Estimating productivity with multi-product firms, pricing heterogeneity and the role of international trade

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Abstract

In this paper, we analyze the relationship between exports, imports and firm productivity taking into account pricing heterogeneity and the importance of multi-product firms. We use a rich firm-product-level dataset providing both revenue and quantities of all products produced, exported and imported for a large panel of Danish manufacturing firms over the period 1999-2006. With this detailed information, we compute a firm level price index to deflate our measure of output and compare our productivity measures when we deflate output with an industry-level deflator. We find that firms only importing have a large productivity premium, but not firms only involved in exporting, while firms involved in both importing and exporting are the most productive. The international trade premia are found to be significantly larger when output is deflated with our firm-specific price index rather than the traditional sector-level PPI, suggesting that pricing heterogeneity plays an important role in productivity measurement. We also find evidence of a self-selection into exporting but not into importing. Finally, we detect the presence of learning by exporting only when we control for pricing heterogeneity; when looking at learning by importing, we find a positive effect in the long run, but the effect is lower when we deflate revenue with a firm-specific price index. These results suggest pricing heterogeneity can significantly affect the way we measure productivity and our assessment about the link between productivity and trade.

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1 Introduction

A large literature has been devoted to explaining the productivity difference between firms involved in international trade and those only selling on the domestic market (see e.g. Bernard et al., 2012 for a recent survey). Both import and export decisions have been shown to be associated with higher productivity, either as a result of self selection or as a consequence of a learning effect. However, studies to date have largely ignored pricing heterogeneity in their analysis. This problem has been discussed in the productivity literature. Klette and Griliches (1996) formally documented the bias arising from deflating firm-level sales with an industry-level price index instead of firm-level prices. They also provided a simple indirect method to correct this bias by incorporating an horizontal product differentation demand system.

Dealing with pricing heterogeneity becomes even more complex in the presence of multiproduct firms.[1] Levinsohn and Melitz (2001) and De Loecker (2011) have provided an elegant solution to this problem by extending the Klette and Griliches framework to the case of multiproduct firms while keeping the analysis at the firm-level. Several authors have chosen an alternative way by directly using price and quantity information at the product level (e.g. Foster, Haltiwanger and Syverson, 2008) or by computing a firm specific price index aggregating the product-level information (Eslava et al., 2004). This latter approach has the advantage that no assumptions have to be made about the nature of competition in a specific market.

A recent literature in international trade has also studied empirically strategic price setting on different export markets. Manova and Zhang (2012) use customs data for China and show that export prices charged by the same firms tend to be higher in richer and more distant countries. This indicates that pricing heterogeneity can be an important issue for a single firm selling on different markets.

In this paper, we use a detailed sample of Danish manufacturing firms providing both values and quantities of domestic and international trade transactions to study the link between international trade and productiv-

[1] See e.g. Bernard et al., 2010, 2011; Mayer, Melitz and Ottaviano, 2011 and Goldberg et al., 2011a,b for a discussion about the importance of multi-product firms.

ity. We exploit the richness of this dataset to define a firm-specific price index and discuss the importance of pricing heterogeneity in productivity measurement. We start by computing simple measures of firm-level productivity frequently used in the literature (labor productivity, TFP estimated with OLS and fixed effect). We also use more modern empirical techniques to deal with input endogeneity.[2] We then analyze the relationship between productivity and international trade, and compare the results when we deflate output with our firm-specific price index to those obtained when we use a common deflator for all firms within the same industry. This simple algorithm provides an assessment of how pricing heterogeneity might affect productivity measurement and the estimated link between productivity and international trade in the presence of multiproduct firms.

We find that importing behaviour is strongly associated with higher productivity, but the effect of exporting only is not significant. Firms involved in both importing and exporting enjoy an even larger productivity premium. More importantly, we also find that the international trade premia are much larger when output is deflated with our firm-specific price index rather than the traditional industry-level PPI. This suggests that pricing heterogeneity plays an important role in productivity measurement and the way we assess the link between productivity and trade. We explain this finding the following way: exporting firms are on average more efficient; however, standard measurements of productivity (i.e. with revenue deflated by PPI) contain a price component; once controlling for pricing heterogeneity and conditional on the quality level, more efficient firms tend to price at a lower level, so that using a common deflator leads to over-deflation for more efficient firms. This finding is in line with empirical evidence provided by Foster, Haltiwanger and Syverson (2008) and also confirms empirical predictions from recent models of international trade such as Melitz and Ottaviano (2008) where more efficient firms charge lower prices and also have higher markups.

We then turn to the estimation of the selection in exporting and exporting

[2] We use a modified version of the Olley and Pakes (1996) and Ackerberg, Caves and Frazier (2006) methodologies to explicitly take into account the fact that firms' input choices is potentially affected by their international trade status. See the discussion in De Loecker (2007, 2012), Ackerberg et al. (2007) and De Loecker and Warzynski (2012).

using our two deflators. We find in line with the existing literature that more productive firms self-select into exporting, but our coefficients are larger when we use the firm-specific deflator. On the other hand, we do not detect the presence of selection into importing.

We also analyze the learning by exporting (LBE) and learning by importing (LBI) hypotheses using matching estimators. While we do not detect any evidence of LBE when we deflate revenue with our industry-level PPI, we find a significant effect once we properly control for pricing heterogeneity. This finding can be explained if firms that start exporting indeed become more productive and reduce their prices, relative to firms that remain non-exporters, so that output for these firms would be over-deflated with an industry PPI. When we look at learning by importing (LBI), we find that firms that start importing become more productive in the long run for both deflator options, while they appear to suffer from a short run negative shock. Moreover, productivity gains appear to be overestimated when firms start importing if we ignore pricing heterogeneity. This could be due to imports leading to product upgrading and higher prices, and this effect would be included in the productivity measure when sales are deflated with a common PPI.

Early research had already documented that importers enjoyed a higher TFP premium than exporters (see table 8 in Bernard et al., 2007). More recent papers (e.g. Muuls and Pisu, 2009; Castellani et al., 2009; Altomonte and Békés, 2009; McCann, 2009) also found that two-way traders were on average more productive than firms only importing or exporting. However, these papers have largely ignored the pricing heterogeneity issue. Our paper focuses on the bias that pricing heterogeneity leads to and suggests a framework to measure and analyze this bias. It also provides some guidance about the expected consequence of pricing heterogeneity for authors who do not have access to price information.

