Report to Department for Trade and Industry

Modelling the Productivity Distribution of Foreign and Domestic Firms in the UK

Mauro Pisu

(GEP, University of Nottingham)

 The authors thank the staff of the Business Data Lab at the Office for National Statistics for their help in accessing the data, in particular Joe Robjohns, Rhys Davies and Felix Ritchie. Financial support from the DTI under the Seed Grant Scheme and the Leverhulme Trust (under Programme Grant F114/BF) is gratefully acknowledged. The author thanks Chiara Criscuolo, Ralph Martin and Fernando Galindo-Rueda and the other participants in the DTI Workshop on Seed-Funding Projects "Trade and FDI Theme" on the 14th of March 2006 for comments and suggestions. All remaining errors are my own.

1. Introduction

One of the main findings of the literature of firm-level studies concerns the large dispersion of firm-level productivity even in narrowly defined industry. Foster, Haltiwanger and Krizan (1998), Haltiwanger (1997) report for the US that within industry firm-level productivity differences are larger than between sector differences.[1] Also, most of the job reallocation process involves firms operating in the same industry (Davis and Haltiwanger 1999). Recent empirical and theoretical studies on the relationship between productivity of firms and their engagement in international trade have shown that the former is one of the main determinants to become an exporter or a multinational. Empirical studies have overwhelmingly reported that foreign affiliates or multinationals are more productive than exporters and the latter are more efficient than non exporting firms.[2] These empirical regularities have been incorporated in recent theoretical models by Melitz (2003) and Helpman, Melitz and Yeaple (2004).[3]

Studies concerning the UK specifically have confirmed that foreign companies and UK multinationals are more productive than exporters, and the latter are more efficient than non-exporters (Girma, Keneller and Pisu 2005). Criscuolo and Martin (2005) also point out that UK multinationals are more productive than the generality of foreign affiliates in the UK. The productivity gap between foreign and domestically owned firms has received a lot of attention in UK policy circles. Different policies have been designed to try to close, at least partly, this gap and therefore to raise the productivity level of the whole UK economy. However, it is unlikely that such policies will have the same impact on firms having different productivity levels. This is because enterprises characterised by different productivity may be intrinsically different and therefore respond differently to the same factors of change. In other words, a certain policy change (or any other cause) may not simply shift the entire firm-level productivity distribution, but changes also its shape and degree of dispersion.

---

[1] These findings have been confirmed for a number of other countries (e.g.: Levinsohn (1999) for Chile; Roberts and Tybout (1999) for developing countries.

[2] Productivity and efficiency are conceptually different (Farrel 1957). However, for the purpose of this paper we can neglect this difference and the two terms will be treated as synonymous.

[3] In these models firms self-select to become exporters or multinationals. This is because only companies with a productivity level above a certain cut-off point will find profitable paying the sunk costs necessary to export or establishing an affiliate abroad.

It is therefore important to understand whether the factors thought to determine productivity affect in the same way the strongest (i.e. highly productive) and weakest (i.e. lowly productive) firms. The aim of this research project is to model the productivity distribution of UK multinationals, foreign and domestic plants focussing on the impact of R&D spending. I concentrate on this variable since it is believed to be one of the major determinants of efficiency.[4] The data from R&D spending come from the third Community Innovation Survey (CIS3) and from the Annual Respondent Data base (ARD).

To model the productivity distribution of foreign, domestic plants and UK multinational enterprises (UK MNEs) I use quantile regression developed by Koeneker and Basset (1998). This allows to fit regression lines at different quantiles of the distribution of the dependent variable (productivity in this study) and therefore to investigate the impact of a certain variable at different point of the distribution, not just at its mean. This allows to model the impact of R&D across the whole productivity distribution and therefore to understand whether or not lowly and highly productive firms respond differently.

The results suggest that additional R&D spending affects the entire productivity of domestic and foreign enterprises in the same fashion.[5] Then, R&D spending appears to have the same effect on the productivity distribution of domestic and foreign companies, thus leaving the productivity gap between them unchanged. There is also evidence that UK multinational enterprises at the higher end of the productivity distribution appear to gain more from R&D spending than domestically owned firms. This result in conjunction with the finding of Criscuolo and Martin (2005) suggest that UK MNEs are likely to increase their productivity advantage through additional R&D spending.

The rest of the paper is organised as follow. The next section describes the empirical methodology. The third section presents the data sets used. The results are discussed in section 4. Finally, section 5 concludes.

---

[4] See Klette and Kortum (2004) and references cited therein.

[5] It is worth stressing that since a single cross-section for the year 2000 was used, no formal causal analysis (from R&D spending to productivity) was undertaken in this study. Therefore, caution is needed in interpreting these results since there could be an issue of reverse causality (from productivity to R&D spending) that I did not address.

