching status and if any a negative one for the lowest quantile, we now perform the same exercise looking along the quantiles of the wage distribution. According to Figure 23, switching into export has a persistent negative impact on the pass-through for the 10th quantile of the conditional wage distribution (until five years after switching). Note that, although for the other quantiles the negative impact on the pass-through is transitory, for the first two years after starting to export the distribution of gains is reduced. At quantile 10, switching into export significantly weakens the wage-productivity pass-through and that weakening effect persists over time. At quantiles 0.5, 0.75, and 0.9 the coefficient of the interaction

[12]We also estimated the model specification only controlling for 2-digit sectoral and year effects, and for size effect. The results are very similar and are available upon request.

term is significantly positive. The above evidence is confirmed by performing a CREM estimation.

The analysis conducted by disaggregating by ownership type (see Figure D.4) reveals that switching into exporting status has a persistent negative impact on the lower tail of the conditional wage distribution for HMT-invested, foreign-invested and private owned enterprises (row 3, 4 and 6 in the figure). Switching into export has some mild positive impact on the pass-through at the upper-tail (75th, 90th) of the conditional wage distribution for SOEs (row 1) only after four years and for shareholding firms (row 5) two years later. For COEs (row 2) the impact is nil. The positive effects on the upper quantiles are instead stronger for HMT-invested. This evidence again is confirmed by the CREM model.[13]

Figure 23: Export-starters only. Quantile regression coefficients of the interaction term (γ, between productivity and export timing dummies) in equation 24 estimated at quantiles 0.1, 0.25, 0.5, 0.75 and 0.9 of the conditional wage distributions.



Note: model controlling for 2-digit sectoral and year dummies, size, age, ownership and region. The vertical bars indicate 95% confidence interval. All regressions with robust standard errors. All variables normalized to zero for index = -1. The red vertical line denotes the first year of exporting ($timing = 0$). Source: our elaboration on CMM.

7. Conclusions

The access of China to the WTO has certainly been a major event for the world economy. However, our evidence shows, it has not been a game-changer for the Chinese economy itself. The impressive growth of labour productivity in all manufacturing sectors which began well before the WTO entry continued thereafter driven by successful processes of learning and catching-up. And also the microeconomics of export growth does not display any major discontinuity.

[13]Models only controlling for sectoral and year dummies, and also for size show very similar results and are available upon request.

Our results show that first of all, exporting firms do not have any productivity and wage premia in the long-run: if present at the beginning, the premia decrease over time in level, while even get negative in terms of growth rates. Second, the access of China to the WTO is associated with an increasing dispersion of labour productivities and wages across-firms/within-sectors and a reduction of the latter across sectors. In that respect, there is hardly any evidence that the access to the WTO has polarised Chinese manufacturing between high-productive exporting firms and low-productive non-exporting ones. What it did has been to make exporting easier both for "good" and "less good" firms. Third, the easier access to international markets did influence the sectoral composition of export, but in directions opposite to the prediction of any "comparative advantage view". Unlike any purported pattern of specialization based on purely cost-competition, after the access to the WTO one sees an increasing share of exports in technologically advanced sectors like manufacturing of telecommunication equipments, computers and other electronic devices (CIC 40) with an ever *decreasing* share of the textile clothing sectors. But, at the same time, inside each sector the between-firm labour productivity and wage heterogeneity increased providing evidence against any reallocation effect generated by exporting.

Did exporting firms have a different pattern of distribution of productivity gains? We checked the dynamic of the pass-through via quantile regression analysis for three distinct populations (never-exporters, always-exporters, export-starters) along the conditional wage distribution. We do not find a statistically different pass-through coefficient for exporting as compared to non-exporting firms. The nil impact upon the gain distribution is confirmed also when comparing the change of the pass-through with respect to never-exporters. However, an event study analysis conducted by quantiles and accounting for the ownership structure shows that the pass-through has been persistently lowered for low-wage foreign-invested enterprises.