The structure of the paper is the following. We first discuss the pricing heterogeneity problem and our empirical methodology in section 2. We then describe our data in section 3, while section 4 shows our main results. We conclude and discuss potential extensions in section 5.

2 Pricing Heterogeneity and Empirical Framework

We start by discussing the different kind of biases that we face when estimating our production function. We first describe the pricing heterogeneity bias and explain how we compute our firm level price index using our detailed firm-product level price data. We then discuss the endogeneity bias and the rest of our specification.

2.1 Pricing heterogeneity

Consider a production function:

$$Q_{it} = \Theta_{it} f(X_{it})$$

where Q is a measure of output, X is a vector of inputs, Θ is an index of technical progress, i is a firm index and t a time index.

Assuming a Cobb-Douglas function and taking logs:

$$q_{it} = \alpha x_{it} + \vartheta_{it}$$

where lower cases denote logs, α is a vector of parameters to be estimated, $\vartheta_{it} = \omega_{it} + \epsilon_{it}$, ω is a measure of "true" (observed by the manager but not by the econometrician) productivity and ϵ is a true noise (unexpected shock to productivity).

Ideally, we would like to have physical quantity as a measure of Q. However, in reality, most researchers use deflated revenue instead ($\widetilde{R}_{it} = R_{it}/P_{jt}$ where $R_{it} = P_{it}Q_{it}$ is firm revenue, P_{it} is the price set by the firm, or a firm-specific price index; and P_{jt} is an industry-level deflator, i.e. a price index in industry j at time t, typically provided by the statistical office based on micro-surveys such as the one we use in this study) so that our typical regression will be:

$$\widetilde{r}_{it} = \alpha X_{it} + (p_{it} - p_{jt}) + \omega_{it} + \epsilon_{it}$$

where $(p_{it} - p_{jt})$ measures the difference between the log of the firm-level price index and the industry level price index. Klette and Griliches and De Loecker mention at least two types of biases that might affect our estimates. First, the choice of inputs might be correlated with the price. Existing evidence has found a correlation between capital, labor and price under various assumptions about the extent of product differentation.[3] Second, productivity will be badly measured as it will include a demand shock. An additional issue that has been noted recently is the negative correlation between price and physical productivity (see Foster, Haltiwanger and Syverson, 2008). While it will not influence the bias in our estimation, it will be an important factor to understand the implications of our results. We will discuss this further.

We should stress that, while we have information about output prices, we do not have access in our dataset to the price of materials. This could play an important role as well in affecting our measurement of productivity (see Atalay, 2012 for a thorough discussion). As most papers in the literature, we adopt a value added specification[4] and use either industry PPI or our firm price index to deflate our measure of output, as we explain in the next subsection. When used separately, materials are deflated using a material price index (MPI) provided by Statistics Denmark.

However, we have detailed information about the composition of the workforce. Fox and Smeets (2011) and Bagger, Christensen and Mortensen (2011) discuss in details the measurement of the labor input using similar Danish data. We ran all our specifications using the wage bill instead of the level of employment, as they suggest, and obtained qualitatively similar results.

Using physical quantity might be problematic when the firm produces more than one output. Indeed, it will be hard to come with an aggregate measure of production at the firm level. Another difficulty is to allocate inputs between the various outputs produced by the firm. Therefore, we decide to compute a firm-level price index following Eslava et al. (2004).[5]

[3]See table 1 in Foster, Haltiwanger and Syverson (2008) for evidence of a low negative correlation between price and capital for a set of homogeneous products. See Kugler and Verhoogen (2012) for evidence about the correlation between price and employment with differentiated products.

[4]Others prefer a gross output specification and add materials as another input. We obtained qualitatively similar results when we followed this approach, although our trade premia were lower. See Gandhi, Navarro and Rivers (2012) for a complete discussion.

[5]Ornaghi (2006) also uses a firm-level price index to deflate revenue and estimates a

An alternative would be to use quantities at the firm-product level and to estimate a production function for multiproduct firms, using different assumptions about the way firms share their inputs between their different products.[6] This approach has the advantage that it generates firm-product level measure of productivity. It therefore allows researchers to study empirical implications from the theoretical literature on multi-product firms (see e.g. Bernard, Redding and Schott, 2010, 2011; Mayer, Melitz and Ottaviano, 2012), such as whether firms might have higher productivity or markups for their core product. Our simpler approach yields a single measure of firm productivity that makes our analysis more comparable to the existing literature and that we relate to the firm's international trade status.

2.2 Computing the firm level deflator

We construct our firm-level price index using detailed information about the price of each product on each market where it is sold. We use a single value for each product, which is the average price weighted by the relative value of each market ($P_{hit} = \sum_c s_{chit} P_{chit}$ where c is a country index, h is a product index, i is a firm index and t is a time index; s_{chit} is the share of country c in the total sales of product h of firm i in t). We then use a Tornqvist index, i.e. a weighted average of the growth in prices for all the individual products:

$$\Delta P_{it} = \sum_h \overline{s}_{hit} \Delta ln(P_{hit})$$

where

$$\Delta ln(P_{hit}) = ln(P_{hit}) - ln(P_{hi(t-1)})$$

and

$$\overline{s}_{hit} = (s_{hit} + s_{hi(t-1)})/2$$

where s_{hit} is the share of product h in firm i's total sales at time t.

production function with GMM using a Spanish survey, but his focus is on the estimates of the production function, not on multi-product firms nor on trade issues.

[6]See De Loecker et al. (2012), Dhyne, Petrin and Warzynski (2012) and Petrin and Warzynski (2012).

We take 1999 as the base year ($P_{i,1999}$=1) and add the computed firm level price change to the index:

$$P_{it} = P_{i(t-1)} + \Delta(P_{it})$$

For firms entering after 1999, we use the industry average for the entry year and then follow a similar procedure. We use a similar strategy in those cases when price is missing, as in Eslava et al. (2004).

2.3 Exporter premium and endogeneity

We use a set of estimation methodologies typically used by researchers to analyze the exporting premium and learning by exporting (see e.g. Bernard and Jensen, 1999; Wagner, 2007). We start by simply computing value added per worker. We then estimate a simple production function with OLS and firm fixed effect.

