Technical Appendix: Product Quality and Firm Heterogeneity in International Trade (Not For Publication)

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1 Introduction

This appendix contains two parts. The first explains the rules of inclusion for constructing the samples used in the empirical analysis. The second reports robustness check results using a second measure of productivity.

2 Data

The sample is constructed using the following restrictions. First, the sample is limited to census years 1987, 1992 and 1997 because export information is not available prior to 1987 and classification changes from SIC to NAICS after 1997 make it difficult to track products (defined as 5-digits SIC codes) past 1997. Second, the sample includes only observations for which information on physical output is available. Only about 28 percent of plant-product-year observations in the census of manufactures (CM) have information on physical quantities. The information is not available when product data is reported for the same period in other surveys (e.g. current industrial reports). The selection occurs at the product level, so that when physical output is recorded in the CM it is available for all plants in that product category.

Third, as in Foster et al. (2008), the sample is limited to the primary product of plants that derive at least 50 percent of their revenue from their primary product. Because the CM does not collect information on factor inputs and export revenue separately by product but rather at the plant level, this reduces measurement problems. In the CM, about 55 percent of plants are specialized. These plants account on average for about 70 percent of aggregate revenue in a given product category. Plants included in the sample generate on average about 90 percent of their revenue from their primary product.

Fourth, in order to limit large reporting errors observations with an output price above 10 times or lower than one-tenth of the product’s median price are dropped. These price outliers represent less than 2.5 percent of observations for which I can compute price. Fifth, to ensure there is enough variation to estimate aggregate and plant fixed effects, the sample is limited to products with at least 10 observations in each year and 50 observations
overall and where more than half of the plant-year observations are related to plants that appear at least twice in the sample. Finally, I remove observations with missing data and drop balancing codes, receipt for contract work, resale, and miscellaneous receipts from the sample because they are unrelated to production.

3 Physical Total Factor Productivity

This appendix presents empirical results using a different measure of productivity, physical total factor productivity (QTFP), defined as the variation in physical quantity produced unexplained by variation in capital stock, labor, energy and material. Following Foster et al. (2008), I compute $QTFP$ for each plant $i$ at time $t$ using the typical constant returns to scale index form:

$$\ln QTFP_{it} = \ln q_{it} - \psi_K \ln K_{it} - \psi_L \ln L_{it} - \psi_E \ln E_{it} - \psi_M \ln M_{it},$$

where $q, K, L, E$ and $M$ represent establishment-level output quantities, capital stocks, labor hours, and energy and materials inputs, and where $\psi_j$ for $j \in \{K, L, E, M\}$ are the factor elasticities for the corresponding inputs.

There are two main difficulties associated with estimating QTFP. The first is the classic estimation in the presence of endogenous variables problem. Foster et al. (2008) argue that instrumental variables procedure or the proxy methods developed by Olley and Pakes (1996) or Levinsohn and Petrin (2003) are best suited to annual panel data. Instead, the input elasticities, $\psi$, are estimated using 5-digits SIC average cost shares over the sample. The estimates are thus subject to the usual criticism. The second difficulty is related to measurement issues. The data reports only materials and energy expenditure. Since plant-level price for material and energy are not available in the data, real inputs are obtain by deflating expenditures using the corresponding input price indices from the NBER Productivity Database. Therefore, idiosyncratic establishment-level variation in input prices will introduce biases (e.g. low input prices will be captured as high measured inputs and in turn low measured productivity). Further, labor, materials, and energy cost shares are computed
from reported expenditures in the CM, while capital cost shares are constructed as reported equipment and building stocks multiplied by their respective capital rental rates for each plants corresponding 2-digits industry. These rental rates are constructed and used by the Bureau of Labor Statistics in computing their Multi-factor Productivity series.

In this paper, I use the productivity measures in two different ways. First, to obtain industry-level estimates for the price elasticity of demand from which plant-level quality measures are derived. Second, to evaluate the impact of changes in productivity on plant outcomes. So, which measure is the best? Since $Q_{Prod}$ and $Q_{TFP}$ are both exogenous to random demand shocks they are both valid instruments for price in the demand regressions and, as result, the associated quality estimates obtained from $Q_{Prod}$ are just as valid as those obtained from $Q_{TFP}$. Therefore, it comes down to which measure more precisely captures variation in technical efficiency across plants.