In another work (Yu et al., 2015), we argue that the core of technological dynamism of Chinese manufacturing are restructured State-owned enterprises and public-private joint venture (SHEs), and these, especially the former, display the highest pass-through from productivity to wages, within a general picture characterised by very low elasticities (Dosi et al., 2020). An easier access to international markets, following the accession to the WTO, does not change the picture. Putting it in another way, there is no general evidence of "wage dumping" following the WTO adherence. There is indeed an overwhelming evidence of a distributive dynamics heavily favouring profits, but this seems to be part of the political economy of the post-liberalization, quite orthogonal to the WTO event. If there is an exception, this is represented by *foreign* owned enterprises, and not by the technological core of Chinese manufacturing.

Acknowledgements

The authors thank Jiasu Lei and several participants to the ICOAE Conference (Milan, 2019). Helpful comments have been received from Nicholas Tsounis. We gratefully acknowledge the support by the European Union Horizon 2020 Research and Innovation programme under grant agreement No. 822781 - GROWINPRO. Xiaodan Yu gratefully acknowledges the support by Martin Lockett, Martin Liu, Sathyaprakash Balaji Makam, the Nottingham Business School China and the ORSS grant. The usual disclaimer applies.

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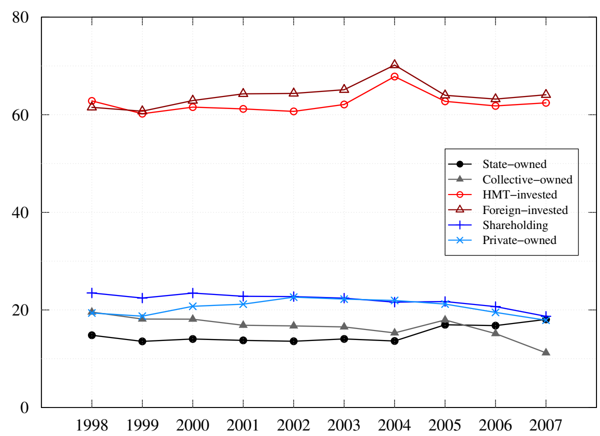
A. Further descriptive statistics

Figure A.1: Fraction of exporters in each ownership.