A well known problem when estimating production functions comes from the endogeneity of inputs. To deal with this issue, we adapt two recent methods to address this issue (see Appendix): the Olley and Pakes (1996) and the Ackerberg, Caves and Frazier (2006) algorithms. These two approaches explicitly take into account the fact that firms' input choices are potentially affected by their international trade status.[7]

As discussed in De Loecker (2012), it is also important to properly model the law of motion of productivity by allowing productivity to depend on past export behavior. The last method provides a flexible treatment of the productivity process.[8]

All estimations are run by 2-digit industry. Once we have generated all our measures of productivity, we run a simple regression to measure the size of the exporter/importer/two-way trader premia:

[7]See De Loecker (2007, 2012) and De Loecker and Warzynski (2012) for more details. See also Kasahara and Rodrigue (2008) for an application to import behavior.

[8]De Loecker (2012) actually recommends to estimate the learning by exporting in a non parametric way directly from the equation describing the law of motion of productivity, as it requires less restrictions on the productivity process. We differ from his analysis for two reasons. First, our approach does not suffer from pricing heterogeneity when deflating output by our firm-specific price index. Second, more pragmatically, we want to be able to compare how pricing heterogeneity affects the relationship between productivity and trade for all the methods, not only for the ACF-modified algorithm.

$$log(Productivity_{it}) = \alpha + \beta_1 EXP_{it} + \beta_3 IMP_{it} + \beta_3 BOTH_{it}$$

$$+ Controls_{it} + \epsilon_{it}$$

where EXP_{it} is a dummy equal to 1 if the firm only exports, IMP_{it} is equal to 1 if the firm only imports, and $BOTH_{it}$ is equal to 1 if the firm both imports and exports. All three variables are equal to zero otherwise. Controls include a full set of year-industry dummies and firm size. Standard errors are also clustered at teh firm level.

As Van Biesebroeck (2007, 2008), we test the robustness of our findings to these various productivity estimation techniques. We then analyze the importance of pricing heterogeneity by comparing our estimates when output is deflated with a standard PPI, and when it is deflated with a firm-level deflator.

2.4 Self-selection vs. learning by exporting and importing

Once we have generated our productivity measures, we can also test the relative importance of self-selection and learning. For this analysis, we consider exporting and importing separately to simplify our treatment and also in line with the literature. We adopt the now standard approach (see Bernard and Jensen, 1999; Wagner, 2007) and run two simple tests: first, we test if past productivity (e.g. with a one-year lag) is also related with exporting/importing behavior for the sample of firms who were not already exporting/importing in the past:

$$log(Productivity_{i(t-1)}) = \alpha + \beta_{EXP} EXP_{it} + Controls_{it} + \epsilon_{1it}$$

$$log(Productivity_{i(t-1)}) = \alpha + \beta_{IMP} IMP_{it} + Controls_{it} + \epsilon_{2it}$$

Second, we test if productivity increases after a firm starts exporting/importing. Following Bernard and Jensen (1999), a standard test is to estimate the gain of productivity over a given time interval over a set of dummies describing the transition of firms regarding their international trade status (entrants, continuers, stoppers, the reference group being firms never involved in trade). Several authors have noted that this technique will not necessarily control for the selection process discussed earlier (see e.g. the discussion in Wagner, 2007). If more productive firms self select in exporting/importing, we would ideally like to compare them with themselves, had they not started to export. Since this is not feasible, we instead try to compare them to a set of firms with similar characteristics (i.e. find a control group) to get a counterfactual. Therefore, we follow the approach suggested by Girma, Greenaway and Kneller (2004) and De Loecker (2007) and use propensity score matching techniques.

The first stage of the algorithm is done by running a probit regression for the probability of starting to export/import.

$$Pr(Start_{it} = 1) = \Phi \left\{ h \left(log(Productivity_{i(t-1)}), Size_{i(t-1)} \right) \right\}$$

where $Start_{it}$ is equal to 1 if the firm exports/imports in t but not in year $t-1$ and 0 if the firm does not export/import during both years. Φ is the normal cumulative distribution function and the function $h(.)$ represents a polynomial in past productivity (for each of the five methods selected) and past size. We then follow the same procedure described in Becker and Ichino (2002) and used in De Loecker (2007).[9] We also match within each 2-digit sector as done in previous studies.

Our approach slightly differs from De Loecker (2007) as the estimated densities of the balancing score had poor overlap in some industries. We use the nearest neighbor approach, but when determining the nearest neighbor, we define a maximum distance (caliper) that provides stronger restrictions on

[9] The algorithm is: 1) split the sample into k equally spaced intervals of the propensity score and test that the average propensity score does not differ between the two groups; ii) if the test fails, split the interval in half and renew the procedure; continue until this holds in all intervals; iii) within each interval, test that the means of each of the co-variates do not differ between treated and control groups (balancing hypothesis); iv) if the test fail, use a less parsimonious specification of $h(.)$.

the matching process. As a consequence, we get less observations, but we are more confident that the treated and control samples are more comparable.

Once we have identified our control group, the rest of the procedure is standard and follows a diff-in-diff approach. Assume N^v firms start exporting/importing ($v = exp, imp$) and we find a control group with C_j firms, then the learning by exporting/importing effect in period s is:

$$\beta^s_{LBE} = \frac{1}{N^{exp}_s}\left(log(Productivity^1_{is}) - \sum_{j\in C(i)} w_{ij} log(Productivity^C_{js})\right)$$

and

$$\beta^s_{LBI} = \frac{1}{N^{imp}_s}\left(Productivity^1_{is} - \sum_{j\in C(i)} w_{ij} Productivity^C_{js}\right)$$

where s is the time horizon (we consider $s = 0, 1, 2, 3, 4$ where $s = 0$ is the time when the treated firm starts exporting), $C(i)$ is a set of control firms matched to firm i, N^{Cv}_i is the number of control firms matched to each firm i by type of trade involved v, $Productivity^1_{is}$ is the productivity of treated firm i in s, $Productivity^C_{js}$ is the productivity of a countrol firm j matched to i in s, and $w_{ij} = \frac{1}{N^{Cv}_i}$ is the weight given to each control firm j within $C(i)$.

As in the previous subsection, we run all these tests comparing our results when we deflate output with PPI with those when we deflate output with our firm-level deflator.

