# Learning-by-doing, learning-by-exporting, and productivity: Evidence from Colombia*

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**Abstract**: This paper examines learning-by-exporting in Colombian manufacturing by extending a production function framework often used in the learning-by-doing literature. Limiting our analysis to a sample of young plants, we find strong evidence that export experience leads to higher total factor productivity.

*Key Words*: learning, trade, total factor productivity, exports, export-led growth

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## 1. Introduction

Trade and development policies have often been supported by arguments stressing improvements in productivity at the microeconomic level. For example, the traditional infant industry argument suggests that new firms operate at such high costs that they would be unable to compete with well-established foreign firms without protection. While such protection would be detrimental to the country's welfare initially, by allowing domestic firms to start operations it would also give them the opportunity to grow and learn-by doing, decreasing production costs over time. At some point, the argument concludes, protection would become unnecessary as the infant firms would mature and be able to compete in the international market.

Similarly, supporters of export-led growth have often argued that a similar learning process takes place when domestic firms start to export. An important channel through which this learning takes place is foreign buyers' requirements of specific product designs and technical assistance in the manufacturing process (Clerides et al., 1998). Opportunities for such transfers of technological knowledge are becoming more widespread, as industrial and developing countries become more integrated through trade links. An alternative channel through which exports may lead to increased productivity is the enhanced motivation of managers to improve performance, stirred by the greater opportunities for increasing profits as well as the higher risks of failure in very competitive export markets. Both channels for increased productivity and learning are often referred to as learning-by-exporting.

While there is strong empirical evidence that manufacturing plants that operate in export markets are considerably more productive than those that sell exclusively in the domestic market, such evidence in itself is not enough to prove that exporting causes increases in productivity, as the learning-by-exporting hypothesis predicts. Recent econometric literature has emphasized that the high correlation between participation in export markets and plant productivity can also be explained by a competitive hypothesis: that the most productive plants self-select into export markets. The self-selection hypothesis, which is rationalized by the existence of fixed sunk cost of entry into export markets that only highly productive plants can afford, suggests that causality might run from productivity to exporting.

Therefore, a critical task of the recent econometric literature has been to distinguish learning-by-exporting effects from self-selection effects. A first identification strategy has been to identify increases in firm productivity before entry into export markets as self-selection effects and increases in firm productivity after entry as learning-by-exporting effects (Bernard and Jensen, 1999). A second strategy has been to estimate a reduced-form model with an equation explaining the firm's decision to participate in export markets and another equation with a performance measure, such as average variable costs, as dependent variable. In Clerides et al. (1998), the participation equation includes lagged values of average variable costs to identify self-selection effects, and the average variable costs equation includes lagged export participation dummies to identify learning-by-exporting effects. A third identification strategy has been to impose restrictions on the joint stochastic process of exports and performance shocks to ensure that estimates of learning-by-exporting effects are not confounded with self-selection effects. Kraay (1999), for example, imposes the identifying restriction that current exports are independent of *future* performance shocks. This restriction does not rule out the possibility of self-selection effects because current exports can still be positively correlated with current and past performance shocks. But *past* exports are independent of current performance shocks and, therefore, can be used to identify learning-by-exporting effects in equations with a performance measure, such as productivity or unit costs, as dependent variable.

In this paper we follow Kraay's (1999) assumption using plant-level data from Colombia's manufacturing sector. Our paper contributes to the literature in a number of ways. First, we draw on the empirical literature of learning-by-doing to specify our econometric model. In particular, we adopt Bahk and Gort's (1993) production function framework, in which a production experience variable is added to account for the Solow residual. Production experience is usually measured as cumulative output of the plant until the previous year, sometimes scaled by the plant's employment, or as plant age. To study potential learning-by-exporting effects, we include in our specification both a measure of production experience and a measure of export experience, defined as cumulative exports or the number of years the plant has exported until the previous year.

Second, in our production function framework, we account for factor quality as well as factor quantity. We account for labor quality by including the skilled intensity of the workforce and the premium of the plant average wage relative to average wages paid in the region where the plant operates. We account for capital quality by including a measure of physical capital vintage. Third, we are particularly careful in deflating separately domestic and imported raw materials as well as sales to domestic markets and sales to export markets given that our sample period is characterized by important fluctuations in the real exchange rate. For that purpose, we construct indexes of domestic and imported raw materials using Colombian input-output matrices and import data and an index of export prices using export data.

Fourth, our estimation procedure accounts for the fact that the plants' variable inputs choices may be affected by productivity shocks observed by plant managers but not by the econometrician. For that purpose we utilize a variant of the Levinsohn and Petrin (2003) (henceforth LP) estimation procedure. In a variant of the analysis, the "two-step approach", we use the LP procedure to estimate the coefficients of industry-level production functions *without including experience variables*, use the residuals from these production functions to construct plant-level estimates of total factor productivity (TFP), and regress TFP on production and export experience. In another variant, the "one-step approach", we include production and export experience variables directly in the production function estimated under a modified LP procedure.

Finally, in our analysis we focus on a sample of relatively new plants that have started operations in or after 1981. We restrict our attention to new plants for two reasons. First, in order to construct experience variables accurately, we want to measure cumulative production and exports of each plant since their first year of operations. We choose plants born in or after 1981 because that is the first year in the dataset when exports are recorded. Second, empirical work on learning-by-doing has typically found evidence of learning during the early years of life of plants. As Bahk and Gort (1993, pp. 561-2) argue, "learning has a finite time dimension beyond which increments to learning approach zero". By analogy, we believe that the best place to look for evidence of learning-by-exporting in the data is to look for it in young plants.

Note that our analysis focuses exclusively on learning-by-exporting, disregarding self-selection effects. One justification for this is that self-selection and learning effects are not incompatible. While a non-exporter plant that experiences a sequence of positive productivity shocks may be able to afford the sunk fixed costs required to break into the export market, nothing prevents this plant to further increase productivity as a result of learning from exporting. Therefore, focusing on learning-by-exporting does not rule out the possibility of self-selection effects being important. More importantly, while the self-selection hypothesis implicitly assumes that productivity shocks are independent of future exports, this might not always be the case. As Tybout (2001) notes, productivity-enhancing technical assistance of foreign buyers is likely to begin before a plant is able to export for the first time. Moreover, case study evidence from Taiwan suggests that the prospects of exports orders often stimulate a firm's efforts to acquire the technological capabilities needed to take advantage of such opportunities (Westphal, 2001). Therefore, learning effects may actually take place before a plant starts exporting, making the evidence of self-selection substantially more difficult to interpret.[1]

The rest of the paper is organized as follows. Section 2 describes the empirical methodology and Section 3 describes the data. The results are presented in Section 4 and Section 5 concludes.

## 2. Empirical Specification

Our empirical analysis is based on two types of estimation, which we refer to as the "two-step approach" and the "one-step approach". Under both approaches, we estimate consistent production function parameters combining parametric and nonparametric techniques as in Levinsohn and Petrin (2003). The difference between the two approaches lies in the treatment of

[1] Technological improvements required by foreign buyers might be embedded in capital goods that need to be installed before starting to export. Isgut (2001) and Alvarez and Lopez (2004) find evidence for Colombia

the production experience and the export experience variables.

Under the "two-step approach", we obtain plant-level total factor productivity (TFP) as the residual from a production function—estimated separately across industries—where output depends on labor, intermediates, capital, and three measures of input quality: wage premium, skill intensity, and vintage of capital. The TFP estimates are then regressed on output experience and export experience measures. In these regressions we restrict the effect of experience on productivity to be the same across industries, although we account for fixed industry and plant effects. Under the "one-step approach", we estimate "augmented" production functions for each industry that include in addition to the aforementioned inputs and input quality variables a measure of production experience and a measure of export experience. In this case, the effects of the experience variables on productivity are estimated separately for each industry.

### 2.1 Two-Step Approach

Our modified LP production function estimation procedure makes use of intermediate inputs to control for the simultaneity bias between input choices and privately known productivity.[2] The theoretical framework underlying the estimation assumes that for each plant, the manager chooses inputs by maximizing expected profits from a Cobb-Douglas production function. Following Bahk and Gort (1993), we assume that the production function includes measures of

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and Chile that exporters experience significantly faster capital accumulation than non-exporters before starting to export. It is likely that these investments are aimed at serving export markets.

[2] Intermediate inputs are obtained as the sum of energy and raw materials consumption. The latter is measured as purchases of raw materials minus the net change in inventories. By adjusting for changes in inventories, this measure captures the amount of raw materials actually consumed during the year. Also, electricity purchased cannot be stored. So, both components of intermediate inputs are surely correlated with current productivity, a requirement for being used as an observable to correct for simultaneity.

both quantity and quality of inputs:

$$Y_{it} = L_{it}^{\beta_l} M_{it}^{\beta_m} K_{it}^{\beta_k} WP_{it}^{\beta_{wp}} \exp\left(\beta_{sk} sk_{it} + \beta_v v_{it} + \omega_{it} + \varepsilon_{it}\right), \qquad (1)$$

where $i$ represents plants, $t$ time periods, $Y$ output, $L$ labor input, $M$ intermediate inputs, $K$ capital, $WP$ wage premium, $sk$ skill intensity, $v$ capital vintage, $\omega$ a plant-specific productivity shock known to the plant manager, and $\varepsilon$ a zero-mean productivity shock realized after variable inputs are chosen. After taking logs and adding a $j$ superscript to represent industries, the production function equation is given by:

$$y_{it}^j = \beta_0 + \beta_l l_{it}^j + \beta_{wp} wp_{it}^j + \beta_{sk} sk_{it}^j + \beta_m m_{it}^j + \beta_k k_{it}^j + \beta_v v_{it}^j + \omega_{it}^j + \varepsilon_{it}^j \qquad (2)$$

In any year $t$, the manager observes its current productivity $\omega_{it}^j$ before choosing the quantity and quality of labor ($l_{it}^j$, $wp_{it}^j$, and $sk_{it}^j$) and intermediates $m_{it}^j$ to be combined with the quasi-fixed input capital $k_{it}^j$ and its quality $v_{it}^j$ for production of output $y_{it}^j$. Since $\omega_{it}^j$ is known to the plant manager but unknown to the econometrician, it generates simultaneity bias as it may be correlated with $l_{it}^j$, $wp_{it}^j$, $sk_{it}^j$ and $m_{it}^j$.

The plant's variable input demands, derived from profit maximization, depend on privately known productivity, capital, and capital vintage. One can invert the intermediate inputs demand function $m_{it}^j = m(\omega_{it}^j, k_{it}^j, v_{it}^j)$ to obtain a productivity function by imposing the following monotonicity assumption: conditional on capital and its vintage, the demand for intermediates increases with productivity.[3] Note that the productivity function $\omega_{it}^j = \omega(m_{it}^j, k_{it}^j, v_{it}^j)$ depends on

[3] LP note that a sufficient condition for this monotonicity assumption to hold is to assume perfect competition in input and output markets; however, they also argue that the assumption is valid for some types of imperfect competition in output markets.

observable variables only. Therefore, Eq. (2) can be rewritten in the partially linear form:

$$y^j_{it} = \beta_l l^j_{it} + \beta_{wp} wp^j_{it} + \beta_{sk} sk^j_{it} + \phi(m^j_{it}, k^j_{it}, v^j_{it}) + \varepsilon^j_{it} \quad (3)$$

where $\phi(m^j_{it}, k^j_{it}, v^j_{it}) = \beta_o + \beta_m m^j_{it} + \beta_k k^j_{it} + \beta_v v^j_{it} + \omega(m^j_{it}, k^j_{it}, v^j_{it})$.[4] Since $E[\varepsilon^j_{it} / m^j_{it}, k^j_{it}, v^j_{it}] = 0$, taking the difference between Eq. (3) and its expectation conditional on intermediate inputs, capital, and vintage generates the following expression:

$$y^j_{it} - E[y^j_{it} / m^j_{it}, k^j_{it}, v^j_{it}] = \beta_l (l^j_{it} - E[l^j_{it} / m^j_{it}, k^j_{it}, v^j_{it}]) + \beta_{wp} (wp^j_{it} - E[wp^j_{it} / m^j_{it}, k^j_{it}, v^j_{it}]) +$$

$$\beta_{sk} (sk^j_{it} - E[sk^j_{it} / m^j_{it}, k^j_{it}, v^j_{it}]) + \varepsilon^j_{it} \quad (4)$$

Eq. (4) is estimated by OLS (with no constant) to obtain consistent parameter estimates for labor, wage premium and skill intensity. The conditional expectations in Eq. (4) are estimated by locally weighted least squares (LWLS) regressions of output, labor, wage premium and skill intensity on $(m^j_{it}, k^j_{it}, v^j_{it})$.[5] We obtain an estimate for the function $\phi(.)$ from a LWLS regression of $y^j_{it} - \hat{\beta}_l l^j_{it} - \hat{\beta}_{wp} wp^j_{it} - \hat{\beta}_{sk} sk^j_{it}$ on $(m^j_{it}, k^j_{it}, v^j_{it})$.

