# Trade Policy, Trade Volumes and Plant-Level Productivity in Colombian Manufacturing Industries

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## Abstract

This paper exploits variation in trade policy in Colombia from 1977 to 1991 and differences in protection across industries, to investigate the link between trade policy and plant productivity, differing from previous studies of a single trade liberalization episode for a country. Using a rich panel of Colombian manufacturing plants, production functions are estimated across industries, using intermediate inputs to control for producer unobservables, correcting the simultaneity bias between input choices and productivity. Variable inputs' coefficients reveal the importance of the bias. Consistent plant productivity measures are related to trade policy measures. We find a strong negative impact of lagged nominal tariffs at different disaggregation levels on plant productivity, even after controlling for real exchange rates, observed and unobserved plant characteristics. Focusing on plant heterogeneity, the negative impact of trade protection on productivity is stronger for large plants, in employment and market shares terms, than for small plants. Focusing on industry heterogeneity, the negative impact of trade protection on productivity is stronger for plants in less competitive industries, according to Herfindahl indices and turnover rates. We check the robustness of the above findings by using effective rates of protection and import penetration ratios as measures of trade protection and find that the negative impact of trade protection and the positive impact of import penetration on productivity are stronger for large plants and for plants in less competitive industries. Finally, we also find evidence of a negative impact of trade protection on plant productivity growth.



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# 1. Introduction

A central issue in trade and development economics is the effect of trade liberalization on productivity in developing countries. During the last three decades, Colombia has experienced significant variation in trade policy, with periods of trade liberalization alternating with periods of increased trade protection. Moreover, there were substantial and varying differences in the level of protection across Colombian industries. An examination of Colombian trade policy during this period can offer new insights on the effect of trade liberalization on industrial productivity. In this paper, we use a panel of Colombian plants between 1977 and 1991 to investigate the relation between plant-level productivity and trade policy.

The empirical literature on the impact of trade liberalization on industrial productivity follows three approaches. First, the macro-level approach uses cross-country GDP growth regressions.[1] However, this aggregate level of analysis masks much of the industry and plant-specific adjustment to trade policy. Furthermore, assuming a single production function for an economy's productive sector is restrictive. Second, the industry-level approach considers regressions of the change in industries' residual TFP (Solow (1957)) on demand growth due to export expansion and to import substitution, as in Nishimizu and Robinson (1984), or on trade-related policy variables, as in Lee (1995) and Kim (2000).[2] Some of these studies do not control for other industry characteristics shifting productivity. Furthermore, having a unique productivity measure per industry and period ignores cross-plant variation, that may be important to identify the impact of trade policy. Third, the micro-level approach uses either firm and plant-level Solow residual TFP measures or consistent productivity measures. Harrison (1994) and Krishna and Mitra (1998) estimate output growth regressions derived in a Solow framework, assuming that the contribution of an input to production equals the share of that input's costs in total revenue. The potential productivity gains due to trade liberalization are measured by the coefficient on a dummy variable for the period of trade reform. However, that variable also captures contemporaneous shocks to the macroeconomic environment and ignores the rich variation in levels and changes of protection across industries.[3] Pavcnik (2000) uses consistent productivity measures and identifies trade

[1] See, for example, Dollar (1992), Sachs and Warner (1995) and Edwards (1994, 1998). For a critical analysis of the literature, see Rodriguez and Rodrik (1999).
[2] Other industry-level empirical studies include, for example, Tybout, de Melo and Corbo (1991) and Levinsohn (1993). For a survey, see Rodrik (1995).
[3]

reform effects from a comparison of plant productivity in import-competing and export-oriented industries relative to nontraded industries over time as the trade reform proceeds. But her approach could be subject to an endogeneity problem if during trade liberalization, unobserved factors change plant productivity and trade orientation.[4] Our paper contributes to the micro-level approach using consistent measures of plant productivity, obtained by a method differing from Pavcnik's. We identify the impact of trade protection on productivity exploiting trade policy measures exhibiting significant variation across industries and over time and reflecting the degree of government intervention.

The major findings of this paper are as follows. First, we provide strong evidence supporting the hypothesis that Colombian plants' productivity is negatively affected by trade protection. Lagged nominal tariffs at 3 and 4-digit industry levels have a significant impact on productivity, even after controlling for the real exchange rate, observed and unobserved plant characteristics. Second, we find that, when plant size is measured by employment and market share, the negative impact of trade protection on productivity is stronger for large plants than for small plants. Third, we present evidence of a differential impact of trade protection on productivity depending on the degree of domestic competition in the industry. The negative impact of trade protection on productivity is stronger for plants in less competitive industries, according to Herfindahl indices and turnover rates. Fourth, we check the robustness of the above findings using lagged effective rates of protection and import penetration ratios as measures of trade protection. Again, we find that the negative impact of trade protection and the positive impact of import penetration on productivity are stronger for large plants and for plants in less competitive industries. Finally, we also find evidence of a negative impact of trade protection on plant productivity growth.

In this paper we follow a two-step procedure. We begin by estimating production function parameters separately across industries, and deriving plant-level time-varying productivity measures. Then, we evaluate the impact of changes in trade policy on plant productivity.

Harrison addresses this criticism by interacting a proxy for markups with annual industry-level import penetration and tariffs in a year before and a year after the trade reform. But the tariff measure, tariff revenues as a fraction of imports, does not accurately reflect the degree of government intervention.

[4] Pavcnik checks the robustness of results considering import penetration at a 4-digit industry level and an average tariff in a subperiod, obtaining qualitatively similar results. However, since tariffs are uniform across Chilean industries, they are equivalent to a year effect. So, the analysis cannot exploit the rich differential variation of trade policy across industries as in the case of Colombia.

The use of ordinary least squares (OLS) for production function estimation is inappropriate, because regressors, such as labor and intermediate inputs, are treated as *exogenous* variables. As Griliches and Mairesse (1995) point out, inputs are *endogenous*, chosen optimally by producers. For example, a producer's input choices may depend on the failure rate of a machine. Consequently, since input choices and productivity are correlated, OLS estimates suffer from a simultaneity bias, as pointed by Marschak and Andrews (1944). Also, industry evolution models, such as Jovanovic (1982), hypothesize that more efficient producers are likely to expand. Variable input coefficients, easier to adjust, tend to be upwardly biased when estimated by OLS.[5] Fixed effects estimation is not appealing, as it eliminates the simultaneity bias only in the restrictive and uninteresting case of constant productivity. In this paper, we follow closely the methodology for production function estimation proposed by Levinsohn and Petrin (2000). Under general conditions, a plant's demand for variable inputs, such as raw materials, increases monotonically with productivity, conditional on its capital stock. Raw materials use, a plant-level time-varying variable in the Colombian dataset, is a good input to correct the simultaneity bias, given its ease of adjustment in face of productivity changes. So, a function of observable raw materials and capital is the instrument for unobservable productivity. The simultaneity bias is corrected and production function coefficients are consistently estimated. The variable inputs' coefficients we obtain are lower than those from OLS estimation, revealing how important the endogeneity of input choices is in most industries.

The impact of trade policy on producers' productivity depends on the output distribution across plants with different productivities and on heterogeneous response patterns. Unfortunately, no theoretical model examines the impact of trade policy on firm technical efficiency levels and growth per se, as trade theory relies mostly on a representative firm framework.[6] Hence, we follow a reduced form approach to identify the link between trade

[5] With more than two inputs, not all biases can be exactly signed, as they depend upon the degree of correlation between each input and the productivity shock.

[6] The contribution of trade openness to economic growth is a theoretically unsettled question. Traditional Ricardian and neoclassical trade theories establish one-time allocative efficiency gains from trade liberalization, as protection precludes an allocation of resources across sectors according to comparative advantage. New trade theory recognizes that trade policy and exposure may interact with producers' performance and market structure (e.g., Helpman and Krugman (1985)). Endogenous growth models consider dynamic effects of trade on productivity (e.g., Grossman and Helpman (1991), Romer (1994) and Young (1991)). In these models, the assumptions imposed on the nature of technology spillovers determine whether trade protection enhances productivity growth.

policy and productivity improvements across plants. Plant-level productivity measures are related in a regression framework to trade policy measures, exploiting cross-industry and temporal variation in protection. We take into account changes in Colombia's real exchange rate that might alter the productivity-trade policy link. In an attempt to capture producer heterogeneity, we allow the effects of trade policy on productivity to vary across plants of different size within industries, as well as across industries with different degrees of domestic competition.

This paper is organized as follows. In Section 2 we present the model and estimation procedure for plant-level productivity. In Section 3 we describe the data. In Section 4 we discuss the results from production function estimation, as well as the corresponding industry productivity levels and growth. In Section 5 we analyze the relation between trade policy, trade volumes and productivity. Section 6 concludes. All tables and figures are provided at the end of the paper.

## 2. Productivity Estimation

We obtain consistent production function estimates following a strategy originally proposed by Olley and Pakes (1996). The authors use plant investment choices as the instrument to correct the simultaneity bias between plants' input choices and privately known productivity. Relying on investment for identification is problematic given the widely documented lumpiness in plant investment, that may lead to unrealistic year-to-year variability in estimated plant productivity. A large fraction of Colombian plants have lumpy investments, positive with significant variation in levels in half the years of plant presence in the sample and null in the remaining years. Furthermore, combining investment (to correct the bias) with the build-up of the capital stock in our dataset, would result in a bias in the capital coefficient.[7] Levinsohn and Petrin (2000) propose a related methodology, that we follow, better suited for developing countries' datasets. Intermediate inputs are the instrument controlling for the part of productivity observed by the plant's decision maker and poten-

[7] The timing of plant $i$'s choices and the build-up of the capital stock in Olley and Pakes (1996) are as follows: plant $i$ starts period $t$ with capital stock $k_{it}^{j}$ and observes productivity $\omega_{it}^{j}$. If it stays in the industry $j$, it chooses labor, intermediate inputs and investment $i_{it}^{j}$, that enters the capital stock at $t+1$. In our data, $i_{it}^{j}$ enters the capital stock at $t$. Since investment is correlated with productivity, $k_{it}^{j}$ entering production at $t$, is also correlated with productivity and the use of the investment instrument cannot correct this bias.

tially correlated with input choices. The appeal of the approach is to combine elements of a structural approach and parametric estimation with a flexible nonparametric estimation of unknown functions. We obtain alternative production function estimates using Olley and Pakes' estimation methods with raw materials rather than investment as the bias correcting instrument.

We use an unbalanced panel, incorporating entry and exit into industries, that partly controls for a potential selection bias, arising if exit decisions by plants are made with knowledge of their productivity. By not incorporating endogenous selection into the estimation, we implicitly assume that producers do not observe productivity when they decide whether to stay in the industry. For Chilean manufacturing data, Levinsohn and Petrin (2000) argue the estimation results are similar whether or not endogenous selection is considered.

Implicit in the estimation procedure is a structural dynamic model of plant production decisions with cross-plant heterogeneity, plant specific uncertainty and the maximization of expected discounted values of future net profits. We now discuss the timing of plant $i$'s decisions within a period $t$ and the estimation procedure when raw materials is the instrument to correct the simultaneity bias. First, the plant decides whether or not to stay in the industry $j$; if staying, it observes productivity $\omega_{it}^{j}$, then chooses variable inputs labor $l_{it}^{j}$, raw materials $m_{it}^{j}$ and electricity and fuels $e_{it}^{j}$ to be combined with the quasi-fixed input capital $k_{it}^{j}$ for production of output $y_{it}^{j} = f(l_{it}^{j}, m_{it}^{j}\ , e_{it}^{j}, k_{it}^{j}, \omega_{it}^{j}, \varepsilon_{it}^{j})$ also a function of observed productivity $\omega_{it}^{j}$ and of an unobserved productivity shock $\varepsilon_{it}^{j}$. The build-up of the capital stock assumed is consistent with the definition and construction of capital in the dataset, $k_{it}^{j} = (1-\delta)k_{it-1}^{j} + i_{it}^{j}$, where $i_{it}^{j}$ is plant-level investment and $\delta$ is the depreciation rate. The only assumption required on plants' investment choices is that they are compatible with the crucial identification assumption in the estimation: $k_{it}^{j}$ does not adjust to the unexpected productivity shock. In the estimation, the functional form chosen for production is Cobb-Douglas in a logarithmic form, with Hicks-neutral technical change. We prefer an output specification to a value-added specification, where all intermediate inputs would be subtracted from output. Steindel and Stiroh (2001) argue that the technical assumption required for value-added to be a valid production index (separability of the production technology in all intermediate inputs) is not verified empirically. The estimating equation for plant $i$ in industry $j$ and period $t$ is given by:

$$y_{it}^{j} = \beta_0 + \beta_l l_{it}^{j} + \beta_e e_{it}^{j} + \beta_m m_{it}^{j} + \beta_k k_{it}^{j} + \omega_{it}^{j} + \varepsilon_{it}^{j}. \tag{1}$$

The error in (1) is constituted by the productivity term $\omega_{it}^{j}$, assumed to be known to the plant manager, possibly correlated with $l_{it}^{j}$, $e_{it}^{j}$ and $m_{it}^{j}$, generating the simultaneity bias and by the productivity shock $\varepsilon_{it}^{j}$ assumed to be mean zero and uncorrelated with the regressors.

Producers maximize profits from output sales and the corresponding optimal variable input demands can be derived. Input choices depend on capital and on observed productivity, evidencing the simultaneity bias. The assumption required to invert the raw materials demand function $m_{it} = m_t(\omega_{it}, k_{it})$ and express productivity as a function of raw materials and capital is an intuitive monotonicity condition: for profit maximizing plants, the use of raw materials increases with productivity, conditional on capital. A sufficient condition for the monotonicity to hold, with a well behaved production function (twice continuously differentiable), is perfect competition in input and output markets, but that is not necessary: output markets can be imperfectly competitive.[8] Inverting the raw materials demand, one obtains the productivity function, $\omega_{it} = \omega_t(m_{it}, k_{it})$ that only depends on plant observables. So, (1) can be written in the partially linear form (omitting industry superscript $j$):

$$y_{it} = \beta_l l_{it} + \beta_e e_{it} + \phi_t(m_{it}, k_{it}) + \varepsilon_{it} \quad \text{with } \phi_t(m_{it}, k_{it}) = \beta_0 + \beta_k k_{it} + \beta_m m_{it} + \omega_t(k_{it}, m_{it}). \tag{2}$$

Since $\varepsilon_{it}$ has zero unconditional mean, $E[\varepsilon_{it} \mid m_{it}, k_{it}]$ is also equal to zero. The difference between (2) and its expectation, conditional on raw materials and capital is given by:

$$y_{it} - E[\, y_{it} \mid m_{it}, k_{it}] = \beta_l(l_{it} - E[\, l_{it} \mid m_{it}, k_{it}]) + \beta_e(e_{it} - E[\, e_{it} \mid m_{it}, k_{it}\,]) + \varepsilon_{it}. \tag{3}$$

Equation (3) is estimated by OLS (without a constant term) -once the conditional expectations are obtained via locally weighted least squares (LWLS) regressions of output, employment and electricity plus fuels on $m$ and $k$- to obtain consistent parameter estimates for the variable inputs not correcting the simultaneity bias: $\beta_l$ and $\beta_e$.[9]Though the raw materials demand function, $m_{it} = m_t(\omega_{it}, k_{it})$ cannot be a function of unobservable plant-level

[8] Levinsohn and Petrin (2000) argue the estimation is valid under some imperfect competition structures, e.g., Cournot oligopoly with linear demand functions.