3 Data

For our analysis, we combine various datasets provided by Statistics Denmark. We start with a transaction level dataset providing values and quantities of all domestic transactions aggregated by product code (8-digit CN) for all manufacturing firms with at least 10 employees over the period 1999-2006. These firms represent around one third of all firms with at least one employee in manufacturing but above 90% of total manufacturing turnover and value added.

We then merge this information with a dataset containing similar information, but regarding import and export transactions for the same period. This dataset covers the entire universe of firms trading. For each transaction, we know the identification number of the firm buying or selling, the 8-digit CN product code, the value, the quantity, and the destination or origin.[10]

Finally, we match our sample with the accounting statistics dataset (Regnskab) that contains information on the population of firms. The variables included are turnover, value added, capital (we use the book value net of depreciation[11]), investment, employment, costs of employees and material costs.

Table 1 provides a few summary statistics for our final matched sample. We observe that around half of our sample is composed of multi-product firms, and that the percentage of observations where firms are involved in both importing and exporting is slightly above 50%. The share of firms involved in international trade is large because of the size threshold but also because of Denmark being a small open economy.[12]

In Appendix B, we show the evolution of the number of firms, products and the average number of products for our sample. The number of firms and products is slightly decreasing (by 15% and 8% respectively), while the average number of products is slightly increasing over the period of analysis. We also notice that 37% of our firm-product observations have missing price information. This occurs when the number of observations for a given product-year is too small for confidentiality reasons or simply when firms fail to report the information. As explained in the previous section, we adapt our price index construction by replacing these missing observations by the average price index of the corresponding industry. This problem is common with these types of datasets. We can nevertheless still use price information for the majority of our sample.

Table 2 shows the standard deviation of our productivity measures when

[10]See Eriksson, Smeets and Warzynski (2009) for a more detailed description of the dataset and stylized facts about Danish firms that trade.

[11]This is the definition of capital provided by Statistics Denmark and also used by Bagger, Christensen and Mortensen (2011). We also conducted our analysis with the perpetual inventory method and obtained similar results.

[12]See table 2 in Eriksson, Smeets and Warzynski (2009).

we deflate output with a PPI deflator and with our firm specific price index.[13] We can see that the dispersion is always higher with the latter. Indeed, by introducing more heterogeneity on our left hand side variable, we generate more dispersion. This is in line with Foster et al. (2008) who document a larger variance of TFPQ compared to TFPR. The dispersion also varies according to the methodology chosen. It is wider with OP, followed by OLS FE and OLS; with ACF and value added per worker showing lower dispersion under both options.[14]

To better understand this result, we look at the correlation between our productivity variables, inputs and the price bias (table 3). We observe that all productivity variables are negatively correlated with the price bias, suggesting that more productive firms will also have lower prices, in line with theory and other empirical studies. The correlation appears to be lower with ACF compared with the other measures. We can also notice that the correlation with inputs is rather small, although negative and significant in the case of capital (around -0.02, compared with -0.04 in Foster et al., 2008). These results suggest that most of the bias in our estimates comes from the bad measurement of TFP rather than a bias in the estimation of the production function.

4 Results

4.1 Exporter, importer and two-way trader premium

Table 4 shows the exporter, importer and two-way trader premia. On the left hand side, output is deflated with a standard PPI at the 2-digit level;

[13] Appendix C shows the coefficients of the production function for the 4 methods chosen and using both deflators for two industries. We notice that the coefficients do not vary a lot when we use the firm-level deflator. This would tend to suggest that, at least for our sample, the presence of pricing heterogeneity does not dramatically affect the estimation of the production function. However, remember that the left hand side variable will be different since it is deflated differently over time, so that our productivity measure will differ. We go back to this point later in the text.

[14] The number of observations is the same in all specifications, except for OP where we only included firms with positive investment. We also ran all our specifications only for the observations from the OP sample. Results were unchanged, and are available from the authors.

on the right hand side, output is deflated with our firm-level deflator. We find that the coefficients vary quite a lot depending on the type of deflator used. With all methodologies, the coefficients are going up when we use the firm-level deflator. These differences between both sets of coefficients can be explained by the correlation previously noted between price and TFPQ. If more efficient firms indeed price at a lower level once we control for pricing heterogeneity and conditional on quality, using a common deflator works as if we were over-deflating output for firms involved in international trade. This leads us to under-estimate the correlation between trade and productivity, especially if firms involved in trade are indeed more productive.

It is interesting to note that firms only exporting do not have higher productivity premium relative to firms that do not trade. The coefficient is small and not significant both using the PPI and firm specific deflator. Firms only importing on the other hand enjoy a sizeable premium, close to 10% and always higher with the firm-level deflator. Firms both exporting and importing enjoy an even higher premium, around 13% when we use the PPI deflator; and around 16% with the firm deflator.

We also notice some differences between the various methodologies, although the relative ranking between the different types of firms does not change; and also the magnitude of the bias due to pricing heterogeneity does not change a lot, even when we use the more advanced techniques. This is in line with the findings in Van Biesebroeck (2007).

We also ran the same analysis dividing firms by size category: small (less than 50 employees), medium (between 50 and 100 employees) and large (above 100 employees). Results are shown in Appendix D. We observe that the premium is much larger for large firms, especially when we use the firm-specific price deflator.

4.2 Selection into exporting/importing and learning

We then follow Bernard and Jensen (1999) and De Loecker (2007) to try to distinguish the learning from the selection issue. We find evidence of selection into exporting but no evidence of selection into importing (table 5): among those firms previously non exporting, the more productive ones will enter into exporting. The size of the coefficient is larger when we use the firm-specific deflator, suggesting that once we correct for pricing heterogeneity, our more precise measure of productivity matters even more to explain entry. Looking at the import side, we find no evidence of selection effect under both options. This implies that the large import premium found in table 5 can be attributed to firms continuing importing over the period of analysis, or to learning by importing.