2. Empirical Methodology

Ordinary least square (OLS) can be interpreted as a way to extend the idea of estimating an *unconditional* mean parameter to estimating a *conditional* mean function (conditional on a certain set of covariates). Analogously, the quantile regression (Koenker and Bassett 1978) can be viewed as an extension of the univariate quantile estimation to *conditional* quantile estimation. OLS fits a single regression line through the conditional mean of the dependent variable and retrieve a single set of parameters. Quantile regression allows to fit regression lines at different conditional quantiles and to obtain different estimates for each quantile. In this way it is possible to assess how a certain variable affect the dependent variable at different points of its conditional distribution. Another advantage of the quantile regression is that it is robust to outliers since they affect the mean, but not the median and other quantiles.[6]

Quantile regression can be written as

$$y_i = x'_i \beta_\theta + u_{\theta i} \qquad\qquad Quant_\theta (y_i | x_i) = x'_i \beta_\theta$$

where $Quant_\theta (y_i| x_i)$ denotes the θ^{th} conditional quantile of y_i. The distribution of $u_{\theta i}$ is left unspecified so this estimation is essentially semi-parametric. It is only assumed that $Quant_\theta (u_{\theta i} | x_i) = 0$. The estimator of the β_θ parameter (i.e. the β for the θ^{th} quantile regression) solves

$$min_\beta \; 1/n \; \{ \; \sum \; \theta \, |y_i - x'_i \beta| \; + \; \sum \; (1-\theta) \, |y_i - x'_i \beta| \; \}$$

This is solved by linear programming.[7] As one keeps increasing θ from 0 to 1, one can trace the entire conditional distribution of plant level productivity, conditional on the set of regressors. Thus, quantile regressions allow us to focus attention on specific parts of the productivity distribution, and help to investigate what is the impact of R&D on firms below, for instance, the 10th and above the 90th percentile level of the productivity distribution.

---

6 Also, as pointed out by Buchinsky (1998) quantile regression can be more efficient than OLS when the error term in non-normal.

7 All estimations in this study are conducted in Stata using the command qreg.

In the regression I estimate, the dependent variable is log of labour productivity. As controls I use the log R&D spending, the log of capital stock, to control for the fact that more capital intensive firms are more likely to have higher productivity levels, an export dummy, since exporting firms have been found to be more productive than non-exporting on, a foreign dummy and a UK MNEs dummy. In a second stage the foreign and UK MNEs dummies are also interacted with the log of R&D spending to investigate whether the impact of R&D on labour productivity is different for domestic, foreign and UK multinational enterprises. This allows to investigate whether these different impacts, if any, change across the entire productivity distribution. This will help to understand how the benefits from additional R&D spending to UK MNEs, foreign and domestic companies change across the conditional labour productivity distribution.

3. Data Set

The data used in this research come mainly from two data sources, namely the ONS Annual Respondent Database (ARD) and the third Community Innovation Survey (CIS3).

The ARD contains the information from the Annual Census of Production (ACOP) until 1997 and thereafter from the Annual Business Inquiry (ABI). These information comes from the response to Census form, which are mandatory under the 1947 Statistics of Trade Act.

The ABI is an annual survey of businesses which, since 1994, has been sampled from the Inter Departmental Business Register (IDBR). The "selected sample" of the ABI is a census of all large businesses employing 250 or more and a sample of smaller businesses. For the firms in the selected sample the ABI provides a rich set of variables to characterise firms. The "non-selected sample" includes those businesses in the sampling frame which were not selected for the survey. For firms that were not selected, the information available is limited to employment, industry and region.

The ABI comprises different aggregation categories. The lowest level of aggregation is the "local unit", which refers to a single production facility at a single address, which corresponds to a production unit or plant. The ``reporting unit" may contain one or more local units. The groping is agreed by the ONS and the firm. The ``enterprise" is essentially a firm or business with a relative degree of autonomy, which may be include different reporting units. Finally, an "enterprise group" is a group of all enterprises under common control. As noted above, an enterprise may record information via several reporting units, but the great majority of enterprises have a single reporting unit.

In this exercise we focus on “reporting units” since this is the common unit of reference in the ARD and CIS3. A problem concerning the ABI is that it does not contain capital stock information. To overcome this problem I merged the ARD with the capital stock data set computed at the level of the reporting unit by Martin (2005) using the perpetual inventory method.

Community Innovations Surveys are part of a EU-wide endeavour to collect information about innovation activities of businesses. The data collected in this survey include a vast array of information about innovation outputs, innovation inputs and source of knowledge of innovation efforts. In the UK there has been three CISs, CIS1 covering 1991-1993, CIS2 covering 1994-1996, CIS3 1998-2000, concerning both the production and the service sector. Production comprises manufacturing, mining, electricity, gas and water, and construction. Service includes wholesale trade, transport, storage, communication, financial intermediation and real estate.

These surveys have been conducted by the ONS on behalf of the Department of Trade and Industry (DTI) by post. CIS3 was sent twice. The first wave covered 13340 enterprises; other 6285 enterprises were added later to make the survey more representative at regional level. 8172 enterprises responded (out of 19625) of which 3605 operated in the service sector and 4567 in the production sector.[8]

I merged CIS3 wit the ARD at the level of reporting unit. Given that the quantile regression has been developed to be used in a cross-section context the analysis in confined to the year 2000 only. The number of available observations is drastically reduced because of missing values. In particular only 6343 observations out of 8172 in CIS3 were merged with the capital stock data. Also 4793 entries in CIS3 have

[8] For more details about the CIS3 and ABI data sets see Haskel and Martin (2002) and Criscuolo, Haskel and Slaughter (2005)

missing R&D spending. No imputation for these missing values was conducted. This leaves us a data set with around 1000 observations.