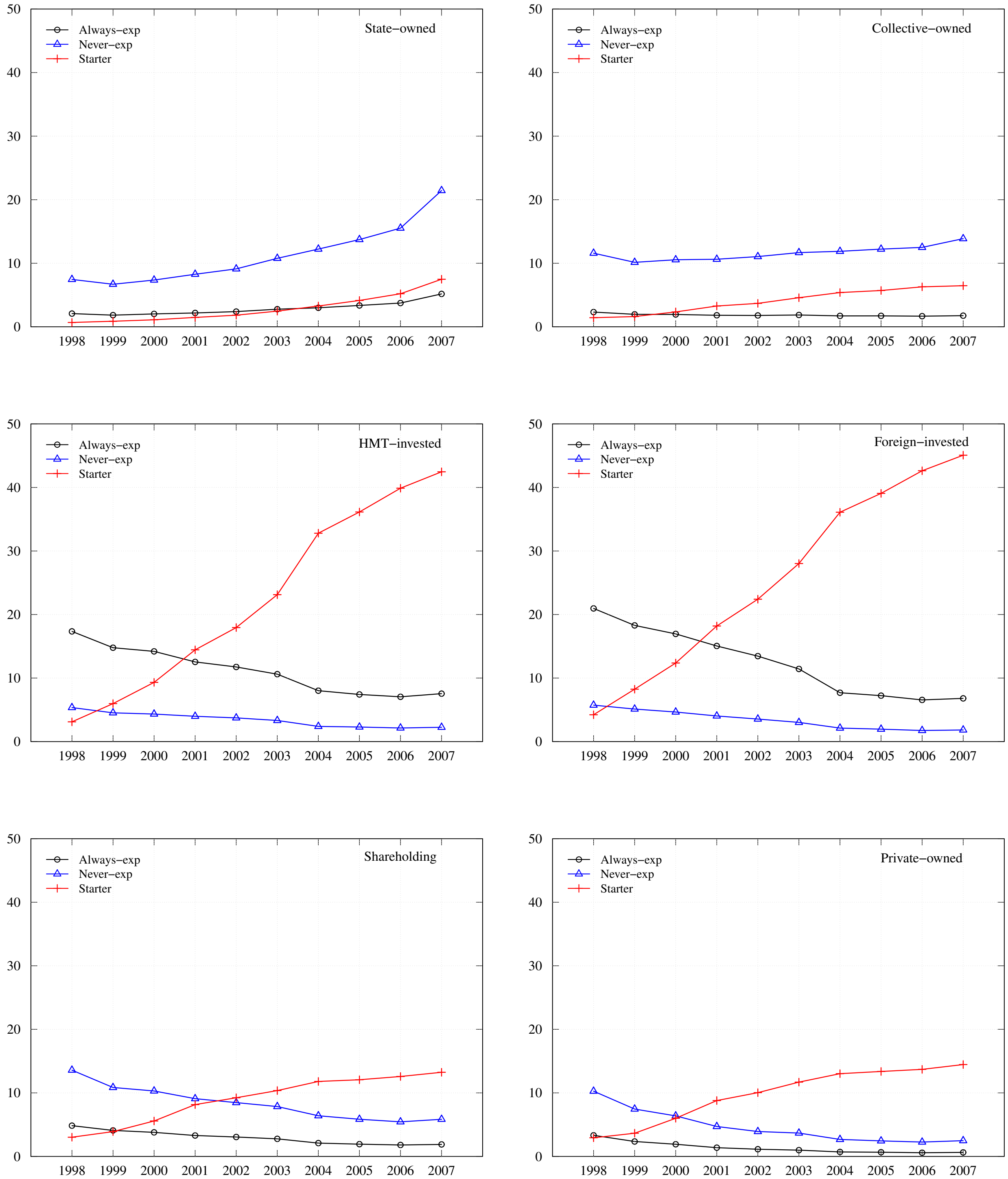


Note: numbers in the vertical axis are in percentages. Source: our elaboration on CMM.