We next turn to the analysis of learning by exporting and/or importing (table 6a and 6b) using the matching estimator. Starting with the LBE hypothesis, we find no strong evidence of learning when we use revenue deflated with a common deflator, although we find some positive and significant estimates when $s = 1$ and $s = 3$ for three out of five methods. However, when we deflate revenue with a firm specific price index, we find a strong and consistent pattern already in $s = 0$ for three out of five estimators, and for all of them when $s = 2$ or $s = 3$. This is again true for all the methods that we use. The magnitude of the LBE efect varies according to the methods though. OP and value added per employee generate larger coefficients in $s = 2$ and $s = 3$, while we get the lowest estimates with the FE estimation. Our result would tend to suggest again that firms that start exporting become more productive and also modify their price behavior, i.e. lower their prices relative to firms that remain active only on the domestic market.

Turning to the LBI, results are a little bit less clear, but it appears that firms become more productive when they start importing after a few years, especially when $s = 3$. Moreover, the coefficient is higher when we deflate output with the PPI, with the exception of the ACF estimator. This could indicate that firms that start importing change their pricing strategy, possibly due to product upgrading. Once we control for pricing heterogeneity, the gain in productivity becomes smaller. In the short run (in $s = 0$), however, results show that productivity is going down, and this effect is stronger when we use the firm-specific deflator, except for value added per worker. This suggests that firms might suffer from a temporary adverse shock when they become importers, what could be explained by a need to adapt their products or supply chain.

5 Conclusion

In this paper, we study the relationship between productivity and firms' international trade decisions controlling for pricing heterogeneity and in the presence of multi-product firms. We use our rich transaction level dataset to compute a firm-specific price index and use it to deflate revenue before computing various measures of productivity and looking at the premium related to international trade involvement. We find that firms both importing and exporting are on average more productive than firms involved in only one of these activities. We also find that controlling for firm specific prices is affecting the magnitude of these effects and is also important to properly measure the selection and learning hypotheses. The economic mechanism that explains this finding is the following: firms involved in trade are indeed more productive, but part of the standard measurement of productivity contains a price component. Once we control for pricing heterogeneity, the trade premium increases because more efficient firms also charge lower prices (conditional on quality), as predicted by Melitz and Ottaviano (2008) and as confirmed empirically by Foster, Haltiwanger and Syverson (2008). This suggests that future studies should seriously consider the relationship between domestic, import and export prices to understand better the causes of firms' trading activities and their consequences on productivity and product quality.

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Table 1: Summary statistics

	Food and beverages		Publishing and printing		Rubber and plastic		Fabricated metals		Machinery and equipment		Furnitures		All industries	
	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD
Value added	137,957	557,213	68,178	502,985	43,253	99,437	29,294	81,810	49,156	170,623	38,978	151,572	56,800	302,292
Capital	90,266	323,417	26,513	157,908	26,524	55,223	13,661	35,655	18,025	75,776	19,544	71,272	28,522	142,738
Labor	183	777	111	1,059	70	148	54	139	87	293	64	185	91	527
Value added/worker	770	1,299	691	377	586	250	525	358	576	802	523	512	600	695
Trade														
Do not trade	14.4%		47.2%		6.8%		33.2%		12.0%		14.5%		22.2%	
Import only	9.3%		10.3%		7.4%		7.0%		4.6%		8.6%		7.4%	
Export only	6.9%		19.3%		9.4%		14.0%		9.2%		13.1%		12.0%	
Import and export	69.4%		23.2%		76.4%		45.8%		74.2%		63.8%		58.4%	
Nbr. of products														
1	22.8%		44.7%		47.4%		56.3%		39.2%		49.2%		43.9%	
2 to 5	45.5%		47.2%		45.2%		40.0%		51.0%		40.2%		45.1%	
More than 5	31.7%		8.1%		7.4%		4.2%		9.8%		10.6%		11.0%	
No. of firms	491		628		359		933		999		609		3,924	
No. of observations	2,442		2,841		1,836		4,305		5,038		2,733		19,195	

Note: Units are 1000dkk for value added, capital and value added per worker. In this table, value added is deflated by PPI. Capital is the book value of tangible fixed assets net of depreciation. Labor is measured as the number of full time equivalent workers. The number of products is defined according to the 8-digit CN nomenclature.

Table 2: Dispersion of Productivity

	PPI deflator				Firm price deflator				N
		Interquartile range				Interquartile range			
	Std dev.	75/25	90/10	95/5	Std dev.	75/25	90/10	95/5	
Value added per worker	0.391	1.070	1.146	1.203	0.550	1.085	1.196	1.298	19,195
OLS	0.516	1.120	1.245	1.326	0.648	1.148	1.293	1.407	19,195
OLS with FE	0.580	1.119	1.233	1.326	0.735	1.134	1.279	1.386	19,195
OP-adjusted	0.777	1.162	1.343	1.481	1.103	1.195	1.479	1.751	17,336
ACF-adjusted	0.475	1.105	1.218	1.287	0.619	1.126	1.266	1.371	19,195

Note: value added is computed from the data. OLS is the productivity mesure obtained from the OLS regression. OLS with FE is another measure where we also include a firm-level dummy in the estimation. OP-adjusted is the measure of productivity obtained using the modified Olley and Pakes algorithm as suggested by De Loecker (2007) and described in Appendix A. ACF-adjusted is the measure of productivity obtained using the modified Ackerberg, Caves and Frazier (2006) algorithm, as discussed in De Loecker and Warzynski (2012) and in Appendix A. Estimation is done by 2-digit industry and the estimates are then pooled together.

Table 3: Correlation between the price bias, inputs and physical productivity

Variables		pi-pj	K	L	TFPQ: Value added per worker	TFPQ: OLS	TFPQ: OLS FE	TFPQ: OP - adjusted
K		-0.021***						
		(0.004)						
L		-0.001	0.707***					
		(0.910)	(0.000)					
TFPQ	Value added per worker	-0.713***	0.179***	0.053***				
		(0.000)	(0.000)	(0.000)				
	OLS	-0.584***	-0.075***	-0.034***	0.798***			
		(0.000)	(0.000)	(0.000)	(0.000)			
	OLS FE	-0.521***	0.405***	0.536***	0.761***	0.659***		
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
	OP-adjusted	-0.679***	0.134***	0.131***	0.925***	0.830***	0.777***	
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
	ACF-adjusted	-0.622***	-0.013*	-0.049***	0.877***	0.978***	0.687***	0.873***
		(0.000)	(0.078)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: see table 2. pi-pj is the difference (in log) between the firm-specific price index and the industry-level price index. K is the log of capital, L is the log of employment. Our measures of TFPQ are obtained after deflating output with our firm-specific deflator and then applying the various methods of measurement.