To estimate $(\beta_m, \beta_k, \beta_v)$ consistently, we assume that productivity follows a first order Markov process as in Olley and Pakes (1996): $\omega^j_{it} = E[\omega^j_{it} / \omega^j_{it-1}] + \xi^j_{it}$ where $\xi^j_{it}$ is the unexpected productivity shock and is independent and identically distributed (i.i.d.). Our estimation strategy is based on the identification assumption that capital and capital vintage may be related to expected

[4] LP allow the functions $m(.)$, $\omega(.)$ and $\phi(.)$ to differ across time periods. In this paper, we restrict those functions to be constant across time periods.

[5] For example in the case of labor, we estimate a weighted linear regression of $l^j_{it}$ on a second order polynomial on $(m^j_{it}, k^j_{it}, v^j_{it})$ using data in the neighborhood of a given data point $(m^j_{it}, k^j_{it}, v^j_{it})$. The intercept from this regression is an estimate for the expected value of $l^j_{it}$ conditional on $(m^j_{it}, k^j_{it}, v^j_{it})$. See Fernandes (2003) for further details on LWLS estimation.

productivity but are uncorrelated with the unexpected productivity shock. The following three moment conditions are obtained by taking the expectation of Eq. (2) conditional on, respectively, lagged intermediates, capital and capital vintage, and replacing $\omega_{it}^{j}$ by its Markov process:

$$E[y_{it}^{j} - \hat{\beta}_{l} l_{it}^{j} - \hat{\beta}_{wp} wp_{it}^{j} - \hat{\beta}_{sk} sk_{it}^{j} - \beta_{m} m_{it}^{j} - \beta_{k} k_{it}^{j} - \beta_{v} v_{it}^{j} - E[\omega_{it}^{j} / \omega_{it-1}^{j}] / m_{it-1}^{j}]$$

$$= E[\varepsilon_{it}^{j} + \xi_{it}^{j} / m_{it-1}^{j}] = 0 \qquad (5)$$

$$E[y_{it}^{j} - \hat{\beta}_{l} l_{it}^{j} - \hat{\beta}_{wp} wp_{it}^{j} - \hat{\beta}_{sk} sk_{it}^{j} - \beta_{m} m_{it}^{j} - \beta_{k} k_{it}^{j} - \beta_{v} v_{it}^{j} - E[\omega_{it}^{j} / \omega_{it-1}^{j}] / k_{it}^{j}]$$

$$= E[\varepsilon_{it}^{j} + \xi_{it}^{j} / k_{it}^{j}] = 0 \qquad (6)$$

$$E[y_{it}^{j} - \hat{\beta}_{l} l_{it}^{j} - \hat{\beta}_{wp} wp_{it}^{j} - \hat{\beta}_{sk} sk_{it}^{j} - \beta_{m} m_{it}^{j} - \beta_{k} k_{it}^{j} - \beta_{v} v_{it}^{j} - E[\omega_{it}^{j} / \omega_{it-1}^{j}] / v_{it}^{j}]$$

$$= E[\varepsilon_{it}^{j} + \xi_{it}^{j} / v_{it}^{j}] = 0 \qquad (7)$$

Eqs. (5), (6) and (7) indicate, respectively, that intermediates in year *t-1*, capital and capital vintage in year *t* are uncorrelated with the unexpected productivity shock in year *t*. The residuals $\varepsilon_{it}^{j} + \xi_{it}^{j}$ are calculated using the estimated coefficients $(\hat{\beta}_{l}, \hat{\beta}_{wp}, \hat{\beta}_{sk})$, some candidate parameter values $(\beta_{m}^{*}, \beta_{k}^{*}, \beta_{v}^{*})$ and a nonparametric estimate for $E[\omega_{it}^{j} / \omega_{it-1}^{j}]$ (also dependent on the candidate parameter values) obtained as a LWLS regression of $(\omega_{it}^{j} + \varepsilon_{it}^{j})^{*} = y_{it}^{j} - \hat{\beta}_{l} l_{it}^{j} - \hat{\beta}_{wp} wp_{it}^{j} - \hat{\beta}_{sk} sk_{it}^{j} - \beta_{m}^{*} m_{it}^{j} - \beta_{k}^{*} k_{it}^{j} - \beta_{v}^{*} v_{it}^{j}$ on

$(\omega_{it-1}^{j})^{*} = \hat{\phi}(m_{it-1}^{j}, k_{it-1}^{j}, v_{it-1}^{j}) - \beta_{m}^{*} m_{it-1}^{j} - \beta_{k}^{*} k_{it-1}^{j} - \beta_{v}^{*} v_{it-1}^{j}$.

We construct a generalized method of moments (GMM) criterion function which weights the plant-year moment conditions by their variance-covariance matrix. Our estimation algorithm starts from candidate values (OLS estimates) for the coefficients on intermediates, capital and capital vintage and iterates on the sample moment conditions to match them to their theoretical value of zero and reach final parameter estimates.[6] The standard errors for the parameter estimates are obtained by bootstrap techniques.[7]

Our estimates of plant-level TFP are obtained as residuals from Eq. (2) $p_{it}^{j} = y_{it}^{j} - \hat{\beta}_{l} l_{it}^{j} - \hat{\beta}_{wp} wp_{it}^{j} - \hat{\beta}_{sk} sk_{it}^{j} - \hat{\beta}_{m} m_{it}^{j} - \hat{\beta}_{k} k_{it}^{j} - \hat{\beta}_{v} v_{it}^{j}$ where $(\hat{\beta}_{l}, \hat{\beta}_{wp}, \hat{\beta}_{sk}, \hat{\beta}_{m}, \hat{\beta}_{k}, \hat{\beta}_{v})$ are the consistent production function parameters. To make TFP comparable across years and industries, we construct relative TFP measures following Aw et al. (2001) and Fernandes (2003). For each plant in a given industry, relative TFP in year *t* is the difference between the plant's TFP in year *t* and the TFP of an hypothetical average plant in the industry in 1981.[8] Let $p_{it}^{j}$ denote relative TFP for plant *i* in industry *j* and year *t*. We then estimate regressions of $p_{it}^{j}$ on production experience, export experience, industry and year controls as follows:

$$\mathrm{p}_{\mathrm{it}}^{\mathrm{j}} = \beta_{0} + \beta_{\mathrm{ye}} \mathrm{y\,exp}_{\mathrm{it}}^{\mathrm{j}} + \beta_{\mathrm{ee}} \mathrm{e\,exp}_{\mathrm{it}}^{\mathrm{j}} + \mathrm{I}^{\mathrm{t}} + \mathrm{I}^{\mathrm{j}} + \mathrm{u}_{\mathrm{it}}^{\mathrm{j}} \qquad (8)$$

## 2.2 One-Step Approach

As in the "two-step approach", we use intermediates to correct for the endogeneity of input choices with respect to productivity. We assume that the plant manager observes its current

[6] We use a derivative optimization routine and complement it with a grid search. When the parameters that minimize the criterion function result from grid search, these parameters are used as initial values for the derivative optimization routine to reach more precise final $(\beta_{m}, \beta_{k}, \beta_{v})$ values.

[7] The bootstrap procedure consists of sampling randomly with replacement plants from the industry's original sample, matching or exceeding in any year the number of plant-year observations in that sample. If randomly selected, a plant is taken as a block (i.e. all of its observations are included in the bootstrap sample). We obtain estimates of $(\beta_{l}, \beta_{wp}, \beta_{sk}, \beta_{m}, \beta_{k}, \beta_{v})$ for 100 bootstrap samples. The standard deviation of a parameter across bootstrap samples constitutes its bootstrapped standard error.

[8] The latter is obtained combining average output and inputs in the industry in 1981 and the corresponding

productivity $\omega_{it}^{j}$ before making profit-maximizing choices of labor, labor quality and intermediates to be combined with the quasi-fixed input capital and its quality and produce output. To investigate learning-by-doing and learning-by-exporting in each industry, we allow two additional variables to affect the plant's output and productivity: production experience until year *t*-1 and export experience until year *t*-1. These variables are assumed to be taken by plants as state variables like capital. The estimating equation for plant *i* in industry *j* in year *t* is as follows:[9]

$$y_{it}^{j} = \beta_0 + \beta_l l_{it}^{j} + \beta_{wp} wp_{it}^{j} + \beta_{sk} sk_{it}^{j} + \beta_m m_{it}^{j} + \beta_k k_{it}^{j} + \beta_v v_{it}^{j} + \beta_{ye} y\exp_{it}^{j} + \beta_{ee} e\exp_{it}^{j} + \omega_{it}^{j} + \varepsilon_{it}^{j} \qquad (9)$$

where $\omega_{it}^{j}$ may be correlated with $l_{it}^{j}$, $wp_{it}^{j}$, $sk_{it}^{j}$ and $m_{it}^{j}$, and $\varepsilon_{it}^{j}$ represents unobserved mean-zero shocks to productivity realized after variable inputs are chosen.

The profit maximizing variable input demands of plants depend on privately known productivity, capital, capital vintage, production experience and export experience. We invert the intermediate inputs demand function $m_{it}^{j} = m(\omega_{it}^{j}, k_{it}^{j}, v_{it}^{j}, v_{it}^{j}, y\exp_{it}^{j}, e\exp_{it}^{j})$ to obtain a productivity function imposing the monotonicity assumption that conditional on capital, capital vintage, production experience and export experience, the demand for intermediates increases with productivity.[10] The productivity function $\omega_{it}^{j} = \omega(m_{it}^{j}, k_{it}^{j}, v_{it}^{j}, y\exp_{it}^{j}, e\exp_{it}^{j})$ depends solely on observables. Eq. (9) can be rewritten in a semi-parametric form:

$$y_{it}^{j} = \beta_l l_{it}^{j} + \beta_{wp} wp_{it}^{j} + \beta_{sk} sk_{it}^{j} + \phi(m_{it}^{j}, k_{it}^{j}, v_{it}^{j}, y\exp_{it}^{j}, e\exp_{it}^{j}) + \varepsilon_{it}^{j} \qquad (10)$$

where

production function coefficients.

[9] Production experience and export experience enter Eq. (9) as ln(1+production experience) and ln(1+export experience).

[10] The same sufficient conditions as in the two-step approach apply.

$$\phi(m_{it}^j, k_{it}^j, v_{it}^j, yexp_{it}^j, eexp_{it}^j) = \beta_o + \beta_m m_{it}^j + \beta_k k_{it}^j + \beta_v v_{it}^j + \beta_{ye} yexp_{it}^j + \beta_{ee} eexp_{it}^j + \omega(m_{it}^j, k_{it}^j, v_{it}^j, yexp_{it}^j, eexp_{it}^j).$$

We use a polynomial approximation to the unknown function $\phi(.)$ instead of a LWLS approximation as we did in the two-step approach.[11] Specifically, we estimate Eq. (10) by OLS including a polynomial of third degree on $(m_{it}^j, k_{it}^j, v_{it}^j, yexp_{it}^j, eexp_{it}^j)$ to approximate the function $\phi(.)$ and obtain consistent parameter estimates for labor, wage premium and skill intensity, and an estimate of $\phi(.)$.

To estimate $(\beta_m, \beta_k, \beta_v, \beta_{ye}, \beta_{ee})$ consistently, we assume that productivity follows a first order Markov process $\omega_{it}^j = E[\omega_{it}^j / \omega_{it-1}^j] + \xi_{it}^j$ where $\xi_{it}^j$ is an i.i.d. productivity shock. The identification assumptions needed for our estimation strategy are that capital, capital vintage, production experience, and export experience may be correlated with expected productivity but are uncorrelated with the unexpected productivity shock.[12] The following five moment conditions are obtained by taking the conditional expectation of Eq. (9) on, respectively, lagged intermediates, capital, capital vintage, production experience and export experience, replacing $\omega_{it}^j$ by its Markov process:

$$E[y_{it}^j - \hat{\beta}_l l_{it}^j - \hat{\beta}_{wp} wp_{it}^j - \hat{\beta}_{sk} sk_{it}^j - \beta_m m_{it}^j - \beta_k k_{it}^j - \beta_v v_{it}^j - \beta_{ye} yexp_{it}^j - \beta_{ee} eexp_{it}^j - E[\omega_{it}^j / \omega_{it-1}^j] / m_{it-1}^j] = E[\varepsilon_{it}^j + \xi_{it}^j / m_{it-1}^j] = 0 \quad (11)$$

[11] This choice is made for computational purposes only. The two types of approximation give very similar results.