[9] Rather than restricting the functional form, we use a flexible data-driven approach to estimate the conditional expectations of the form $m(x_1, x_2) = E[Y \mid X_1 = x_1, X_2 = x_2]$. For any given pair $(x_1, x_2)$, a weighted linear regression of $Y$ on a constant term plus a second order polynomial on $(X_1, X_2)$ is estimated on the data

input prices, we partly address that restrictiveness by allowing it (as well as the productivity function resulting from its inversion and $\phi_t(m_{it}, k_{it})$ in (2)) to differ across two intervals. Cycles of growth in Colombian manufacturing output may give rise to different conditions in input markets, affecting input demands, e.g., through variation in unobservable input prices. So, $\phi_t(m_{it}, k_{it})$ is estimated separately across two intervals (1977-1983, a period of slow growth or stagnation and 1984-1991, a period of faster growth) as a LWLS regression of output net of the contribution of variable inputs (except the input controlling for the bias) $(y_{it} - \widehat{\beta}_l l_{it} - \widehat{\beta}_e e_{it})$ on $(m_{it}, k_{it})$.[10]

To obtain consistent estimates for $(\beta_m, \beta_k)$, we pursue a strategy whose crucial identification assumption is that capital may adjust to expected productivity, but does not adjust to an unexpected productivity shock, $\xi_{it}$, when productivity is assumed to follow a first order Markov process $\omega_{it} = E[\omega_{it}|\ \omega_{it-1}] + \xi_{it}$, with $\xi_{it}$ being independent identically distributed (i.i.d.). This stochastic productivity process has been used in models of industrial evolution and productivity estimation such as Olley and Pakes (1996) and Ericson and Pakes (1995). Two moment conditions are estimated by GMM. The first says that capital at $t$ is uncorrelated with the productivity shock at $t$. The second says that raw materials at $t-1$ is uncorrelated with the productivity shock at $t$. Both conditions hold conditioning out the expected part of productivity given lagged productivity. Given the Markov process followed by productivity, lagged raw materials, depending on lagged productivity and capital, satisfy also the other condition defining an instrument, i.e., being correlated with current raw materials. Taking the conditional expectation of (1) separately with respect to capital and to lagged raw materials and replacing productivity $\omega_{it}$ by its Markov process, we obtain:

$$E[y_{it} - \beta_l l_{it} - \beta_e e_{it} - \beta_m m_{it} - \beta_k k_{it} - E[\omega_{it} \mid \omega_{it-1}] \ \mid k_{it}] = E[\varepsilon_{it} + \xi_{it} \mid k_{it}] = 0, \qquad (4)$$

neighboring $(x_1, x_2)$. The bandwidth matrix is diagonal, with differing diagonal elements (corresponding to smoothing in $X_1$ and $X_2$ directions) according to Fan and Gijbels (1996, p. 47). The weighting kernel is a bivariate Normal density function, decaying fast enough to eliminate the weight given to points far from $(x_1, x_2)$. For each point $(x_1, x_2)$, the estimated conditional expected value, $\widehat{E}[Y \mid X_1 = x_1, X_2 = x_2]$, is the intercept of the LWLS regression. This regression is estimated as many times as there are points on a grid chosen to be exactly the sample.

[10]The time subscript in $m_t(.)$, $\omega_t(.)$, $\phi_t(.)$ is such that $t = t+1$ if $t < 1983$ (same function in 1977-1983); $t \neq t+1$ if $t = 1983$ and $t = t+1$ if $t \geq 1984$ (same function in 1984-1991). For the LWLS obtaining $\phi_t(.)$ estimates for each industry, weighting and smoothing are applied to data points observed before or in 1983 and data points observed in or after 1984.

$$E[y_{it} - \beta_l l_{it} - \beta_e e_{it} - \beta_m m_{it} - \beta_k k_{it} - E[\omega_{it} \mid \omega_{it-1}] \ \mid m_{it-1}] = E[\varepsilon_{it} + \xi_{it} \mid m_{it-1}] = 0. \tag{5}$$

The estimation algorithm starts from candidate OLS estimates $(\beta_m^*, \beta_k^*)$ and iterates on the sample moment conditions to match them to their theoretical zero value, reaching final parameter estimates. Our GMM criterion function weighs plant-year moment conditions by their variance-covariance matrix. The residuals in the moment conditions, $\varepsilon_{it} + \xi_{it}$, are obtained combining the estimated coefficients $(\widehat{\beta}_l, \widehat{\beta}_e)$ and an estimate for $E[\omega_{it} \mid \omega_{it-1}]$. The error $\varepsilon_{it}$ has zero unconditional mean, so it is uncorrelated with lagged productivity: $E[\omega_{it} + \varepsilon_{it} \mid \omega_{it-1}] = E[\omega_{it} \mid \omega_{it-1}]$ . The conditional expectation $E[\omega_{it} \mid \omega_{it-1}]$ is estimated by LWLS of $\widehat{\omega_{it} + \varepsilon_{it}} = y_{it} - \widehat{\beta}_l l_{it} - \widehat{\beta}_e e_{it} - \beta_m^* m_{it} - \beta_k^* k_{it}$ on lagged transmitted productivity $\widehat{\omega}_{it-1} = \widehat{\phi}_t(m_{it-1}, k_{it-1}) - \beta_m^* m_{it-1} - \beta_k^* k_{it-1}$. No year dummies are included at any stage of the estimation, temporal variation is accounted for by estimating different $\phi_t(m_{it}, k_{it})$ functions across two intervals. A derivative optimization routine is used, complemented by a grid search, given the existence of multiple minima for the weighted GMM criterion function in several industries. The final estimates minimize the criterion function under the grid or the derivative optimization routine. For all industries where minimizers result from the grid search, these are used as starting values in the derivative optimization routine to reach more precise final values for $(\widehat{\beta}_m, \widehat{\beta}_k)$.

In the estimation of alternative production function parameter estimates, closer to Olley and Pakes (1996), we obtain variable inputs' coefficients and the function $\phi_t(m_{it}, k_{it})$ estimating the following equation by OLS:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_e e_{it} + P_t(m_{it}, k_{it}) + \varepsilon_{it}, \tag{6}$$

where $\varepsilon_{it}$ is i.i.d. $P_t(m_{it}, k_{it})$, a fourth degree polynomial in materials and capital including all interaction terms, separately estimated across the periods 1977-1983 and 1984-1991 is the estimate for $\phi_t(m_{it}, k_{it})$. Raw materials and capital coefficients are obtained by the nonlinear minimization of the sum of squared errors from the equation:

$$(y_{it} - \widehat{\beta}_l l_{it} - \widehat{\beta}_e e_{it}) = \beta_c + \beta_m m_{it} + \beta_k k_{it} + P(\widehat{\omega}_{it-1}) + \eta_{it} \tag{7}$$

where $\eta_{it}$ is i.i.d..[11]

[11]OLS estimates are the initial values for the iterative search of the non-linear least squares estimation. $P(\widehat{\omega}_{it-1})$ is a fourth degree polynomial on $\widehat{\omega}_{it-1} = \widehat{\phi}_t(m_{it-1}, k_{it-1}) - \beta_m^* m_{it-1} - \beta_k^* k_{it-1}$. The estimate of $\phi_t(m_{it-1}, k_{it-1})$ is $P_t(m_{it-1}, k_{it-1})$ evaluated at the coefficients on the polynomial terms estimated in (6).

The standard errors for the production function coefficient estimates are bootstrapped as several estimated regressors are used more than once at different stages of the estimation.[12]

We make here a crucial remark regarding the concept of productivity obtained from the estimation procedure. Productivity is intangible and concerns the efficiency with which inputs are transformed into output, technical efficiency which can come through learning-by-doing, adopting newer and better methods of production, improving managerial practices, worker training, short run adjustments by plants to external shocks (changes in labor or capital utilization), omitted inputs such as expenditures in research and development, among others. We consider an encompassing concept of productivity incorporating all elements that increase the productive efficiency of inputs by more or less standard ways. An important part of the productivity measures may relate to capital utilization, as costs rise when plants operate below capacity. The use of electricity or raw materials to correct the simultaneity between input choices and unobserved productivity parallels its use to correct unobserved variation in labor and capital utilization, as in Basu (1996). So, productivity estimates may partly reflect changes in capital or labor utilization. The consideration of a broad definition of productivity is interesting for the analysis in section 5, as it gives trade policy more leeway to affect some or all the components of plant productivity.

## 3. Data

Our productivity analysis is based on plant-level panel data from the Colombian Manufacturing census provided by DANE (Colombian national statistical institute) for the years 1977 through 1991. Small plants (less than 10 employees) are included in the survey during 1977-1982, excluded during 1983-1984 and included as a small proportion of the sample after 1985. The unbalanced nature of the panel allows the identification of entering and exiting plants each year. Naturally, the concept of entry and exit are relative to the DANE survey

[12] Our specific bootstrap procedure consists of sampling randomly, with replacement, plants from the dataset, matching in any year the number of plants in the original sample. Each plant is taken as a block (i.e., all of the plant's observations are included in the bootstrap sample) if the plant is randomly selected, given that the estimation procedure uses a lag structure. The total number of observations differs across bootstrap samples. The estimation procedure is run for 100 bootstrap samples obtaining estimates of $(\beta_l, \beta_e, \beta_m, \beta_k)$ at each step. The standard deviation of a coefficient estimate across the different bootstrap samples constitutes the standard error for that coefficient. The procedure is computationally burdensome for the largest industries since where LWLS is used, for each observation in the industry sample, a regression is estimated with the sole purpose of obtaining the value of the constant term.

e.g., an entering plant may or may not represent a movement out of the informal sector. The survey covers extensively formal production in the Colombian industrial sector.

For each plant and year, the survey collects data on production and sales revenues, value added, input use (labor categories, raw materials, electricity, fuels), inventories, investments (buildings, machinery, transportation, office, land), exports (from 1981 to 1991), plant ownership type, location, 3 and 4-digit ISIC industry code, a plant identification number and year of start-up operations (plant age). Capital stock measures are constructed according to the perpetual inventory method for each plant and each of five types of capital. Several corrections are implemented to obtain a satisfactory capital stock variable. Nominal variables in current pesos are converted to 1980 pesos by the corresponding price deflator.[13] The selection of observations, from the original total of 102,911, is based on different types of data problems such as incomplete series or zero values of output, employment, intermediate inputs, capital or clear reporting errors. Further observations are eliminated given their ambiguous industrial classification, as productivity estimation is done at the level of the industry, to reach a final sample of 97,107 observations when materials controls for the correlation between input choices and unobservable productivity.

A large degree of plant-level heterogeneity is found for plant size, ownership type, location, age, output and inputs (labor, capital, raw materials, electricity and fuels).[14] For output and inputs, standard deviations are more than twice the size of means across all industries. The distribution of plant size is relatively stable over time, with plants with less than 50 employees representing over 70 percent of the manufacturing sector in any given year. The geographical distribution of plants is concentrated in the regions around Bogota, Cali and Medellin (over 62 percent of plants). The median plant age increases from 10 to 14 years between 1977 and 1991.[15] The major manufacturing industries in Colombia, accounting in any year for more than half of the plants are food, apparel, textiles, printing,

[13]We thank Mark Roberts (Penn State University) for providing us with output price indexes at a 3-digit ISIC level (28 industries) that are used to deflate plants' nominal sales generating plant-level output values. The procedure of deflating sales by industry price indices is not innocuous, as Klette and Griliches (1995) point out, but is the more correct in the absence of plant-level price data. Specific price indexes from the Colombian Central Bank are used to deflate the different types of capital and intermediate inputs.

[14]The sample statistics discussed here and the results in sections 4.1-4.2 refer to the sample with materials. Further comments and results can be found in the Data Appendix, available from the author upon request.

[15]Curiously, the age of entering plants is not always zero years. Many entrants are in operation previous to entry, but are not included in the survey. This may be interpreted as evidence of the importance of the informal manufacturing sector in Colombia.

nonmetallic minerals and metal products. The distribution of plants across industries is relatively stable over time, but there is significant entry and exit in various industries. Average entry and exit rates into manufacturing during 1977-1991 are 11.4% and 9.8%, respectively. The cohorts of entrant and exiting plants contribute only a small percentage to total output produced, are much smaller than incumbents and have lower labor productivity. Average entry and exit rates are computed across industries and periods: trade liberalization (1977-1981), increased trade restrictions (1981-1985), early trade liberalization (1985-1988), and further trade liberalization (1988-1991). For most industries, entry increases from 1977-1981 to 1981-1985 and from 1981-1985 to 1985-1988, but decreases from 1985-1988 to 1988-1991. For most industries, exit decreases continuously between 1977-1981 and 1988-1991. These findings on unconditional exit rates are contrary to trade liberalization leading to significant industry contraction. Years of high entry are also years of high exit, so there is divergence of outcomes for plants within an industry during the same period.

# 4. Results from Estimation

## 4.1 Production Function Estimates

In this section, we discuss the results from the estimation procedure described in section 2, as well as those from OLS and fixed effects, presented in Table 1 and Figure 1. Plants in different industries operate with different technologies, so production functions are estimated separately across a slightly modified 3-digit level industry classification.[16] In Table 1, the labor coefficients by nonparametric/GMM estimation are higher in industries generally characterized as labor intensive, e.g., ceramics. Most variable inputs' coefficients are precisely estimated in all industries. If more employees are hired and more electricity plus fuels are consumed in periods of high productivity, OLS estimates of variable inputs' coefficients would be upwardly biased. In Figure 1, the coefficients from OLS and nonparametric/GMM estimation are plotted for all industries and inputs in descending order of the nonpara-

[16]Less than 1% of plants in the original sample are classified in different industries across years. All of a plant's observations enter production function estimation for a single industry, since the procedure uses lagged inputs. So, we reclassify plants into the industry to which they belong in the majority of years and eliminate plants for which no majority industry is identified. The pairs food plus food-miscellaneous, textiles plus apparel, wood products plus furniture are considered as three industries (instead of six) for estimation, as too many plants belong equal numbers of years to the two industries in the pair. Moreover, it is plausible to consider production processes to be similar for each of these industry pairs.

metric/GMM coefficients.[17] Figures 1(a)-(d) allow us to conclude that in most Colombian industries, OLS estimates of the contribution of labor and electricity plus fuels to output are higher than those obtained with materials as the instrument to correct the simultaneity bias. One can expect a similar type of bias on the OLS raw materials' coefficient relative to that by nonparametric/GMM estimation, as it is also a variable input. In fact, figures 1(e)-(f) show that the OLS raw materials coefficient is upward biased in most industries. The estimated capital coefficient covers the widest range of values across industries and is not precisely estimated in over half the industries. But among the larger Colombian industries, capital is significant except in food plus food-miscellaneous and nonelectrical machinery. On the one hand, capital is a quasi-fixed input that may be correlated with current expected or lagged productivity, so an upward bias in the OLS estimate is possible. This is entirely consistent with the identification assumption in the estimation, that capital does not adjust to unexpected productivity shocks. But on the other hand, if capital is uncorrelated with expected productivity, the positive bias in OLS variable inputs' coefficients may be transmitted into a negative bias in the capital coefficient, if capital and variable inputs are positively correlated. Figures 1(g)-(h) show that in half the industries, the OLS capital coefficient is higher than that obtained by nonparametric/GMM estimation, whereas in the other half the OLS coefficient is lower. A test for constant returns to scale from nonparametric/GMM estimates is rejected only in printing and rubber products. Naturally, these estimates are lower than OLS returns to scale for a large majority of industries.

A novelty of our study is that we can assess the robustness of results from our main estimation method. The coefficients obtained by polynomials/NLLS estimation do not differ much from those obtained by nonparametric/GMM estimation. In fact, in several intermediate and capital goods industries, the capital coefficient is almost identical under both estimation methods.

The comparison of parameters obtained by nonparametric/GMM estimation to average input revenue shares is interesting, as the productivity literature often uses Solow TFP residuals, that assume the contribution of an input to production is equal to that input's revenue share. Labor and electricity plus fuels revenue shares are lower than estimated coefficients in

[17]In Table 1 we indicate the total number of observations in the industry used for OLS and fixed effects estimation. Nonparametric/GMM estimation uses lagged variables so the actual number of observations is smaller. OLS and fixed effects estimates with the smaller number of observations are very similar.

most industries, whereas capital revenue shares are higher than capital coefficients.[18] Raw materials revenue shares are lower than estimated coefficients in half the industries. All results hold if the comparison is made to median input revenue shares. Using Solow residual productivity measures, we would introduce unnecessary biases in the estimated relation between plant productivity and trade policy.

In most industries, fixed effects estimates for labor, electricity plus fuels and raw materials coefficients are smaller than nonparametric/GMM estimates. In half the industries, the fixed effects capital coefficient is larger than the nonparametric/GMM. These results are expected, as downward biases due to measurement error in inputs are exacerbated with fixed effects estimates, obtained from within-plant variation in output and inputs.

We estimated production functions for a different sample, with electricity as the instrument to correct the simultaneity bias, since electricity is also an input relatively easy to adjust to changes in productivity.[19] But we prefer using the estimates obtained with raw materials controlling for the bias to conduct the analysis of productivity and its link to trade policy. In contrast to Levinsohn and Petrin (2000), materials is a good choice for the Colombian dataset because information on materials use, not just purchase, is available, capturing storage or running down of materials' inventories, possibly correlated with year-to-year variations in productivity. Also, across industries, the number of plants reporting use of raw materials is larger than that of plants reporting use of electricity.