Table 4: the relationship between trade on productivity using PPI and firm deflator

	PPI deflator			Firm deflator			N
	Export	Import	Export and Import	Export	Import	Export and Import	
Value added per worker	0.012	0.098***	0.147***	0.018	0.112***	0.162***	19,195
	(0.012)	(0.017)	(0.013)	(0.017)	(0.023)	(0.019)	
OLS	0.011	0.092***	0.135***	0.016	0.108***	0.149***	19,195
	(0.011)	(0.016)	(0.012)	(0.017)	(0.023)	(0.018)	
OLS FE	0.007	0.088***	0.128***	0.007	0.093***	0.138***	19,195
	(0.012)	(0.017)	(0.013)	(0.017)	(0.024)	(0.018)	
OP	-0.001	0.073**	0.132***	0.010	0.095**	0.148***	17,336
	(0.022)	(0.031)	(0.024)	(0.033)	(0.045)	(0.035)	
ACF	0.013	0.094***	0.138***	0.023	0.111***	0.154***	19,195
	(0.012)	(0.017)	(0.013)	(0.017)	(0.023)	(0.018)	

Note: see table 2. All estimations include industry-year fixed effects and firm size. Standard errors are in parentheses and clustered by firm. ***/**/* indicates statistical significance at 1%/5%/10% respectively.

Table 5: Selection into trade using PPI and firm deflator

	Start exporting in t			Start importing in t		
Dep. var.:	PPI deflator	P deflator	N	PPI deflator	P deflator	N
Value added per worker in t-1	0.076*** (0.018)	0.086*** (0.025)	3,435	0.028 (0.018)	0.022 (0.026)	3,715
OLS in t-1	0.063*** (0.017)	0.067*** (0.024)	3,435	0.021 (0.017)	0.013 (0.026)	3,715
FE in t-1	0.063*** (0.018)	0.079*** (0.025)	3,435	0.025 (0.018)	0.021 (0.026)	3,715
OP in t-1	0.087** (0.034)	0.103** (0.049)	3,043	-0.002 (0.035)	-0.033 (0.053)	3,412
ACF in t-1	0.062*** (0.017)	0.075*** (0.024)	3,435	0.023 (0.017)	0.018 (0.026)	3,715

Note: See tables 2 and 4. In our sample, excluding firms exiting and entering the sample or switching trade status, we end up with 546 firms starting exporting (493 in our OP sample) and 313 firms starting importing (285 in our OP sample). The control group consists respectively of firms that never export (for export starters) or never import (for import starters). Those are respectively for exports 866 in the full sample and 846 in the OP sample, 1002 in the full sample and and 978 in the OP sample for imports.

Table 6A: Learning by exporting using PPI and firm deflator

s		0			1			2			3		
		PPI	P	PPI-P	PPI	P	PPI-P	PPI	P	PPI-P	PPI	P	PPI-P
Value added per worker	β_{LBE}	-0.024***	0.004	-0.028***	0.035***	0.066***	-0.031***	-0.002	0.091***	-0.093***	0.005	0.162***	-0.157***
		(0.004)	(0.004)	(0.002)	(0.006)	(0.004)	(0.006)	(0.006)	(0.006)	(0.004)	(0.007)	(0.008)	(0.008)
	Nr treated		247			184			154			126	
	Nr controls		316			314			270			220	
OLS	β_{LBE}	0.000	0.013**	-0.013***	0.053***	0.077***	-0.023***	-0.027***	0.061***	-0.088***	0.015***	0.091***	-0.076***
		(0.003)	(0.006)	(0.005)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)	(0.005)	(0.007)
	Nr treated		253			194			157			131	
	Nr controls		314			313			269			220	
FE	β_{LBE}	-0.010***	0.014***	-0.024***	0.037***	0.019***	0.018***	-0.012**	0.030***	-0.042***	0.016**	0.042***	-0.025***
		(0.003)	(0.006)	(0.006)	(0.002)	(0.004)	(0.004)	(0.005)	(0.008)	(0.009)	(0.007)	(0.003)	(0.006)
	Nr treated		242			186			149			122	
	Nr controls		314			313			269			220	
OP-adjusted	β_{LBE}	-0.089***	-0.022***	-0.067***	-0.023*	0.002	-0.025	-0.006	0.137***	-0.143***	-0.095***	0.207***	-0.302***
		(0.007)	(0.008)	(0.005)	(0.013)	(0.018)	(0.018)	(0.007)	(0.008)	(0.011)	(0.015)	(0.014)	(0.013)
	Nr treated		205			152			134			110	
	Nr controls		267			260			224			182	
ACF-adjusted	β_{LBE}	-0.017***	0.021***	-0.038***	0.006	0.088***	-0.082***	-0.012**	0.061***	-0.073***	0.032***	0.086***	-0.054***
		(0.004)	(0.003)	(0.002)	(0.008)	(0.003)	(0.006)	(0.006)	(0.008)	(0.010)	(0.008)	(0.007)	(0.010)
	Nr treated		251			194			166			139	
	Nr controls		314			313			269			220	

Note: see tables 2 and 4. For each period s, the first column provides the premium to start exporting β_{LBE} using an industry deflator, the second column provides the premium to start exporting β_{LBE} using a firm-level deflator and the third column reports the difference between the two. The premiums to export β_{LBE} have been computed using matching estimation techniques (and is the average treatment effect (ATT) of starting to export). The control group is firms that never export. We use the pscore and psmatch2 stata commands. As the estimated densities of the balancing score have poor overlap in some industries, we impose the following conditions to obtain the best matches possible: joint support, trim below 0.1 and caliper(0.05) so that we only match treated with controls relatively close to them on the support. The matching is done by industry and includes a polynomial in past productivity and firm size, and year fixed effects. The balancing property was achieved in every case. All standard errors have been boostrapped with 250 replications.