Table A.1: Percentage share of the number of firms by ownership types

Ownership types	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
				Always-exporter (6,142 firms)						
State-owned	9.9	9.3	8.5	7.5	7.0	6.3	5.4	5.2	4.9	4.9
Collective-owned	15.5	14.4	12.9	10.5	9.3	8.1	5.8	5.5	4.6	4.0
HMT-invested	34.1	34.0	34.2	34.4	34.2	34.0	32.6	31.8	32.1	32.5
Foreign-invested	29.3	29.3	29.4	29.5	29.6	29.9	31.5	31.9	31.6	31.5
Shareholding	6.2	7.4	8.8	10.6	11.6	12.1	13.0	13.1	13.5	13.4
Private-owned	4.3	4.9	5.6	7.1	8.0	9.3	11.4	12.2	13.0	13.3
				Never-exporter (10,148 firms)						
State-owned	21.4	20.6	18.8	17.2	16.0	14.8	13.4	12.9	12.4	12.2
Collective-owned	47.1	45.2	42.5	37.4	34.9	30.9	24.2	23.5	20.6	19.3
HMT-invested	6.4	6.3	6.3	6.6	6.6	6.5	5.9	6.0	5.9	5.9
Foreign-invested	4.9	5.0	4.9	4.8	4.7	4.8	5.3	5.2	5.1	5.1
Shareholding	10.5	11.9	14.5	17.6	19.4	20.7	24.1	24.0	24.7	25.0
Private-owned	8.1	9.3	11.4	14.7	16.7	21.0	26.2	27.2	30.4	31.6
				Export starter pooling all cohorts						
State-owned	9.8	7.6	4.9	3.0	2.3	1.7	1.0	0.9	0.8	0.9
Collective-owned	29.1	20.4	16.4	11.1	8.3	6.1	3.1	2.7	2.1	1.8
HMT-invested	18.6	23.6	23.6	23.1	22.5	22.5	22.6	22.8	22.4	22.5
Foreign-invested	18.0	22.7	22.6	20.8	21.2	22.2	25.1	25.3	25.3	25.7
Shareholding	11.8	12.2	13.6	15.3	15.1	13.7	12.4	12.0	11.6	11.5
Private-owned	11.6	13.0	18.6	26.4	30.4	33.5	35.7	36.1	37.5	37.4
				Export starter in cohort 1999						
State-owned	3.9	4.6	4.1	3.5	3.3	3.0	2.4	2.1	2.1	2.2
Collective-owned	22.2	13.4	11.7	9.1	8.3	7.2	5.0	4.8	4.4	3.8
HMT-invested	31.3	32.7	32.5	33.7	33.7	32.8	30.7	30.9	31.3	31.4
Foreign-invested	23.3	29.4	29.9	28.9	29.0	30.0	32.4	32.4	31.9	32.3
Shareholding	8.3	9.4	10.9	11.9	12.1	12.0	13.2	13.1	12.9	12.9
Private-owned	10.2	10.3	10.7	12.7	13.4	14.9	16.2	16.5	17.3	17.2
				Export starter in cohort 2003						
State-owned	11.5	10.3	7.7	3.7	2.2	0.9	0.7	0.7	0.7	0.7
Collective-owned	34.5	28.4	23.0	15.9	9.4	4.4	2.5	2.5	2.0	1.8
HMT-invested	12.1	16.2	13.4	13.2	16.2	25.1	25.5	25.2	25.6	25.6
Foreign-invested	15.2	13.7	15.7	14.6	15.1	24.7	26.7	26.8	26.4	26.8
Shareholding	12.7	15.7	15.0	18.9	19.1	10.8	11.0	10.6	10.8	10.8
Private-owned	13.3	15.2	24.6	33.3	37.8	34.0	33.5	34.2	34.4	34.2
				Export starter in cohort 2007						
State-owned	19.2	16.9	11.8	7.9	6.0	4.3	2.2	1.8	1.1	1.4
Collective-owned	33.7	30.5	27.6	18.0	14.1	10.0	5.0	4.0	2.8	2.3
HMT-invested	11.5	11.5	11.1	9.1	9.8	8.6	9.0	9.6	11.0	11.6
Foreign-invested	12.5	11.1	11.5	7.9	7.8	9.1	10.3	11.1	14.8	14.9
Shareholding	12.5	13.6	15.5	24.1	23.0	21.2	20.4	19.8	15.9	16.0
Private-owned	9.6	15.6	22.3	32.4	38.9	46.2	52.7	53.2	54.0	53.4

Figure A.2: Fraction of always-exporters, never-exporters and export-starters (pooling cohorts) in each ownership.



Note: numbers in the vertical axis are in percentages. Source: our elaboration on CMM.

B. Shift-and-share analysis of aggregate productivity growth

To measure the contributions of structural change to aggregate productivity growth, it is crucial to distinguish between the contributions of shifts between sectors and the contributions of productivity growth within sectors. We adopt van Ark and Timmer (2003) shift-share model.

The difference in aggregate labour productivity levels at time 0 and T can be written as:

$$P^T - P^0 = \sum_{i=1}^{n}(P_i^T - P_i^0)\overline{S}_i + \sum_{i=1}^{n}(S_i^T - S_i^0)\overline{P}_i \tag{25}$$

with P_i^0 and P_i^T the labour productivity of sector i at year 0 and T; S_i^0 and S_i^T the employment share of sector i at year 0 and T; $\overline{S}_i$ sector's period average share of total employment, and $\overline{P}_i$ sector's period average labour productivity. The aggregate productivity growth can be decomposed into intra-sectoral productivity growth (the first term on the right-hand side of equation (25), called "intra-effect") and the effects of changes in the sectoral allocation of labour (the second term, called "shift-effect"). Let C_i denote the contribution of sector i to the aggregate labour productivity growth. We have:

$$P^T - P^0 = \sum_{i=1}^{n} C_i = \sum_{i=1}^{n}(C_i^{intra} + C_i^{shift}). \tag{26}$$

van Ark and Timmer (2003) reallocate all shift effects (C^{shift}) from sectors that experienced shrinking labour shares to sectors that expanded their share in total labour. Suppose K is the set of sectors which expand their labour shares; J is the set of sectors with declining labour share. For expanding sectors k and shrinking sectors j:

$$C_k = C_k^{intra} + C_k^{shift} = (P_k^T - P_k^0)\overline{S}_k + (S_k^T - S_k^0)(\overline{P}_k - \overline{P}_J) \qquad \forall k \in K \tag{27}$$

$$C_j = C_j^{intra} = (P_j^T - P_j^0)\overline{S}_j \qquad \forall j \in J \tag{28}$$

with average labour productivity overall shrinking sectors and averaging over years:

$$\overline{P}_J = \frac{\sum_{j\in J}(S_j^T - S_j^0)\overline{P}_j}{\sum_{j\in J}(S_j^T - S_j^0)}. \tag{29}$$

C. Using difference-in-difference approach to estimate the before-and-after (export) effects

Here we distinguish firms into two groups: never-exporters (NEXP), and export-starters (EXPS).

Let Y_{1ijt} be firm characteristic (e.g. labour productivity level) at firm i in group s and period t if the firm is in exporting status, and let Y_{0ijt} be firm characteristic at firm i in group s and period t if the firm is in non-exporting status. We assume that the potential outcomes in the no-treatment group (i.e. never-exporters) is:

$$E[Y_{0ist}] = \gamma_s + \lambda_t \tag{30}$$

where s denotes group (never-exporter or export-starter) and t denotes period. This equation says that in the absence of exporting status, firm characteristic is determined by the sum of a time-invariant group effect and a year effect that is common across groups. Let D_{st} be a dummy for firms in exporting status and periods. Assuming that $E[Y_{1ist} - Y_{0ist}|s, t]$ is a constant, denoted σ, observed firm characteristic, Y_{ist}, can be written:

$$Y_{ist} = \gamma_s + \lambda_t + \sigma D_{st} + \epsilon_{ist} \tag{31}$$

where $E(\epsilon_{ist}|s, t) = 0$. From here, we get:

$$\begin{aligned} &E[Y_{ist}|s = \text{NEXP}, t = \text{POST-EXP}] - E[Y_{ist}|s = \text{NEXP}, t = \text{PRE-EXP}] \\ &\quad = \lambda_{\text{POST-EXP}} - \lambda_{\text{PRE-EXP}} \end{aligned} \tag{32}$$

and:

$$\begin{aligned} &E[Y_{ist}|s = \text{EXPS}, t = \text{POST-EXP}] - E[Y_{ist}|s = \text{EXPS}, t = \text{PRE-EXP}] \\ &\quad = \lambda_{\text{POST-EXP}} - \lambda_{\text{PRE-EXP}} + \sigma \end{aligned} \tag{33}$$