The dependent variable, labour productivity, was computed as value added per worker. All variables in the following regression are computed as logarithmic deviation from the 4-digit industry median, for the year 2000, to make them comparable across industry. Table 1 shows some summary statistics of labour productivity. As it possible to note it appears to be strongly non-normal (the kurtosis being more than 14). As it was pointed out in the previous section qantile regression is appropriate in this circumstance since its parameter estimates are robust to outliers.

Table 1:

Table1: Summary statistics of dependent variable

	Mean	Median	Skewness	Kurtosis
Log labour productivity	-0.314	0	-0.135	14.957

Source ONS; author's calculation. Notes: Labour productivity is value added per worker.

4. Results

Table 2 shows the OLS results of the labour productivity regressions. Column 1 presents the basic specification. As it is possible to note the only significant variable is the log of capital stock, whose parameter is estimated to be positive and highly significant. Column 2 exhibits the result without capital stock. The export dummy becomes significant, but the log R&D spending still does not seem to have any explanatory power. These initial results suggest that one of the main determinants of labour productivity is the level of capital stock and that exporting firms have higher productivity levels than non-exporting ones because they are more capital intensive.

To assess whether or not domestic, foreign and UK multinational plants respond differently to higher R&D spending, in column 3, the log R&D spending is interacted with the dummy indicating whether the plant is domestically owned, foreign owned, or part of a UK MNE. Anew, the log of capital stock is positively associated with labour productivity, whereas R&D spending and the export dummy are insignificant.

Table 2:

Labour productivity OLS results (manufacturing and services)

	(1)	(2)	(3)
Log capital	0.1424**		0.1422**
	(0.0360)		(0.0360)
Log R&D spending	-0.2040	0.0124	
	(0.0157)	(0.0128)	
Export dummy	1.4384	3.1876**	1.3387
	(1.1281)	(1.0106)	(1.1372)
Domestic: Log R&D spending			-0.0353
			(0.0361)
Foreign: Log R&D spending			0.0193
			(0.0167)
UK MNE: Log R&D spending			0.1054
			(0.0649)
Foreign dummy	-0.3560	-1.5405	-0.2562
	(1.2225)	(1.0626)	(1.2235)
UK MNE dummy	-0.7558	-0.3258	-1.4356
	(1.1362)	(1.1784)	(1.2091)
Industry dummy	Yes	Yes	Yes
Region dummy	Yes	Yes	Yes
Observations	1090	1312	1090

Source: ONS; author's calculation. Notes: Robust standard errors in parenthesis; ** significant at 1 percent, * significant at 5 percent, + significant at 10 percent; continuous variables are log deviation from 4-digit industry median.

Thus, from these first results it appears that capital stock is the only variable that is associated positively with labour productivity. However, as it was pointed out in the previous section, OLS fits a regression line through the conditional mean. For this reason, it is unable to distinguish whether or not lowly and highly productive firms respond differently to additional R&D spending. To investigate this point I turn to quantile regression which allows to model the effect of R&D across the entire productivity distribution (conditional on a set of covariates). In addition, it permits to assess how the productivity gap between domestic, foreign and multinational enterprises is affected in different part of the productivity distribution.

Table 3 reports the results of quantile regressions. The estimates for three quantiles (the 25th, the median and the 75th) are reported in order to have a broad idea how lowly productive, median and highly productive plants react to R&D spending.

Table 3:

Labour productivity quantile regressions (manufacturing and service sectors)

	25th percentile (1)	50th percentile (2)	75th percentile (3)	25th percentile (4)	50th percentile (5)	75th percentile (6)
Log capital	0.2005**	0.1475**	0.0250	0.1945**	0.1479**	0.0216
	(0.0272)	(0.0224)	(0.0332)	(0.0277)	(0.0190)	(0.0290)
Log R&D spending	-0.0065	-0.0164	-0.0263+			
	(0.0152)	(0.0155)	(0.0137)			
Export dummy	0.6372	0.4681	0.7681	0.7170	0.4351	0.5884
	(0.5020)	(0.3511)	(0.4910)	(0.4933)	(0.3480)	(0.4930)
Foreign dummy	-0.2987	0.3584	0.2865	-0.2337	0.3276	0.3579
	(0.4498)	(0.3192)	(0.5292)	(0.5434)	(0.3673)	(0.5527)
UK MNE dummy	0.0190	0.0860	-0.4425	0.2256	-0.1763	-1.0633
	(0.3763)	(0.3312)	(0.4550)	(0.5410)	(0.4589)	(0.5757)
Domestic: Log R&D				-0.0143	-0.0127	-0.0626+
				(0.0530)	(0.0316)	(0.0368)
Foreign: Log R&D spending				0.0015	-0.0171	-0.0268+
				(0.0158)	(0.0154)	(0.0133)
UK MNE: Log R&D spending				-0.0297	0.0164	-0.0912
				(0.0557)	(0.0517)	(0.0671)
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Region dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1090	1090	1090	1090	1090	1090
F Test: $\beta_{25} = \beta_{50} = \beta_{75}$		0.69				
F Test Domestic: $\beta_{25} = \beta_{50} = \beta_{75}$					1.29	
F Test Foreign: $\beta_{25} = \beta_{50} = \beta_{75}$					1.01	
F Test UK MNE: $\beta_{25} = \beta_{50} = \beta_{75}$					2.12	