Table 6B: Learning by importing using PPI and firm deflator

s		0			1			2			3		
		PPI	P	PPI-P	PPI	P	PPI-P	PPI	P	PPI-P	PPI	P	PPI-P
Value added per worker	β_{LBI}	-0.066***	-0.014***	-0.052***	0.047***	0.061***	-0.014	0.006	0.005	0.001	0.086***	0.032***	0.054***
		(0.003)	(0.002)	(0.004)	(0.004)	(0.006)	(0.010)	(0.005)	(0.011)	(0.011)	(0.007)	(0.012)	(0.010)
	Nr treated		237			173			117			82	
	Nr controls		388			388			342			280	
OLS	β_{LBI}	-0.031***	-0.072***	0.041***	0.073***	-0.014***	0.087***	0.043***	-0.065***	0.108***	0,172***	0.082***	0.090***
		(0.003)	(0.005)	(0.004)	(0.002)	(0.003)	(0.004)	(0.005)	(0.011)	(0.010)	(0.010)	(0.019)	(0.013)
	Nr treated		229			167			117			81	
	Nr controls		386			386			340			280	
FE	β_{LBI}	-0.052***	-0.100***	0.049***	0.042***	-0.022***	0.064***	0.014***	-0.111***	0.125***	0.117***	0.011	0.106***
		(0.003)	(0.004)	(0.003)	(0.003)	(0.005)	(0.007)	(0.004)	(0.014)	(0.015)	(0.006)	(0.009)	(0.005)
	Nr treated		232			173			122			83	
	Nr controls		386			386			340			280	
OP-adjusted	β_{LBI}	-0.120***	-0.156***	0.036***	0.012*	-0.051***	0.063***	-0.125***	-0.296***	0.171***	0.206***	0.110*	0.096*
		(0.009)	(0.013)	(0.010)	(0.007)	(0.012)	(0.016)	(0.007)	(0.044)	(0.041)	(0.020)	(0.064)	(0.053)
	Nr treated		178			127			95			63	
	Nr controls		331			330			294			237	
ACF-adjusted	β_{LBI}	-0.011***	-0.057***	0.046***	0.105***	0.017***	0.091***	0.037***	-0.045**	0.082***	0.117***	0.181***	-0.064***
		(0.004)	(0.004)	(0.003)	(0.002)	(0.004)	(0.006)	(0.005)	(0.018)	(0.016)	(0.007)	(0.012)	(0.007)
	Nr treated		227			172			124			80	
	Nr controls		386			386			340			280	

Note: see tables 2 and 4. For each period s, the first column provides the premium to start importing β_{LBI} using an industry deflator, the second column provides the premium to start importing β_{LBI} using a firm-level deflator and the third column reports the difference between the two. The premiums to import β_{LBI} have been computed using matching estimation techniques (and is the average treatment effect (ATT) of starting to import). The control group is firms that never import. We use the pscore and psmatch2 stata commands. As the estimated densities of the balancing score have poor overlap in some industries, we impose the following conditions to obtain the best matches possible: joint support, trim below 0.1 and caliper(0.05) so that we only match treated with controls relatively close to them on the support. The matching is done by industry and includes a polynomial in past productivity and firm size, and year fixed effects. The balancing property was achieved in every case. All standard errors have been boostrapped with 250 replications.

Appendix A: Estimation algorithms

a. Modified OP

We use a modified version of the widely used Olley and Pakes (1996) methodology following De Loecker (2007). Their model delivers an investment policy function that depends on productivity and capital:

$$i_t = i_t(k_t, \omega_t)$$

so that we can invert it to write productivity as a function of investment and capital:

$$\omega_{it} = h_t(i_{it}, k_{it})$$

In addition, we take into account the fact that exporting firms are facing different market structures and factor prices when they make their decisions about exit and investment. In other words:

$$i_t = i_{exp,t}(k_t, \omega_{it})$$

and therefore

$$\omega_{it} = h_{exp,t}(i_{it}, k_{it})$$

We can follow a similar logic for importing firms:

$$i_t = i_{imp,t}(k_t, \omega_{it})$$

and

$$\omega_{it} = h_{imp,t}(i_{it}, k_{it})$$

The first stage of the estimation algorithm consists in estimating the coefficient of labor semi-parametrically using a polynomial in k and i and allowing the coefficients to be different for importing and exporting firms, as explained above.

$$q_{it} = \alpha_{Lit}\ l_{it} + +\phi_{exp,imp,t}(i_{it}, k_{it}) + \epsilon_{it}$$

where

$$\phi_{exp,imp,both,t}(i_{it}, k_{it}) = \alpha_{Kit}\ k_{it} + h_{exp,imp,t}(i_{it}, k_{it})$$

The second stage estimates the survival decision where the coefficients also depend on international trade status.

$$Pr(\chi_{i(t+1)} = 1\,|I_t) = p_{exp,imp,t}(i_{it}, k_{it})$$

The last stage involves the non-linear least square estimation of the coefficient of capital:

$$q_{it} - \hat{\alpha}_{Lit}\ l_{it} = \alpha_{Kit}\ k_{it} + g(\hat{\phi} - \alpha_{Kit}\ k_{it}, \hat{p}_{i,t+1})$$

b. Modified ACF

Following ACF, assume that the log of value added is given by $y_{it} = \ln VA_{it} + \epsilon_{it}$, where ϵ_{it} are unanticipated shocks to production and *i.i.d.* shocks including measurement error. Firms do not observe ϵ_{it} when making optimal input decisions. We estimate the following production function for each industry separately:

$$y_{it} = f(x_{it}, k_{it}; \beta) + \omega_{it} + \epsilon_{it} \tag{1}$$

where x_{it} contains all variable inputs and β is the vector of coefficients to be estimated. We use a standard Cobb Douglas (CD) production function.

As suggested by Levinsohn and Petrin (2003), we use materials to proxy for productivity:

$$m_{it} = m_t(k_{it}, \omega_{it}, \mathbf{z}_{it}) \tag{2}$$

where $\mathbf{z}_{it}$ is a vector containing other variables potentially affecting optimal input demand choice, such as importing and exporting.[1]

In a first stage, we run

$$y_{it} = \phi_t(l_{it}, k_{it}, m_{it}, \mathbf{z}_{it}) + \epsilon_{it} \tag{3}$$

This gives us estimates of expected output ($\widehat{\phi}_{it}$) and ϵ_{it}. Define productivity as $\omega_{it}(\beta) = \widehat{\phi}_{it} - \beta_l l_{it} - \beta_k k_{it}$.