Since it is not clear how measurement error and estimation bias distort $Q_{TFP}$ estimates it is also unclear that $Q_{TFP}$ is a more accurate measure of plant productivity than $Q_{Prod}$. Fortunately, the two measures generally agree on which plants are the most productive, the correlation between the $Q_{TFP}$ and $Q_{Prod}$ is 0.68 in the sample. $Q_{Prod}$ is relatively simple, transparent, more widely applicable and, as explained in Ghandi et al. (2011) it is a valid measure of productivity even in the presence of many inputs as long as the production function is Leontief. Of course, this may not be the case in practice, but since the impact of quality on input mix is outside the scope of the model, it seems like a natural assumption in the current context.
Table 1: Correlations

<table>
<thead>
<tr>
<th>Quality_{QProd}</th>
<th>Quality_{Markup}</th>
<th>Advert. exp.</th>
<th>Hourly wage</th>
<th>Cost of mat.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation</td>
<td>0.94</td>
<td>0.83</td>
<td>0.25</td>
<td>0.22</td>
</tr>
</tbody>
</table>

Notes: This table presents standard deviation for the product quality measures and correlation between quality and other plant characteristics for the pooled sample of 51,434 observations except for the advertising regressing which contains a smaller sample of 33,304 plant-year observations.

Computing $QTFP$ requires additional information which is not available for all plants in the benchmark sample. As a results, the $QTFP$ sample is smaller and contains 51,434 observations across 143 product categories. The standard deviation of $QTFP$ across plants (0.60) is smaller than that of $QProd$ (0.77). The correlation between $QTFP$ and revenue, quantity, price and exporter ID are 0.21, 0.49, -0.81 and 0.01 respectively – similar to the $QProd$ counterpart. The properties of the estimated elasticities are generally the same, but at 1.17 the average estimated elasticity is smaller in absolute value than when using $QProd$. However, it is still larger than the average OLS estimates.

Table 1 reports the correlation between the new measures of product quality derived from $QTFP$ and the two measures used in the main text and other indicators of product quality. The quality estimates derived from $QTFP$ are strongly correlated with the other measures of quality. Further, the correlation between those estimates and advertising expenditures, wages and costs of material are similar the benchmark.

Table 2 reports the main results for each of the empirical models estimated in the main text. These results should be compared with the benchmark IV results. The first column regresses the price on quality and QTFP. Comparing the results with those column (4) of panel A in Table 4 in the paper shows that the results are essentially unchanged. The second column present results from regressing revenue on quality and productivity. Again, the point estimates are very close to those obtain using QProd as can be seen from column (4) of panel B in Table 4 in the paper. Using QTFP leads to the same conclusion that variations in prices and revenue across plant-level follow the predictions of the theoretical model.
Table 2: The Impact of QTFP on Firm Outcomes

<table>
<thead>
<tr>
<th></th>
<th>Price</th>
<th>Revenue</th>
<th>Premium</th>
<th>Selection</th>
<th>Exp. Rev.</th>
<th>Tobit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Quality</td>
<td>0.265</td>
<td>0.862</td>
<td>0.262</td>
<td>0.307</td>
<td>0.373</td>
<td>0.071</td>
</tr>
<tr>
<td>(0.043)</td>
<td>(0.010)</td>
<td>(0.043)</td>
<td>(0.010)</td>
<td>(0.015)</td>
<td>(0.015)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Log QTFP</td>
<td>-0.766</td>
<td>0.198</td>
<td>-0.765</td>
<td>0.020b</td>
<td>0.086</td>
<td>0.009a</td>
</tr>
<tr>
<td>(0.017)</td>
<td>(0.015)</td>
<td>(0.022)</td>
<td>(0.013)</td>
<td>(0.014)</td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>Exporter ID</td>
<td>0.054</td>
<td>0.016b</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.005)</td>
<td>(0.010)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Std. error of regr.</td>
<td>0.613</td>
<td>0.411</td>
<td>0.613</td>
<td>.</td>
<td>0.907</td>
<td>.</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.621</td>
<td>0.830</td>
<td>0.622</td>
<td>.</td>
<td>0.144</td>
<td>.</td>
</tr>
</tbody>
</table>

Notes: All variables are in logs and are standardized by removing the corresponding product-year mean and dividing by the product-year standard deviation. The sample is the pooled sample of 51,434 plant-year observations. Bootstrap standard errors clustered by product-year are in parenthesis. Estimated coefficients are significant at the 1 percent level unless indicated – a superscript a indicates that the coefficient is significant at the 5 percent level while a b indicates the coefficient is not significant at the 10 percent level.

Turning to the export behavior, the column “Premium” evaluates the impacts of quality and productivity on the difference between exporter and non-exporter prices. As reported in the main text, the premium is no longer statistically significant once variation in measured quality and productivity across plants is accounted for. The column “Selection” evaluates the impact of quality and productivity on the probability a plant will export. In this case using QTFP makes a difference. Table 6 in the paper reports that the estimated impact of Qprod on selection is negative and significant. Instead, when using QTFP, the coefficient becomes positive, although not statistically significant at conventional levels. The last two columns of the table look at the intensive margin of trade. Column “Exp. Rev.” regresses export revenue on quality and productivity measure for plant that report foreign sales. The last column “Tobit” uses the Tobit censored regression framework and uses information on the whole sample. As can be seen by comparing the results with those of column (4) in table 7 in the paper, the results are overall the same as when using QProd.

References
