# Do Exports Raise Productivity? Plant-level Evidence from the Colombian Agri-food Industries

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***Selected paper Prepared for Presentation at the Agricultural and Applied Economics Association's 2011 AAEA &NAREA Joint Annual Meeting Pittsburgh, Pennsylvania, July 24-26, 2011***

## I. Introduction

In the last 15 years a growing empirical literature has documented that exporting establishments are more productive than those supplying for the domestic market alone (see, for example, Bernard and Jensen (1999)). This has lead to a number of important theoretical contributions in the international trade literature, notably the heterogeneous trade models that attempt to explain this empirical regularity. Most of these models contend that the causality goes one way – more productive firms self-select into exporting (see, for example, Melitz (2003)). Previous empirical work, however, shows mixed evidence of the effect of exports on productivity. Clerides, Lach, and Tybout (1998), Bernard and Jensen (1999), as well as Aw, Chung, and Roberts (2000) find no impact of exports on firm's efficiency. On the other hand, a small but growing empirical literature provides evidence that exports do lead to productivity improvements via "learning-by-exporting" – see, for example, Van Biesebroeck (2003), Yasar and Morrison Paul (2008).

In our research, we investigate if exports contribute to increased productivity in the Colombian agri-food industry. More importantly, we seek to determine if exporting makes a difference for all exporters or for persistent exporters only. Using detailed plant-level manufacturing census data from the Colombian agri-food industries, we show that exports raise plant-level productivity for persistent exporters, but not for occasional exporters. To identify the impact of exports on plant-level productivity we employ the state-of-the-art Levinsohn-Petrin (2003) measure of total factor productivity, which corrects for the endogeneity of input choices to firm-level productivity dynamics, and a difference-in-differences propensity score matching estimator that evaluates the causal impact of exporting on plant-level productivity.

We find a positive, economically and statistically significant impact of exporting on firms' efficiency. Overall, exporting in the Colombian agri-food industry raises productivity by about 15 to 20 percent. On the other hand, the estimates reveal that efficiency in plants that become persistent exporters, i.e. plants that service foreign markets at least 30 percent of the time during our sample years 1981-1991, increases about 30 percent upon their entry into foreign markets, while productivity in plants that become only occasional exporters does not change at all. We perform a number of robustness checks with nearest-neighbor, kernel, and radius matching, all of which confirm our baseline results.

Our work contributes to the growing literature that attempts to estimate the causal impact of exports on establishment-level productivity in two important ways. First, we show that in the case of the Colombian agri-food industry, the overall impact is positive, which would support the hypothesis of "learning-by-exporting". Second, and more importantly, we provide strong evidence that the positive impact is not homogenous – only persistent exporters "learn" and in turn their productivity benefits from servicing foreign markets – firm-level efficiency of occasional exporters, on the other hand, does not change with exposure to foreign consumers.

These results here are important for policymakers – if the selection hypothesis is the only explanation for the observed positive correlation between plant-level productivity and exports, i.e. if more efficient establishments become exporters and there are no positive benefits of exporting on productivity, exports subsidies are inefficient – they only encourage inefficient producers to increase output and supply to foreign consumers without any real productivity gains. However, if exporting increases efficiency, as we show is the case in the Colombian agri-food industries, export subsidies may well be welfare-improving.

## II. Data

To identify the impact of exports on productivity in the agri-food industry, we use the Colombian manufacturing Census annual plant-level data from 1981 to 1987. This is the same panel previously used in Roberts and Skoufias (1997), and it includes all manufacturing establishments with at least 10 employees. The data were originally collected by the Colombian Statistical Institute (Departamento Administrativo Nacional de Estadistica, DANE), and it is described in detail in Roberts and Tybout (1996). An establishment is not necessarily a single-plant firm; however, most Colombian firms operate only one plant (Das et al. (2007)). For each establishment, the survey collects data on production, value added, sales, employment, wages, exports, investment, and a small number of other plant characteristics. Plant's capital stock is constructed using the perpetual inventory method, and cash ow is calculated as the after tax operating profits plus depreciation.[1] All plants are classified into 28 3-digit ISIC (International Standard Industrial Classification, revision 2) industries.