[12] This assumption is consistent with Kraay (1999) identification strategy described in Section 1. Plant managers may choose to self-select into the export market based on their contemporaneous productivity shock. This implies that if productivity is autocorrelated, period t's exports may be correlated with expected productivity in period t+1.

$$\begin{aligned}&E[y_{it}^{j} - \widehat{\beta}_{l} l_{it}^{j} - \widehat{\beta}_{wp} wp_{it}^{j} - \widehat{\beta}_{sk} sk_{it}^{j} - \beta_{m} m_{it}^{j} - \beta_{k} k_{it}^{j} - \beta_{v} v_{it}^{j} - \beta_{ye} y\exp_{it}^{j} - \beta_{ee} e\exp_{it}^{j} - \\ &E[\omega_{it}^{j} / \omega_{it-1}^{j}] / k_{it}^{j}] = E[\varepsilon_{it}^{j} + \xi_{it}^{j} / k_{it}^{j}] = 0\end{aligned} \tag{12}$$

$$\begin{aligned}&E[y_{it}^{j} - \widehat{\beta}_{l} l_{it}^{j} - \widehat{\beta}_{wp} wp_{it}^{j} - \widehat{\beta}_{sk} sk_{it}^{j} - \beta_{m} m_{it}^{j} - \beta_{k} k_{it}^{j} - \beta_{v} v_{it}^{j} - \beta_{ye} y\exp_{it}^{j} - \beta_{ee} e\exp_{it}^{j} - \\ &E[\omega_{it}^{j} / \omega_{it-1}^{j}] / v_{it}^{j}] = E[\varepsilon_{it}^{j} + \xi_{it}^{j} / v_{it}^{j}] = 0\end{aligned} \tag{13}$$

$$\begin{aligned}&E[y_{it}^{j} - \widehat{\beta}_{l} l_{it}^{j} - \widehat{\beta}_{wp} wp_{it}^{j} - \widehat{\beta}_{sk} sk_{it}^{j} - \beta_{m} m_{it}^{j} - \beta_{k} k_{it}^{j} - \beta_{v} v_{it}^{j} - \beta_{ye} y\exp_{it}^{j} - \beta_{ee} e\exp_{it}^{j} - \\ &E[\omega_{it}^{j} / \omega_{it-1}^{j}] / y\exp_{it}^{j}] = E[\varepsilon_{it}^{j} + \xi_{it}^{j} / y\exp_{it}^{j}] = 0\end{aligned} \tag{14}$$

$$\begin{aligned}&E[y_{it}^{j} - \widehat{\beta}_{l} l_{it}^{j} - \widehat{\beta}_{wp} wp_{it}^{j} - \widehat{\beta}_{sk} sk_{it}^{j} - \beta_{m} m_{it}^{j} - \beta_{k} k_{it}^{j} - \beta_{v} v_{it}^{j} - \beta_{ye} y\exp_{it}^{j} - \beta_{ee} e\exp_{it}^{j} - \\ &E[\omega_{it}^{j} / \omega_{it-1}^{j}] / e\exp_{it}^{j}] = E[\varepsilon_{it}^{j} + \xi_{it}^{j} / e\exp_{it}^{j}] = 0\end{aligned} \tag{15}$$

Eqs. (11), (12), (13), (14), (15) indicate, respectively, that intermediates in year *t-1*, capital, capital vintage, production experience and export experience in year *t* are uncorrelated with the unexpected productivity shock in year *t*.

The residuals $\varepsilon_{it}^{j} + \xi_{it}^{j}$ are calculated using the estimated coefficients $(\widehat{\beta}_{l}, \widehat{\beta}_{wp}, \widehat{\beta}_{sk})$, candidate parameter values $(\beta_{m}^{*}, \beta_{k}^{*}, \beta_{v}^{*}, \beta_{ye}^{*}, \beta_{ee}^{*})$ and a nonparametric estimate for $E[\omega_{it}^{j} / \omega_{it-1}^{j}]$ (also dependent on the candidate values) obtained as a LWLS regression of $(\omega_{it}^{j} + \varepsilon_{it}^{j})^{*} = y_{it}^{j} - \widehat{\beta}_{l} l_{it}^{j} - \widehat{\beta}_{wp} wp_{it}^{j} - \widehat{\beta}_{sk} sk_{it}^{j} - \beta_{m}^{*} m_{it}^{j} - \beta_{k}^{*} k_{it}^{j} - \beta_{v}^{*} v_{it}^{j} - \beta_{ye}^{*} ye_{it}^{j} - \beta_{ee}^{*} ee_{it}^{j}$ on

$$\begin{aligned}&(\omega_{it-1}^{j})^{*} = \widehat{\phi}(m_{it-1}^{j}, k_{it-1}^{j}, v_{it-1}^{j}, y\exp_{it-1}^{j}, e\exp_{it-1}^{j}) - \beta_{m} m_{it-1}^{j} - \beta k k_{it-1}^{j} - \beta_{v} v_{it-1}^{j} - \beta_{ye} y\exp_{it-1}^{j} \\ &- \beta_{ee} e\exp_{it-1}^{j}.\end{aligned}$$

The GMM criterion function to be minimized weights the plant-year moment conditions by their variance-covariance matrix. As in the "two-step approach", the estimation algorithm starts from OLS candidate values for the intermediates, capital, capital vintage, production experience and export experience parameters.[13] Standard errors for the parameter estimates are obtained by bootstrap techniques as in the two-step approach.

## 3. Data

The dataset used in this study is constructed from the 1981-1991 annual surveys of manufacturing plants conducted by Colombia's Departamento Administrativo Nacional de Estadística (DANE). These surveys cover all manufacturing plants with ten or more employees. The variables included in the surveys are in current pesos, except for the number of employees and consumption of electric energy. Therefore, we use a series of price indexes to express all the nominal variables in constant pesos of 1986. We obtain implicit price indexes for different types of physical capital formation and producer price indexes (PPI) at 3-digit ISIC (revision 2) from DANE, and construct our own indexes for domestic and imported raw materials and for exports. Details on the construction of price indexes and other data issues are provided in the Appendix.

The main variables employed in our analysis are output, labor, intermediate inputs, capital, skilled ratio, wage premium, capital vintage, production experience, and export experience. Output is obtained as the sum of (a) the value of production of the plant minus the value of exports deflated by PPI and (b) the value of exports deflated by the exports price index. Labor is the total number of workers in the plant. Intermediate inputs is the sum of raw materials and energy consumption in constant pesos. Raw materials in constant pesos is the sum of the values of domestic and imported raw materials consumed during the year deflated by the price indexes of, respectively, domestic and imported raw materials. Energy in constant pesos is the sum of electric energy consumed during the year valued at 1986 prices plus consumption of fuels and lubricants deflated by the PPI of the petroleum refineries sector. Capital is obtained from information on purchases, sales, and book values of four types of fixed assets: buildings and structures, machinery and equipment, transportation equipment, and office equipment. Each type of asset is deflated by its corresponding price index[14] before applying a permanent inventory method to obtain a measure of the capital stock that accounts for the effects of depreciation and maintenance expenditures.

The skilled ratio and the wage premium account for differences in the quality of labor across plants. The skilled ratio is the number of skilled workers (managers, white collar workers, and technicians) divided by the total number of workers. Bahk and Gort (1993) suggest using the average wage of a plant as a measure of labor quality, relying on the assumption that plants face a common labor market and variations in wages "mainly measure differences in skills rather than differences in the prices of identical classes of labor" (p. 565). Given the lower degree of labor mobility in Colombia compared to the U.S., which was the focus of Bahk and Gort's study, we assume that the relevant labor market in Colombia is the regional rather than the national one. Therefore, we measure labor quality as the plant's wage premium, defined as the average wage paid by a plant in a given year divided by the average wage paid that year in the region where the plant is located. In this study we consider thirteen regions: eight major metropolitan areas (Bogotá, Medellín, Cali, etc.), four regions in the interior, and the rest of the country.

Because of continuous technological improvements in the international capital goods industry, it is likely to be expected that newer plants and plants that invest more frequently will

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[13] The derivative optimization routine is complemented by a grid search as in the "two-step approach".
[14] Since there is no separate price deflator for office equipment during our sample period, we deflate this

embody these technological improvements in their capital stock.[15] For that purpose we include in our production function specification a measure of capital vintage. Production experience at time *t* is measured either as cumulated output scaled by labor input up to *t* -1 or as the number of years the plant has been in operation (age). The main variable of interest, export experience at time *t*, is similarly measured either as cumulated exports scaled by labor input up to t – 1 or as the number of years in which the plant has exported up to *t* -1.

In order to measure the experience variables correctly it is necessary to limit the sample to newborn plants. Therefore, we select as our main sample the set of plants that were born in or after 1981, the first year when information on exports was included in the annual manufacturing surveys. A limitation of this procedure is that some of the "new" plants in 1981 could have actually been born before 1981, but were smaller than the cutoff level of ten employees required to complete the survey. Similarly, if a new owner acquires a previously operating plant and registers it under a different name, it might be coded in the survey as a new plant. Since we do not have information to sort out these possible sources of error, we will consider plants that appear for the first time in the survey as new plants.

Besides limiting our sample to plants born in or after 1981, we require them to have a minimum of three years of data and have positive values for the key variables output, labor, intermediate inputs, capital, and wage premium. We exclude plants that do not report data in some year between their first and their last year in the survey and plants belonging to industries with less

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asset using the machinery and equipment price index.

[15] The effect of embedded technological change on productivity is quantitatively significant. Jensen et al. (2001) find that the 1992 cohort of new entrants into the U.S. manufacturing industry were, on average, more than 50% more productive than the 1967 entrants in their year of entry, even after accounting for industry-wide factors and factor differences.

than 100 plant-year observations.[16] Applying these criteria we obtain a sample of 3,296 plants and 19,859 plant-year observations. Finally, because some of our estimation procedures are sensitive to outliers, we reduce further our sample to 3,075 plants and 18,475 plant-year observations. The criterion for the elimination of outliers is described in the Appendix.

Compared to all the Colombian manufacturing plants in the 1981-1991 annual manufacturing surveys, our sample of young plants represents 26.6% of the plants, 11.2% of the employment, 6.7% of the value of production, and 3.5% of the value of exports. Our young plants are small, employing on average 30 workers compared to 52 for the average manufacturing plant during that period. Interestingly, although their labor productivity is about 36.4% less than average, their average wages are only 7.5% less than average. This difference might be explained by their relatively high capital to labor ratios, which are only 12.5% less than average, and by the more recent vintage of their capital stock.

## 4. Results

The results from production function estimation by the modified LP procedure in our "two-step approach" are shown in Appendix Table A1. The coefficients are in line with those obtained in previous studies. For most industries the LP capital coefficient is larger in magnitude than the OLS coefficient, which is expected given the simultaneity bias. The opposite is true for labor coefficients in several industries showing the correction of the bias. Bootstrapped standard errors

[16] The excluded industries are tobacco (ISIC 314), petroleum refineries (ISIC 353), miscellaneous products of petroleum and coal (ISIC 354), glass and glass products (ISIC 362), and non-ferrous metal basic industries (ISIC 372).

for the LP procedure tend to be much higher than OLS standard errors (especially in smaller industries), thus some of the coefficients are imprecisely estimated. Our measures of labor quality are in all industries positive and generally significant. Our measure of capital quality is positive in 15 out of 24 industries and not significant.

TFP measures obtained as residuals from the production function using the LP coefficients are used as the dependent variable in Eq. (8) and the estimation results are shown in Table 1. In all specifications we report robust standard errors (White correction for heteroskedasticity) and include year effects to account for the influence of macroeconomic shocks on plants' TFP.

Table 1 provides strong evidence of learning-by-exporting effects on productivity. In columns (1) and (2), we show results from OLS estimation. The effect of export experience on plant TFP is positive and significant. The effect is larger and more significant after controlling for industry-wide differences in TFP in column (2), and it increases further when plant heterogeneity is controlled for with plant fixed effects in column (3).

Production experience, however, has a negative and significant effect on TFP even controlling for plant fixed effects. This finding differs from those in Bahk and Gort (1993) and we investigate it further considering alternative specifications. We add to Eq. (8) the square of the production experience variable to allow for non-linearities in learning-by-doing effects. The corresponding results from OLS regressions suggest that plant TFP decreases with production experience but at a decreasing rate. So it appears as if production experience needs to reach a certain threshold in order to start having a positive effect on TFP. However, plant fixed effects regressions results suggest a different effect: i.e., TFP increases with production experience at a decreasing rate. One could argue that production experience is proxying for plant size, and if smaller plants are more productive, this would lead to negative effects of production experience on TFP. To address this concern we add a measure of plant size (in its initial year or as an average across the sample period) to Eq. (8). The results show a negative effect of production experience on TFP and show that within industries, smaller plants are actually less productive. It is important to note that in these various specifications, the positive and significant effect of export experience on TFP is maintained.[17] We consider in columns (4)-(6) of Table 1 plant age and its square as alternative measures of production experience. The results are qualitatively similar for OLS and fixed effects and indicate that plant TFP decreases with plant age at a decreasing rate and that there are learning-by-exporting effects on TFP.

Columns (7)-(12) of Table 1 show the results from estimating Eq. (8) with export experience measured by the number of years in which the plant has exported until t-1. Positive and significant learning-by-exporting effects on plant TFP are obtained.