Source: ONS; author's calculation. Notes: Bootstrapped standard errors in parenthesis (200 replications); ** significant at 1 percent, * significant at 5 percent, + significant at 10 percent; continuous variables are log deviation from 4-digit industry median. The F statistics testing for the equality of the effect of R&D on productivity in 25th, 50th and 75th quantiles for the generality of firms has an F(2, 1036) distribution. The analogous statistics for domestic, foreign and UK multinational enterprises have an F(2, 1034) distribution.

The first three columns of table 3 show the results where the log of R&D spending is not interacted with the ownership dummy. In the last three columns the effect of R&D variables is estimated separately for domestic, foreign and UK multinational enterprises.

As it is possible to see from table 3 the results are somewhat disappointing since only capital stock still appears to be associated, positively, with labour productivity. Its effect is higher for plants at the lower end of the productivity distribution and becomes insignificant for highly productive plants. The F-statistics at the bottom of the table test whether the parameters of the log f R&D spending are the same for the three quantiles considered.[9] As it is possible to observe, these tests do not reject the null hypothesis that the effect of R&D spending is the same across the productivity distribution.

The same general picture emerges from the last three columns of table 3, where the R&D spending variable is interacted with the ownership dummies. The effect of capital stock is positive and significant in the 25th, 59th and 75th quantiles. R&D spending is insignificant throughout. The F-statistics testing, separately for domestic, foreign and UK multinational enterprises, the null hypothesis that the effect of R&D spending on productivity is constant across the entire productivity distribution do not reject it.

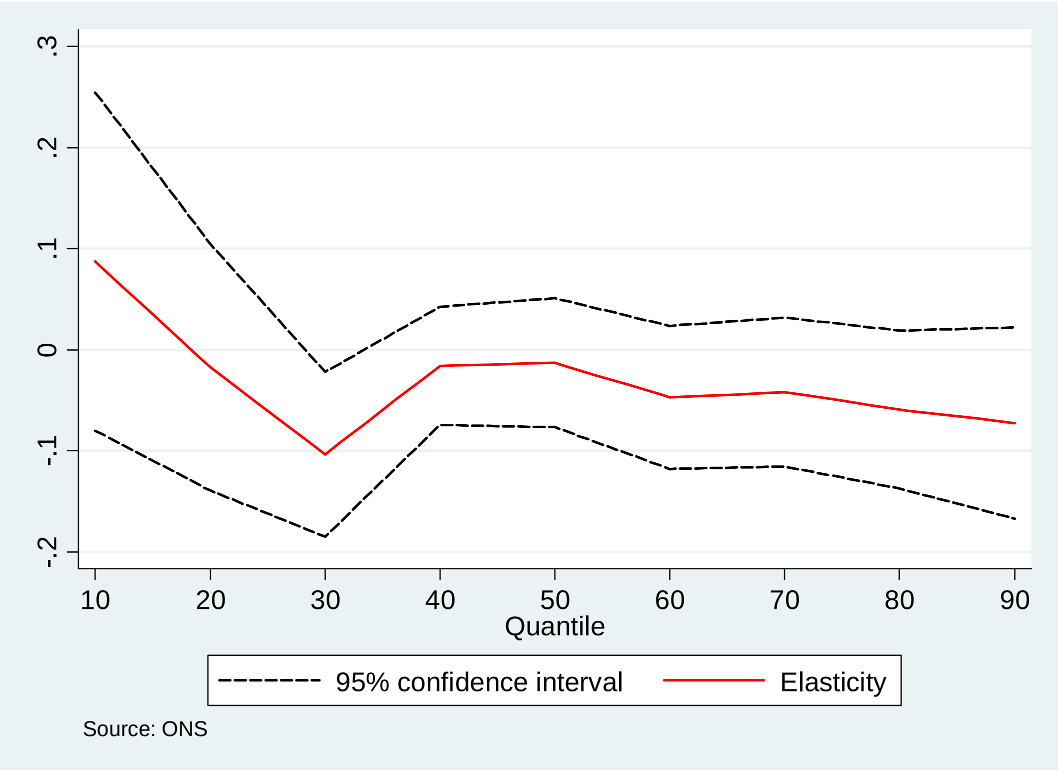
Figure 1 to 3 shows the estimated elasticity and its confidence interval of the impact of R&D on labour productivity for domestic, foreign, and UK multinational enterprises separately. These are derived from the same set of regression of table 3 (last 3 columns). However, the parameters are estimated for each decile to have a more precise view of the impact of R&D on the whole productivity distribution. As it is possible to see, the estimated elasticity of R&D spending on labour productivity for domestic plants appears to decrease the higher the productivity level and it is characterised by a confidence interval. We have a similar picture concerning foreign plants (figure 2). The estimated elasticity is decreasing the higher the productivity level and its standard errors are large. The estimates referring to UK MNEs appear to

[9] The standard errors of these tests are computed correctly considering the covariance matrix of the parameters estimated. This is made possible by the fact that the three quantiles are estimated simultaneously, so it is possible to obtain the covariance of the estimates pertaining to different quantiles.

be different since the effect of R&D appears to increase with productivity. Thus, the association between R&D spending and productivity is larger for those UK MNEs at the higher end of the labour productivity distribution, although it is still insignificant.