## 4.2 Industry and Plant-Level Productivity Estimates

In this section, we briefly analyze the dynamics of productivity across Colombian industries, mainly to investigate the changes in productivity across trade regimes. We construct different measures of logarithmic productivity for the two estimation methods depending on whether a TFP measure or a no-shock productivity measure (excluding a non-forecastable

[18]For any industry, average and median input revenue shares are taken across all plants and years. The capital revenue share is obtained as one minus the share of labor, electricity plus fuels and raw materials.

[19]With electricity, equation (1) has variable inputs labor, raw materials plus fuels and electricity. The main findings are similar to those with materials and are provided in the Data Appendix. Namely, the OLS estimates of labor, raw materials plus fuels and electricity coefficients are higher than the nonparametric/GMM estimates in most industries and in half the industries have an upwardly biased OLS capital coefficient relative to the nonparametric/GMM estimate. Most coefficients are close whether obtained by polynomial/NLLS or by nonparametric/GMM estimation, except the coefficient on the instrument correcting the simultaneity bias, electricity. For several industries, the coefficients on labor and capital obtained by nonparametric/GMM differ depending on the instrument used to correct the bias. That is expected as electricity and raw materials control for the endogeneity of variable inputs at different degrees.

productivity shock) is considered. From equation (1) evaluated at parameter estimates, the TFP measure is given by $\widehat{\omega_{it}+\varepsilon_{it}} = y_{it} - \widehat{\beta}_l l_{it} - \widehat{\beta}_e e_{it} - \widehat{\beta}_m m_{it} - \widehat{\beta}_k k_{it}$. The no-shock productivity measure results from combining the estimated $\phi_t(m_{it}, k_{it})$ with the estimated capital and materials coefficients: $\widehat{\omega_{it}} = \widehat{\phi}_t(m_{it}, k_{it}) - \widehat{\beta}_k k_{it} - \widehat{\beta}_m m_{it}$. There is consistency across productivity measures: TFP and no-shock productivity obtained by nonparametric/GMM and polynomials/NLLS estimation are significantly positively correlated. In Table 2, the contribution of the variance of $\widehat{\omega_{it}}$ to the variance of $\widehat{\omega_{it}+\varepsilon_{it}}$ is presented for each industry and both estimation methods, to identify the major source of cross-plant variation in productivity. The variance of no-shock productivity contributes on average 60 percent to the variance of TFP for the measures resulting from nonparametric/GMM estimation.

A measure of productivity in industry $j$ and year $t$ is given by an output-share weighted sum of plant-level productivities, $\Omega_t^j = \sum_{i=1}^{N_{jt}} s_{it}^j \omega_{it}^j$, where $\omega_{it}^j$ and $s_{it}^j$ represent plant $i$'s productivity and market share in industry output in year $t$, respectively, and $N_{jt}$ represents the number of plants in industry $j$ in year $t$. From these measures, we compute year-to-year industry TFP growth rates from nonparametric/GMM estimation, for which a large degree of heterogeneity is found: short periods of productivity growth alternate repeatedly with short periods of productivity decline. For most industries, these industry TFP growth rates are very similar to those from polynomials/NLLS estimation. The frequent changes are not always associated in a consistent way with the swings in trade policy directed at those industries. This emphasizes the importance of considering an impact of trade policy on plant productivity.

Changes in productivity are calculated over two sample subperiods to find the 'procyclical' or 'countercyclical' nature of industry productivity relative to aggregate manufacturing output. An industry is characterized by 'procyclical' productivity if during 1977-1983 productivity grows by less or declines by more than it grows or declines, respectively, during 1984-1991, or if it declines during 1977-1983 and grows during 1984-1991. Most industries are characterized by procyclical productivity, except beverages, leather products, printing, plastics, nonelectrical and electrical machinery and professional equipment.

We compare our industry productivity growth rates from nonparametric/GMM estimates to those obtained by M. Roberts in Worldbank (1991) for the same Colombian dataset (1977-1987). Roberts obtains TFP Tornqvist index numbers, using industry-level inputs, output and input cost shares, assuming constant returns to scale and computes productivity growth rates for 3-digit industries. These growth rates differ much from ours derived from nonparametric/GMM estimates. One of the reasons for this divergence is the difference in methods to compute industry productivity, consistent measures versus Solow residual calculation. Another reason for the divergence is the type of aggregation (even when productivity is computed by a similar method): obtaining growth rates at the level of the industry or at the level of the plant aggregated as a weighted sum to the level of the industry.[20]

Given the skewness in the size distribution of all Colombian industries, movements of output across plants with different productivity may affect industry productivity levels and changes. So, we follow Olley and Pakes (1996) to decompose industry TFP levels into unweighted average productivity and a covariance between plant productivity and output share: $\Omega_t^j = \bar{\omega}_t^j + \sum_{i=1}^{N_{jt}} (s_{it}^j - \bar{s}_t^j)(\omega_{it}^j - \bar{\omega}_t^j)$,where $\bar{s}_t^j$and $\bar{\omega}_t^j$represent industry average output share and average productivity, respectively. The covariance is positive in all years in all but four industries, i.e., the allocation of output is such that more productive than average plants have higher than average output shares.[21] Deriving the corresponding decomposition of industry productivity changes, we identify whether industry productivity growth is driven by growth in unweighted average productivity or by the reallocation of output to more productive plants. Across industries, short periods when more productive plants are allocated increased shares of output repeatedly alternate with periods when the reverse occurs. So, in some years and industries, output reallocations from less to more productive plants drive productivity growth, rather than the unweighted average productivity growth.[22] A sustained reallocation of output to less productive plants occurs in paper (1982-1990) and transport equipment (1978-1986). Curiously, these periods cover both years of tightened trade restrictions and years of tariff declines. In most years, only half the industries undergoes

[20]In fact, we obtain plant TFP Tornqvist index numbers and aggregate plant productivity growth rates to the industry level using output-share weights, as with our nonparametric/GMM measures. These productivity growth rates are very different from those calculated by Roberts.

[21]Food, food-miscellaneous, glass and iron and steel have an allocation of output accrues disproportionately to less productive plants in some years. This phenomenon could be partly due to industry regulation. Interestingly, in most years when the covariance is negative, capital is also disproportionately allocated to less productive than average plants.

[22]We also compute for each industry and year, the percentage of plants experiencing an increase in productivity, to find whether plant productivity uniformly increases when industry productivity does so. Often, industry productivity increases despite declines in productivity of a majority of plants. We state these results with confidence, as standard errors for the changes in plant productivity indicate that these are significantly positive or significantly negative for more than 99 percent of observations.

productivity-enhancing output reallocations. But, during 1980-1982, output is reallocated to more productive plants in most industries and during 1982-1983 and 1990-1991, the opposite occurs. Trade protection may permit an inefficient reallocation of resources (e.g., output) from more to less productive plants. So, it is interesting to note that Colombian trade barriers were liberalized in most industries at different degrees until 1982, whereas they were substantially tightened between 1982 and 1983.

Overall, our results point to some heterogeneity in productivity growth across industries over time. The possibilities for technological progress vary across Colombian industries and that is reflected in divergent patterns for industry productivity. The analysis in the section that follows captures one of the reasons for this heterogeneity, variation in trade policy. Also, there is evidence of intra-industry heterogeneity: at a given point in time, some plants experience a different evolution of productivity than that of industry productivity. This finding reinforces the need to use plant-level data for an accurate analysis of trade and productivity, as industry data masks differences in plant behavior.

## 5. Trade and Productivity

In this section, we analyze the impact of trade protection on manufacturing plants' productivity. There are several means by which trade liberalization may impact firm or plant productivity levels and growth. First, Levinsohn (1993) argues that as imports expand, the increased competitive pressure felt by domestic producers can be transmitted into higher productivity (the 'imports-as-market-discipline' hypothesis). In face of lower trade protection, producers are forced to modernize and cut costs to remain competitive vis-a-vis foreign producers. Development economists believe that trade protection seriously damages the industrial sector productive efficiency, by tolerating high levels of 'X-inefficiency' among producers in import-competing industries. Vousden and Campbell (1994) examine the efficiency of a firm with internal informational asymmetries and show that trade protection induces slack, by reducing competition. All these arguments are consistent with our results below, that Colombian plants' productivity improves in face of trade liberalization. In contrast, limited, selected protection and moderate import penetration could allow for productivity gains in infant industries, initially high cost industries, where learning-by-doing plays a role. Second, trade liberalization may affect plant performance by allowing for increases in imports of capital goods and intermediate inputs, embodying technologies unavailable in developing countries, that contribute to reduced costs and productivity gains. Also, trade liberalization may allow for technology diffusion, as producers learn from technologies embodied in the increasingly available imported final goods, as well as from exporting. In fact, previous studies and government agencies in Colombia attribute weak industrial productivity in the early 1980s to existing trade protection mechanisms that reduced the incentives to invest in technological innovation (e.g., Zerda (1992)). Models that examine investment in productivity improvement, such as technology acquisition have opposite predictions. These models consider only protection to imports of final goods and do not specify whether this technology is domestic or imported. Goh (2000) focuses on the opportunity cost of acquisition and implementation of new technology. As protection raises the foregone profits from delayed commercialization of the plant's output (the opportunity cost), it reduces the incentive for a producer to engage in technological effort to improve productivity. Rodrik (1991) finds that the degree of trade protection received by a firm can raise its level of investment in technological upgrading, when the incentive to invest in cost-reducing technologies depends on the firm's market share (possibly) reduced by trade liberalization. Traca (1997) analyzes the impact of competition from imports on investments in productivity improvement in the context of a monopolistic domestic market. When the direct effect from import competition (as plant output and imports are substitutes, demand and output decline) dominates the pro-competitive effect (the plant's market power and markup decline, so output increases), plant productivity worsens given that investments in productivity improvement increase with plant output. The evidence for Colombia agrees with Goh (2000) and Traca (1997) when the pro-competitive effect dominates.[23]

## 5.1 Colombian Trade Policy

The selected empirical framework has to account for the significant swings in Colombian trade policy during the sample period.[24] Frequent changes occurred in the instruments used

[23]The exploitation of scale economies is often cited as another means by which trade liberalization leads to plant and industry-level productivity gains. In our setting, we only capture intra-plant improvements unrelated to scale economies across industries, as those are embodied in our productivity measures.

[24]See Lopez and Castro (1987), Garcia (1988), World Bank (1984, 1989, 1991) GATT (1990) and Garay (1991) on Colombian trade policy.

by authorities: a foreign exchange budget for import expenditures, prior import deposits, tariffs and quantitative restrictions in the form of an import licensing system, whereby each item in the tariff code was classified into one of three regimes (free import list, prior-licensing, prohibited import list). During the sample period, Colombian trade protection was characterized by a large dispersion in tariff levels and a cascading tariff structure: lower tariffs on raw materials and intermediate inputs not produced domestically and higher tariffs on consumer and finished products produced domestically.

Until 1981, import barriers were decreased, the average tariff declined to around 26 percent in 1980. In 1981, the proportion of items under the free import regime (69 percent) was 16 percent higher than in 1978. An interesting feature of this liberalization was that it essentially responded to exchange rate pressures due to an increase in world coffee prices, government foreign borrowing and illegal drug trade, so it favored a larger decrease in protection of sectors with larger response elasticities. The liberalization was strong for tobacco, some intermediate goods and raw materials, (e.g., nonmetallic products) but weak for beverages, textiles, wood and furniture. Strong real exchange appreciation, hurting producers in tradable goods sectors, combined with a world recession, lead to a reversal of liberalization starting in 1982, with a significant increase in trade restrictions. Tariffs increased for all items three times between 1982 and 1984, reaching a 41 percent average in 1984. A large number of items was transferred to the prior-licensing list, the importance of the free list decreased from 36 percent of items in 1981 to 0.5 percent in 1984.[25] The prohibited import list was reactivated in 1984 and all manufacturing was covered by import restrictions. The more protected sectors were non-durable and durable consumer goods with average tariffs of 70 and 62 percent in 1984, 13 and 11 percent higher than in 1983, respectively. After 1985, a gradual shift to trade liberalization occurred. In 1985 and 1986, the major goal was an 'administrative rationalization' of the structure controlling imports; 36 percent of items were free imports in 1986. Reductions in tariff rates and dispersion proceeded in 1987. In 1988, the average tariff (27 percent) was 15 percent below that in 1985, unrestricted tariff items represented 38 percent of total imports and only 82 percent of manufacturing was covered by import restrictions. The priority in the elimination of protective distortions were capital

[25]Also, the number of approved requested import licenses (30 percent of total licenses requested in 1980, only 2.5 percent in 1984). This feature challenges the fully correct measurement of trade policy, as data on licenses' approval is unavailable.

goods and intermediate goods. But, important reductions in tariffs occurred in all sectors.

Broad trends in trade orientation across industries are presented in Table 3.[26] Most industries experience a decrease in import penetration between 1980 and 1984 and 1984 and 1985, and an increase between 1985 and 1988, continuing onto 1991. But in 1991, less than half the industries have import penetration ratios higher than in 1980. Export orientation declines for most industries between 1980 and 1984, partly due to increased restrictions and mostly due to a real exchange rate (RER) appreciation, then increases between 1984 and 1985, and between 1988 and 1991. For most industries, export orientation in 1991 is higher than in 1980. The pattern of trade policy in Colombia makes it an interesting case to identify the dynamics of plant productivity adjustment to *trade policy changes*.

## 5.2 Trade Policy Measures: Correlations

A challenge to the empirical analysis of trade and productivity is that commercial policies and trade openness are not fully described by a single variable. The use of trade policy measures or trade volumes has advantages and drawbacks. Edwards (1998) criticizes the use of trade volumes, which are not necessarily related to the actual trade orientation of a country. Tariff levels or quota coverage reflect the degree of government intervention, the protection at the sector level and are better suited to capture a significant opening of trade policy that raises productivity, without being reflected in trade volumes. But export orientation and import penetration ratios are also valuable, by reflecting how important foreign consumers and producers are to domestic producers. In Table 4, we relate levels and changes of different measures of trade exposure to trade, to check the consistency of the measures in indicating the relative openness of industries and the evolution of protection over time.[27] High tariffs and effective rates of protection (ERP) are associated with low import penetration into 3 and 4-digit industries but not clearly related to export orientation

[26]Export orientation ratios are the ratio of exports to total output (domestic output plus exports). Import penetration ratios are the ratio of imports to domestic demand (domestic output plus imports).

[27]Tariff levels at 2, 3 and 4-digit ISIC levels were obtained from J. G. Garcia at the World Bank (for 1976, 1978, 1980, 1983-1988) and from Colombia's National Planning Department (DNP) 3-digit ISIC level (for some of those years plus 1979, 1989 and 1990). The two data sources provide slightly different values for tariffs in the common years for some industries. Effective rates of protection at a 3-digit ISIC level were obtained from DNP (for years 1979, 1983, 1984, 1989, 1990). A report with coverage of domestic production by import licenses in 1989 was obtained from the World Bank. Imports and exports at 3 and 4-digit ISIC levels were obtained from J. G. Garcia (for 1980-1991).

(Table 4a).[28] Reductions in tariffs or ERP are weakly associated with increases in import penetration and decreases in export orientation (Table 4b). Across different trade policy regimes (between liberalization in 1980, protection in 1983 and liberalization in 1988), tariff reductions are weakly associated with reductions in import penetration (Table 4c). Between protection in 1984 and liberalization in 1990, reductions in ERP are weakly associated with increases in import penetration (Table 4d). In the years of available 3-digit tariffs and ERP data, the corresponding levels and changes are highly correlated (Table 4e). This finding is also verified across different trade regimes (Table 4f). We find that a different group of Colombian industries experiences the largest relative increase or decline in protection between 1980 and 1984 and between 1984 and 1990 depending on how trade exposure is measured. This finding is similar to that by Tybout and Westbrook (1995) for Mexican industries (1984-1990). Licenses that limit imports of some items across tariff lines are an important instrument in Colombian trade policy during the sample period. These would ideally be measured by tariff or price equivalents. Unfortunately, only data for coverage ratios of domestic production by import licenses is available for the year 1989.[29] These measure imprecisely the restrictiveness of import barriers, providing no indication of which licenses are truly binding or are issued automatically.[30] In 1989, prior licenses, tariff and ERP levels are highly correlated (Table 4g). In Worldbank (1989, 1991) it is argued that Colombian tariffs are higher for the commodities subject to import licenses. Even if licenses are important, tariffs place a minimum bound on the protection of items for which licenses are the binding constraint on imports. So the finding of an impact of tariffs on productivity would be strengthened by the use of quantitative restrictions measures.