A potential concern with our results in Table 1 is that they are driven by the noise in the TFP measures. In the LP procedure TFP is obtained as a residual from the production function (Eq. (2)) thus it is equal to the sum of a no-noise productivity measure $\omega_{it}$ and a residual $\varepsilon_{it}$. However, when Eq. (8) is estimated using as a dependent variable an estimate for the no-noise productivity measure, very similar results to those in Table 1 are obtained for all specifications.

Another concern with the results in Table 1 is that the comparison group of non-exporters in our sample is qualitatively different from the group of exporters, in a way that plant fixed plant effects alone cannot capture. In an experimental setting control and treatment groups are drawn randomly from the same pool of subjects, ensuring that the observable results of the treatment cannot be attributed to the composition of the groups. In a non-experimental setting, it is possible to address this concern by constructing a control group that is as similar as possible as the treatment group. In this context, the approach that we follow is to construct a comparison group of non-exporters that could have exported if they had wished, but decided to sell exclusively to the domestic market. That way, if we find a positive effect of export experience on TFP, we can be confident that such effect truly reflects exposure to export markets and not fundamental differences between exporters and non-exporters.

To control for these potential sample composition effects, we use matching techniques recently applied by Girma et al. (2004) when analyzing the effect of exports on U.K. plants' TFP. We identify for each exporting plant a matched non-exporter plant similar to the exporting plant in terms of observable characteristics (except for the export status). This is done by propensity score matching based on a probit regression of an indicator variable for exporting plants on plant characteristics.[18] The estimated probability of exporting constitutes each plant's propensity score. A nearest-neighbor matching method is used to identify the control non-exporter plant matching each exporter plant.[19] We construct a new sample constituted by exporting plants and their matched non-exporting plants and reestimate Eq. (8). The results are shown in Table 2 and indicate that export experience has a positive and significant effect on plant TFP.[20] Hence, we show that

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[17] The results from these alternative specifications are available from the authors upon request.

[18] The plant characteristics included are lagged TFP, lagged real wages, a lagged size dummy, lagged royalty payments, a corporation dummy, an advertisement dummy, and industry, region and year dummies.

[19] See Girma et al (2004) for further details.

[20] In fact, we applied these matching techniques for three different indicator variables for exporting plant i in year t : (i) = 1 for plant i in year t if plant i exports some output in year t; (ii) =1 for plant i in year t if plant i has positive export experience (cumulative ratio of exports to labor) in year t regardless of whether the plant

learning-by-exporting effects in our sample of young plants are robust to the composition of the comparison group of non-exporting plants.

Yet another source of concern with our estimates is that in our modified LP methodology for production function estimation, we allow productivity to follow a Markov process. If this is indeed the case in the data, our estimated measures of TFP are serially correlated, which could lead to an endogeneity bias in the estimated effects of cumulative output and cumulative exports on TFP.[21] We consider a specification that adds lagged TFP to Eq. (8) to control for serial correlation in TFP but focuses on the output experience and export experience measures for which the aforementioned endogeneity bias is not present – age and age squared and the cumulated export dummy:[22]

$$p_{it} = \beta_0 + \beta_1 p_{it-1} + \beta_{ye1} age_{it} + \beta_{ye2} agesq_{it} + \beta_{ee} cum\exp_{it} + I^t + \varepsilon_{it} \qquad (16)$$

In Table 3, columns (1) and (2) we show the results from estimating Eq. (16) by OLS and plant fixed effects. Export experience has positive and significant effects on plant TFP, smaller than those in Table 1 where lagged TFP is not controlled for. The fixed effects coefficient on export experience is larger than that obtained by OLS. The age variables have insignificant effects in the OLS regression and suggest that plant TFP decreases with age but at a decreasing rate in the fixed effects regressions. The coefficient on lagged TFP is positive and significant and is upward biased

actually exports in that year; (iii) = 1 for all years t of plant i if in at least in one year plant i has positive export experience. In Table 2, we show the results from matching using the export indicator (ii). The results using the other indicator variables for exporting plants lead to different matched exporter-nonexporter samples but were qualitatively very similar and are available upon request.

[21] The reasoning is as follows. On the one hand, output in period t-1, which is part of the cumulative output experience measure, is affected by the productivity shock in period t-1, which is correlated with the productivity shock in period t. On the other hand, we allow exports to be contemporaneously correlated with the productivity shock; hence, exports in period t-1, which are part of the export experience measure, are correlated with the productivity shock in period t if the latter is serially correlated.

under OLS estimation relative to plant fixed effects estimation as expected by theory.

Taking first differences of Eq. (16), plant fixed effects are eliminated and the following expression is obtained (ignoring year effects for simplicity):

$$\Delta \mathrm{p}_{\mathrm{it}} = \beta_0 + \beta_1 \Delta \mathrm{p}_{\mathrm{it-1}} + \beta_{\mathrm{ye1}} \Delta \mathrm{age}_{\mathrm{it}} + \beta_{\mathrm{ye2}} \Delta \mathrm{agesq}_{\mathrm{it}} + \beta_{\mathrm{ee}} \Delta \mathrm{cum\,exp}_{\mathrm{it}} + \Delta \varepsilon_{\mathrm{it}} \qquad (17)$$

Under certain identifying assumptions on the residuals and on the explanatory variables, Eq. (17) can be consistently estimated by the GMM techniques proposed by Arellano and Bond (1991).[23] More specifically, assuming that (i) the residuals are serially uncorrelated and (ii) production experience and export experience are pre-determined, values of TFP, age, age squared and the cumulated export dummy lagged two periods or more can be used as instruments for the first differences regression.[24] The validity of the instruments can be assessed from the Sargan test and tests for serial correlation of the residuals.

The results from GMM estimation are shown in column (3) of Table 3. The effect of export experience is positive and significant and larger than that obtained by OLS or plant fixed effects. The overall validity of the identifying assumptions cannot be rejected by the Sargan test. The serial correlation tests suggest that the residuals from the first differences regression exhibit first order serial correlation (which is expected if they satisfy the assumption of being serially uncorrelated in levels) and but do not exhibit second order serial correlation (at a 6% confidence level).

Blundell and Bond (1998) show that when the dependent and explanatory variables are highly persistent – which is likely in our case – the GMM estimator of the first differences

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[22] Industry superscript j is ignored in the equations that follow.
[23] See Arellano and Bond (1991) and Blundell and Bond (1998).
[24] For example for the cumulated export dummy, the assumption that it is pre-determined implies $\mathrm{E}[\mathrm{cum\,exp}_{\mathrm{it}}\, \varepsilon_{\mathrm{is}}] = 0$ for all s>t that is export experience does not depend on future TFP.

regression can be biased and imprecise since lagged values of the dependent and explanatory variables are only weakly correlated with subsequent first differences. So, we also estimate Eq. (17) using their more efficient GMM system estimator that exploits additional moment conditions using the information from the regression in levels (Eq. (16)). Assuming that the endogenous and explanatory variables in differences are not correlated with the plant fixed effect, the lagged first differences of the dependent variable and explanatory variables can be used as instruments for the regression in levels.[25] The system GMM estimator simultaneously estimates the first difference regression and the levels regression and the results are shown in Table 3, columns (4) and (5). In column (4) we use TFP, age, age squared and the cumulated export dummy lagged between two and four periods as the instruments for the first differences regression and one period lags of the first difference of TFP, age, age squared and of the cumulated export dummy as instruments for the regression in levels. The results suggest that export experience has a positive and significant effect on plant TFP. This effect is smaller in magnitude than that estimated by plant fixed effects or the GMM difference estimator. In contrast, the effect of lagged TFP is larger under system GMM than under the difference GMM estimator. However, we reject in the validity of the instruments and we cannot reject that the residuals of the first differences regression exhibit second order serial correlation.

In column (5), we apply the Blundell and Bond system estimator using higher lags of the variables as instruments, given the evidence of serial correlation in the residuals. We use three period lags or higher of the levels of TFP, age, age squared and the cumulated export dummy as

[25] This assumption allows for correlation between the explanatory variables in levels and the plant fixed effect. This could be relevant in our case for the cumulative export dummy.

instruments for the first differences regression and two period lags of the first difference of TFP, age, age squared and of the cumulated export dummy as instruments for the regression in levels. The results show learning-by-exporting effects on plant TFP and we cannot reject the validity of the moment conditions.

The results from the "one-step approach" estimation are shown in Table 4. The export experience coefficient is positive in twenty out of twenty-four manufacturing sectors, and of the twenty positive coefficients thirteen are statistically significant. In the remaining four industries where the coefficient is negative, it is not significantly different from zero. By comparison, the production experience coefficient is negative in sixteen out of twenty-four industries, but it is significantly different from zero in only three industries (with a negative coefficient). These results are consistent with the results from the two-stage approach.

## 5. Conclusion

In this paper, we study the presence of learning-by-exporting effects in a sample of Colombian plants that started operations in or after 1981. We use a production function framework that accounts for the quantity and quality of production inputs and hypothesises that experience contributes to explaining the Solow residual. Extending previous work by Bahk and Gort (1993) we consider an export experience variable along with a production experience variable. Our estimation procedure accounts for the simultaneity biases that can arise when plant managers observe productivity shocks before choosing variable inputs. In a "two-step approach" we first use

Levinsohn and Petrin's (2003) method to obtain estimates of the production parameters excluding those of the experience variables, use these parameter estimates to obtain estimates of plant-level TFP, and regress these TFP estimates on measures of experience. In a "one-step approach", we estimate the parameters of the experience variables directly with the Levinsohn and Petrin (2003) methods.

The results show a robust positive effect of export experience on TFP, in different variants of the "two-step approach" and in the "one-step approach". Contrary to previous empirical work, the effect of production experience on TFP is found to be either negative or not statistically significant.

In future work we intend to explore whether this positive effect of export experience on productivity is an exclusive characteristic of new plants, or whether it extends to older plants. Unfortunately, we cannot use the same specification with old plants, because we are unable to measure export experience since the first year of operations for plants born before 1981. Our plan is to use a different specification where export experience is defined as cumulative exports in the previous three years. With that modified definition, will be able to replicate our estimation procedures for young and older plants (though for a shorter sample) in order to answer that question.

REFERENCES

Alvarez, R. and R López, 2004, 'Exporting and Firm Performance: Evidence from Chilean Plants,' Mimeo, Indiana University.

Arellano, M., and S. Bond, 1991. 'Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations,' *Review of Economic Studies* 58(2), 277-297.

Aw, B., X. Chen, and M. Roberts, 2001, 'Firm-Level Evidence on Productivity Differentials and Turnover in Taiwanese Manufacturing,' *Journal of Development Economics* 66(1), 51-86.

Bahk, B. and M. Gort, 1993, 'Decomposing Learning by Doing in New Plants,' *Journal of Political Economy* 101(4), 561-583.

Bernard, A. and J. Jensen, 1999, 'Exceptional Export Performance: Cause, Effect, or Both?,' *Journal of International Economics* 47(1), 1-25.

Blundell, S., and S. Bond, 1991. 'Initial Conditions and Moment Restrictions in Dynamic Panel Data Models,' *Journal of Econometrics* 87(1), 29-52.

Clerides, S., S. Lach, and J. Tybout, 1998, 'Is Learning-by-Exporting Important? Micro-dynamic Evidence from Colombia, Mexico, and Morocco,' *Quarterly Journal of Economics* 113(3), 903-47.

Fernandes, A., 2003, 'Trade Policy, Trade Volumes and Plant-Level Productivity in Colombian Manufacturing Industries,' World Bank Working Paper No. 3064.

Girma, S., D. Greenaway, and R. Kneller, 2004, 'Entry to Export Markets and Productivity: A Microeconometric Analysis of Matched Firms,' forthcoming *Review of International Economics*.

Isgut, A., 2001, 'What's Different about Exporters: Evidence from Colombian Manufacturing,' *Journal of Development Studies* 37(5), 57-82.

Jensen, J., R. McGuckin, and K. Stiroh, 2001, 'The Impact of Vintage and Survival on Productivity: Evidence from Cohorts of U.S. Manufacturing Plants,' *Review of Economics and Statistics* 83(2), 323-332.

Kraay, A., 1999, 'Exportations et Performances Economiques: Etude d'un Panel d'Entreprises

Chinoises,’ *Revue d’Economie du Developpement* 0(1-2), 183-207.

Levinsohn, J. and A. Petrin, 2003, ‘Estimating Production Functions Using Inputs to Control for Unobservables,’ *Review of Economic Studies* 70(2), 317-341.

Olley, G. and A. Pakes, 1996, ‘The Dynamics of Productivity in the Telecommunications Equipment Industry,’ *Econometrica* 64(6), 1263-1297.

Pombo C., (1999), "Productividad Industrial en Colombia: Una aplicación de números índice", *Revista de Economía del Rosario* 2 (3), pp. 107-139.

Tybout, J., 2001, ‘Plant- and Firm-Level Evidence on “New” Trade Theories,’ NBER Working Paper No. 8418.