Figure 1:

Effect of R&D spending on labour productivity: Domestic plants



Notes: estimated elasticity from quantile regression; the specification is the same as in table 3 (last three columns)

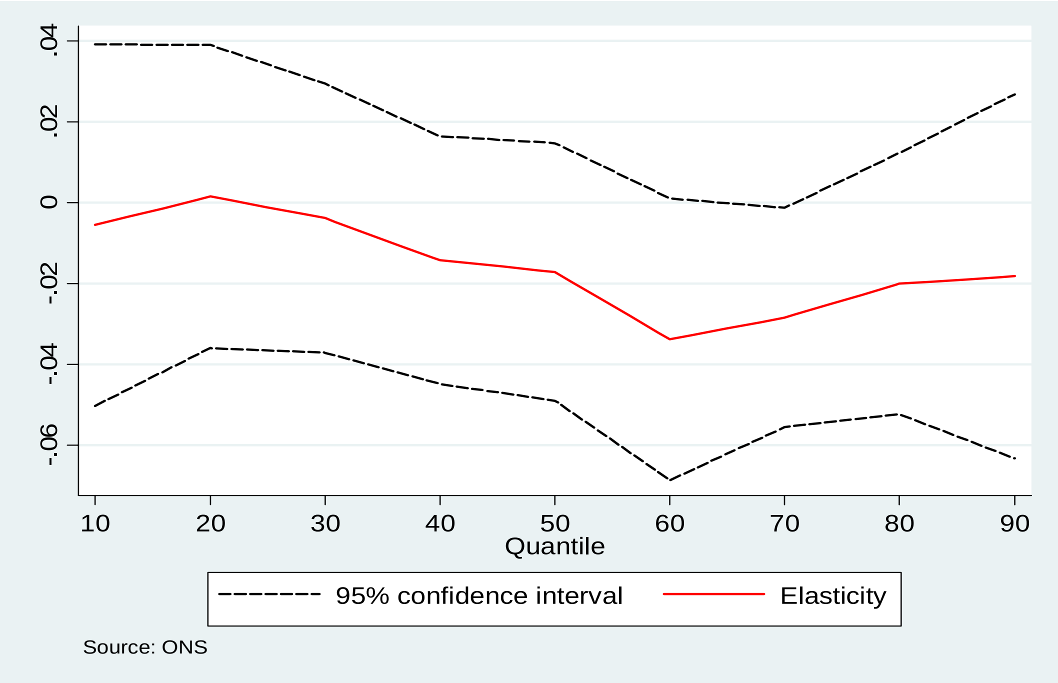
Then, from figure 1 to 3 it is possible to observe that the elasticity of the impact of R&D on productivity are estimated imprecisely.[10] Furthermore, these estimates could in principle be biased because of unobserved heterogeneity, which cannot be dealt with in a cross-section context. Another limitation of the elasticities so far computed is that they do not say much about the productivity gap between domestic, foreign and multinational enterprises.

---

[10] This could be due to the number of replications (200) used in the bootstrap to compute the standard errors.

Figure 2:

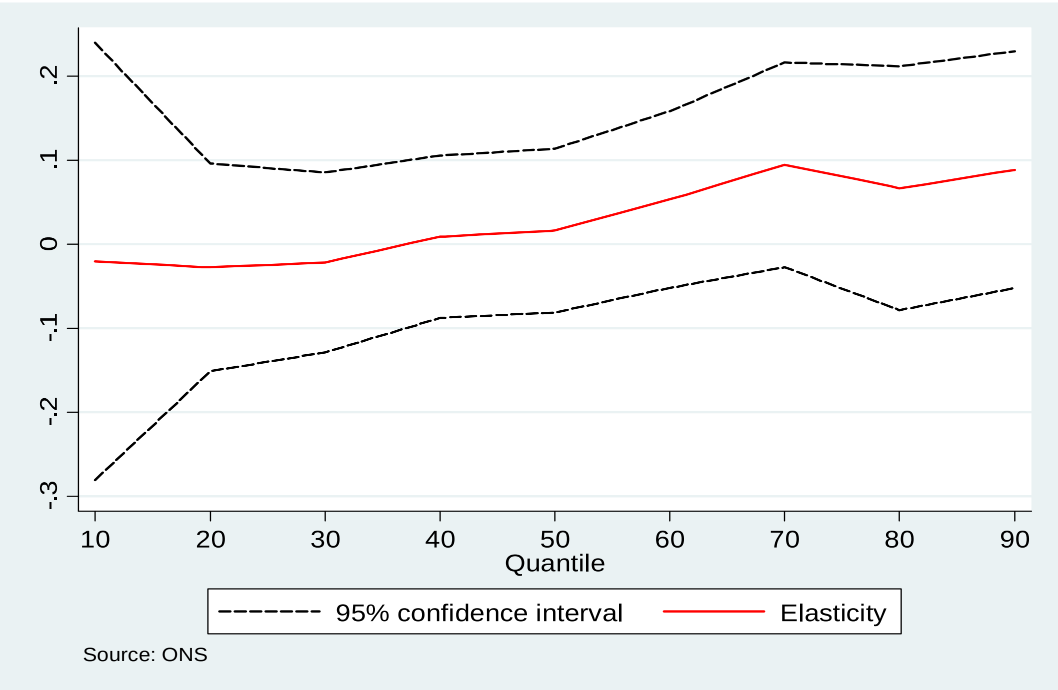
Effect of R&D spending on labour productivity: Foreign plants