[28] The ERP for a given industry is obtained by subtracting from the tariff on the final good, a weighted average of tariffs on inputs (according to their contribution to total costs).

[29] The coverage ratio indicates the percentage of domestic production for which competing imports are subject to licensing restrictions.

[30] In fact, during the sample period, some tariff items are kept in the prior import list for government control of over and underinvoicing of imports, but are in fact freely importable. Also, a foreign exchange budget is rationed among importers through import licenses. So, the degree to which import restrictions are binding is variable, depending on the availability of foreign exchange. This uncertainty for producers of import substitutes likely raises the protective effect of the trade barriers.

## 5.3 Endogeneity of Trade Policy

Consider the following specification:

$$\omega_{it}^{j} = \beta_0 + \lambda_t + \beta_1 TP_t^j + I^j + u_{it}, \tag{8}$$

where $\omega_{it}^{j}$ is a measure of plant productivity comparable across industries, $TP_t^j$ is a measure of trade policy varying over time and across industries, $\lambda_t$ are year effects and $I^j$ are fixed industry effects. Using (8) to analyze the link between trade policy and productivity assuming that $TP_t^j$ is exogenously given to plants can be subject to an endogeneity problem. That is the case if government authorities change trade policy in response to political pressures by specific industries or, alternatively, if they change it to adjust to different industries' relative productivities or both, if political pressures for lower import quotas and higher tariffs come from industries with productivity disadvantages where inefficient influential firms lobby successfully for protection.[31] In such cases, a negative $\beta_1$ does not unambiguously show that trade protection harms productivity but rather it shows that industries with a productivity disadvantage obtain higher protection by lobbying the government.[32]

We could instrument trade policy with political economy determinants of protection, to address the endogeneity problem. But most political economy models, such as Grossman and Helpman (1994) empirically tested by Goldberg and Maggi (1999), predict cross-sectional patterns of protection. We would need a dynamic model with simultaneous determination of protection and economic performance (productivity) to provide instruments for time-varying cross-sectional patterns of protection. Developing the mechanism by which trade policies are endogeneized is beyond our scope in this paper. Moreover, most of the covariates of protection in such models cannot be used in the Colombian case due to lack of data.[33]

[31] There could be a distinction between productivity disadvantages relative to foreign competitors or relative to domestic industries. Pack (1994) considers trade policy adjusting to cost disadvantages (value-added labor productivity) of domestic industries relative to potential foreign competitors to test the importance of this infant industry argument in explaining a cross-section of ERP on Indonesian manufacturing.

[32] To find whether trade policy adjusts to relative productivities, nominal tariffs for 3 and 4-digit industries (1980, 1983-1988) are regressed on average industry productivity. We find a negative and significant impact of average productivity on tariffs. More insight is gained by testing Granger causality between average productivity and tariffs. Average productivity (3 and 4-digit industries) is not significant in explaining contemporaneous tariffs, once lagged tariffs are controlled for. This finding is true with further lags of tariffs and further lags of average productivity.

[33] Nevertheless, we follow Trefler (1993) adapting to our panel setting his cross-sectional equation explaining U.S. nontariff barriers with variables from political economy models regarding political economy pressures and the propensity of industries to get organized. Tariffs for 3-digit industries depend negatively on Herfindahl indices and total capital, positively on total employment and a proxy for minimum efficient scale and not

An examination of the political economy of tariff policy in Colombia enables us to argue that endogeneity is unlikely to be a problem for our trade policy measures. Political economy pressures in Colombia are important during the sample period, but widespread across industries. Regarding the 1977-1981 liberalization, Urrutia (1994, p. 290) states that "opposition from industrialists was strong and unanimous since most saw a protected national market as a source of growth." Since the import substitution industrialization strategy followed in Colombia in the 1950s, producers expected government protection from outside competition. Several authors emphasize that movements in tariffs are cyclical, driven by macroeconomic conditions for short-run stabilization purposes. Urrutia (1994, p. 297) argues that until the 1980s, "trade liberalization [was] stimulated by a desire to control money supply and inflation without an export-destroying revaluation." Hallberg and Takacs (1994) argue that "import controls [were] alternatively tightened or eased to smooth out aggregate expenditure in response to external payment deficits [1982-1984] or coffee booms [1977-1981]." Across any two years, we find that tariffs move almost uniformly in the direction of increase or decrease, though the magnitude of changes varies across industries. This evidence sustains our claim that the government is not asymetrically changing tariffs of the least productive industries in response to their possible lobbying pressures. The differential changes in tariffs across industries are mostly due to the interest in changing more strongly the tariffs on goods with higher demand elasticities, so that imports increase (1977-81) or decline (1982-84) more rapidly. For most of our sample period, there is no evidence that trade policy adjusts to relative productivities. Garcia (1988, p. 168) argues that "import liberalization was not (...) a way to accelerate the country's rate of growth or to improve the allocation of resources." Urrutia (1994, pp. 304-305) points out though, that in 1990 the official justification for trade liberalization by DNP was that the "economy [needed] a major shake-up to start achieving

significantly on changes in output and changes in import penetration. Tariffs for 4-digit industries depend negatively on changes in output, changes in import penetration and total capital, positively on total employment and not significantly on Herfindahl indices and scale. Justifications for the covariates are found in Trefler's paper (pp. 141-142), we comment only on a few coefficients. The coefficient on total employment is expected if a larger labor force bringing more votes leads to higher protection. The coefficient on total capital is expected if entry barriers restrict domestic and foreign entry, decreasing the required level of protection. The sign of the coefficient on output growth in 4-digit tariff regressions is expected if protection is progressive in aiding disadvantaged industries as they face lower opportunity costs of lobbying. The regressions are augmented with average productivity. The results on all other regressors are unchanged and a negative coefficient on average productivity is found. But, most of the instruments above exhibit weak time variation, so they are not helpful in correcting the potential endogeneity of protection.

greater productivity growth and efficiency." Also, by the end of the 1980s, exporters became a strong pressure group and most industrialists realized that the internal market was not a dynamic source of growth and protection had high costs, such as the necessity to produce an inefficiently large range of products.

In our approach, we consider the impact of lagged trade policy measures on plant productivity. This partly circumvents the endogeneity problem of contemporaneous trade policy and also addresses Tybout's (1992) concern that uncertainty about the sustainability of trade policy changes delays the resulting change in productive efficiency.[34] This uncertainty may be relevant in Colombia, given the frequent changes in trade regime. Moreover, even without policy uncertainty, plants require time to adjust their production processes to changing trade protection. We are aware though, that the dynamic structure may be more complex than just one-period lagged tariffs affecting productivity.

## 5.4 Impact of Nominal Tariffs

Our plant-level dataset is a valuable source to examine how trade policy affects plants' technological performance. We do not identify trade liberalization from a before-after change in plant behavior, a shortfall of most studies of trade and productivity. Rather, we consider empirical specifications exploiting time-series and cross-industry differences in trade policy and trade volumes, to analyze how differences in trade policy across sectors shape the variation in plant productivity. We focus in this section on nominal tariffs. Technology (via production function parameters) differs across industries. But as productivity is associated with a specific technology, it is not comparable across industries. We follow Aw, Chen and Roberts (2001) and Pavcnik (2000) to obtain a relative productivity measure, comparable across years and industries. For each plant in an industry, relative productivity is the difference between the plant's productivity and productivity of an average plant in 1977. The average plant in 1977 in an industry has average (logarithmic) output, average (logarithmic) inputs which combined with estimated parameters, discussed in section 4.1, give an average

[34]Uncertainty about the sustainability of trade policy changes might actually strengthen the impact of trade policy on productivity rather than weaken it, e.g., if producers choose more flexible labor-intensive production techniques, not the most cost-efficient in the absence of uncertainty (Lambson (1991)). Lopez and Castro (1987) believe the instability in Colombian tariffs before 1985, translating into variability of imported raw materials' prices, had adverse consequences for the manufacturing sector, making production planning difficult and leading plants to choose less efficient combinations of inputs, harming productivity.

TFP level. We estimate pooled regressions including plants in all industries as follows:

$$\omega_{it}^{j} = \beta_0 + \lambda_t + \beta_1 TP_{t-1}^{j} + I^j + u_{it}^{j}, \tag{9}$$

where $\omega_{it}^{j}$ is TFP relative to an average plant in 1977, $TP_{t-1}^{j}$ is a lagged trade policy measure at 3 or 4-digit industry levels, year dummies $\lambda_t$ capture common shocks to productivity (e.g., macroeconomic factors or overall technological progress) affecting plants in all industries and $I^j$ is an indicator of the 3 or 4-digit industry the plant belongs to. The error $u_{it}^{j}$ is i.i.d. across plants and years in OLS specifications, and includes unobserved permanent plant effects in fixed effects specifications.[35] The results from estimating equation (9) are presented in Table 5, for OLS estimation with robust standard errors, correcting for possible heteroskedasticity and for plant fixed effects, with lagged 3 and 4-digit level tariffs. Changes in the macroeconomic environment in any year affecting equally plants in all industries are accounted for by year effects, included in all specifications. Our coefficient of interest, $\beta_1$, is negative and precisely estimated for more and less disaggregated tariffs. When including industry effects, our estimates reflect the impact of trade policy on plant productivity levels within industries, as productivity differences across industries are controlled for. Controlling for a possible correlation of the disturbance term within a plant over time, we also find a negative precisely estimated impact of tariffs on productivity. In columns (5) and (10), industry effects are identified of changes in plant classification across 4-digit industries. Tariffs are measured in fractional terms, so a percentage point reduction in nominal tariffs changes logarithmic productivity by $\beta_1$ percent. For example, column (7) implies that reducing 4-digit industries' tariffs by 10 percentage points leads to an increase in logarithmic plant productivity of almost 3 percent and in plant productivity of almost 20 percent. These results provide strong support for the hypothesis that plants in industries less protected from foreign competition exhibit, with other things equal, higher productivity. The coefficients on tariffs are systematically more negative for more disaggregated tariffs. As the number of observations differs using 3 or 4-digit tariffs, due to unavailable tariff data for some 4-digit

[35]The time subscripts in (**??**) and all equations to follow need a careful interpretation. Plant productivity $\omega_{it}^{j}$ is affected by tariffs $TP_{t-1}^{j}$, where $t$ and $t-1$ are consecutive sample years. But in the next pair considered (in chronological order), $\omega_{i\tau}^{j}$ and $TP_{\tau-1}^{j}$, $\tau-1$ may be larger than $t$, not equal to $t$, if tariffs at $t$ are unavailable (but a one-year-distance exists from $t-1$ to $t$ and from $\tau-1$ to $\tau$). For example, plant productivity in 1981 is affected by tariffs in 1980, but the next pair is productivity in 1984 and tariffs in 1983, as tariff data in 1981-1982 is not available.

industries (for disclosure reasons), we reestimate all regressions with 3-digit tariffs and the 4-digit tariffs' sample and find tariff coefficients close to those in columns (1)-(5).

In order to obtain as accurate an impact of trade policy on plant productivity as possible, we introduce further plant-level control variables that may exert an independent effect on productivity. But we deliberately leave much heterogeneity in plant productivity unexplained, as our interest is only in one factor affecting productivity: changes in trade policy. There is theoretical and empirical evidence of a link between plant productivity, age and exit.[36] Plant productivity increases with age if learning-by-doing effects or improvements in the workforce quality are important, if plant size increases as plants age and productivity-improving economies of scale are achieved or if older plants manage to modernize their capital. The relation between productivity and age may actually be concave, productivity increasing rapidly for younger plants, then slowly for older plants. Equation (9) is augmented to include plant age, age squared and an indicator for plant exit (a variable equal to one in the last year of plant presence in the sample) and the results from estimation are presented in Table 6. In all specifications, productivity increases with age at a decreasing rate. The coefficient on exit is positive in OLS specifications without industry effects, but negative controlling for industry unobservables, in both cases insignificant. Exit may be proxying for the clear separation of industries into high and low turnover. Interestingly, once omitted plant characteristics, possibly affecting exit and productivity are controlled for, exit is negatively associated with productivity with a precise estimate. One could conjecture the productivity gains associated with tariff declines shown in Table 5, reflect large numbers of less efficient plants going out of business in face of decreased trade protection. The results in Table 6 suggest otherwise, as the impact of tariffs on productivity remains negative and significant when plant exit is controlled for. But the specifications in Table 6 can be criticized given the likely endogeneity of exit with respect to productivity. To investigate further the importance of plant exit in the productivity changes in face of changes in protection, we decompose changes in industry productivity across tariff data years into changes in continuing plants' productivity, output share reallocation across continuing plants and a term representing the differences in productivity between cohorts of entrant and exiter plants. According to both types of decomposition presented in Appendix A, for all industries and years

[36] See, e.g., Campbell (1997), Power (1995), Jensen, McGuckin and Stiroh (2001).

(except professional equipment) the differences in entrants and exiter plants' productivity are not a major source of change in industry productivity, mostly due to changes in continuing plants' productivity. Also, we investigate how exit probabilities vary with trade policy, conditional on productivity. We consider a probit regression of plant exit on lagged tariffs and plant productivity.[37] We define trade regime periods relative to the liberalization period 1977-1981, as period 1 of protection 1984-1985 and period 2 of liberalization 1986-1989 and investigate how exit probabilities vary by trade regime, conditional on productivity.[38] The results from these specifications indicate that exit probabilities increase with tariff increases and are lower in both periods 1 and 2 relative to the 1977-1981 period. We take the probit results with caution, since plant productivity (obtained from our estimation) is measured with error therefore problematic to include as a right-hand side variable in the estimation. Overall not only does lower productivity of exiting plants contribute little to changes in industry productivity but also across industries exit probabilities do not increase in face of trade liberalization (this finding was mentioned also at the end of section 3). So it seems that the increased plant productivity associated with lower tariffs in Table 5, does reflects more within-plant changes in productivity than large numbers of less productive plants exiting industries in face of lower trade protection.

Variation in real exchange rates (RER) could confound the impact of protection on productivity. Year effects account for changes in macroeconomic conditions, but RER are worth a separate analysis, since they may affect plants differently depending on their industry's trade orientation (Levinsohn (1999)). In Colombia, during trade liberalization in 1977-1981, the peso's RER appreciates, whereas during trade liberalization in 1985-1990, the peso's nominal and real exchange rates devalue.[39] A RER devaluation increases the demand for (and profitability of ) tradable industries' output. This results in an increase in producers' measured productivity, if, in the short run, plants respond by exploiting unobserved unused capacity, before adjusting input choices. If such a devaluation accompanies trade liberalization the productivity gains observed across plants could result from this capacity adjustment.

[37]In this specification, the coefficient on productivity is 0.007 imprecisely estimated and the coefficient on 3-digit tariffs is 0.281 precisely estimated (with $N = 57861$).

[38]In that specification, the coefficient on productivity is $-0.002$, the coefficient on period 1 is $-0.025$, both imprecisely estimated and that on period 2 is $-0.21$ and significant (with $N = 57861$).

[39]Variation in RER is taken as exogenous to changes in industrial productivity. RER data is taken from IMF International Financial Statistics (REER based on relative consumer prices).

Given our wide concept of productivity, discussed at the end of section 2, an increase in input utilization is a productivity gain, so this RER effect does not change the interpretation of our results. Nevertheless, we shortly present some evidence on plants' changes in capacity utilization using, as Pavcnik (2000), correlations of plant-level productivity growth and output growth in Colombian industries. If in response to RER revaluation output expands in nontraded industries and contracts in traded industries without changes in inputs, and correspondingly measured productivity expands in nontraded industries and contracts in traded industries, the correlation between changes in plant output and changes in plant productivity should be strong and positive. These correlations are small across industries ranging from 0.052 in glass to 0.349 in furniture. Also following Pavcnik (2000), we compute average levels of finished goods inventories across traded and nontraded industries from 1980 to 1991, to see whether inventories significantly decrease in traded industries in years of RER devaluation. We follow Nishimizu and Robinson (1984) in classifying 3 and 4-digit industries according to their average degree of trade orientation in 1980-1991. Traded import-competing industries have an average import penetration ratio above 10 percent, traded export-oriented industries have an average export orientation ratio above 10 percent and the remaining industries are nontraded.[40] For 3 and 4-digit industries, only in few years is RER devaluation accompanied by a decline in average output inventories in traded industries and is RER appreciation accompanied by a decline in inventories in nontraded industries.[41] So, this evidence does not attribute observed changes in plant productivity to changes in capacity utilization resulting from variation in RER.