Westphal, L. (2001), ‘Technology Strategies for Economic Development in a Fast Changing Global Economy,’ Mimeo, Swarthmore College.

Table 1. The Effect of Learning-by-Doing and Learning-by-Exporting on Productivity

Panel A

| | OLS | OLS | Fixed Effects | OLS | OLS | Fixed Effects |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Export Experience | 0.008*** | 0.015*** | 0.021*** | 0.008*** | 0.0159* | 0.021*** |
| | (0.002) | (0.001) | (0.002) | (0.002) | (0.001) | (0.002) |
| Production Experience | -0.002** | -0.003*** | -0.003*** | | | |
| | (0.001) | (0.001) | (0.001) | | | |
| Age | | | | -0.012*** | -0.02*** | -0.026*** |
| | | | | (0.004) | (0.003) | (0.003) |
| Age Squared | | | | 0.001** | 0.001*** | 0.002*** |
| | | | | (0.0004) | (0.0003) | (0.0002) |
| Industry Effects (3-digit) | | Yes | | | Yes | |
| Year Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| N. Observations | 18475 | 18475 | 18475 | 18475 | 18475 | 18475 |
| R-squared | 0.01 | 0.47 | 0.8 | 0.01 | 0.47 | 0.8 |

Panel B

| | OLS | OLS | Fixed Effects | OLS | OLS | Fixed Effects |
|---|---|---|---|---|---|---|
| | (7) | (8) | (9) | (10) | (11) | (12) |
| Cumulated Export Dummy | 0.025*** | 0.03*** | 0.051*** | 0.0242*** | 0.0321*** | 0.0505*** |
| | (0.004) | (0.003) | (0.004) | (0.004) | (0.003) | (0.004) |
| Production Experience | -0.002*** | -0.003*** | -0.003*** | | | |
| | (0.001) | (0.001) | (0.001) | | | |
| Age | | | | -0.0123*** | -0.0192*** | -0.0246*** |
| | | | | (0.004) | (0.003) | (0.003) |
| Age Squared | | | | 0.0010** | 0.0011*** | 0.0013*** |
| | | | | (0.000) | (0.000) | (0.000) |
| Industry Effects (3-digit) | | Yes | | | Yes | |
| Year Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| N. Observations | 18475 | 18475 | 18475 | 18475 | 18475 | 18475 |
| R-squared | 0.01 | 0.47 | 0.8 | 0.01 | 0.47 | 0.8 |

Notes: Robust standard errors in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% confidence level, respectively. Export experience is cumulated exports scaled by labor input up to t -1 and production experience is cumulated output scaled by labor input up to t -1.

Table 2. The Effect of Learning-byDoing and Learning by Exporting on Productivity using a Control Group of Nonexporters Obtained by Propensity Score Matching

Panel A

| | OLS | OLS | Fixed Effects | OLS | OLS | Fixed Effects |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Export Experience | 0.006*** | 0.01*** | 0.02*** | 0.006*** | 0.01*** | 0.021*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Production Experience | -0.002 | -0.004*** | -0.003*** | | | |
| | (0.002) | (0.001) | (0.001) | | | |
| Age | | | | -0.013* | -0.024*** | -0.029*** |
| | | | | (0.007) | (0.005) | (0.005) |
| Age Squared | | | | 0.001* | 0.002*** | 0.002*** |
| | | | | (0.001) | (0.001) | (0.000) |
| Industry Effects (3-digit) | | Yes | | | Yes | |
| Year Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| N. Observations | 7218 | 7218 | 7218 | 7218 | 7218 | 7218 |
| R-squared | 0.01 | 0.49 | 0.79 | 0.01 | 0.5 | 0.79 |

Panel B

| | OLS | OLS | Fixed Effects | OLS | OLS | Fixed Effects |
|---|---|---|---|---|---|---|
| | (7) | (8) | (9) | (10) | (11) | (12) |
| Cumulated Export Dummy | 0.021*** | 0.022*** | 0.049*** | 0.021*** | 0.024*** | 0.05*** |
| | (0.004) | (0.003) | (0.004) | (0.004) | (0.003) | (0.004) |
| Production Experience | -0.002 | -0.003*** | -0.001 | | | |
| | (0.002) | (0.001) | (0.001) | | | |
| Age | | | | -0.013* | -0.023*** | -0.025*** |
| | | | | (0.007) | (0.005) | (0.005) |
| Age Squared | | | | 0.001* | 0.001** | 0.001*** |
| | | | | (0.001) | (0.001) | (0.000) |
| Industry Effects (3-digit) | | Yes | | | Yes | |
| Year Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| N. Observations | 7218 | 7218 | 7218 | 7218 | 7218 | 7218 |
| R-squared | 0.01 | 0.49 | 0.8 | 0.01 | 0.5 | 0.8 |

Notes: Robust standard errors in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% confidence level, respectively. Export experience is cumulated exports scaled by labor input up to t -1 and production experience is cumulated output scaled by labor input up to t -1. Probit regressions underlying the propensity score matching use an indicator variable for exporting plant i in year t =1 if plant i has positive export experience in year t .

Table 3. The Effect of Learning-by-Doing and Learning-by-Exporting on Productivity Controlling for Lagged Productivity

| | OLS | Fixed Effects | GMM diff | GMM system | GMM system |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Lagged productivity | 0.856*** | 0.211*** | 0.208*** | 0.501*** | 0.89*** |
| | (0.006) | (0.013) | (0.019) | (0.017) | (0.029) |
| Cumulated Export Dummy | 0.013*** | 0.042*** | 0.049*** | 0.019*** | 0.012*** |
| | (0.002) | (0.004) | (0.004) | (0.003) | (0.002) |
| Age | 0.001 | -0.02*** | -0.007 | -0.004 | 0.0028 |
| | (0.003) | (0.003) | (0.012) | (0.004) | (0.006) |
| Age Squared | 0.00001 | 0.001*** | 0.001*** | 0.0004 | -0.0001 |
| | (0.0003) | (0.0003) | (0.0002) | (0.0004) | (0.0004) |
| Year Effects | Yes | Yes | Yes | Yes | Yes |
| N. Observations | 15400 | 15400 | 12325 | 15400 | 15400 |
| Tests of GMM Consistency (P-values) | | | | | |
| Sargan Test (chi 2 ) | | | 0.8316 | 0 | 0.254 |
| Test of no 1st order serial correl. (m1) | | | 0 | 0 | 0 |
| Test of no 2nd order serial correl. (m2) | | | 0.0515 | 0 | 0 |

Notes: Standard errors in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% confidence levels, respectively. In column (3) all lags higher than or equal to two periods of the dependent and explanatory variables are used as instruments for the first differences regression. In column (4), between two and four period lags of the dependent and explanatory variables are used as instruments for the first differences regression and one period lags of the first difference of the dependent and explanatory variables are used as instruments for the regression in levels. In column (5) all lags higher than or equal to three periods of the dependent and explanatory variables are used as instruments for the first differences regression and two period lags of the first difference of the dependent and explanatory variables are used as instruments for the regression in levels.

Table 4: Production Function Coefficients "One-Step" Approach

| Industry (3-digit ISIC) | Input | OLS | Levinsohn Petrin |
|---|---|---|---|
| 311 Food Products | Labor | 0.157 *** | 0.175 *** |
| | | (0.008) | (0.016) |
| | Wage premium | 0.146 *** | 0.145 *** |
| | | (0.013) | (0.022) |
| | Skill intensity | 0.225 *** | 0.222 *** |
| | | (0.022) | (0.036) |
| N.obs | Intermediates | 0.789 *** | 0.793 *** |
| 1922 | | (0.006) | (0.043) |
| | Capital | 0.045 *** | -0.058 |
| | | (0.005) | (0.099) |
| | Vintage | 0.011 *** | 0.071 |
| | | (0.002) | (0.051) |
| | Production experience | 0.017 *** | -0.074 |
| | | (0.005) | (0.047) |
| | Export experience | 0.024 *** | 0.077 * |
| | | (0.002) | (0.042) |
| 312 Miscellaneous Food | Labor | 0.152 *** | 0.157 |
| | | (0.021) | (0.174) |
| | Wage premium | 0.197 *** | 0.130 |
| | | (0.028) | (0.424) |
| | Skill intensity | 0.181 *** | 0.037 |
| | | (0.055) | (0.570) |
| N.obs | Intermediates | 0.744 *** | 0.405 |
| 376 | | (0.013) | (0.247) |
| | Capital | 0.092 *** | 0.140 |
| | | (0.01) | (0.235) |
| | Vintage | 0.00588 | 0.125 |
| | | (0.004) | (0.134) |
| | Production experience | 0.004 | -0.037 |
| | | (0.013) | (0.223) |
| | Export experience | 0.036 *** | -0.245 |
| | | (0.005) | (0.664) |
| 313 Beverages | Labor | 0.202 *** | 0.178 |
| | | (0.067) | (0.187) |
| | Wage premium | 0.246 *** | 0.243 |
| | | (0.07) | (2.022) |
| | Skill intensity | 0.075 | 0.169 |
| | | (0.155) | (2.344) |
| N.obs | Intermediates | 0.649 *** | 0.635 |
| 129 | | (0.038) | (0.824) |
| | Capital | 0.137 *** | 0.171 |
| | | (0.031) | (0.617) |
| | Vintage | -0.027 ** | -0.066 |
| | | (0.013) | (0.226) |
| | Production experience | 0.074 ** | 0.023 |
| | | (0.031) | (0.765) |
| | Export experience | -0.014 | -0.031 |
| | | (0.016) | (0.261) |
| 321 Textiles | Labor | 0.214 *** | 0.222 *** |
| | | (0.015) | (0.022) |
| | Wage premium | 0.217 *** | 0.183 *** |
| | | (0.026) | (0.035) |
| | Skill intensity | 0.405 *** | 0.312 *** |
| | | (0.048) | (0.077) |
| N.obs | Intermediates | 0.663 *** | 0.606 *** |
| 984 | | (0.01) | (0.059) |
| | Capital | 0.096 *** | 0.072 * |
| | | (0.007) | (0.042) |
| | Vintage | 0.012 *** | 0.030 |
| | | (0.003) | (0.029) |
| | Production experience | 0.002 | 0.034 |
| | | (0.009) | (0.035) |
| | Export experience | 0.022 *** | 0.012 |
| | | (0.005) | (0.012) |
| 322 Apparel | Labor | 0.385 *** | 0.358 *** |
| | | (0.008) | (0.014) |
| | Wage premium | 0.168 *** | 0.157 *** |
| | | (0.016) | (0.024) |
| | Skill intensity | 0.370 *** | 0.337 *** |
| | | (0.03) | (0.046) |
| N.obs | Intermediates | 0.584 *** | 0.379 |
| 3041 | | (0.005) | (0.385) |
| | Capital | 0.035 *** | 0.115 |
| | | (0.005) | (0.164) |
| | Vintage | 0.021 *** | 0.021 |
| | | (0.002) | (0.053) |
| | Production experience | 0.025 *** | -0.099 |
| | | (0.005) | (0.084) |
| | Export experience | 0.025 *** | 0.062 * |
| | | (0.003) | (0.034) |
| 323 Leather Products | Labor | 0.217 *** | 0.261 *** |
| | | (0.025) | (0.049) |
| | Wage premium | 0.060 | 0.120 |
| | | (0.041) | (0.082) |
| | Skill intensity | 0.153 * | 0.193 |
| | | (0.091) | (0.142) |
| N.obs | Intermediates | 0.757 *** | 0.728 *** |
| 246 | | (0.019) | (0.097) |
| | Capital | 0.040 *** | 0.024 |
| | | (0.013) | (0.068) |
| | Vintage | 0.027 *** | 0.038 |
| | | (0.005) | (0.034) |
| | Production experience | 0.021 | 0.036 |
| | | (0.015) | (0.081) |
| | Export experience | 0.023 *** | 0.031 ** |
| | | (0.004) | (0.015) |
| 324 Footwear | Labor | 0.240 *** | 0.229 *** |
| | | (0.017) | (0.022) |
| | Wage premium | 0.180 *** | 0.196 *** |
| | | (0.024) | (0.041) |
| | Skill intensity | 0.308 *** | 0.270 ** |
| | | (0.06) | (0.125) |
| N.obs | Intermediates | 0.700 *** | 0.711 *** |
| 847 | | (0.012) | (0.068) |
| | Capital | 0.032 *** | 0.045 |
| | | (0.008) | (0.077) |
| | Vintage | 0.005 * | 0.034 |
| | | (0.003) | (0.052) |
| | Production experience | 0.016 * | 0.021 |
| | | (0.009) | (0.048) |
| | Export experience | 0.027 *** | 0.032 *** |
| | | (0.004) | (0.011) |
| 331 Wood Products | Labor | 0.299 *** | 0.250 ** |
| | | (0.025) | (0.110) |
| | Wage premium | 0.160 *** | 0.138 |
| | | (0.033) | (0.148) |
| | Skill intensity | 0.437 *** | 0.321 * |
| | | (0.074) | (0.173) |
| N.obs | Intermediates | 0.657 *** | 0.571 *** |
| 428 | | (0.015) | (0.163) |
| | Capital | 0.075 *** | 0.091 * |
| | | (0.01) | (0.052) |
| | Vintage | 0.011 *** | 0.021 |
| | | (0.004) | (0.015) |
| | Production experience | 0.017 | -0.012 |
| | | (0.013) | (0.114) |
| | Export experience | 0.008 | -0.011 |
| | | (0.01) | (0.035) |
| 332 Furniture | Labor | 0.355 *** | 0.368 *** |
| | | (0.021) | (0.040) |
| | Wage premium | 0.117 *** | 0.146 *** |
| | | (0.029) | (0.054) |
| | Skill intensity | 0.380 *** | 0.408 *** |
| | | (0.077) | (0.126) |
| N.obs | Intermediates | 0.628 *** | 0.641 *** |
| 571 | | (0.013) | (0.084) |
| | Capital | 0.038 *** | 0.092 |
| | | (0.009) | (0.070) |
| | Vintage | -0.030 *** | -0.009 |
| | | (0.004) | (0.039) |
| | Production experience | 0.005 | -0.003 |
| | | (0.011) | (0.060) |
| | Export experience | 0.036 *** | 0.051 |
| | | (0.006) | (0.034) |
| 341 Paper Products | Labor | 0.172 *** | 0.131 |
| | | (0.024) | (0.146) |
| | Wage premium | 0.074 ** | 0.088 |
| | | (0.035) | (0.228) |
| | Skill intensity | 0.098 | 0.073 |
| | | (0.078) | (0.375) |
| N.obs | Intermediates | 0.833 *** | 0.736 *** |
| 267 | | (0.016) | (0.130) |
| | Capital | 0.071 *** | 0.032 |
| | | (0.012) | (0.075) |
| | Vintage | 0.006 | 0.012 |
| | | (0.004) | (0.017) |
| | Production experience | -0.013 | -0.016 |
| | | (0.013) | (0.122) |
| | Export experience | 0.006 | 0.021 |
| | | (0.004) | (0.018) |
| 342 Printing | Labor | 0.300 *** | 0.277 *** |
| | | (0.018) | (0.036) |
| | Wage premium | 0.241 *** | 0.239 *** |
| | | (0.021) | (0.039) |
| | Skill intensity | 0.317 *** | 0.321 *** |
| | | (0.043) | (0.062) |
| N.obs | Intermediates | 0.645 *** | 0.583 *** |
| 827 | | (0.012) | (0.060) |
| | Capital | 0.062 *** | 0.045 |
| | | (0.009) | (0.056) |
| | Vintage | 0.014 *** | 0.046 |
| | | (0.003) | (0.030) |
| | Production experience | 0.023 ** | -0.030 |
| | | (0.009) | (0.057) |
| | Export experience | 0.006 | 0.032 * |
| | | (0.004) | (0.018) |
| 351 Industrial Chemicals | Labor | 0.131 *** | 0.137 *** |
| | | (0.027) | (0.052) |
| | Wage premium | 0.177 *** | 0.197 *** |
| | | (0.037) | (0.057) |
| | Skill intensity | 0.113 ** | 0.019 |
| | | (0.057) | (0.105) |
| N.obs | Intermediates | 0.777 *** | 0.832 *** |
| 220 | | (0.018) | (0.137) |
| | Capital | 0.089 *** | 0.080 |
| | | (0.013) | (0.081) |
| | Vintage | 0.014 *** | 0.086 ** |
| | | (0.005) | (0.034) |
| | Production experience | 0.002 | 0.040 |
| | | (0.014) | (0.075) |
| | Export experience | 0.010 ** | 0.009 |
| | | (0.005) | (0.018) |