Table 1 presents a simple comparison of the exporters and non-exporters in their baseline period. We have around 300 plants that exported at least once, and around 4000 plants that never exported. Among the exporters, about 50% exported at least 30 % of their time in our data. The summary statistics show that the exporters are more productive, are more capital intensive, have operated for longer times, have more skill workers, pay higher wages on average and higher wages to skilled workers before they start to export. They also use more imported labor and intermediate inputs than the non-exporters.

**III. Econometric Strategy**

To evaluate the impact of exports on productivity, we employ a propensity score matching (PSM) estimator that was proposed in Rosenbaum and Rubin (1983). This method was

[1] See Liu (1993) for detailed description of the construction of the capital measure in this data set.

originally designed for cross-sectional data and was extended to panel data setting in Heckman, Ichimura, and Todd (1998). Given that we have panel data, we use the difference-in-difference (DID) version of the PSM method. Different from the PSM method for cross-sectional data, the DID version overcomes problems with selection on time-invariant (plant-level) unobservables, i.e. the DID version of the matching model controls for selection on time-invariant unobservable factors by allowing for time-invariant differences in the outcome variable between exporting plants and non-exporting plants. [2]

The PSM method matches (and then compares) plants that serve international markets with plants that serve only domestic markets based on their observable characteristics before exporting (pre-treatment characteristics). The difference in the differences in the post-exporting and pre-exporting productivity between the matched exporting and non-exporting plants is the estimated effect of exports on productivity.

We implement this method in three stages. In the first stage, we estimate the probability that a plant becomes an exporter using a set of pre-treatment conditional (right-hand side) variables and a logistic regression. We include all variables that affect both the incidence of exporting and plant productivity as conditional variables in the logistic regression. In the second stage, we match exporters and non-exporters with the similar estimated propensity scores and test whether our matched exporters and non-exporters are observationally equivalent using a standard t-test. Third, we compare the outcome variable (productivity) between the two matched

[2] The method is also analogous to the standard DID regression but it does not impose a linear functional form restriction in estimating the conditional expectation of the outcome variable. Also, the DID propensity score matching model re-weights the observations according to the weighting functions used by matching estimator.

groups of plants (exporters and non-exporters). We calculate the impact of exporting on the productivity of those plants which served international markets (i.e. the average treatment effect on the treated) by taking the difference in the differences (post-exporting productivity minus pre-exporting productivity) of the outcomes between the group of plants.

Let's define $Y_D^T$ as the plant productivity for treatment status $D$, i.e. exporting status, in period *T*. The treatment variable *D* takes a value of 1 if a plant has sold any goods in the international markets at least once and 0 otherwise. $T$ takes on two values: $T = 0$ during the pre-treatment period, i.e. in the years before a plant first started to export, and $T = 1$ for the post-treatment period, i.e. during the years after the plant started to export. Specifically, our pre-treatment period for non-exporters is the period from 1981 to 1983 and the pre-treatment values for outcomes or conditional variables are the average of their values in 1981, 1982, and 1983. Similarly, the pre-treatment period for exporters is the three periods prior to the plants first export, and the pre-treatment values are the average of those variables in those periods. For example, if a plant started exporting in 1982, the pre-treatment period is 1981. The pre-treatment period is 1981 and 1982 if the plant start to export in 1983, and pre-treatment values are the average of 1981 and 1982, and they are the average of 1981, 1982 and 1983 if the plant fist exported in 1984 or afterwards. Those observations after plants first export are post-treatment observations for which we are going to construct counterfactual.