To investigate directly whether RER exert a different impact on plant productivity across traded and nontraded industries, we estimate a specification where productivity depends on RER individually and interacted with an indicator for traded industries, that indicator individually, a time trend and the trend interacted with the traded industries' indicator.

[40]If an industry has export orientation and import penetration ratios above 10 percent (which occurs for some 4-digit industries and for the 3-digit industry professional equipment), it is classified as traded. The data on exports for petroleum derivatives and iron and steel has irregularities, so these industries' trade orientation is not defined.

[41]Similar results are found using output inventories as a fraction of total output. Also, when comparing the percentage of plants running down output and materials' inventories (i.e., having lower inventories in December than in January of a given year) across traded and nontraded industries to fluctuations in RER, we found qualitatively similar results: only in few years of RER devaluation does the percentage of plants running down inventories in traded industries increase and that percentage is far from a majority.

The use of a trend in place of year effects is due to the singularity induced if year effects and RER are combined. The results are presented in Table 7 for estimation with data for years 1980-1991. In all specifications, a RER devaluation (RER decrease according to the IMF definition) is associated with a decrease in plant productivity in traded industries, relative to a productivity gain in nontraded industries, with precise estimates. This result holds controlling for unobserved plant characteristics affecting productivity. The positive coefficient on the interaction of the trend with the traded industries' indicator shows that productivity increases over time in those industries. Overall, the impact of the RER on productivity is opposite to the prediction related to demand changes.

The discussion on RER departed from the concern that the finding of productivity gains in face of decreased tariffs could be modified when considering explicitly changes in RER. So, we estimate equation (9) with lagged nominal tariffs, RER, a time trend, plant age and exit indicators for years 1981, 1984-1989. The results are presented in Table 7. We find a negative impact of lagged tariffs on productivity, precisely estimated in all specifications. Relative to Table 6, the impact is lower for OLS specifications without industry controls and higher for OLS with industry controls and for fixed effects.[42]

Finally, from a long-run perspective, a RER devaluation accompanying trade liberalization may have a protective effect across producers, by increasing the relative price of imports, partly counteracting the pressure for productivity improvement, cost reduction and survival brought by tariff reductions. We estimate (9) using only data for the period of trade liberalization and RER devaluation (1985-1989) and find a negative impact of 3 and 4-digit tariffs on productivity, with larger magnitudes than in Tables 5 and 6 (except for OLS without industry effects). Including explicitly RER (replacing year effects with a trend), qualitatively similar results are found. So, the effect of RER devaluation on import-competing producers' incentives does not overcome the impact of tariff liberalization. Overall, our findings of a negative impact of tariffs on productivity are robust to the consideration of movements in Colombian RER.[43]

[42]A specification differentiating the impact of RER across traded and nontraded industries and including tariffs cannot be estimated, given the endogeneity of trade orientation with respect to tariffs. Most Colombian nontraded industries have extremely high average tariffs.

[43]To investigate differences in the evolution of productivity for plants in industries with different trade orientation, amidst the variation in Colombian trade policy during 1980-1991, we estimate a specification close to Pavcnik (2000). That specification identifies the impact of trade on plant productivity, exploiting variation in productivity over time and across plants in industries with different trade orientation. Our

## 5.5 Differential Impact of Tariffs by Plant Size

The within-industry heterogeneity found in sections 3 and 4.2 implies that the impact of trade policy on productivity may vary depending on plant characteristics. In this section, we introduce cross-plant variation in the impact of trade policy according to plant size. There are no theoretical nor empirical results regarding the effect of trade policy on productivity across firms of different sizes. Some conclusions are drawn regarding the effect of trade policy on related plant outcomes. Dutz (1996) develops an oligopoly model showing how incumbents adjust output to loosened import quotas, concluding that small plants, with lower market shares and higher marginal costs, experience relatively larger output contractions than large plants, in response to increased imports. Preliminary evidence in Roberts and Tybout (1996) for the Colombian dataset (1977-1985) suggests that size and ownership type influence the way in which plants are affected by foreign competition. The authors find that within industries facing increased import penetration, large producers face stronger declines in price-cost margins than small ones. A different argument holds that developing countries' manufacturing sectors are characterized by a dualistic structure, i.e., industries accommodate a few oligopolistic producers and a large number of small firms under stronger competition, more sensitive to the economic environment and more flexible to change. This could lead to a larger impact of changes in trade protection on small plants' productivity. We consider the robust specification:

$$\omega_{it}^{j} = \beta_{0S} + \beta_{0L} + \lambda_t * I^S + \lambda_t * I^L + \beta_{1S}(TP_{t-1}^{j} * I^S) + \beta_{1L}(TP_{t-1}^{j} * I^L) + I^j + u_{it}^{j}, \quad (10)$$

where $I^S$, $I^L$ are indicator variables for small and large plants. Plant size is defined according to average employment over the sample period.[44] In Table 8, we present results from

results do not show significant differences in the evolution of productivity of plants in import-competing, export-oriented and nontraded 3-digit industries until 1984 and 4-digit industries until 1986. We believe the contrast between our results and Pavcnik's clear-cut results rests in the fact that her Chilean plants are analyzed only in years following a trade liberalization, whereas Colombian plants are analyzed in years that follow liberalization, years that follow increased protection and again years that follow liberalization. Pavcnik's specification is not suited to identify the effects of trade on productivity in a case of alternating trade regimes. Also, the assumption required to interpret her results (plant productivity in import-competing industries increases with trade liberalization whereas that of plants in nontraded sectors does not change) does not seem to be verified for Colombian plants.

[44] If $I^S$, $I^L$ were indexed by time, the sample spliting criterion would be endogenous, given the potential impact of trade liberalization on plant size and scale efficiency. On the one hand, increased exposure to foreign competition may increase plant size by increasing the elasticity of demand (reinforced by entry and exit). On the other hand, import competition may reduce demand, causing industry contraction and

estimating (10) with small plants having on average less than 50 employees. The effect of tariffs on productivity is more negative for large plants. F-tests confirm that the effect of tariffs differs significantly across large and small plants. In contrast to Table 5, when 4-digit tariffs are interacted with plant size variables, the resulting coefficients are not higher than those on the interactions with 3-digit tariffs. Large plants are significantly more productive than small plants, as the F-test for a differential intercept indicates. All results are very similar restricting year effects to be equal across large and small plants. Also, all results are robust to a change in the cutoff defining small plants to 20 or 100 employees.

An alternative definition of plant size is its market share in total industry output in any given year. The following specification is estimated, allowing for a non-linear relation between plant size and productivity:

$$\omega_{it}^{j} = \beta_0 + \lambda_t + \beta_1 (msh)_{it}^{j} + \beta_2 (msh^2)_{it}^{j} + \beta_3 TP_{t-1}^{j} + \beta_4 (TP_{t-1}^{j} * (msh)_{it}^{j}) + I_t^j + u_{it}^{j}, \quad (11)$$

where $(msh)_{it}^{j}$ denotes plant market share. The results are presented in Table 9 for plant market shares relative to 3-digit industry output. Endogeneity could be a problem if variation in plant market shares over time is related to variation in tariffs. Ignoring this caveat, the results are interesting. Plant productivity increases with plant market share, at a diminishing rate. Tariffs affect negatively productivity with a precisely estimated coefficient in all specifications, as in Table 5. The interaction of tariff levels and plant market shares is negative and significant for more and less disaggregated tariffs, i.e., tariff protection has a more negative impact on the productivity of plants with higher market shares. The marginal impact of market shares, $\widehat{\beta}_1 + \widehat{\beta}_2 \overline{msh} + \widehat{\beta}_4 \overline{TP}$ ($\overline{msh}$, $\overline{TP}$ are sample average market share and sample average tariffs, respectively) is significantly positive in all specifications. When controlling for omitted plant characteristics affecting plant productivity and market shares, there is no evidence that tariffs affect plants differently, depending on their market shares. All results are qualitatively similar when estimating (11) with plant market shares relative to 4-digit industry output.

Overall, we find that Colombian industries are characterized by stronger productivity gains for large plants, as a result of trade liberalization. Decreases in trade protection bring a larger decline in 'inefficiency rents' that large producers might be benefiting from.

decreasing plant size. Empirically, some studies show that trade liberalization is associated with reductions in plant size (e.g., Dutz (1996), Roberts and Tybout (1991) and Tybout and Westbrook (1995)).

A plausible explanation is that large producers' output likely competes more directly with imports. Our evidence complements the results in Roberts and Tybout (1996) on price-cost margins of large plants, more strongly reduced than small plants' in face of increased import penetration into the industry.

### 5.6 Differential Impact of Tariffs by the Degree of Domestic Competition in the Industry

Plant productivity may be affected by changes in protection differently depending on industry characteristics. In this section, we introduce cross-industry variation in the effects of trade policy according to the degree of domestic competition in the industry. Investigating this claim faces the difficult task of measuring the degree of competition in an industry. We choose two measures commonly used in the industrial organization literature capturing different dimensions of competition: Herfindahl indices and industry turnover rates.[45] The Herfindahl index summarizes the degree of inequality of market shares across plants in an industry. The turnover rate reflects, at least imperfectly, the market power of large plants and their ability to inhibit entry into an industry, as well as sunk costs preventing exit. This measure enables us to investigate the claim that in industries with low costs of entry, productivity is less affected by trade liberalization if the adjustment occurs through plant entry. Given the potential impact of trade policy on concentration, entry and exit, domestic competition is taken as a time-invariant characteristic of the industry (sample average Herfindahl index and turnover rate). It is interesting to view this analysis as that of the interrelation (substitutes or complements) between domestic and foreign competition in their effect on plant productivity. Previous studies find two types of results for a subsample of our dataset (1977-1985). At the industry level, Roberts and Tybout (1996) find that the reduction in price-cost margins due to increased import penetration is larger in more concentrated 3-digit industries. At the plant level, they find no contemporaneous correlation between import penetration and entry and exit into Colombian industries. If trade policy is to affect entry and exit, it likely does it with a lag, as producers require time to gain certitude about the irreversibility of any policy

[45]The Herfindahl index for an industry and year is the sum of plants' squared market shares relative to 3 or 4-digit industries' output. The turnover rate for an industry and period is the sum of entry and exit rates.

change. Our specification is

$$\omega_{it}^{j,k} = \beta_0 + \lambda_t + \beta_1 TP_{t-1}^{j} + \beta_2 \overline{DC}^{j} + \beta_3 (TP_{t-1}^{j} * \beta_2 \overline{DC}^{j}) + I^k + u_{it}^{j,k}, \qquad (12)$$

where $\overline{DC}^{j}$ represents the average degree of domestic competition in industry $j$. Since $\overline{DC}^{j}$ is a fixed characteristic of industries indexed by $j$, only industry effects at a greater level of aggregation, $I^k$, can be identified in (12). The results from estimating (12) with average Herfindahl indices are presented in Table 10 and depend on the disaggregation level of tariffs and Herfindahl indices. With Herfindahl indices for 3-digit industries' output, in columns (1)-(2), 3 and 4-digit lagged tariffs affect more negatively plant productivity in more concentrated industries, i.e., foreign competition induces greater productivity change in less competitive domestic industries. With all else constant, plants in more concentrated domestic industries have higher productivity, though not significantly higher with 4-digit tariffs. But, the marginal impact of Herfindahl indices on productivity at mean tariff levels is negative. So, both types of competition operate in the same direction, namely, plants have lower productivity when faced with less competition. With Herfindahl indices for 4-digit industries' output, in columns (3)-(4), 3-digit tariffs affect less negatively plants in more concentrated industries. Productivity is significantly lower in more concentrated industries. But, with 3-digit industry effects, the marginal impact of 4-digit Herfindahl indices on productivity at mean tariff levels is not different from zero. Finally, with 4-digit Herfindahl indices, in columns (5)-(6), 4-digit tariffs also affect less negatively plants in more concentrated industries. Productivity is lower in more concentrated industries, but that coefficient as well as the marginal impact of Herfindahl indices on productivity at mean 4-digit tariff levels is not different from zero controlling for 3-digit industry effects.

The results from estimating (12) with average 3-digit industries' turnover rates are presented in Table 10, columns (5)-(6). In industries with high turnover rates, presumably facing a higher degree of domestic competition, tariffs affect less negatively plant productivity. This suggests that entry and exit into different industries dampen the within-plant productivity adjustment to changes in trade protection. Plant productivity is significantly lower in industries with higher turnover rates. But, the marginal impact of turnover rates on productivity at mean tariff levels is positive and significant. Though relative to a different dimension of competition, the less negative impact of tariffs on productivity in 3-digit industries with higher turnover matches the finding with 3-digit Herfindahl indices. This similarity is curious, as the classification of several industries into high and low domestic competition differs depending on whether Herfindahl indices or turnover rates are considered.

## 5.7 Impact of Effective Rates of Protection

To check the robustness of the results obtained in the previous sections, we use an alternative measure of trade protection: effective rates of protection. ERP constitute an index of protection to productive processes summarizing information on the protective structure resulting from tariffs on output and imported inputs.

The results from estimating (9) with lagged 3-digit ERP are presented in Table 11.[46] The impact of ERP on plant productivity is positive, imprecisely estimated when industry effects are included. The coefficients on ERP, in fixed effects specifications, are positive and significant. The contrast between the positive impact of ERP and the negative impact of nominal tariffs on productivity could stem from a difference in samples. Therefore, we present in Table 11, columns (1')-(5'), the results from estimating (9) with tariffs but the ERP sample: as in Table 5, we find a negative impact of protection on plant productivity.[47] So, there is a genuine difference between the impact of nominal protection to final output on plant productivity and the impact of effective protection to final output. Analyzing residuals and leverage from the specifications with ERP and tariffs, we conclude that the different results are not driven by outliers and are not significantly changed by dropping the observations with highest leverage. But curiously, nominal tariffs and ERP are highly positively correlated in any year and across the whole period in Table 11. Intuitively, we would expect ERP coefficients to be insignificant, as data restrictions (e.g., coefficients from input-output tables) introduce serious noise in the calculation of ERP. This is confirmed in OLS specifications with industry effects but not in fixed effects specifications. ERP on a final good decline if either tariffs on the final good decline (in relative terms) or if tariffs on intermediate inputs increase (in relative terms). So, an interpretation for the different results with fixed effects could be: lowering tariffs in final goods generates gains in plant

[46]The ERP is calculated by the Colombian National Planning Department according to the Corden formula, using an input output matrix for Andean countries in 1982.

[47]The 3-digit tariff data for years 1980, 1984, 1985, 1990, 1991 is from DNP, a different source than that used in Tables 5-10. In two of the common years across the two sources of data (1984, 1985) the values of tariffs differ, but the differences are negligeable, except for printing and transport equipment.

productivity but lowering ERP via increased tariffs in intermediate inputs generates losses in plant productivity.[48] This implies that a specification relating plant productivity to both tariffs and ERP should obtain a negative coefficient on tariffs and a positive coefficient on ERP. In the OLS specification with 3-digit industry effects, we find a coefficient on tariffs of $-1.443$ and on ERP of 0.011 and in the fixed effects specification, we find a coefficient on tariffs of $-1.128$ and on ERP of 0.009, all precisely estimated.

In Table 12 Part A, we present results from estimating (10) with lagged ERP and small plants having less than 50 employees on average across the sample. The impact of ERP on plant productivity is positive and precisely estimated for small plants but negative and precisely estimated for large plants. F-tests indicate that the effect of ERP differs significantly across large and small plants. We find qualitatively unchanged results when year effects are restricted to be equal across large and small plants. Also, all results are robust to a change in the cutoff defining small plants to 20 or 100 employees. The main result that large plants are more negatively affected by protection is similar to that with tariffs and a different sample in Table 8 and with tariffs and the ERP sample in Table 12 Part A, columns (1')-(3').