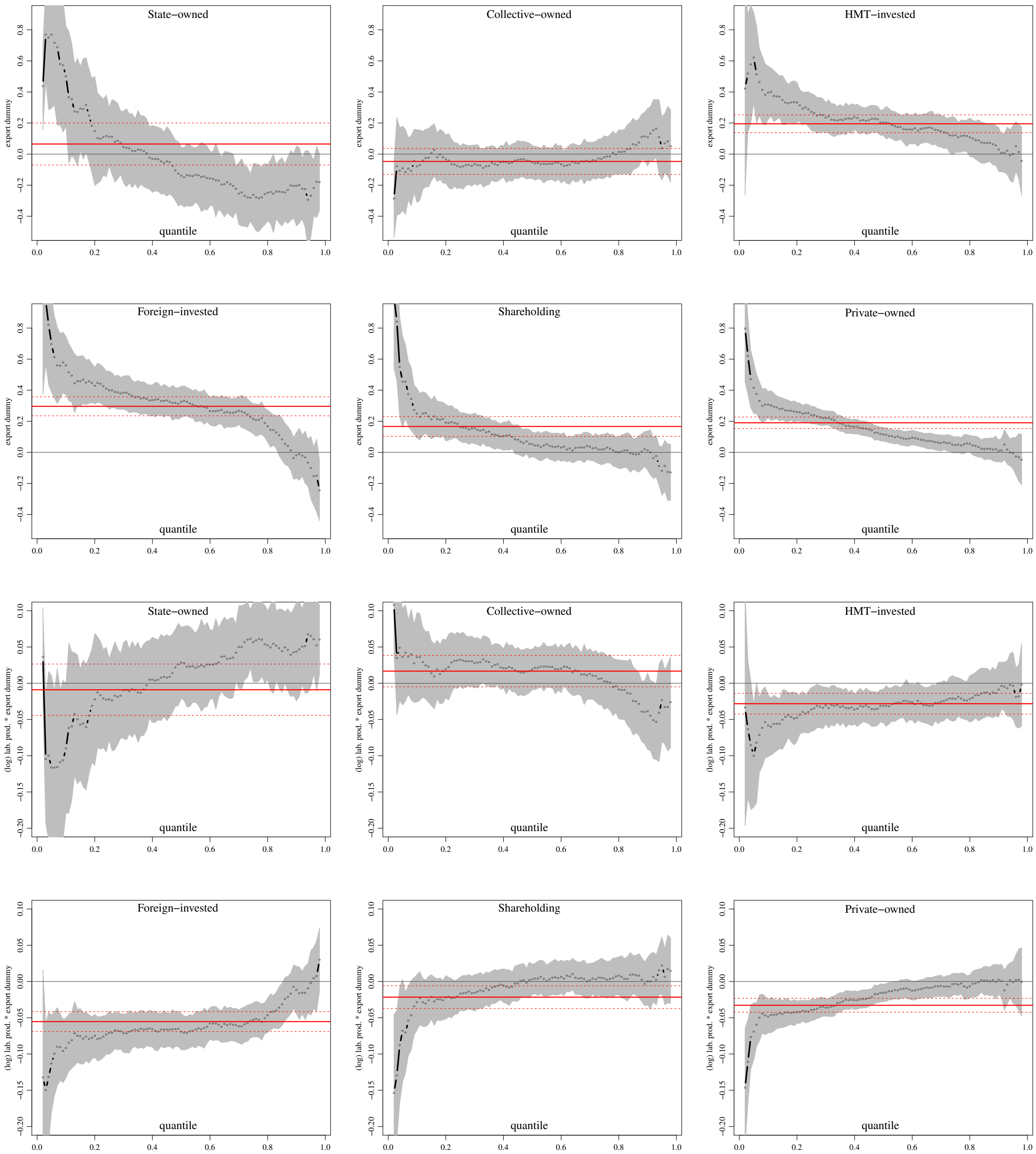
The population difference-in-differences,

$$\begin{aligned} &\{E[Y_{ist}|s = \text{EXPS}, t = \text{POST-EXP}] - E[Y_{ist}|s = \text{EXPS}, t = \text{PRE-EXP}]\} \\ &\quad - \{E[Y_{ist}|s = \text{NEXP}, t = \text{POST-EXP}] - E[Y_{ist}|s = \text{NEXP}, t = \text{PRE-EXP}]\} = \sigma \end{aligned} \tag{34}$$

is the causal effect of interest. This is estimated using the sample analogous of the population means (for each 2-digit sector).