The basic assumption of the DID matching method is Conditional Mean Independence (CMI). This assumption asserts that the evolution of the unobserved part of the productivity in plants that served the international markets had it served only domestic markets is independent of exporting conditional on a set of covariates $X_0$. The variables in $X_0$ are measured in the period prior to exporting, i.e. the covariates used to estimate the propensity score represent pre-treatment values. The CMI assumption can be expressed as:

$$E(Y_0^1 - Y_0^0 | P(X_0), D = 1) = E(Y_0^1 - Y_0^0 | P(X_0), D = 0).$$

Control observations (non-exporting plants) are matched to the treated ones (exporters) based on their propensity scores (probability of being treated). The average treatment effect on the treated is the difference in differences in the pre- and post-treatment outcomes between the treated and their matched control observations:

$$\begin{aligned}\Delta^{ATT} &= E(Y_1^1 - Y_1^0 | P(X_0), D = 1) - E\left(\widehat{Y_0^1 - Y_0^0} \,|\, P(X_0), D = 1\right) \\ &= E(Y_1^1 - Y_1^0 | P(X_0), D = 1) - E\{E[(Y_0^1 - Y_0^0) | P(X_0), D = 0] | D = 1\}\end{aligned}$$

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As we discussed above, the CMI assumption requires that we choose a set of conditioning variables (covariates) that affect both a plant's likelihood of becoming an exporter and its productivity. Since more productive plants tend to become exporters (the self-selection hypothesis), we include the plants' initial productivity as a conditional variable. The initial productivity also affects the plant's productivity in the post-exporting period if high productivity tends to persist. We also include the capital to labor ratio, the share of skilled workers, the average wage, the skill premium (the average ration of high-skilled to low-skilled wage), the percentage of expenditure on advertisement, the firm's age, and fraction of total expenditure on imported inputs. We also include sector dummies in our propensity score model.

We construct the counterfactual for each exporting plant using non-exporting plants with similar estimated propensity scores. We use three matching protocols to estimate the impact of exporting on plant productivity and also to check robustness of our estimations. We use nearest neighbor matching with 10 neighbors, radius matching, and kernel matching with normal kernel type. We impose a bandwidth of either 0.001 or 0.01 for our matching methods. Since we have an unbalanced panel, we match an exporter using only the non-exporters that appear in our data from the same year as the exporter in order to construct the counterfactual. Such a restriction on the sample allows us to eliminate the bias from any potentially unobserved shocks.

More formally, the constructed counterfactual is

$$E\left(\widehat{Y_0^1 - Y_0^0} \mid P(X), D = 1\right) = \left(\sum_{j \in \{D_j = 0\}} w(i,j)(Y_0^1 - Y_0^0) \mid P(X), D_j = 0\right).$$

where $j$ indexes non-exporting plants and $i$ indexes exporting plants (with plant $j$ being matched to plant $i$ based on their estimated propensity scores). The matrix, $w(i, j)$, contains the weights assigned to the $j^{\text{th}}$ control plant that is matched to the $i^{\text{th}}$ treated plant. The matching estimator constructs an estimate of the expected unobserved counterfactual for each exporting plant by taking a weighted average of the difference in pre-treatment and post-treatment outcomes using the matched non-exporting plants.

The standard definition of the average impact of exporting on the plant productivity for treated plants, the Average Treatment Effect on the Treated (ATT), or $\Delta^{ATT}$ is:

$$\Delta^{ATT} = \frac{1}{N}\sum_{i=1}^{N}\left\{\left[\left(Y_{i1}^1 - Y_{i1}^0\right) - \left(\widehat{Y_0^1 - Y_0^0}\right)\right] \mid D = 1\right\}.$$

In the equation above, $N$ is the number of the exporting plants, $(Y_{i1}^1 - Y_{i1}^0)$ is the difference in post-treatment and pre-treatment outcomes in a exporting plant $i$, and $\left(\left(\widehat{Y_0^1 - Y_0^0}\right) \mid D_i = 1\right)$ is the constructed counterfactual for plant $i$. The average impact of exporting is therefore the mean difference in the pre-treatment and post-treatment differences in the outcomes between the exporting plants and the constructed counterfactual outcomes from the matched non-exporting plants.

After matching, we check if the matched exporting plants and non-exporting plants are balanced on covariates, i.e. if the two groups have similar characteristics in the pre-exporting period. If unbalanced, the estimated $\Delta^{ATT}$ may not reflect solely the impact of the exporting. Instead, it may be a combination of the impacts of exporting and the unbalanced covariates. We rely on t-tests to check if the means for each covariate are statistically the same between the two groups of plants. The balancing criteria are satisfied for all of our covariates, including the dummy variables for sectors. This indicates that the two groups of plants are indeed observationally equivalent, and it also implies that our estimated $\Delta^{ATT}$ reflects solely the impact of exporting.