Considering time-varying market shares relative to 3-digit industry output as the measure of plant size, equation (12) is estimated with lagged ERP and the results are presented in Table 12 Part B. We find evidence that ERP impact negatively the productivity of plants with higher market shares with a precise negative coefficient in OLS specifications. But when plant fixed effects are included, the differential effect disappears. These findings match those with tariffs and a different sample in Table 9 and those with tariffs and the ERP sample in Table 12 Part B, columns (1')-(5'). The marginal impact of ERP on productivity at average market shares is positive but insignificant when industry effects are included, reflecting the partial impact. All results are qualitatively similar using plant market shares relative to 4-digit industry output.

The results from estimating (12) with ERP and average Herfindahl indices are presented in Table 13 and vary with the disaggregation level of the indices. With Herfindahl indices for 3-digit industries, in column (1), ERP impact negatively plant productivity in more

[48]In the beginning of section 5, we argued that restricted access to a large variety of imported intermediate inputs, possibly of better quality, in face of high tariffs has adverse consequences on productivity. Given our lack of knowledge regarding the specific intermediate inputs imported and used in each Colombian industry, we cannot guarantee this interpretation is correct. But as is shown below, one of its implications is verified.

concentrated industries. This indicates a stronger role of foreign competition in generating productivity gains in less competitive domestic industries. Average concentration does not significantly affect productivity. The finding of a differential impact of protection in more concentrated industries according to 3-digit Herfindahl indices is similar to that with tariffs, in Table 10 with a different sample and in Table 13, column (1') with the ERP sample. With Herfindahl indices for 4-digit industries, in column (2), the coefficients on ERP and Herfindahl indices are imprecisely estimated. The impact of ERP (or tariffs in column (2')) on plant productivity in more concentrated 4-digit industries is significantly positive. Including 3-digit industry effects, in column (3), the interaction term loses significance.

The results from estimating (12) with ERP and average turnover rates for 3-digit industries are presented in Table 13, column (4). Interestingly, in this specification the impact of ERP on plant productivity is negative and significant, matching that of tariffs. Productivity is not significantly different in industries with higher turnover rates. But, the marginal impact of turnover rates, at mean tariffs or ERP, is positive as in Table 10. ERP affect less negatively plant productivity in industries with higher turnover rates or potentially higher domestic competition. This weaker role of increases in foreign competition in improving productivity in more competitive 3-digit domestic industries is consistently found across trade policy and domestic competition measures: in Table 10 with tariffs, Herfindahl indices and turnover rates, in Table 13, columns (1) and (1') with Herfindahl indices and in column (4') with tariffs and the ERP sample.

## 5.8 Impact of Import Penetration Ratios

Another interesting robustness check to perform to the finding of a negative impact of trade protection on plant productivity across Colombian industries, is to use a measure of exposure to foreign competition based on trade volumes (the outcome of trade policy): import penetration ratios, exhibiting variation over time and across industries. No theoretical reasons point to imports being determined by domestic industries' average productivity, but, as in the previous sections, our specifications use lagged import penetration ratios, to allow for plant adjustment to changes in protection.[49]

[49]A positive impact of import penetration on productivity could result not only from plants lowering costs, becoming more efficient in face of trade liberalization, but also from productivity being procyclical (if imports lead to output contraction in the corresponding domestic industry and that is transmitted into lower

Equation (9) is estimated using import penetration ratios for 3 and 4-digit industries in 1981-1991. The results, correcting for possible heteroskedasticity, are presented in Table 14. Import penetration has a positive and precisely estimated impact on plant productivity (except in column (6)). This impact has a considerable magnitude, e.g., in column (4), an increase in import penetration by 10 percentage points increases logarithmic plant productivity by 4.4 percent. Year-to-year changes in import penetration ratios of such magnitude are common for most Colombian industries during the sample period. In contrast to the findings with tariffs, the coefficients on import penetration ratios are systematically larger in magnitude for the more aggregate industry level. In specifications controlling for plant age and an indicator of plant exit, the positive impact of import penetration on plant productivity is almost unchanged. Overall, these findings with trade volumes strengthen our findings with trade policy measures. Furthermore, this evidence complements that in Roberts (1996) of a mechanism by which trade liberalization leads to productivity gains: price-cost margins in Colombian industries (1977-1985) decline with increases in import penetration. As the samples in Tables 5 and 14 differ, we estimate equation (9) with tariffs and with import penetration ratios on a sample for which data on both measures is available (1981, 1984-1989). All coefficients are precisely estimated, slightly smaller than those in Table 14, but the same strong conclusion is drawn: import penetration affects positively plant productivity and tariffs affect it negatively.

In Table 15 part A, we present the results from estimating (10) with import penetration and small plants having less than 50 employees on average across the sample. Import penetration impacts positively large plants' productivity in all specifications. Small plants are negatively affected by 4-digit import penetration with and without 3-digit industry effects and positively or not significantly affected in the remaining cases. F-tests show that the impact of import penetration differs significantly across large and small plants. All results are robust to a change in the cutoff defining small plants to 20 or 100 employees. These findings parallel those in section 5.5 where large plants are found to be more negatively affected by tariffs. A possible explanation proposed for these findings gets here further support: in any

productivity, via reduced capacity utilization). Given that in our framework increases in capacity utilization are increases in productivity, this alternative interpretation is ultimately indistinguishable from that of trade liberalization generating within-plant productivity gains. In fact in section 4.2, we found that most industries have procyclical productivity growth.

industry, the output produced by large plants competes more directly with imports.

Equation (11) is estimated with market shares and lagged import penetration ratios and the results are presented in Table 15 Part B. Import penetration affects more positively the productivity of plants with higher market shares in OLS specifications. But controlling for omitted plant characteristics affecting plant productivity and market shares, import penetration affects less positively the productivity of plants with higher market shares. This finding parallels those in Table 9 with tariffs and in Table 12 Part B with ERP. The marginal impact of import penetration on productivity, at average market shares, and the marginal impact of market shares, at average import penetration ratios and market shares, are significantly positive in all specifications.

In Table 16, we present results from estimating (12) with import penetration ratios and average Herfindahl indices that depend on disaggregation levels of Herfindahl indices and import penetration ratios. With Herfindahl indices for 3-digit industries, in columns (1)-(2), higher industry concentration impacts negatively productivity. Import penetration into 3-digit industries does not differently affect plant productivity in more or less concentrated industries. In less competitive domestic 3-digit industries, stronger foreign competition via 4-digit import penetration affects more positively plant productivity. With Herfindahl indices for 4-digit industries, in columns (3)-(6), the results depend on whether industry effects are included. For both 3 and 4-digit import penetration ratios, the impact of industry concentration on productivity changes from positive to negative if 3-digit industry effects are included. The results controlling for 3-digit industry effects are more interesting, as they show the coefficient of import penetration on plant productivity within industries, and indicate that import penetration at 3 and 4-digit levels affects more positively plant productivity in more concentrated 4-digit industries. Some of these findings, namely in Table 16, column (2), complement those in Roberts (1996) that price-cost margins decline more strongly in more concentrated 3-digit industries in face of increased import penetration.

Finally, we estimate (12) with import penetration ratios and 3-digit industries' average turnover rates, and present the results in Table 16, columns (7)-(8). Curiously, we find that import penetration affects negatively plant productivity and that it affects it positively for plants in more competitive industries. These results differ from those with tariffs and ERP.

## 5.9 Impact on Plant Productivity Growth

Some arguments for an impact of trade liberalization on productivity are dynamic in nature. Several endogenous growth models consider dynamic effects of trade on productivity: increases in the variety and quality of inputs, increases in product sophistication, knowledge diffusion and learning-by-doing. Tybout (2000) argues that trade protection may improve productivity growth if it promotes industries whose production processes benefit from learning-by-doing and generate knowledge spillovers. But in contrast, trade protection may reduce productivity growth, if as we mentioned in the beginning of section 5, producers gain access to better technologies from the exposure to imported final goods or from exporting.

In Table 17, we present the estimation results for a specification that relates plant productivity growth rates to tariffs, ERP and import penetration ratios, controlling for yearly differences in productivity growth. It is plausible to think of the argument in section 5.3 concerning the possible endogeneity of trade policy with respect to productivity in a dynamic setting . If government authorities changed trade policy in response to pressures by industries experiencing less productivity growth there would be simultaneity between trade policy at $t$ and productivity growth from $t-1$ to $t$. So, we consider the impact of trade protection at $t-1$ on plant productivity growth from $t-1$ to $t$. The estimates suggest that protection affects negatively plant productivity growth. In particular, allowing for permanent differences in plant productivity growth rates, we find higher lagged 3 and 4-digit tariffs and ERP to be associated with lower productivity growth rates. Also, higher import penetration ratios have a positive and precisely estimated impact on productivity growth.

# 6. Conclusion

This study provides new plant-level evidence of a link between trade policy and industrial productivity. Our analysis circumvents the shortfalls of studies that focus on a single episode of liberalization, the predominant approach in microeconomic studies of trade and productivity, by exploiting cross-industry and time variation in trade policy. Using Colombian data from 1977 to 1991, we find that lagged nominal tariffs have a strong negative impact on plant productivity controlling for factors such as the exchange rate, observed and unobserved plant characteristics. The negative impact of trade protection on productivity is stronger for large plants, in employment and market shares terms, than for small plants. The negative impact of trade protection on productivity is stronger for plants in less competitive industries, according to Herfindahl indices and turnover rates. These findings are robust to the use of alternative measures of trade protection such as effective rates of protection and import penetration ratios. We also find evidence of a negative impact of trade protection on plant productivity growth. It would be interesting to extend the analysis to the post-1991 period, when Colombian tariff reductions continued. Our evidence shows important productive efficiency gains from trade liberalization, but these are not necessarily translated into equal welfare gains due to the unmeasured short-run costs of liberalization.

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# Appendix A

One of the decompositions of changes in industry productivity whose summary of results we report in section 5.4 is given by:

$$\Omega_t^j - \Omega_{t-1}^j = \sum_{i \in Cont} s_{it-1}^j(\omega_{it}^j - \omega_{it-1}^j) + \sum_{i \in Cont} \omega_{it}^j(s_{it}^j - s_{it-1}^j) + \sum_{i \in Ent} s_{it}^j \omega_{it}^j - \sum_{i \in Ex} s_{it-1}^j \omega_{it-1}^j,$$

where $\Omega_t^j$ is industry productivity as defined in section 4.2, $\omega_{it}^j$ and $s_{it}^j$ are plant $i$'s productivity and market share in industry $j$ output for continuing plants $Cont$, entrant plants $Ent$ and exiter plants $Ex$. The first term in the decomposition represents the change in continuing plants' productivity, the second term represents the output share reallocation among continuing plants with different productivity, the third and fourth terms represents average productivity of entrant and exiter plants, respectively.

Another decomposition as in Aw, Chen and Roberts (2001) is given by:

$$\begin{aligned}\Omega_t^j - \Omega_{t-1}^j \quad = \quad & \sum_{i \in Cont} (\frac{s_{it-1}^j + s_{it}^j}{2})(\omega_{it}^j - \omega_{it-1}^j) + \sum_{i \in Cont} (\frac{\omega_{it-1}^j + \omega_{it}^j}{2})(s_{it}^j - s_{it-1}^j) \\ & + (\frac{s_{Ext-1}^j + s_{Ent\,t}^j}{2})(\omega_{Ext-1}^j - \omega_{Ent\ t}^j) + (\frac{\omega_{Ext-1}^j + \omega_{Ent\,t}^j}{2})(s_{Ext-1}^j - s_{Ent\ t}^j),\end{aligned}$$

where $\omega_{it}^j$ and $s_{it}^j$ are defined as above, $s_{Ext-1}^j$, $s_{Ent\,t}^j$ represent the market share of entrant and exiter plants in industry $j$ and $\omega_{Ext-1}^j$, $\omega_{Ent\,t}^j$ represent an output share-weighted average productivity of entrant and exiter plants in industry $j$. The first term represents the the change in continuing plants' productivity, the second term represents the output share reallocation among continuing plants with different productivity, the third term represents the difference between the productivity of entrant plants in period $t$ and of exiter plants in period $t-1$, the fourth term represents the output share reallocation between entrant and exiter plants.

The detailed results from these decompositions of changes in productivity for Colombian industries are available from the author upon request.

**Table 1** **Production Function Estimates with Materials Controlling for Simultaneity Bias**

| | Input | OLS | R. scale | Fixed effects | Input evenue shares | Materials correcting endog. bias | R. scale | Polynomials | R. scale |
|---|---|---|---|---|---|---|---|---|---|
| 321+322 Textiles | Labor | 0.316 * | | 0.136 * | 0.275 | 0.242 * | | 0.263 * | |
| and Apparel | | (0.004) | | (0.005) | | (0.014) | | (0.003) | |
| | Intermediates | 0.146 * | 0.982 | 0.111 * | 0.018 | 0.115 * | 1.028 | 0.1 * | 0.904 |
| | | (0.003) | | (0.003) | | (0.007) | | (0.002) | |
| N.obs | Materials | 0.471 * | | 0.497 * | 0.500 | 0.66 * | | 0.429 * | |
| 20379 | | (0.003) | | (0.003) | | (0.053) | | (0.005) | |
| | Capital | 0.049 * | | 0.098 * | 0.207 | 0.011 | | 0.112 * | |
| | | (0.003) | | (0.004) | | (0.03) | | (0.007) | |
| 311+312 Food | Labor | 0.22 * | | 0.134 * | 0.149 | 0.154 * | | 0.176 * | |
| products | | (0.005) | | (0.005) | | (0.008) | | (0.004) | |
| | Intermediates | 0.16 * | 1.055 | 0.108 * | 0.034 | 0.095 * | 1.058 | 0.104 * | 0.875 |
| | | (0.004) | | (0.004) | | (0.007) | | (0.003) | |
| N. obs. | Materials | 0.588 * | | 0.562 * | 0.647 | 0.731 * | | 0.529 * | |
| 17651 | | (0.002) | | (0.003) | | (0.043) | | (0.004) | |
| | Capital | 0.088 * | | 0.08 * | 0.170 | 0.077 * | | 0.066 * | |
| | | (0.003) | | (0.004) | | (0.042) | | (0.007) | |
| 381 Metal | Labor | 0.329 | | 0.291 * | 0.266 | 0.288 * | | 0.243 * | |
| products | | (0.006) | | (0.008) | | (0.012) | | (0.005) | |
| | Intermediates | 0.095 * | 1.060 | 0.012 * | 0.024 | 0.053 * | 0.962 | 0.074 * | 0.985 |
| | | (0.004) | | (0.005) | | (0.007) | | (0.003) | |
| N.obs | Materials | 0.587 * | | 0.595 * | 0.509 | 0.523 * | | 0.573 * | |
| 8581 | | (0.004) | | (0.005) | | (0.046) | | (0.006) | |
| | Capital | 0.048 * | | 0.015 * | 0.201 | 0.098 * | | 0.095 * | |
| | | (0.003) | | (0.005) | | (0.031) | | (0.009) | |
| 331+332 Wood | Labor | 0.234 * | | 0.255 * | 0.302 | 0.21 * | | 0.22 * | |
| products and | | (0.007) | | (0.011) | | (0.015) | | (0.007) | |
| furniture | Intermediates | 0.115 * | 1.016 | 0.081 * | 0.021 | 0.096 * | 0.886 | 0.096 * | 0.943 |
| | | (0.005) | | (0.006) | | (0.008) | | (0.005) | |
| N.obs | Materials | 0.635 * | | 0.616 * | 0.496 | 0.48 * | | 0.587 * | |
| 5652 | | (0.005) | | (0.007) | | (0.069) | | (0.008) | |
| | Capital | 0.033 * | | 0.046 * | 0.181 | 0.1 * | | 0.04 * | |
| | | (0.003) | | (0.007) | | (0.026) | | (0.01) | |
| 342 Printing | Labor | 0.586 * | | 0.384 * | 0.295 | 0.516 * | | 0.399 * | |
| | | (0.011) | | (0.015) | | (0.025) | | (0.01) | |
| | Intermediates | -0.026 * | 1.120 | -0.081 * | 0.017 | -0.055 * | 1.096 | 0.042 * | 1.026 |
| | | (0.007) | | (0.008) | | (0.013) | | (0.006) | |
| N.obs | Materials | 0.484 * | | 0.488 * | 0.443 | 0.523 * | | 0.453 * | |
| 5224 | | (0.007) | | (0.009) | | (0.04) | | (0.01) | |
| | Capital | 0.077 * | | 0.002 | 0.244 | 0.112 * | | 0.132 * | |
| | | (0.005) | | (0.009) | | (0.03) | | (0.012) | |
| 382 Nonelectrical | Labor | 0.302 * | | 0.256 * | 0.280 | 0.284 * | | 0.247 * | |
| machinery | | (0.01) | | (0.014) | | (0.016) | | (0.01) | |
| | Intermediates | 0.056 * | 1.055 | 0.075 * | 0.023 | 0.046 * | 0.842 | 0.065 * | 0.946 |
| | | (0.006) | | (0.008) | | (0.009) | | (0.006) | |
| | Materials | 0.612 * | | 0.548 * | 0.468 | 0.381 * | | 0.563 * | |
| N.obs | | (0.005) | | (0.009) | | (0.162) | | (0.007) | |
| 4585 | Capital | 0.084 * | | 0.094 * | 0.229 | 0.131 | | 0.071 * | |
| | | (0.005) | | (0.009) | | (0.084) | | (0.01) | |
| 369 Nonmetallic | Labor | 0.405 * | | 0.314 * | 0.330 | 0.381 * | | 0.367 * | |
| minerals | | (0.01) | | (0.016) | | (0.02) | | (0.009) | |
| | Intermediates | 0.212 * | 1.070 | 0.189 * | 0.090 | 0.186 * | 0.992 | 0.19 * | 0.987 |
| | | (0.005) | | (0.008) | | (0.012) | | (0.005) | |
| N.obs | Materials | 0.406 * | | 0.3 * | 0.344 | 0.31 * | | 0.315 * | |
| 4502 | | (0.004) | | (0.007) | | (0.084) | | (0.008) | |
| | Capital | 0.047 * | | 0.058 * | 0.237 | 0.116 * | | 0.115 * | |
| | | (0.005) | | (0.009) | | (0.038) | | (0.014) | |
| 352 Other | Labor | 0.287 * | | 0.198 * | 0.194 | 0.269 * | | 0.25 * | |
| Chemicals | | (0.007) | | (0.009) | | (0.014) | | (0.007) | |
| | Intermediates | 0.018 * | 1.083 | 0.009 * | 0.012 | 0.008 | 0.996 | 0.015 * | 0.992 |
| | | (0.004) | | (0.005) | | (0.009) | | (0.004) | |
| N.obs | Materials | 0.707 * | | 0.657 * | 0.521 | 0.658 * | | 0.651 * | |
| 4296 | | (0.005) | | (0.007) | | (0.045) | | (0.01) | |
| | Capital | 0.071 * | | 0.021 * | 0.273 | 0.061 * | | 0.076 * | |
| | | (0.004) | | (0.006) | | (0.027) | | (0.012) | |