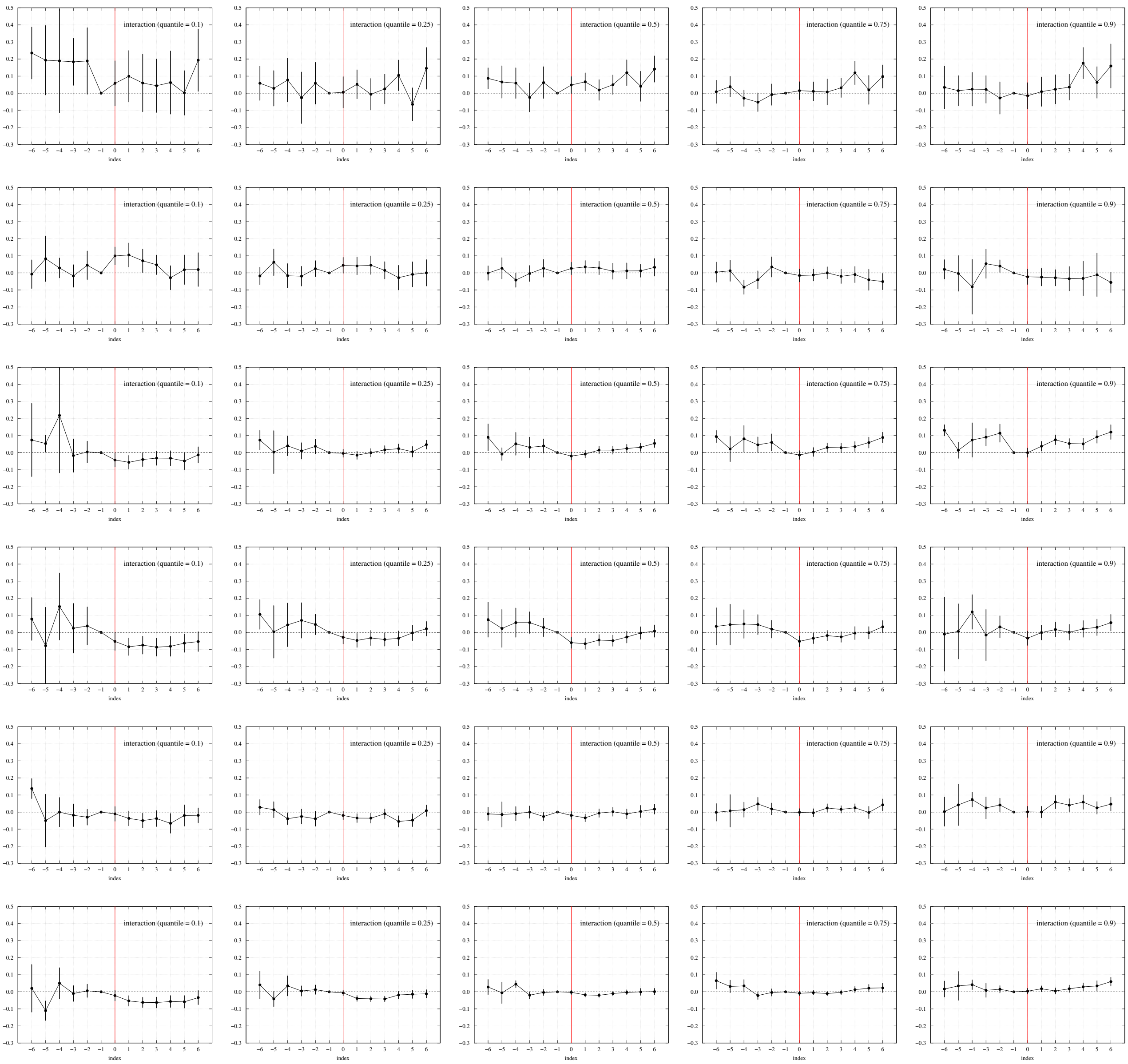
D. Additional results by ownership type

Figure D.3: Quantile regression estimation of equation (21) for six ownership types respectively showing the coefficients of export status dummy (first and second rows) and the interaction between log- labour productivity and export status dummy (third and fourth rows).



Estimation with 2-digit sectoral dummies and year dummies. Bootstrapped standard errors. The shaded area shows the 95% confidence intervals. The red line is the OLS estimate. The dashed line shows the 95% confidence interval. Source: our elaboration on CMM.

Figure D.4: Export-starters only, by ownership type. Quantile regression coefficients of the interaction term γ between productivity and export timing dummies in equation 24.



Note: the model includes 2-digit sectoral and year dummies, size, age and regional dummies. State-owned (row 1), collective-owned (row 2), HMT-invested (row 3), foreign-invested (row 4), shareholding (row 5) and private-owned (row 6). The vertical bars indicate 95% confidence interval. All regressions with robust standard errors. All variables normalized to zero for index = -1. The red vertical line denotes the first year of exporting ($timing = 0$). Source: our elaboration on CMM.