In addition to using different matching protocols, we check the robustness of our results by limiting matching among the plants within the same manufacturing sector, such as foods, tobacco, alcohol, wood, and textiles.

As we discussed in the introduction section, we distinguish between occasional exporters and persistent exporters. If some firms export for a short period due to random shock, exporting activities are likely to have very little impact on their productivity. We define the two types of exporters based on how often the firm exports (the number of periods the firm exports as a fraction of the total number of periods in the sample). The cut-off value that we use is 30 percent of the time, that is, persistent exporters are the firms that export at least 30 percent of time and occasional exporters are firms that export at least once but less than 30 percent of time. We implement the matching and calculate the ATT for the two groups of exporters separately.

## IV. Results and Discussion

We start by estimating the propensity score model, which is a logistic regression that predicts the likelihood of positive exports. The results, which are presented in Table 2, show that initially more productive firms tend to be more likely to export at least once throughout the sample period. The same is true for firms that have higher initial capital to labor ratio as well as higher initial skill premium (high-skilled to low-skilled wage ratio). While we do estimate a positive impact of higher advertising costs and higher imported intermediates, these effects are not statistically significant. Based on the predicted probabilities from this logistic regression, we compute the propensity score for each plant and use it in the propensity score matching procedure.

The outcome variable of interest is plant-level productivity. We employ two measures of productivity. The first is a simple measure – the logarithm of the ratio of value added per worker. While this is a rather crude measure, it does provide a useful starting point. The second measure is estimated as a production function residual and utilizes the econometric methodology of Levisohn-Petrin (2003). This is a state-of-the-art measure of total factor productivity, which corrects for the endogeneity of input choices to firm-level productivity dynamics.

The first set of matching results is presented in Table 3. These estimates document the overall impact of exporting on firm-level productivity in the Colombian agri-food industries. For example, using the Levinsohn-Petrin productivity measure and the nearest neighbor PSM method, the results suggests that exporting has a positive (causal) impact of about 20 percent on firm-level productivity. The positive impact is estimated to be somewhat larger with the value added per worker measure of total factor productivity. The radius and the kernel matching results confirm the nearest neighbor estimates, implying that exporting tends to increase firm-level productivity by about 20 percent. The positive impacts estimated with kernel matching are the smallest – about 15 percent. All of this evidence provides strong support for the “learning-by-exporting” hypothesis.

Because likely there are key differences between persistent exporters, those firms that export often, and occasional exporters, those firms that do export but only infrequently for a period, in the next set of results, we present the impact of exporting on productivity separately for these two different types of exporters. One would expect that if a firm is a persistent exporter, the benefits of servicing foreign markets will keep accruing over time and produce larger positive impacts on firm's productivity compared to the effects of exports for occasional exporter, which service foreign markets infrequently and likely only as a result of a random positive shock.

First, note that there are some differences in pre-treatment characteristics between persistent and occasional exporters. Among other things, Table 4 suggests that the capital-labor ratio, the high-skill premium (the ration of high-skilled to the low-skilled wage), and the costs of imported intermediates are somewhat higher for persistent exporters. Next, all of the three matching estimators, whose results are presented in Table 5, imply that the impact of exports on total factor productivity for occasional exporters is nearly zero (small, positive, and not statistically significantly different from zero). On the other hand, all three PSM estimators suggest that the impact exports on productivity for persistent exporter is between 30 and 40 percent, implying that the difference of the impact between the two types of exporters is over 30 percent. In Table 6, we check if our estimates are roust by restricting the matching to occur only within three-digit manufacturing sectors (such as foods, alcohol, tobacco, textiles). This method produces even larger differences (up to 43 percentage points for the Levinsohn-Petrin productivity measure with the radius matching protocol) in the effects of exports on productivity between persistent and occasional exporters.