Table 1 (continued)

| | Input | OLS | R. scale | Fixed effects | Input evenue shares | Materials correcting endog. bias | R. scale | Polynomials | R. scale |
|---|---|---|---|---|---|---|---|---|---|
| 356 Plastics | Labor | 0.325 * | | 0.237 * | 0.196 | 0.303 * | | 0.225 * | |
| | | (0.008) | | (0.011) | | (0.015) | | (0.007) | |
| | Intermediates | 0.014 * | 1.047 | -0.017 * | 0.032 | -0.015 | 1.032 | 0.043 * | 0.954 |
| | | (0.005) | | (0.006) | | (0.008) | | (0.004) | |
| N.obs | Materials | 0.596 * | | 0.554 * | 0.548 | 0.642 * | | 0.59 * | |
| 4059 | | (0.005) | | (0.007) | | (0.034) | | (0.008) | |
| | Capital | 0.112 * | | 0.021 * | 0.224 | 0.103 * | | 0.096 * | |
| | | (0.005) | | (0.008) | | (0.03) | | (0.01) | |
| 324 Footwear | Labor | 0.259 * | | 0.161 * | 0.255 | 0.228 * | | 0.199 * | |
| | | (0.008) | | (0.009) | | (0.021) | | (0.007) | |
| | Intermediates | 0.109 * | 1.003 | 0.02 * | 0.010 | 0.067 * | 1.018 | 0.104 * | 0.993 |
| | | (0.006) | | (0.007) | | (0.029) | | (0.006) | |
| N.obs | Materials | 0.608 * | | 0.647 * | 0.531 | 0.674 * | | 0.615 * | |
| 3594 | | (0.006) | | (0.008) | | (0.049) | | (0.01) | |
| | Capital | 0.027 * | | 0.062 * | 0.204 | 0.049 | | 0.075 * | |
| | | (0.005) | | (0.008) | | (0.032) | | (0.012) | |
| 384 Transport equipment | Labor | 0.372 * | | 0.361 * | 0.274 | 0.353 * | | 0.233 * | |
| | | (0.012) | | (0.016) | | (0.025) | | (0.01) | |
| | Intermediates | 0.025 * | 1.069 | -0.035 * | 0.024 | 0.009 | 0.922 | 0.047 * | 0.923 |
| | | (0.007) | | (0.009) | | (0.012) | | (0.006) | |
| N.obs | Materials | 0.574 * | | 0.522 * | 0.491 | 0.47 * | | 0.559 * | |
| 3310 | | (0.006) | | (0.01) | | (0.083) | | (0.009) | |
| | Capital | 0.097 * | | -0.006 * | 0.211 | 0.09 | | 0.084 * | |
| | | (0.007) | | (0.012) | | (0.058) | | (0.016) | |
| 383 Electrical machinery | Labor | 0.291 * | | 0.283 * | 0.264 | 0.286 * | | 0.233 * | |
| | | (0.01) | | (0.013) | | (0.022) | | (0.01) | |
| | Intermediates | 0.04 * | 1.067 | -0.005 | 0.018 | 0.031 * | 0.907 | 0.047 * | 0.981 |
| | | (0.006) | | (0.008) | | (0.012) | | (0.006) | |
| N.obs | Materials | 0.669 * | | 0.635 * | 0.518 | 0.526 * | | 0.636 * | |
| 2824 | | (0.007) | | (0.009) | | (0.121) | | (0.012) | |
| | Capital | 0.068 * | | 0.004 | 0.200 | 0.064 | | 0.065 * | |
| | | (0.006) | | (0.008) | | (0.055) | | (0.015) | |
| 341 Paper | Labor | 0.2 * | | 0.191 * | 0.181 | 0.204 * | | 0.178 * | |
| | | (0.01) | | (0.015) | | (0.03) | | (0.009) | |
| | Intermediates | 0.065 * | 1.056 | 0.053 * | 0.032 | 0.043 * | 0.917 | 0.053 * | 0.991 |
| | | (0.005) | | (0.009) | | (0.007) | | (0.005) | |
| N.obs | Materials | 0.723 * | | 0.68 * | 0.581 | 0.57 * | | 0.668 * | |
| 2017 | | (0.005) | | (0.01) | | (0.09) | | (0.011) | |
| | Capital | 0.067 * | | 0.035 * | 0.205 | 0.1 * | | 0.092 * | |
| | | (0.005) | | (0.01) | | (0.044) | | (0.011) | |
| 313 Beverages | Labor | 0.265 * | | 0.208 * | 0.197 | 0.233 * | | 0.182 * | |
| | | (0.016) | | (0.024) | | (0.03) | | (0.015) | |
| | Intermediates | 0.193 * | 1.063 | 0.07 * | 0.027 | 0.119 * | 0.909 | 0.122 * | 1.030 |
| | | (0.009) | | (0.012) | | (0.021) | | (0.008) | |
| N. obs. | Materials | 0.555 * | | 0.442 * | 0.438 | 0.543 * | | 0.63 * | |
| 1975 | | (0.01) | | (0.011) | | (0.079) | | (0.014) | |
| | Capital | 0.05 * | | 0.033 * | 0.338 | 0.014 | | 0.096 * | |
| | | (0.009) | | (0.012) | | (0.056) | | (0.016) | |
| 351 Industrial chemicals | Labor | 0.095 * | | 0.138 * | 0.148 | 0.116 * | | 0.102 * | |
| | | (0.017) | | (0.02) | | (0.03) | | (0.013) | |
| | Intermediates | 0.084 * | 0.973 | 0.085 * | 0.062 | 0.08 * | 0.913 | 0.081 * | 0.924 |
| | | (0.009) | | (0.009) | | (0.022) | | (0.007) | |
| N.obs | Materials | 0.555 * | | 0.596 * | 0.497 | 0.278 * | | 0.563 * | |
| 1713 | | (0.008) | | (0.013) | | (0.121) | | (0.019) | |
| | Capital | 0.238 * | | 0.049 * | 0.294 | 0.439 * | | 0.178 * | |
| | | (0.011) | | (0.013) | | (0.132) | | (0.024) | |
| 323 Leather products | Labor | 0.198 * | | 0.198 * | 0.233 | 0.243 * | | 0.213 * | |
| | | (0.01) | | (0.017) | | (0.019) | | (0.009) | |
| | Intermediates | 0.035 * | 0.951 | 0.007 | 0.014 | 0.009 | 0.845 | 0.038 * | 0.941 |
| | | (0.007) | | (0.012) | | (0.013) | | (0.007) | |
| N.obs | Materials | 0.684 * | | 0.66 * | 0.571 | 0.53 * | | 0.615 * | |
| 1462 | | (0.009) | | (0.012) | | (0.1) | | (0.01) | |
| | Capital | 0.035 * | | 0.033 * | 0.182 | 0.063 | | 0.075 * | |
| | | (0.006) | | -0.013 | | (0.048) | | 0.012) | |

Table 1 (continued)

| | Input | OLS | R. scale | Fixed effects | Input evenue shares | Materials correcting endog. bias | R. scale | Polynomials | R. scale |
|---|---|---|---|---|---|---|---|---|---|
| 355 Rubber | Labor | 0.294 * | | 0.213 * | 0.234 | 0.261 * | | 0.216 * | |
| products | | (0.013) | | (0.017) | | (0.025) | | (0.013) | |
| | Intermediates | 0.046 * | 1.064 | -0.01 * | 0.035 | 0.051 * | 0.862 | 0.072 * | 0.973 |
| | | (0.009) | | (0.012) | | (0.014) | | (0.009) | |
| N.obs | Materials | 0.673 * | | 0.608 * | 0.511 | 0.53 * | | 0.628 * | |
| 1196 | | (0.01) | | (0.015) | | (0.054) | | (0.017) | |
| | Capital | 0.051 * | | -0.014 * | 0.220 | 0.02 | | 0.057 * | |
| | | (0.009) | | (0.014) | | (0.057) | | (0.017) | |
| 385 Professional | Labor | 0.39 * | | 0.282 * | 0.321 | 0.396 * | | 0.369 * | |
| equipment | | (0.02) | | (0.03) | | (0.04) | | (0.018) | |
| | Intermediates | 0.042 * | 1.063 | 0.046 * | 0.019 | 0.017 | 0.898 | 0.015 * | 0.988 |
| | | (0.013) | | (0.015) | | (0.016) | | (0.011) | |
| N. obs. | Materials | 0.539 * | | 0.529 * | 0.423 | 0.418 * | | 0.541 * | |
| 935 | | (0.012) | | (0.017) | | (0.135) | | (0.013) | |
| | Capital | 0.091 * | | 0.021 * | 0.238 | 0.075 | | 0.063 * | |
| | | (0.01) | | (0.018) | | (0.09) | | (0.015) | |
| 371 Iron and steel | Labor | 0.238 * | | 0.258 * | 0.227 | 0.201 * | | 0.187 * | |
| | | (0.019) | | (0.031) | | (0.029) | | (0.017) | |
| | Intermediates | 0.07 * | 1.060 | 0.085 * | 0.049 | 0.051 * | 1.041 | 0.064 * | 0.956 |
| | | (0.012) | | (0.016) | | (0.013) | | (0.01) | |
| N.obs | Materials | 0.674 * | | 0.573 * | 0.528 | 0.78 * | | 0.603 * | |
| 823 | | (0.009) | | (0.017) | | (0.183) | | (0.018) | |
| | Capital | 0.078 * | | 0.047 * | 0.196 | 0.009 | | 0.102 * | |
| | | (0.01) | | (0.018) | | (0.131) | | (0.018) | |
| 362 Glass | Labor | 0.35 * | | 0.353 * | 0.272 | 0.342 * | | 0.329 * | |
| | | (0.015) | | (0.022) | | (0.031) | | (0.015) | |
| | Intermediates | 0.119 * | 1.075 | 0.107 * | 0.075 | 0.102 * | 1.124 | 0.106 * | 1.015 |
| | | (0.008) | | (0.012) | | (0.016) | | (0.008) | |
| N.obs | Materials | 0.581 * | | 0.534 * | 0.435 | 0.67 * | | 0.529 * | |
| 815 | | (0.011) | | (0.016) | | (0.071) | | (0.021) | |
| | Capital | 0.025 * | | 0.009 | 0.218 | 0.01 | | 0.051 * | |
| | | ( 0.01) | | (0.016) | | (0.056) | | (0.023) | |
| 361 Ceramics | Labor | 0.5 * | | 0.487 * | 0.455 | 0.506 * | | 0.468 * | |
| | | (0.026) | | (0.035) | | (0.067) | | (0.027) | |
| | Intermediates | 0.12 * | 1.096 | 0.135 * | 0.092 | 0.081 * | 1.050 | 0.09 * | 1.038 |
| | | ( 0.014) | | (0.021) | | (0.022) | | (0.014) | |
| N.obs | Materials | 0.45 * | | 0.359 * | 0.259 | 0.386 * | | 0.369 * | |
| 503 | | (0.018) | | (0.026) | | (0.133) | | (0.024) | |
| | Capital | 0.026 * | | 0.038 * | 0.194 | 0.077 | | 0.111 * | |
| | | (0.012) | | (0.03) | | (0.094) | | (0.02) | |
| 372 Nonferrous | Labor | 0.355 * | | 0.409 * | 0.230 | 0.315 * | | 0.267 * | |
| metals | | (0.035) | | (0.043) | | (0.047) | | (0.032) | |
| | Intermediates | 0.17 * | 1.079 | 0.028 * | 0.039 | 0.08 * | 0.978 | 0.088 * | 0.860 |
| | | (0.023) | | (0.024) | | (0.035) | | (0.018) | |
| N.obs | Materials | 0.416 * | | 0.409 * | 0.489 | 0.549 * | | 0.466 * | |
| 435 | | (0.019) | | (0.021) | | (0.17) | | (0.021) | |
| | Capital | 0.138 * | | -0.115 * | 0.242 | 0.034 | | 0.039 | |
| | | (0.018) | | (0.028) | | (0.176) | | (0.033) | |
| 354 Petroleum | Labor | 0.213 * | | 0.19 * | 0.104 | 0.283 * | | 0.216 * | |
| derivatives | | (0.041) | | (0.021) | | (0.079) | | (0.034) | |
| | Intermediates | 0.052 * | 1.094 | -0.066 * | 0.042 | 0.027 | 1.001 | 0.049 * | 1.123 |
| | | (0.017) | | (0.021) | | (0.029) | | (0.012) | |
| N.obs | Materials | 0.821 * | | 0.63 * | 0.634 | 0.52 * | | 0.713 * | |
| 306 | | (0.019) | | (0.034) | | (0.159) | | (0.028) | |
| | Capital | 0.007 | | -0.102 * | 0.220 | 0.171 * | | 0.145 * | |
| | | (0.022) | | (0.026) | | (0.087) | | (0.025) | |
| 314 Tobacco | Labor | 0.266 * | | 0.22 * | 0.202 | 0.322 * | | 0.224 * | |
| | | (0.053) | | (0.066) | | (0.08) | | (0.041) | |
| | Intermediates | 0.187 * | 1.066 | -0.0003 | 0.009 | 0.018 * | 0.917 | 0.079 * | 0.6466 |
| | | (0.035) | | (0.05) | | (0.039) | | (0.025) | |
| N.obs | Materials | 0.535 * | | 0.392 * | 0.52 | 0.389 * | | 0.332 * | |
| 269 | | (0.034) | | (0.039) | | (0.224) | | (0.03) | |
| | Capital | 0.077 * | | -0.135 * | 0.3 | 0.188 | | 0.011 * | |
| | | (0.029) | | (0.064) | | (0.193) | | (0.055) | |

Notes: Bootstrapped standard errors in parenthesis * and ** are significance at 5 and 10% levels, respectively. Intermediates are fuels and electricity.