Table 4 (continued)

| Industry (3-digit ISIC) | Input | OLS | | Levinsohn Petrin | |
|---|---|---|---|---|---|
| 352 Other Chemicals | Labor | 0.266 | *** | 0.278 | *** |
| | | (0.018) | | (0.039) | |
| | Wage premium | 0.253 | *** | 0.309 | *** |
| | | (0.033) | | (0.065) | |
| | Skill intensity | 0.194 | *** | 0.207 | * |
| | | (0.054) | | (0.111) | |
| N.obs | Intermediates | 0.704 | *** | 0.715 | *** |
| 503 | | (0.016) | | (0.058) | |
| | Capital | 0.070 | *** | 0.074 | |
| | | (0.011) | | (0.051) | |
| | Vintage | 0.016 | *** | -0.011 | |
| | | (0.005) | | (0.044) | |
| | Production experience | 0.026 | * | 0.032 | |
| | | (0.014) | | (0.054) | |
| | Export experience | 0.023 | *** | 0.009 | |
| | | (0.005) | | (0.019) | |
| 355 Rubber products | Labor | 0.256 | *** | 0.231 | |
| | | (0.029) | | (0.176) | |
| | Wage premium | 0.309 | *** | 0.217 | |
| | | (0.046) | | (0.306) | |
| | Skill intensity | 0.592 | *** | 0.596 | |
| | | (0.121) | | (0.395) | |
| N.obs | Intermediates | 0.668 | *** | 0.660 | *** |
| 201 | | (0.025) | | (0.161) | |
| | Capital | 0.003 | | -0.056 | |
| | | (0.019) | | (0.058) | |
| | Vintage | 0.006 | | 0.010 | |
| | | (0.006) | | (0.027) | |
| | Production experience | 0.034 | * | 0.109 | |
| | | (0.019) | | (0.112) | |
| | Export experience | 0.042 | *** | 0.046 | |
| | | (0.008) | | (0.053) | |
| 356 Plastics | Labor | 0.258 | *** | 0.247 | *** |
| | | (0.014) | | (0.027) | |
| | Wage premium | 0.235 | *** | 0.228 | *** |
| | | (0.024) | | (0.037) | |
| | Skill intensity | 0.261 | *** | 0.260 | *** |
| | | (0.047) | | (0.078) | |
| N.obs | Intermediates | 0.693 | *** | 0.677 | *** |
| 904 | | (0.01) | | (0.152) | |
| | Capital | 0.073 | *** | 0.071 | |
| | | (0.007) | | (0.118) | |
| | Vintage | -0.027 | *** | -0.026 | |
| | | (0.003) | | (0.056) | |
| | Production experience | -0.050 | *** | -0.032 | |
| | | (0.008) | | (0.047) | |
| | Export experience | 0.036 | *** | 0.031 | ** |
| | | (0.005) | | (0.015) | |
| 362 Glass | Labor | 0.253 | *** | 0.267 | |
| | | (0.035) | | (0.261) | |
| | Wage premium | 0.284 | *** | 0.327 | |
| | | (0.058) | | (0.345) | |
| | Skill intensity | 0.202 | | 0.136 | |
| | | (0.131) | | (0.440) | |
| N.obs | Intermediates | 0.727 | *** | 0.701 | *** |
| 172 | | (0.024) | | (0.164) | |
| | Capital | 0.025 | | 0.015 | |
| | | (0.022) | | (0.131) | |
| | Vintage | 0.008 | | -0.008 | |
| | | (0.008) | | (0.037) | |
| | Production experience | -0.026 | | 0.026 | |
| | | (0.02) | | (0.121) | |
| | Export experience | 0.064 | *** | 0.066 | * |
| | | (0.008) | | (0.034) | |
| 369 Nonmetallic Minerals | Labor | 0.277 | *** | 0.286 | |
| | | (0.027) | | (0.184) | |
| | Wage premium | 0.267 | *** | 0.187 | |
| | | (0.035) | | (0.549) | |
| | Skill intensity | 0.017 | | 0.085 | |
| | | (0.101) | | (0.903) | |
| N.obs | Intermediates | 0.642 | *** | 0.655 | *** |
| 616 | | (0.016) | | (0.086) | |
| | Capital | 0.095 | *** | 0.079 | |
| | | (0.014) | | (0.059) | |
| | Vintage | -0.011 | ** | 0.005 | |
| | | (0.005) | | (0.019) | |
| | Production experience | 0.014 | | -0.037 | |
| | | (0.014) | | (0.082) | |
| | Export experience | 0.018 | | 0.043 | |
| | | (0.042) | | (0.038) | |
| 371 Iron and Steel | Labor | 0.221 | *** | 0.250 | |
| | | (0.039) | | (0.294) | |
| | Wage premium | 0.047 | | 0.107 | |
| | | (0.047) | | (0.145) | |
| | Skill intensity | 0.561 | *** | 0.708 | ** |
| | | (0.099) | | (0.312) | |
| N.obs | Intermediates | 0.689 | *** | 0.630 | *** |
| 168 | | (0.018) | | (0.120) | |
| | Capital | 0.083 | *** | -0.043 | |
| | | (0.021) | | (0.106) | |
| | Vintage | 0.014 | * | 0.179 | *** |
| | | (0.008) | | (0.046) | |
| | Production experience | 0.033 | * | -0.083 | |
| | | (0.019) | | (0.153) | |
| | Export experience | 0.018 | * | -0.039 | |
| | | (0.01) | | (0.163) | |

| Industry (3-digit ISIC) | Input | OLS | | Levinsohn Petrin | |
|---|---|---|---|---|---|
| 381 Metal Products | Labor | 0.314 | *** | 0.284 | *** |
| | | (0.016) | | (0.024) | |
| | Wage premium | 0.206 | *** | 0.211 | *** |
| | | (0.024) | | (0.034) | |
| | Skill intensity | 0.439 | *** | 0.387 | *** |
| | | (0.047) | | (0.071) | |
| N.obs | Intermediates | 0.649 | *** | 0.610 | *** |
| 1204 | | (0.01) | | (0.063) | |
| | Capital | 0.049 | *** | 0.040 | |
| | | (0.007) | | (0.087) | |
| | Vintage | 0.002 | | 0.080 | * |
| | | (0.003) | | (0.047) | |
| | Production experience | 0.008 | | -0.100 | ** |
| | | (0.009) | | (0.051) | |
| | Export experience | 0.016 | *** | 0.050 | *** |
| | | (0.004) | | (0.012) | |
| 382 Nonelectrical Machinery | Labor | 0.278 | *** | 0.251 | *** |
| | | (0.026) | | (0.046) | |
| | Wage premium | 0.164 | *** | 0.145 | ** |
| | | (0.03) | | (0.060) | |
| | Skill intensity | 0.269 | *** | 0.103 | |
| | | (0.068) | | (0.089) | |
| N.obs | Intermediates | 0.617 | *** | 0.641 | *** |
| 569 | | (0.015) | | (0.106) | |
| | Capital | 0.083 | *** | 0.098 | |
| | | (0.012) | | (0.151) | |
| | Vintage | 0.023 | *** | 0.069 | |
| | | (0.004) | | (0.083) | |
| | Production experience | 0.035 | *** | -0.061 | |
| | | (0.013) | | (0.083) | |
| | Export experience | 0.007 | * | 0.022 | * |
| | | (0.004) | | (0.012) | |
| 383 Electrical Machinery | Labor | 0.341 | *** | 0.280 | ** |
| | | (0.031) | | (0.126) | |
| | Wage premium | 0.387 | *** | 0.318 | |
| | | (0.051) | | (0.249) | |
| | Skill intensity | 0.351 | *** | 0.271 | |
| | | (0.072) | | (0.219) | |
| N.obs | Intermediates | 0.624 | *** | 0.315 | ** |
| 329 | | (0.019) | | (0.130) | |
| | Capital | 0.028 | * | 0.185 | ** |
| | | (0.017) | | (0.076) | |
| | Vintage | -0.011 | | 0.043 | |
| | | (0.007) | | (0.072) | |
| | Production experience | 0.086 | *** | -0.288 | ** |
| | | (0.018) | | (0.129) | |
| | Export experience | 0.012 | | 0.046 | * |
| | | (0.009) | | (0.026) | |
| 384 Transport Equipment | Labor | 0.295 | *** | 0.314 | ** |
| | | (0.03) | | (0.141) | |
| | Wage premium | 0.181 | *** | 0.195 | |
| | | (0.042) | | (0.188) | |
| | Skill intensity | 0.457 | *** | 0.295 | |
| | | (0.084) | | (0.182) | |
| N.obs | Intermediates | 0.634 | *** | 0.667 | *** |
| 462 | | (0.016) | | (0.141) | |
| | Capital | 0.079 | *** | 0.031 | |
| | | (0.017) | | (0.091) | |
| | Vintage | -0.015 | *** | 0.040 | |
| | | (0.005) | | (0.066) | |
| | Production experience | -0.011 | | -0.024 | |
| | | (0.015) | | (0.137) | |
| | Export experience | 0.029 | *** | 0.048 | * |
| | | (0.01) | | (0.027) | |
| 385 Professional Equipment | Labor | 0.350 | *** | 0.401 | *** |
| | | (0.049) | | (0.111) | |
| | Wage premium | 0.368 | *** | 0.346 | ** |
| | | (0.073) | | (0.145) | |
| | Skill intensity | 0.404 | *** | 0.125 | |
| | | (0.102) | | (0.233) | |
| N.obs | Intermediates | 0.681 | *** | 0.586 | *** |
| 162 | | (0.026) | | (0.108) | |
| | Capital | 0.073 | *** | 0.220 | * |
| | | (0.021) | | (0.116) | |
| | Vintage | -0.025 | *** | -0.023 | |
| | | (0.009) | | (0.065) | |
| | Production experience | -0.027 | | -0.178 | * |
| | | (0.024) | | (0.100) | |
| | Export experience | -0.009 | | 0.019 | |
| | | (0.008) | | (0.024) | |
| 390 Other Manufacturing | Labor | 0.393 | *** | 0.444 | *** |
| | | (0.041) | | (0.078) | |
| | Wage premium | 0.138 | ** | 0.331 | *** |
| | | (0.062) | | (0.097) | |
| | Skill intensity | 0.600 | *** | 0.387 | ** |
| | | (0.112) | | (0.167) | |
| N.obs | Intermediates | 0.590 | *** | 0.592 | *** |
| 252 | | (0.029) | | (0.129) | |
| | Capital | 0.026 | | -0.022 | |
| | | (0.022) | | (0.132) | |
| | Vintage | -0.005 | | 0.107 | |
| | | (0.008) | | (0.099) | |
| | Production experience | 0.015 | | -0.120 | |
| | | (0.026) | | (0.123) | |
| | Export experience | 0.023 | *** | 0.082 | ** |
| | | (0.008) | | (0.032) | |

Notes: Bootstrapped standard errors are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Export experience is cumulated exports scaled by labor input up to t -1 and production experience is cumulated output scaled by labor input up to t -1.