## V. Conclusion

We investigate if exports contribute to increased productivity in the Colombian agri-food industry. In our analysis, we distinguish between persistent and occasional exporters. Using detailed plant-level manufacturing census data from the Colombian agri-food industries, we show that exports raise plant-level productivity for persistent exporters, but not for occasional exporters. To identify the impact of exports on plant-level productivity we employ the Levinsohn-Petrin (2003) measure of total factor productivity, which corrects for the endogeneity of input choices to firm-level productivity dynamics, and a difference-in-differences propensity score matching estimator that evaluates the causal impact of exporting on plant-level productivity.

We find a positive, economically and statistically significant impact of exporting on firms' efficiency. Overall, exporting in the Colombian agri-food industry raises productivity by about 15 to 20 percent. On the other hand, the estimates reveal that efficiency in plants that become persistent exporters, i.e. plants that service foreign markets at least 30 percent of the time during our sample years 1981-1991, increases about 30 percent upon their entry into foreign markets, while productivity in plants that become only occasional exporters does not change much. These results suggest that only persistent exporters "learn-by-exporting."

References

Aw, B., Chung, S., and Roberts, M. 2000. "Productivity and Turnover Patterns in the Export Market: Firm-level Evidence from Taiwan and South Korea," *World Bank Economic Review* 14(1), 65-90.

Bernard, A. and Jensen, J.B. 1999. "Exceptional Exporters Performance: Cause, Effect or Both?" *Journal of International Economics*, 47:1-25.

Clerides, S., Lach, S. and Tybout, J. 1998. "Is Learning by Exporting Important? Microdynamic Evidence from Columbia, Mexico and Morocco," *Quarterly Journal of Economics* 113:903-948.

Das, S., Roberts, M., and Tybbout, J., 2007. "Market Entry Costs, Producer Heterogeneity, and Export Dynamics" *Econometrica* 75(3), 837-873.

Heckman, J., Ichimura, H., and Todd, P. 1997. "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme." *Review of Economic Studies* 64(4): 605-654.

Levinsohn, J. and Petrin, A. 2003. "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies* 70(2), 317-342.

Liu, L. 1993. "Entry-exit, learning, and productivity change: Evidence from Chile," *Journal of Development Economics*, 42(2), 217-242.

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

Roberts, M. J. and Skoufias, E. 1997. "The Long-Run Demand for Skilled and Unskilled Labor in Colombian Manufacturing Plants" *Review of Economics and Statistics* 79(2), 330-334.

Rosenbaum, P. and Rubin, D. 1983. “The Central Role of the Propensity Score in Observational Studies for Causal Effects.” *Biometrika* 70: 41-55.

Van Biesebroeck, J. 2005. Exporting Raises Productivity in sub-Saharan African Manufacturing Firms,” *Journal of International Economics*, *67*(*2*), 373-391.

Yaşar, M., Morrison Paul, C. (2008). “Foreign Technology Transfer and Productivity: Evidence from a Matched Sample,” *Journal of Business and Economic Statistics* 26(1), 105-112.

TABLES

Table 1. Summary Statistics for the Outcome Variable and the Conditioning Variables in the Pre-exporting Period.

| **Variable** | **Exporters (N=298)** | | **Non-exporters (N=4,062)** | |
|---|---|---|---|---|
| | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** |
| Exporters ( =1 if export at least once) | 1 | 0 | 0 | 0 |
| Persistent Exporters (=1 if export at least 30 percent of the time) | 0.47 | 0.5 | 0 | 0 |
| Productivity (Levinsohn-Petrin) | 62.4 | 0.8 | 61.9 | 0.6 |
| *log* (Value Added per Worker) | 9.9 | 0.9 | 9.4 | 0.7 |
| *log* (Capital-Labor Ratio) | 9 | 1.3 | 8.3 | 1.3 |
| High-skilled Labor Share | 0.25 | 0.13 | 0.28 | 0.12 |
| *log* (Average Wage) | 8.5 | 0.65 | 8.21 | 0.54 |
| Ratio of High-skilled/Low-skilled Wage | 0.53 | 0.39 | 0.42 | 0.33 |
| Advertising Share (in Total Expenditure) | 0.05 | 0.08 | 0.04 | 0.06 |
| Firm Age | 14.5 | 14 | 13.1 | 11.6 |
| Cost of Imported Labor and Intermediate Inputs as a Share of the Costs of Total Inputs | 0.55 | 1.36 | 0.35 | 1.8 |