Assume the following law of motion for productivity:

$$\omega_{it} = g_t(\omega_{it-1}) + z_{it} + \xi_{it} \tag{4}$$

Finally, by non parametrically regressing $\omega_{it}(\beta)$ on its lag, import and export behavior, we can recover the innovation to productivity $\xi_{it}(\beta)$.

As suggested by ACF, we use the following moments to obtain our estimates of the production function

$$E\left(\xi_{it}(\beta)\begin{pmatrix} l_{it-1} \\ k_{it}\end{pmatrix}\right) = 0 \tag{5}$$

[1]See De Loecker (2011b) and De Loecker and Warzynski (2012) for a more complete discussion of the algorithm.

Appendix B

TABLE B1 - Summary Statistics for Domestic Transactions

Year	# Firms	# Firm-product observations	# Firm-product observations with price information	Average # of products by firm	# Single Product Firms
1999	2,554	7,585	4,202	2.97	1,124
2000	2,542	7,654	4,161	3.01	1,106
2001	2,523	7,807	4,744	3.09	1,104
2002	2,485	7,979	5,172	3.21	1,086
2003	2,422	7,701	4,758	3.18	1,063
2004	2,298	7,146	4,487	3.11	1,021
2005	2,214	6,888	4,916	3.11	977
2006	2,157	6,955	5,033	3.22	959
Total	19,195	59,715	37,473	3.11	8,440

Appendix C: Production function estimates

Table C1: Food and beverages

	PPI deflator			Firm deflator		
	labor	capital	RTS	labor	capital	RTS
OLS	0.82***	0.19***	1.02	0.82***	0.19***	1.01
	(0.01)	(0.08)		(0.02)	(0.01)	
FE	0.61***	0.07***	0.68	0.43***	0.13***	0.56
	(0.02)	(0.01)		(0.03)	(0.02)	
OP-adjusted	0.77***	0.09***	0.85	0.79***	0.05**	0.84
	(0.01)	(0.02)		(0.02)	(0.02)	
ACF-adjusted	0.92***	0.11***	1.03	0.90***	0.12***	1.02
	(0.05)	(0.02)		(0.05)	(0.02)	

Table C2: Rubber and plastic

	PPI deflator			Firm deflator		
	labor	capital	RTS	labor	capital	RTS
OLS	0.91***	0.12***	1.03	0.90***	0.14***	1.04
	(0.011)	(0.008)		(0.016)	(0.01)	
FE	0.84***	0.08***	0.92	0.74***	0.08***	0.82
	(0.02)	(0.01)		(0.04)	(0.15)	
OP-adjusted	0.81***	0.12***	0.93	0.78***	0.12***	0.90
	(0.01)	(0.01)		(0.02)	(0.020)	
ACF-adjusted	0.96***	0.09***	1.05	0.95***	0.09***	1.04
	(0.03)	(0.02)		(0.03)	(0.02)	

Note: standard errors for the ACF estimation using a bootstrap procedure with 200 replications

Appendix D

Table D1: Effect of trade on productivity using PPI and firm deflator (by size category)

SMALL (employment<50)

	PPI deflator			Firm deflator			N
	Export	Import	Export and Import	Export	Import	Export and Import	
Value added per worker	0.028**	0.099***	0.164***	0.031*	0.110***	0.182***	13,249
	(0.013)	(0.020)	(0.015)	(0.019)	(0.028)	(0.021)	
OLS	0.025**	0.089***	0.153***	0.026	0.100***	0.170***	13,249
	(0.012)	(0.019)	(0.014)	(0.018)	(0.028)	(0.020)	
OLS FE	0.025*	0.096***	0.154***	0.022	0.102***	0.167***	13,249
	(0.013)	(0.020)	(0.014)	(0.018)	(0.028)	(0.020)	
OP-adjusted	0.022	0.081**	0.163***	0.020	0.094*	0.177***	11,940
	(0.024)	(0.037)	(0.028)	(0.036)	(0.054)	(0.039)	
ACF-adjusted	0.029**	0.093***	0.158***	0.033*	0.104***	0.176***	13,249
	(0.012)	(0.020)	(0.014)	(0.018)	(0.028)	(0.020)	

MEDIUM (50<=employment <100)

	PPI deflator			Firm deflator			N
	Export	Import	Export and Import	Export	Import	Export and Import	
Value added per worker	-0.030	0.132***	0.137***	0.026	0.172***	0.160***	2,935
	(0.041)	(0.047)	(0.037)	(0.048)	(0.054)	(0.041)	
OLS	-0.028	0.098**	0.110***	0.016	0.132**	0.123***	2,935
	(0.039)	(0.045)	(0.036)	(0.047)	(0.053)	(0.042)	
OLS FE	-0.051	0.102**	0.106***	-0.000	0.130**	0.119***	2,935
	(0.040)	(0.047)	(0.037)	(0.046)	(0.053)	(0.042)	
OP-adjusted	-0.097	0.043	0.088	0.038	0.111	0.142*	2,644
	(0.078)	(0.081)	(0.070)	(0.087)	(0.097)	(0.078)	
ACF-adjusted	-0.028	0.112**	0.119***	0.036	0.155***	0.147***	2,935
	(0.039)	(0.045)	(0.036)	(0.047)	(0.053)	(0.042)	

LARGE (employment >=100)

	PPI deflator			Firm deflator			N
	Export	Import	Export and Import	Export	Import	Export and Import	
Value added per worker	-0.018	0.177***	0.177***	0.118	0.265***	0.247***	3,011
	(0.086)	(0.065)	(0.064)	(0.120)	(0.096)	(0.107)	
OLS	-0.022	0.193***	0.164**	0.103	0.274***	0.220**	3,011
	(0.081)	(0.065)	(0.064)	(0.120)	(0.099)	(0.111)	
OLS FE	-0.033	0.167**	0.150**	0.089	0.246**	0.201*	3,011
	(0.086)	(0.068)	(0.067)	(0.121)	(0.099)	(0.110)	
OP-adjusted	-0.069	0.247**	0.179	0.106	0.405*	0.284	2,752
	(0.140)	(0.120)	(0.118)	(0.241)	(0.213)	(0.227)	
ACF-adjusted	-0.01	0.194***	0.179***	0.131	0.289***	0.256**	3,011
	(0.083)	(0.065)	(0.064)	(0.119)	(0.096)	(0.108)	

Note: see table 4