APPENDIX

**A- Price indexes**

To obtain price indexes of domestic raw materials we aggregate data from Colombia's input-output matrices of Colombia for years 1992 to 1998 to construct a matrix *A* with typical element $\{a_{ij}\}$ = share of raw materials originating in industry *i* in the total value of raw materials used by industry *j*. The industries are aggregated into a national accounts classification that is broader than the ISIC revision 2. The matrix has 22 rows and 17 columns. The number of rows exceeds the number of columns because some raw materials used in manufacturing originate in the primary sector. We aggregate data from 7 input-output matrices rather than using data for a single year to obtain a more robust measure of raw materials shares. Unfortunately, we were unable to obtain input-output matrices for the sample period, 1981-1991, but we believe that input-output relationships are relatively stable over these two decades.

Notice that by construction $\sum_{i=1}^{22} a_{ij} = 1$. Therefore, our domestic raw materials price indexes are weighted averages of producer price indexes: for each manufacturing industry $j = 1, \ldots, 17$ and time *t*, the domestic raw materials price index is defined as $p_{jt}^{RM} = \sum_{i=1}^{22} a_{ij} p_{it}$. To perform this calculation we had to aggregate 29 manufacturing producer price indexes at the 3-digit ISIC revision 2 into 17 producer price indexes at the broader national accounts classification used in Colombia. We used production weights for the period 1975-1989 to aggregate these price indexes. For the primary sectors included in the computation we used wholesale price indexes.

The construction of exports price indexes was more involved because the series available from Banco de la República (Colombia's central bank) starts only in 1990. For the period 1975-1990 we construct export price indexes using detailed international trade information from the Dirección de Impuestos y Aduanas Nacionales (DIAN). Export transactions during that period are recorded at an 8-digit Colombian trade classification (NABANDINA) based on the Brussels Tariff Nomenclature. For each NABANDINA and year, we compute export prices in pesos per unit of weigh by dividing the value of exports of each NABANDINA by its weight. This is an imprecise proxy for unit export prices but was the best available because only 5% of the observations had data on units other than weight. Even with better information on units, the calculation can be subject to errors due to variation in the mix of products included within each NABANDINA.

To minimize potential spurious variations due the aforementioned measurement problems we follow two procedures. First, we remove from the computations outliers defined as unit export prices whose average annual rate of growth exceeds the 90$^{th}$ percentile or is less than the 10$^{th}$ percentile for the whole sample. Second, we regress the log of the unit export price on a fixed NABANDINA effect, a set of time-industry dummies, and a variable representing the deviation of each export price from the law of one price[1]. Since NABANDINA positions with very small values of exports are more likely to be affected by measurement problems, we estimate our regression using weighted least squares, with weights proportional to the square root of the constant dollar value of exports. These regressions generate predicted log unit export

[1] This variable is defined log($EXPPES_{it}$/$EXPDOL_{it}$)-log($E_t$), where $EXPPES_{it}$ is the value of exports in pesos of NABANDINA *i* at time *t*, $EXPDOL_{it}$ is the same value but in dollars, and $E_t$ is the average exchange rate at time *t*.

values for every NABANDINA and year with export data (including positions excluded from the calculations due to outliers).

We use these smoothed unit export prices to compute Tornqvist price indexes per each ISIC industry $j$: $\log p^X_{jt} - \log p^X_{jt-1} = \sum_{i=1}^{I_j} 0.5\left(w^j_{it} + w^j_{it}\right)\left(\log p^j_{it} - \log p^j_{it-1}\right)$, where $\log p^j_{it}$ is the estimated log unit export price of NABANDINA $i$ belonging to industry $j$ at time $t$. The weights $w^j_{it}$ are the share of the value of exports in pesos of NABANDINA $i$ in industry $j$ at time $t$.

To obtain price indexes for imported raw materials, we first construct import price indexes from the DIAN trade data, following the same procedure as for the export price indexes. After obtaining import price indexes we follow a similar procedure to the one used to construct domestic raw materials price indexes, but instead of using general input-output matrices we use the 1994 Colombian input-output matrix for imported inputs.

## B- Capital stock and capital vintage

For each type of asset $j$ (buildings and structures, machinery and equipment, transportation equipment, and office equipment) we apply the following permanent inventory method to construct measures of the capital stock of plant $i$ at time $t$. All the variables employed are expressed in constant pesos of 1986, as explained in the text. If $BV_{ijt}$ and $K^1_{ijt}$ denote, respectively, the book value and a transient measure of the capital stock of asset $j$ for plant $i$ at the end of time $t$ and $F_i$ is the first year when plant $i$ is in the sample, first set $K^1_{ijF_i} = BV_{ijF_i}$ and then compute

$$K^1_{ijt} = (1-d_j) * Max\{K^1_{ijt-1}, BV_{t-1}\} + (I_{ijt} - S_{ijt}), \quad t > F_i,$$

where $I_{ijt}$ and $S_{ijt}$ are purchases and sales of capital, and $d_j$ is the depreciation rate of asset $j$. Letting $L_i$ denote the last year of the plant in the sample, next set $K_{ijL_i} = K^1_{ijL_i}$ and compute

$$K_{ijt-1} = \frac{K^1_{ijt} - (I_{ijt} - S_{ijt})}{1 - d_j}, \quad t \in [1, L_i].$$

This method corrects for the usual downward bias in the book value of capital due to high inflation and accelerated depreciation schemes by exploiting adjustments in the book values to market values that plants often undertake. The depreciation rates used are taken from Pombo (1999): 3.0% for buildings and structures, 7.7% for machinery and equipment, 11.9% for transportation equipment, and 9.9% for office equipment. After computing individual measures of capital for each asset type, we obtain a measure of the plant capital stock at the end of period $t$ by summing the individual capital stocks: $K_{it} = \sum_{j=1}^{4} K_{ijt}$ .

Two modifications were applied to the measure of capital obtained above. First, as Bahk and Gort (1993) point out, the physical decay of the capital stock, usually measured as we do using a constant depreciation rate, might be offset by maintenance expenditures that keep machines and buildings working in good condition. While Bahk and Gort assume that maintenance expenditures fully offset physical decay, we prefer to measure the degree of offset by adding to the above measure of capital maintenance expenditures in constant pesos of 1986. Second, we follow Bahk and Gort (1993) in half-lagging our measure of capital, so that capital captures capital expenditures done during both the first semester of the current year and the second semester of the previous year.

In order to account for the quality of the capital stock we compute a measure of capital vintage. First define the plant gross capital stock as $GK_{it} = FIRSTK_i + \sum_{\tau=F_i}^{t-1}(I_{i\tau} - S_{i\tau}) + (I_{it} - S_{it})/2$,

where $FIRSTK_i$ is capital the plant had before its first year in the sample, $F_i$ is the first year when plant $i$ is in the sample, and where $I_{it}$ and $S_{it}$ are purchases and sales of capital. Although relatively few plants had a positive value for $FIRSTK_i$, their existence confirms that some plants "were born" before starting operations. Notice that this measure of gross capital is half-lagged. Our measure of capital vintage is a weighted average of calendar years when investment took place, with the weights defined as the share of gross capital that took place in a particular year. We assume that the investment associated with $FIRSTK_i$ took place the year before the plant started operations. Therefore, in the first year of a plant life ($t = F_i$), capital vintage is defined as $V_{it} = \frac{FIRSTK_i}{GK_{it}}(t-1) + \frac{(I_{it} - S_{it})/2}{GK_{it}}t$. In any subsequent period ($t > F_i$), it is defined iteratively as $V_{it} = \frac{GK_{it-1}}{GK_{it}}V_{it-1} + \frac{(GK_{it} - GK_{it-1})}{GK_{it}}t$.

**C- Outliers**

To define outliers we first computed log differences between four production inputs (capital, labor, wage premium, and intermediate inputs) and output. We then computed the first and third quartiles, and the inter-quartile range, of each of these log differences for each industry. For most industries we define an outlier as a plant for which in one year at least one of the four log differences (a) exceeded the third quartile by 2.5 times the inter-quartile range or more, or (b) was less than the first quartile by 2.5 times the inter-quartile range or more. In two industries, paper (ISIC 341) and transport equipment (ISIC 384) we applied a stricter criterion, lowering the threshold to 2 times the inter-quartile range, due numerical problems with our estimation algorithm. We should point out that even a threshold of 2 inter-quartile ranges is very conservative. Assuming that the distribution of the log differences is normal, with that criterion the probability of finding an outlier would be only 0.074%.[2]

[2] With the criterion of 2.5 inter-quartile ranges, the probability of finding an outlier would be 0.005%.

Appendix Table 1: Production Function Coefficients "Two-Step" Approach

| Industry (3-digit ISIC) | Input | OLS | Levinsohn Petrin |
|---|---|---|---|
| 311 Food Products | Labor | 0.143 *** | 0.140 *** |
| | | (0.007) | (0.015) |
| | Wage Premium | 0.147 *** | 0.144 *** |
| | | (0.011) | (0.018) |
| | Skill Intensity | 0.233 *** | 0.234 *** |
| | | (0.021) | (0.034) |
| N.obs | Intermediates | 0.811 *** | 0.802 *** |
| 2294 | | (0.004) | (0.048) |
| | Capital | 0.049 *** | 0.082 |
| | | (0.004) | (0.074) |
| | Vintage | 0.009 *** | 0.015 |
| | | (0.002) | (0.048) |
| 312 Miscellaneous Food | Labor | 0.165 *** | 0.190 *** |
| | | (0.02) | (0.039) |
| | Wage Premium | 0.249 *** | 0.189 *** |
| | | (0.026) | (0.058) |
| | Skill Intensity | 0.211 *** | 0.226 *** |
| | | (0.053) | (0.080) |
| N.obs | Intermediates | 0.740 *** | 0.839 *** |
| 465 | | (0.009) | (0.093) |
| | Capital | 0.093 *** | 0.022 |
| | | (0.01) | (0.112) |
| | Vintage | 0.000 | 0.022 |
| | | (0.004) | (0.062) |
| 313 Beverages | Labor | 0.150 *** | 0.314 *** |
| | | (0.051) | (0.120) |
| | Wage Premium | 0.243 *** | 0.001 |
| | | (0.067) | (0.196) |
| | Skill Intensity | 0.283 ** | 0.663 *** |
| | | (0.14) | (0.223) |
| N.obs | Intermediates | 0.663 *** | 0.579 |
| 151 | | (0.031) | (0.363) |
| | Capital | 0.149 *** | 0.213 |
| | | (0.026) | (0.227) |
| | Vintage | -0.026 ** | 0.027 |
| | | (0.012) | (0.189) |
| 321 Textiles | Labor | 0.225 *** | 0.215 *** |
| | | (0.014) | (0.019) |
| | Wage Premium | 0.216 *** | 0.189 *** |
| | | (0.024) | (0.031) |
| | Skill Intensity | 0.448 *** | 0.373 *** |
| | | (0.046) | (0.079) |
| N.obs | Intermediates | 0.653 *** | 0.657 *** |
| 1176 | | (0.008) | (0.143) |
| | Capital | 0.093 *** | 0.120 |
| | | (0.006) | (0.122) |
| | Vintage | 0.009 *** | 0.031 |
| | | (0.003) | (0.052) |
| 322 Apparel | Labor | 0.377 *** | 0.335 *** |
| | | (0.007) | (0.014) |
| | Wage Premium | 0.187 *** | 0.184 *** |
| | | (0.014) | (0.020) |
| | Skill Intensity | 0.376 *** | 0.423 *** |
| | | (0.028) | (0.057) |
| N.obs | Intermediates | 0.596 *** | 0.555 *** |
| 3638 | | (0.004) | (0.072) |
| | Capital | 0.043 *** | 0.066 |
| | | (0.004) | (0.045) |
| | Vintage | 0.023 *** | 0.026 |
| | | (0.002) | (0.020) |
| 323 Leather Products | Labor | 0.239 *** | 0.293 *** |
| | | (0.022) | (0.039) |
| | Wage Premium | 0.068 * | 0.110 ** |
| | | (0.039) | (0.049) |
| | Skill Intensity | 0.142 * | 0.317 *** |
| | | (0.086) | (0.100) |
| N.obs | Intermediates | 0.781 *** | 0.828 *** |
| 299 | | (0.015) | (0.126) |
| | Capital | 0.052 *** | 0.035 |
| | | (0.012) | (0.109) |
| | Vintage | 0.026 *** | 0.056 |
| | | (0.005) | (0.065) |