Table 2. Propensity Score Model (Logit). Dependent Variable – Likelihood of Positive Exports.

| **Variable** | |
|---|---|
| Initial Productivity (Levinsohn-Petrin) | 0.712*** |
| | (0.200) |
| Initial Capital-Labor Ratio | 0.517*** |
| | (0.093) |
| Initial Share of High-skilled Labor | -6.761*** |
| | (1.592) |
| Initial Average Wage | 0.066 |
| | (0.359) |
| Initial Ratio of High-skilled to Low-skilled Wage | 1.916*** |
| | (0.440) |
| Initial Share of Advertising | 1.387 |
| | (1.404) |
| Age | -0.009 |
| | (0.019) |
| Age Squared (x100) | 0.017 |
| | (0.034) |
| Initial Costs of Imported Labor and Intermediate Inputs | 0.247 |
| | (0.169) |
| Constant | -52.110*** |
| | (11.200) |
| | |
| *N* | 3,960 |
| Pseudo R-squared | 0.179 |

Note: Standard errors in parentheses. * indicates significance at the 10 percent level, ** indicates significance at the 5 percent level, and *** indicates significance at the 1 percent level.

Table 3. The Overall Impact of Exporting on Firm-level Productivity in the Colombian Agri-food Industries.

| **Method** | **Variable** | **Bandwidth** | |
|---|---|---|---|
| | | **0.001** | **0.01** |
| Nearest Neighbor | Productivity (Levinsohn-Petrin) | 0.220*** | 0.175*** |
| | | (0.037) | (0.027) |
| | *log*(Value Added per Worker) | 0.299*** | 0.236*** |
| | | (0.040) | (0.030) |
| | No. Matched Exporting Firms/Total Observations | 175/700 | 252/1062 |
| Radius | Productivity (Levinsohn-Petrin) | 0.219*** | 0.167*** |
| | | (0.036) | (0.027) |
| | *log*(Value Added per Worker) | 0.302*** | 0.231*** |
| | | (0.040) | (0.030) |
| | No. Matched Exporting Firms/Total Observations | 175/700 | 252/1062 |
| Kernel | Productivity (Levinsohn-Petrin) | 0.152*** | 0.133*** |
| | | (0.027) | (0.026) |
| | *log*(Value Added per Worker) | 0.210*** | 0.189*** |
| | | (0.031) | (0.028) |
| | No. Matched Exporting Firms/Total Observations | 269/1116 | 288/1180 |

Note: Standard errors in parentheses. * indicates significance at the 10 percent level, ** indicates significance at the 5 percent level, and *** indicates significance at the 1 percent level.

Table 4. Summary Statistics for the Outcome and the Conditioning Variables in the Pre-exporting Period for Occasional and Persistent Exporters.

| **Variable** | **Occasional Exporters (N=158)** | | **Persistent Exporters (N=140)** | |
|---|---|---|---|---|
| | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** |
| Productivity (Levinsohn-Petrin) | 62.5 | 0.7 | 62.4 | 0.9 |
| *log* (Value Added per Worker) | 9.9 | 0.8 | 9.9 | 1 |
| *log* (Capital-Labor Ratio) | 8.9 | 1.2 | 9.2 | 1.4 |
| High Skilled Labor Share | 0.24 | 0.12 | 0.26 | 0.14 |
| *log* (Average Wage) | 8.57 | 0.4 | 8.42 | 0.85 |
| Ratio of High-skilled to Low-skilled Wage | 0.5 | 0.38 | 0.58 | 0.39 |
| Advertising Share (in Total Expenditure) | 0.06 | 0.09 | 0.04 | 0.07 |
| Firm Age | 15.3 | 14.5 | 13.5 | 13.5 |
| Cost of Imported Labor and Intermediate Inputs as a Share of the Costs of Total Inputs | 0.46 | 1.04 | 0.65 | 1.65 |

Table 5. The Impact of Exports on Productivity – Occasional vs. Consistent Exporters (Bandwidth = 0.001).