Notes: estimated elasticity from quantile regression; the specification is the same as in table 3 (last three columns)

Figure 3:

Effect of R&D spending on labour productivity: UK multinational plants



Notes: estimated elasticity from quantile regression; the specification is the same as in table 3 (last three columns)

To investigate how the productivity gap between these kinds of plants might change because of R&D spending, it is possible to compute the difference between the estimates of the effect of R&D on productivity of, for instance, foreign and domestic plants, for each decile. These new point estimates would also have the benefit to cancel part or all of the bias affecting the estimates computed for foreign and domestic plants separately. Indeed if these are biased in the same direction it is obvious that taking the difference between them would reduce the error or cancel it out completely if the bias is exactly the same. In this way, we would be able to obtain consistent estimate of the difference of the impact of R&D spending on the productivity of foreign and domestic plants across the whole productivity distribution and to say something how their productivity gap may change because of R&D spending.

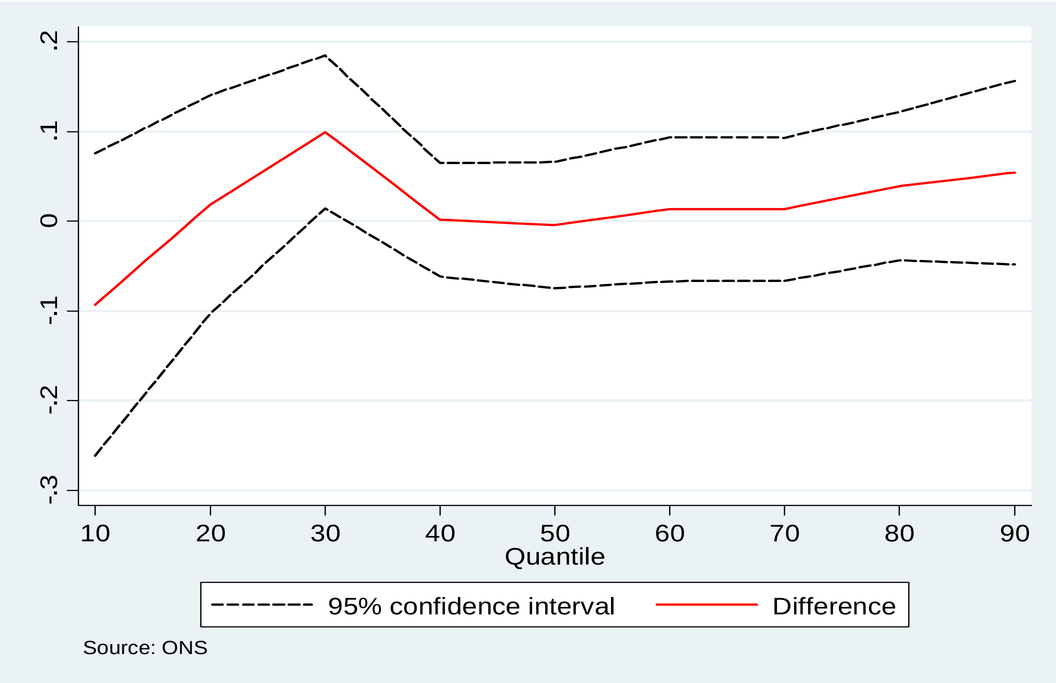
Figure 4 to 6 exhibit the estimated difference and their confidence intervals for each couple of plants considered. Figure 4 presents the difference between foreign and domestic firms and its related confidence interval. As it is possible to observe, the difference of the impact of R&D spending on productivity between these two types of plants is mostly positive although insignificant. Thus, it does seem that the productivity difference between foreign and domestic plants is not affected by R&D spending across the whole distribution.

The difference between UK MNE and foreign plants is showed in the next figure. This is increasing in the productivity level and is significant (although just at 5 percent level) towards the higher end of the productivity distribution. This means that highly productive UK MNEs appear to benefit more from R&D spending than foreign plants having similar productivity. Therefore, this finding suggests only those UK MNEs at the higher end of the distribution will be able to increase their productivity leadership through additional R&D spending.

Figure 6 shows the difference of the impact of R&D spending on productivity between UK MNEs and domestic plants. As for the UK MNEs – foreign plants difference, this is increasing in the productivity level and significant (although only at 5 percent) for high productivity levels only. Then, it appears again that the most productive UK MNEs gain more from R&D than their purely domestic counterparts and therefore may further increase the productivity gap separating them.