| Industry (3-digit ISIC) | Input | OLS | Levinsohn Petrin |
|---|---|---|---|
| 324 Footwear | Labor | 0.255 *** | 0.219 *** |
| | | (0.015) | (0.024) |
| | Wage Premium | 0.195 *** | 0.231 *** |
| | | (0.02) | (0.032) |
| | Skill Intensity | 0.350 *** | 0.382 *** |
| | | (0.053) | (0.092) |
| N.obs | Intermediates | 0.711 *** | 0.676 *** |
| 1036 | | (0.01) | (0.094) |
| | Capital | 0.038 *** | 0.066 |
| | | (0.007) | (0.084) |
| | Vintage | 0.007 ** | 0.048 |
| | | (0.003) | (0.077) |
| 331 Wood Products | Labor | 0.299 *** | 0.242 *** |
| | | (0.024) | (0.043) |
| | Wage Premium | 0.176 *** | 0.205 *** |
| | | (0.032) | (0.046) |
| | Skill Intensity | 0.450 *** | 0.356 *** |
| | | (0.074) | (0.115) |
| N.obs | Intermediates | 0.662 *** | 0.678 *** |
| 509 | | (0.013) | (0.075) |
| | Capital | 0.076 *** | 0.062 |
| | | (0.01) | (0.106) |
| | Vintage | 0.010 *** | 0.019 |
| | | (0.004) | (0.045) |
| 332 Furniture | Labor | 0.370 *** | 0.373 *** |
| | | (0.02) | (0.034) |
| | Wage Premium | 0.203 *** | 0.211 *** |
| | | (0.025) | (0.036) |
| | Skill Intensity | 0.454 *** | 0.510 *** |
| | | (0.076) | (0.100) |
| N.obs | Intermediates | 0.630 *** | 0.681 *** |
| 692 | | (0.012) | (0.118) |
| | Capital | 0.035 *** | 0.065 |
| | | (0.009) | (0.113) |
| | Vintage | -0.023 *** | -0.044 |
| | | (0.004) | (0.056) |
| 341 Paper Products | Labor | 0.187 *** | 0.197 *** |
| | | (0.021) | (0.036) |
| | Wage Premium | 0.096 *** | 0.144 *** |
| | | (0.032) | (0.039) |
| | Skill Intensity | 0.155 ** | 0.180 |
| | | (0.072) | (0.118) |
| N.obs | Intermediates | 0.816 *** | 0.791 *** |
| 319 | | (0.011) | (0.080) |
| | Capital | 0.064 *** | 0.055 |
| | | (0.01) | (0.073) |
| | Vintage | 0.006 | -0.011 |
| | | (0.004) | (0.038) |
| 342 Printing | Labor | 0.297 *** | 0.309 *** |
| | | (0.016) | (0.024) |
| | Wage Premium | 0.251 *** | 0.275 *** |
| | | (0.02) | (0.029) |
| | Skill Intensity | 0.298 *** | 0.315 *** |
| | | (0.04) | (0.049) |
| N.obs | Intermediates | 0.656 *** | 0.571 *** |
| 971 | | (0.011) | (0.060) |
| | Capital | 0.063 *** | 0.012 |
| | | (0.007) | (0.076) |
| | Vintage | 0.016 *** | 0.040 |
| | | (0.003) | (0.032) |
| 351 Industrial Chemicals | Labor | 0.132 *** | 0.198 *** |
| | | (0.026) | (0.046) |
| | Wage Premium | 0.157 *** | 0.150 ** |
| | | (0.032) | (0.062) |
| | Skill Intensity | 0.164 *** | 0.092 |
| | | (0.058) | (0.103) |
| N.obs | Intermediates | 0.800 *** | 0.859 *** |
| 261 | | (0.015) | (0.122) |
| | Capital | 0.070 *** | 0.132 |
| | | (0.013) | (0.168) |
| | Vintage | 0.010 ** | 0.031 |
| | | (0.005) | (0.096) |

Appendix Table 1 (continued)

| Industry (3-digit ISIC) | Input | OLS | Levinsohn Petrin |
|---|---|---|---|
| 352 Other Chemicals | Labor | 0.252 *** | 0.193 *** |
| | | (0.017) | (0.041) |
| | Wage Premium | 0.258 *** | 0.247 *** |
| | | (0.03) | (0.061) |
| | Skill Intensity | 0.183 *** | 0.309 *** |
| | | (0.052) | (0.114) |
| N.obs | Intermediates | 0.733 *** | 0.725 *** |
| 606 | | (0.014) | (0.138) |
| | Capital | 0.065 *** | 0.097 |
| | | (0.009) | (0.123) |
| | Vintage | 0.014 *** | 0.033 |
| | | (0.005) | (0.082) |
| 355 Rubber products | Labor | 0.270 *** | 0.248 *** |
| | | (0.026) | (0.046) |
| | Wage Premium | 0.333 *** | 0.171 ** |
| | | (0.044) | (0.071) |
| | Skill Intensity | 0.689 *** | 0.353 * |
| | | (0.12) | (0.193) |
| N.obs | Intermediates | 0.667 *** | 0.426 *** |
| 57 | | (0.021) | (0.103) |
| | Capital | 0.034 * | 0.285 *** |
| | | (0.018) | (0.098) |
| | Vintage | 0.007 | -0.188 ** |
| | | (0.006) | (0.078) |
| 356 Plastics | Labor | 0.296 *** | 0.301 *** |
| | | (0.014) | (0.020) |
| | Wage Premium | 0.251 *** | 0.199 *** |
| | | (0.021) | (0.025) |
| | Skill Intensity | 0.324 *** | 0.260 *** |
| | | (0.044) | (0.066) |
| N.obs | Intermediates | 0.674 *** | 0.741 *** |
| 1085 | | (0.008) | (0.162) |
| | Capital | 0.051 *** | 0.118 |
| | | (0.006) | (0.166) |
| | Vintage | -0.024 *** | -0.022 |
| | | (0.003) | (0.089) |
| 362 Glass | Labor | 0.232 *** | 0.256 *** |
| | | (0.036) | (0.060) |
| | Wage Premium | 0.223 *** | 0.269 *** |
| | | (0.056) | (0.061) |
| | Skill Intensity | 0.372 *** | 0.028 |
| | | (0.126) | (0.225) |
| N.obs | Intermediates | 0.744 *** | 0.498 *** |
| 206 | | (0.023) | (0.106) |
| | Capital | 0.041 ** | 0.258 ** |
| | | (0.02) | (0.115) |
| | Vintage | 0.008 | -0.016 |
| | | (0.008) | (0.134) |
| 369 Nonmetallic Minerals | Labor | 0.278 *** | 0.283 *** |
| | | (0.024) | (0.046) |
| | Wage Premium | 0.245 *** | 0.153 *** |
| | | (0.03) | (0.044) |
| | Skill Intensity | 0.053 | 0.216 |
| | | (0.093) | (0.157) |
| N.obs | Intermediates | 0.662 *** | 0.558 *** |
| 732 | | (0.012) | (0.096) |
| | Capital | 0.085 *** | 0.157 |
| | | (0.012) | (0.105) |
| | Vintage | -0.007 | -0.081 |
| | | (0.005) | (0.055) |
| 371 Iron and Steel | Labor | 0.225 *** | 0.293 *** |
| | | (0.035) | (0.055) |
| | Wage Premium | 0.104 ** | 0.083 |
| | | (0.042) | (0.070) |
| | Skill Intensity | 0.693 *** | 0.840 *** |
| | | (0.09) | (0.267) |
| N.obs | Intermediates | 0.703 *** | 0.664 *** |
| 197 | | (0.013) | (0.152) |
| | Capital | 0.077 *** | 0.192 |
| | | (0.018) | (0.157) |
| | Vintage | 0.004 | 0.066 |
| | | (0.007) | (0.105) |

| Industry (3-digit ISIC) | Input | OLS | Levinsohn Petrin |
|---|---|---|---|
| 381 Metal Products | Labor | 0.296 *** | 0.271 *** |
| | | (0.015) | (0.021) |
| | Wage Premium | 0.213 *** | 0.250 *** |
| | | (0.021) | (0.031) |
| | Skill Intensity | 0.423 *** | 0.437 *** |
| | | (0.045) | (0.082) |
| N.obs | Intermediates | 0.662 *** | 0.696 *** |
| 1455 | | (0.008) | (0.075) |
| | Capital | 0.049 *** | 0.073 |
| | | (0.006) | (0.083) |
| | Vintage | -0.003 | 0.028 |
| | | (0.003) | (0.050) |
| 382 Nonelectrical Machinery | Labor | 0.268 *** | 0.300 *** |
| | | (0.024) | (0.043) |
| | Wage Premium | 0.203 *** | 0.161 *** |
| | | (0.026) | (0.046) |
| | Skill Intensity | 0.325 *** | 0.276 *** |
| | | (0.062) | (0.080) |
| N.obs | Intermediates | 0.622 *** | 0.565 *** |
| 690 | | (0.013) | (0.078) |
| | Capital | 0.094 *** | 0.044 |
| | | (0.01) | (0.123) |
| | Vintage | 0.020 *** | 0.056 |
| | | (0.004) | (0.073) |
| 383 Electrical Machinery | Labor | 0.284 *** | 0.246 *** |
| | | (0.027) | (0.030) |
| | Wage Premium | 0.311 *** | 0.254 *** |
| | | (0.04) | (0.070) |
| | Skill Intensity | 0.334 *** | 0.183 * |
| | | (0.069) | (0.103) |
| N.obs | Intermediates | 0.675 *** | 0.365 * |
| 397 | | (0.016) | (0.206) |
| | Capital | 0.054 *** | 0.148 |
| | | (0.014) | (0.149) |
| | Vintage | -0.012 ** | -0.075 |
| | | (0.006) | (0.107) |
| 384 Transport Equipment | Labor | 0.267 *** | 0.306 *** |
| | | (0.027) | (0.056) |
| | Wage Premium | 0.201 *** | 0.256 *** |
| | | (0.037) | (0.047) |
| | Skill Intensity | 0.452 *** | 0.092 |
| | | (0.079) | (0.116) |
| N.obs | Intermediates | 0.654 *** | 0.637 *** |
| 557 | | (0.013) | (0.195) |
| | Capital | 0.074 *** | 0.103 |
| | | (0.015) | (0.214) |
| | Vintage | -0.021 *** | 0.026 |
| | | (0.005) | (0.140) |
| 385 Professional Equipment | Labor | 0.331 *** | 0.328 *** |
| | | (0.039) | (0.049) |
| | Wage Premium | 0.342 *** | 0.066 |
| | | (0.065) | (0.103) |
| | Skill Intensity | 0.423 *** | 0.012 |
| | | (0.094) | (0.098) |
| N.obs | Intermediates | 0.678 *** | 0.728 *** |
| 192 | | (0.021) | (0.122) |
| | Capital | 0.058 *** | 0.246 |
| | | (0.017) | (0.170) |
| | Vintage | -0.025 *** | -0.095 |
| | | (0.008) | (0.095) |
| 390 Other Manufacturing | Labor | 0.337 *** | 0.311 *** |
| | | (0.034) | (0.075) |
| | Wage Premium | 0.097 * | 0.039 |
| | | (0.053) | (0.099) |
| | Skill Intensity | 0.646 *** | 0.400 ** |
| | | (0.102) | (0.194) |
| N.obs | Intermediates | 0.630 *** | 0.595 ** |
| 311 | | (0.024) | (0.247) |
| | Capital | 0.027 | 0.164 |
| | | (0.019) | (0.248) |
| | Vintage | -0.018 ** | -0.004 |
| | | (0.008) | (0.134) |

Notes: Bootstrapped standard errors are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.