| **Method** | | **Occasional Exporter** | **Persistent Exporter** | **Difference** | **t-value** |
|---|---|---|---|---|---|
| | Nearest Neighbor Matching (10 neighbors) | | | | |
| Productivity (Levinsohn-Petrin) | Average Treatment Effect on the Treated (ATT) | 0.037<br>(0.042) | 0.374<br>(0.056) | -0.337 | -4.64 |
| | No. Matched Exporting Firms/Total Observations | 93/315 | 79/375 | | |
| *log*(Value-Added per Worker) | Average Treatment Effect on the Treated (ATT) | 0.119<br>(0.046) | 0.452<br>(0.061) | -0.333 | -4.22 |
| | No. Matched Exporting Firms/Total Observations | 96/321 | 79/379 | | |
| | Radius Matching | | | | |
| Productivity (Levinsohn-Petrin) | Average Treatment Effect on the Treated (ATT) | 0.051<br>(0.042) | 0.359<br>(0.056) | -0.308 | -4.27 |
| | No. Matched Exporting Firms/Total Observations | 93/315 | 79/375 | | |
| *log*(Value-Added per Worker) | Average Treatment Effect on the Treated (ATT) | 0.132<br>(0.046) | 0.446<br>(0.061) | -0.314 | -3.98 |
| | No. Matched Exporting Firms/Total Observations | 96/321 | 79/379 | | |
| | Kernel Matching | | | | |
| Productivity (Levinsohn-Petrin) | Average Treatment Effect on the Treated (ATT) | -0.038<br>(0.034) | 0.300<br>(0.040) | -0.338 | -6.21 |
| | No. Matched Exporting Firms/Total Observations | 142/483 | 124/621 | | |
| *log*(Value-Added per Worker) | Average Treatment Effect on the Treated (ATT) | 0.001<br>(0.040) | 0.374<br>(0.044) | -0.373 | -6.13 |
| | No. Matched Exporting Firms/Total Observations | 145/490 | 124/626 | | |

Note: Standard errors in parentheses.

Table 6. The Impact of Exports on Productivity – Occasional vs. Consistent Exporters. Robustness check-controlling for sector heterogeneity by limiting matching with firms within the same three-digit sector (Bandwidth=0.001).

| **Method** | | **Occasional Exporter** | **Persistent Exporter** | **Difference** | **t-value** |
|---|---|---|---|---|---|
| | Nearest Neighbor Matching (10 neighbors) | | | | |
| Productivity (Levinsohn-Petrin) | Average Treatment Effect on the Treated (ATT) | 0.160<br>(0.059) | 0.587<br>(0.094) | -0.427 | -3.76 |
| | No. Matched Exporting Firms/Total Observations | 57/188 | 50/206 | | |
| *log*(Value-Added per Worker) | Average Treatment Effect on the Treated (ATT) | 0.285<br>(0.065) | 0.655<br>(0.101) | -0.370 | -3.02 |
| | No. Matched Exporting Firms/Total Observations | 58/192 | 79/379 | | |
| | Radius Matching | | | | |
| Productivity (Levinsohn-Petrin) | Average Treatment Effect on the Treated (ATT) | 0.156<br>(0.059) | 0.586<br>(0.094) | -0.430 | -3.79 |
| | No. Matched Exporting Firms/Total Observations | 57/188 | 50/206 | | |
| *log*(Value-Added per Worker) | Average Treatment Effect on the Treated (ATT) | 0.278<br>(0.065) | 0.655<br>(1.101) | -0.377 | -3.08 |
| | No. Matched Exporting Firms/Total Observations | 58/192 | 50/209 | | |
| | Kernel Matching | | | | |
| Productivity (Levinsohn-Petrin) | Average Treatment Effect on the Treated (ATT) | 0.034<br>(0.036) | 0.300<br>(0.045) | -0.266 | -4.45 |
| | No. Matched Exporting Firms/Total Observations | 130/440 | 110/556 | | |
| *log*(Value-Added per Worker) | Average Treatment Effect on the Treated (ATT) | 0.095<br>(0.043) | 0.354<br>(0.050) | -0.260 | -3.84 |
| | No. Matched Exporting Firms/Total Observations | 133/447 | 124/626 | | |

Note: Standard errors in parentheses.