Figure 4:

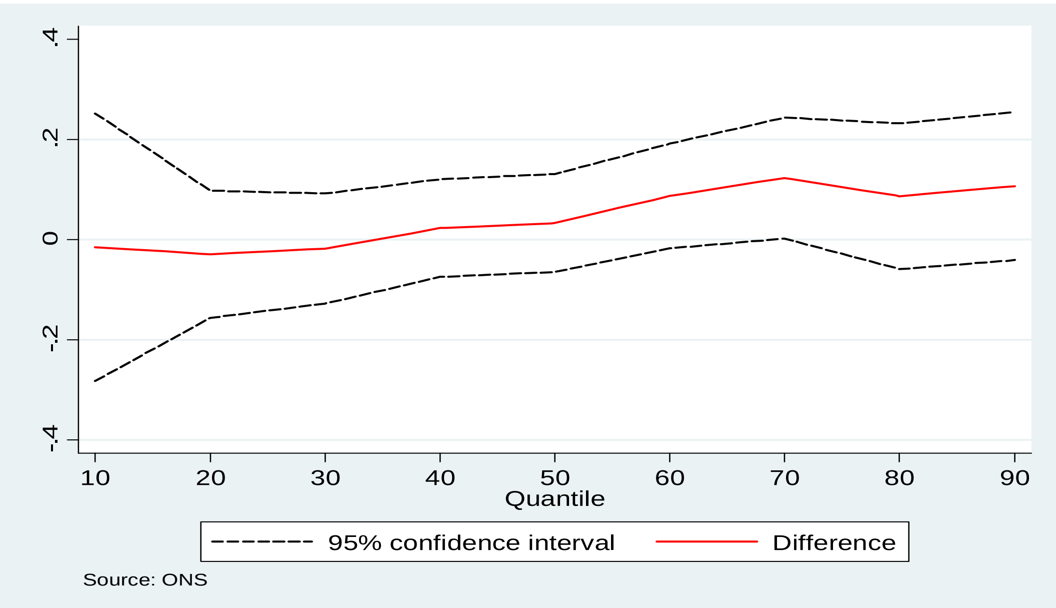
Estimated difference of the effect of R&D spending on labour productivity between foreign and domestic plants



Notes: estimated elasticity from quantile regression; the specification is the same as in table 3 (last three columns)

Figure 5:

Estimated difference of the effect of R&D spending on labour productivity between UK multinationals and foreign plants

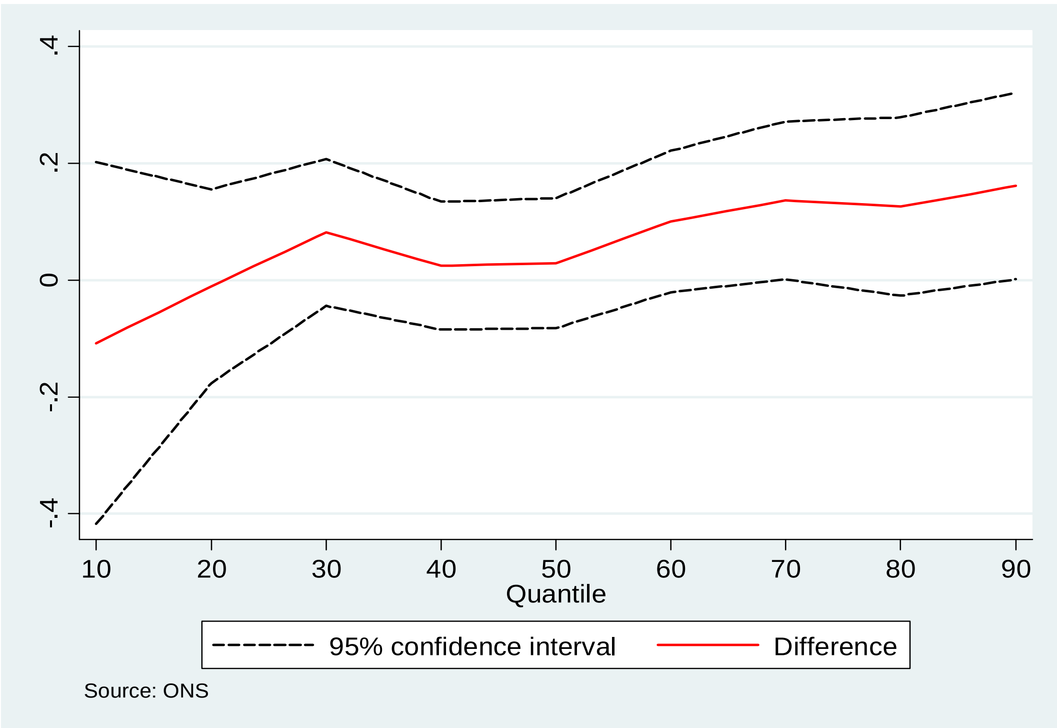


Notes: estimated elasticity from quantile regression; the specification is the same as in table 3 (last three columns)

Overall, these results suggest that the productivity gap between UK MNEs, foreign and domestic firms is affected by additional R&D spending only at the higher end of the productivity distribution. Thus, it appears that quantile regression has a distinctive advantage over OLS since the latter is simply able to capture shift in the entire productivity distribution and whereas the former permits to model different effects of R&D across the whole productivity distribution.

Figure 6:

Estimated difference of the effect of R&D spending on labour productivity between UK multinationals and domestic plants



Notes: estimated elasticity from quantile regression; the specification is the same as in table 3 (last three columns)

5. Conclusion

The aim of this research project is to model the impact of R&D spending on the entire productivity distribution. This is relevant since a vast empirical literature has ascertained that firms are greatly heterogenous with respect to productivity even in even in narrowly defined industries (Haltiwanger and Krizan 1998; Bartelsman and Doms 2000). Therefore it is important to investigate how R&D spending impact on the productivity of firms that are at different points of the distribution. This may help to understand how the entire productivity distribution evolve because of additional R&D spending.

More specifically, I analysed the impact of R&D spending on three different kinds of plants, namely domestically owned, foreign owned and those belonging to UK multinationals. Previous works have shown that firms involved in international markets in different fashion are characterised by different productivity levels. More specifically, for the UK Criscuolo and Marin (2005) and Girma, Kneller and Pisu (2005) have reported that UK multinationals and foreign companies are more productive than purely domestic ones. From a policy perspective it is important to understand how the productivity gap between these plants might change because of additional R&D spending.

To examine this issue I used UK plant level data for the manufacturing and service for the year 2000. Data on R&D spending come from the CIS3 survey; information on plants from the Annual Respondent Data base. To model the impact of R&D on the whole productivity distribution I used quantile regression (Koeneker and Basset 1978) which allows to fit regressions not just at the mean, but also at different points of the productivity distribution.

The results indicate UK MNEs, which are at the higher end of the productivity distribution, have higher R&D spending than foreign and domestic plants. This suggests that they might be able to extend further their productivity advantage with respect the most productive foreign and domestic plants.

Although this study is the first to examine the impact of R&D on the whole productivity distribution several points need to be addressed in future works. Further research should concentrate on exploring more formally the causal relationship between R&D spending and productivity of firms at different points of the productivity distribution.[11]. This can provide useful evidence to devise appropriate policies to increase the productivity of the less efficient firms and to close the productivity gap between foreign and domestic firms observed in the UK.

[11] Note that since I used a cross section, the results reported cannot strictly be interpreted as causation.

Reference

Bartelsman, Eric J. and Mark Doms (2000) "Understanding Productivity: Lessons from Longitudinal Microdata" *Journal of Economic Literature*, Vol 38(3), pp. 569-694

Buchinsky, M. (1998). "Recent Advances in Quantile Regression Models: A practical guide for empirical researcher" *Journal of Human Resources*, Vol 33, pp. 88-126.

Criscuolo, C., Haskel J.E. and M.J. Slaughter (2005). "Global Engagement and the Innovation Activities of UK Firms". *NBER Working Paper No 11479.*

Criscuolo Chiara and Ralf Martin, (2005). "Multinationals and US Productivity Leadership: Evidence from Great Britain," *CEP Discussion Papers dp0672*, Centre for Economic Performance, LSE.

David S. and Haltiwanger J. (1999) Gross Job Flows. In *Handbook of Labour Economics 3B*, ed. Oelry Ashenfelter and David Card. North Holland pp. 2711-2805

Farrell, M. J. (1957), The Measurement of Productive Efficiency", Journal of the Royal Statistical Society, Series A, 120, part 3, pp. 253-281.

Foster L., Haltiwanger J. and Krizan C.J. (1998), Aggregate Productivity Growth: Lessons from Microecoomic Evidence, *NBER Working Paper No. 6803.*

Girma S., Kneller R. and M. Pisu (2005), Export versus FDI: An empirical test, *Review of World Economics*, Vol 141(2), pp. 193--218.

Haltiwanger J. (1997). "Measuring and Analysing Aggregate Fluctuation: The Importance of Building from Microeconomic Evidence" *Federal Reserve Bank f St Louis Economic Review*, pp 55-77

Helpman, E., Melitz, M. and Yeaple, S. (2004). "Export versus FDI with Heterogeneous Firms". *American Economic Review*, Vol. 94(1), pp. 300-316.

Haskel, J.E. and R. Martin (2002), "The UK Manufacturing Productivity Spread", *Ceriba mimeo*

Klette, T.J. and Kortum S. (2004). “Innovating Firms and Aggregate Innovation” *Journal of Political Economy*, Vol. 112(5), pp. 986-1018

Koeneker, R. and G. Bassett (1978). “Regression Quantiles” *Econometrica*, Vol. 46, pp. 33-50

Levinsohn, J. (1999). “Employment Responses to Trade Liberalisation” *Journal of International Economics*, Vol 47, pp. 321--344

Martin, R. (2002) “Building Capital stock” *Ceriba mimeo*

Melitz M.J. (2003), "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica,* Vol. 71(6), pp.1695-1725.

Roberts M. and Tybout J. (1996). *Industrial Evolution in Developing Countries*. Oxford University Press