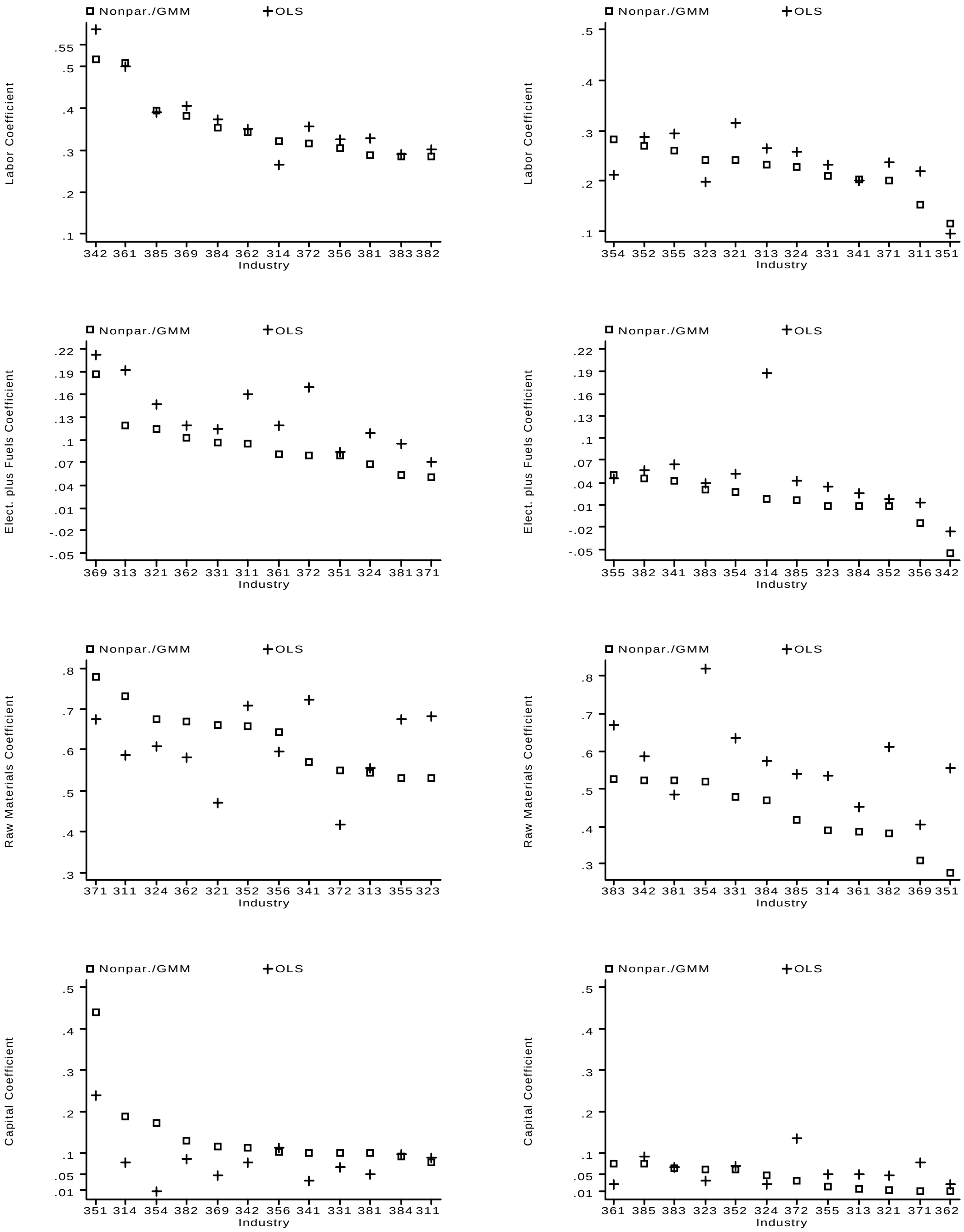


Figure 1 Production Function Estimates

Table 2 Contribution of the Variance of the Productivity Measure Excluding the Shock to the Variance of TFP

| Industry | Materials - Nonpar./GMM | | | Materials - Polynomials/NLLS | | |
|---|---|---|---|---|---|---|
| | Average % | Minimum % | Maximum % | Average % | Minimum % | Maximum % |
| 311/2 Food/Food-miscellaneous | 75 | 60 | 92 | 71 | 59 | 84 |
| 313 Beverages | 62 | 49 | 73 | 18 | 4 | 74 |
| 314 Tobacco | 93 | 56 | 151 | 99 | 71 | 123 |
| 321/2 Textiles/Apparel | 56 | 39 | 65 | 41 | 28 | 53 |
| 323 Leather products | 79 | 69 | 94 | 51 | 30 | 96 |
| 324 Footwear | 45 | 28 | 59 | 26 | 8 | 40 |
| 331/2 Wood products/Furniture | 45 | 32 | 53 | 17 | 11 | 26 |
| 341 Paper | 82 | 56 | 105 | 63 | 44 | 82 |
| 342 Printing | 29 | 14 | 47 | 31 | 20 | 45 |
| 351 Industrial chemicals | 79 | 68 | 94 | 55 | 27 | 78 |
| 352 Other chemicals | 48 | 38 | 65 | 42 | 32 | 56 |
| 354 Petroleum derivatives | 91 | 61 | 120 | 81 | 54 | 114 |
| 355 Rubber products | 38 | 21 | 77 | 43 | 21 | 66 |
| 356 Plastics | 57 | 33 | 74 | 47 | 34 | 66 |
| 361 Ceramics | 46 | 17 | 82 | 47 | 22 | 71 |
| 362 Glass | 48 | 16 | 66 | 32 | 17 | 54 |
| 369 Nonmetallic minerals | 47 | 31 | 57 | 42 | 32 | 50 |
| 371 Iron and steel | 79 | 64 | 96 | 65 | 44 | 97 |
| 372 Nonferrous metals | 73 | 52 | 95 | 89 | 71 | 104 |
| 381 Metal products | 58 | 49 | 70 | 36 | 28 | 62 |
| 382 Nonelectrical machinery | 78 | 67 | 90 | 37 | 27 | 50 |
| 383 Electrical machinery | 65 | 57 | 76 | 28 | 19 | 37 |
| 384 Transport equipment | 64 | 53 | 74 | 31 | 22 | 58 |
| 385 Professional equipment | 72 | 53 | 89 | 48 | 26 | 70 |

Notes: The variance of the TFP measure and its components (variance of the no-shock productivity, variance of the shock and covariance between these) are computed separately for each industry and year.
Averages, minima and maxima are calculated for each industry across years.

Table 3 Import Penetration Ratios and Export Orientation Ratios across Industries, Selected Years

| Industry | Export Orientation Ratio (%) | | | | | Import Penetration Ratio (%) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Year | | | | | Year | | | | |
| | 1980 | 1984 | 1985 | 1988 | 1991 | 1980 | 1984 | 1985 | 1988 | 1991 |
| 311 Food | 9.1 | 3.6 | 3.8 | 5.8 | 11.4 | 6.4 | 5.3 | 4.0 | 4.5 | 3.4 |
| 312 Food-miscellaneous | 2.4 | 5.1 | 6.6 | 7.0 | 7.1 | 2.3 | 3.2 | 3.2 | 2.8 | 2.0 |
| 313 Beverages | 0.0 | 0.2 | 0.2 | 0.2 | 0.6 | 1.5 | 1.4 | 1.4 | 1.9 | 1.0 |
| 314 Tobacco | 0.6 | 0.9 | 0.7 | 3.1 | 13.4 | 9.5 | 4.4 | 3.1 | 1.8 | 4.1 |
| 321 Textiles | 7.7 | 5.3 | 5.7 | 7.6 | 16.8 | 3.1 | 1.9 | 2.1 | 2.8 | 4.8 |
| 322 Apparel | 17.6 | 7.3 | 9.8 | 27.7 | 47.3 | 1.9 | 3.1 | 2.7 | 3.3 | 4.5 |
| 323 Leather products | 13.2 | 14.6 | 23.9 | 34.9 | 45.0 | 1.7 | 1.2 | 1.3 | 2.0 | 3.5 |
| 324 Footwear | 10.4 | 5.0 | 8.4 | 11.4 | 31.6 | 0.8 | 1.0 | 1.1 | 0.7 | 0.6 |
| 331 Wood products | 10.5 | 5.1 | 12.6 | 6.5 | 15.8 | 7.3 | 6.6 | 3.2 | 5.2 | 5.4 |
| 332 Furniture | 4.6 | 2.4 | 6.2 | 4.1 | 8.1 | 1.5 | 0.9 | 0.3 | 0.9 | 1.0 |
| 341 Paper | 5.1 | 4.5 | 3.3 | 1.8 | 2.9 | 16.6 | 15.7 | 17.2 | 17.0 | 16.9 |
| 342 Printing | 10.1 | 7.0 | 11.9 | 16.9 | 26.5 | 11.5 | 7.9 | 11.2 | 6.2 | 5.3 |
| 351 Industrial chemicals | 7.0 | 6.4 | 8.1 | 12.1 | 18.1 | 40.5 | 38.6 | 65.6 | 44.3 | 43.9 |
| 352 Other chemicals | 2.9 | 2.9 | 3.1 | 2.3 | 3.2 | 14.4 | 14.5 | 16.9 | 12.6 | 11.8 |
| 354 Petroleum derivatives | n.a. | n.a. | n.a. | n.a. | n.a. | 5.8 | 4.2 | 3.3 | 3.5 | 4.7 |
| 355 Rubber products | 2.0 | 1.3 | 1.5 | 4.2 | 6.1 | 11.3 | 8.5 | 8.0 | 8.6 | 10.1 |
| 356 Plastics | 2.8 | 2.1 | 2.1 | 1.3 | 2.5 | 2.0 | 2.2 | 1.9 | 2.1 | 3.6 |
| 361 Ceramics | 9.9 | 2.8 | 5.1 | 7.0 | 28.3 | 7.2 | 3.8 | 2.0 | 2.9 | 6.1 |
| 362 Glass | 9.7 | 5.2 | 4.3 | 4.2 | 10.6 | 9.5 | 6.1 | 5.7 | 4.7 | 8.2 |
| 369 Nonmetallic minerals | 8.6 | 4.0 | 5.1 | 5.6 | 9.1 | 3.5 | 2.5 | 2.9 | 3.5 | 2.9 |
| 371 Iron and steel | n.a. | n.a. | n.a. | n.a. | n.a. | 38.5 | 35.8 | 82.0 | 34.0 | 39.7 |
| 372 Nonferrous metals | 2.6 | 10.3 | 13.9 | 7.4 | 4.8 | 51.2 | 51.8 | 92.2 | 45.4 | 50.2 |
| 381 Metal products | 7.1 | 3.4 | 3.8 | 4.6 | 10.1 | 15.1 | 14.4 | 14.6 | 12.3 | 15.9 |
| 382 Nonelectrical machinery | 12.1 | 4.1 | 6.6 | 5.7 | 17.6 | 71.8 | 70.5 | 178.8 | 68.3 | 70.2 |
| 383 Electrical machinery | 3.1 | 1.4 | 3.3 | 4.6 | 9.6 | 38.6 | 37.8 | 42.4 | 36.4 | 43.5 |
| 384 Transport equipment | 3.0 | 0.9 | 1.2 | 0.7 | 5.6 | 40.7 | 31.8 | 46.6 | 28.3 | 29.7 |
| 385 Professional equipment | 14.6 | 7.6 | 8.6 | 6.8 | 14.4 | 57.4 | 53.6 | 116.8 | 46.3 | 54.1 |
| 390 Other manufacturing | 37.0 | 18.4 | 17.5 | 42.9 | 58.1 | 11.7 | 9.6 | 5.7 | 7.2 | 12.4 |

Notes: n.a. the data on exports for Petroleum derivatives and Iron and Steel has irregularities.
Export orientation ratios are defined as the ratio of exports to total output (domestic output plus exports).
Import penetration ratios are defined as the ratio of imports to domestic demand (domestic output plus imports).

**Table 4 Relation between Measures of Trade Exposure**

**Table 4a Levels Correlations across Industries and Over Time**

| (3 digit industries) | Import penetration | Export orientation |
|---|---|---|
| Nominal tariffs | -0.537* | 0.007 |
| | *-0.702** | *-0.029* |
| Effective rate of protection | -0.545* | -0.045 |
| | *-0.674** | *-0.081* |
| Import penetration | | -0.074 |
| | | *-0.024* |

| (4 digit industries) | Import penetration | Export orientation |
|---|---|---|
| Nominal tariffs | -0.398* | -0.08 |
| | *-0.413** | *-0.026* |
| Import penetration | | 0.086* |
| | | *0.291* |

Notes: Spearman rank correlation coefficient in italics. * and ** represent significance at 5 and 10% levels, respectively
Nominal tariff levels for years 1980 and 1983-1988 and ERP for years 1983, 1984, 1989, 1990.
Correlations with export orientation are computed excluding petroleum derivatives and iron and steel.

**Table 4b Changes Correlations across Industries and Over Time**

| (3 digit industries) | Change imp. penet. | Change export orient. |
|---|---|---|
| Change tariffs | -0.038 | -0.301* |
| | *0.058* | *-0.193** |
| Change in eff. rate protection | -0.317* | -0.56* |
| | *-0.494** | *-0.628** |
| Change imp. penet. | | 0.137 |
| | | *0.201** |

| (4 digit industries) | Change imp. penet. | Change export orient. |
|---|---|---|
| Change tariffs | -0.028 | -0.005 |
| | *-0.049* | *-0.081* |
| Change imp. penet. | | -0.05 |

Notes: Spearman rank correlation coefficient in italics. * and ** represent significance at 5 and 10% levels, respectively
Nominal tariff changes for 1983-1984 to 1987-1988 and ERP for 1983-1984 and 1989-1990.
Correlations with changes in export orientation are computed excluding petroleum A90derivatives and iron and steel.

**Table 4c Tariff Changes Correlations across Industries and Trade Policy Regimes**

| (3 digit industries) | Change imp. penet. | Change export orient. |
|---|---|---|
| Change tariffs | 0.242 | -0.56* |
| | *0.358** | *-0.59** |
| Change imp. penet. | | -0.092 |
| | | *-0.138* |

| (4 digit industries) | Change imp. penet. | Change export orient. |
|---|---|---|
| Change tariffs | 0.088 | -0.0416 |
| | *0.155* | *-0.249** |
| Change imp. penet. | | -0.139 |
| | | *0.068* |

Notes: Spearman rank correlation coefficient in italics. * and ** represent significance at 5 and 10% levels, respectively
Nominal tariff changes for 1980-1983 and 1983-1988.
Correlations with changes in export orientation are computed excluding petroleum derivatives and iron and steel.

**Table 4d ERP Changes Correlations across Industries and Trade Policy Regimes**

| (3 digit industries) | Change imp. penet. | Change export orient. |
|---|---|---|
| Change in eff. rate protection | -0.117 | -0.366 |
| | *-0.262* | *-0.155* |
| Change imp. penet. | | 0.067 |
| | | *0.048* |

Notes: Spearman rank correlation coefficient *in italics.* * and ** represent significance at 5 and 10% levels, respectively
ERP changes for 1984-1990.
Correlations with changes in export orientation are computed excluding petroleum derivatives and iron and steel.

**Table 4e Tariffs and ERP Levels and Changes Correlations across Industries**

| (3 digit industries) | ERP | Change in ERP |
|---|---|---|
| Tariffs | 0.909* | |
| | *0.914** | |
| Changes in tariffs | | 0.973* |
| | | *0.984** |

Notes: Spearman rank correlation coefficient *in italics.* * and ** represent significance at 5 and 10% levels, respectively
Tariffs, ERP levels 1983, 1984, 1989, 1990 changes 1983-1984 and 1989-1990.

**Table 4f Tariffs and ERP Changes Correlations across Industries and Trade Regimes**

| (3 digit industries) | Change in ERP |
|---|---|
| Changes in tariffs | 0.974* |
| | *0.976** |

Notes: Spearman rank correlation coefficient *in italics.* * and ** represent significance at 5 and 10% levels, respectively
Tariffs changes 1980-1984, 1984-1988 and ERP changes 1979-1984, 1984-1990.

**Table 4g Licenses, Tariffs and ERP Levels Correlations across Industries**

| | Tariffs 3dig.1989 | ERP 3dig.1989 | Tariffs 4dig.1988 |
|---|---|---|---|
| License coverage 3 dig. 1989 | 0.636* | 0.644* | |
| | *0.747** | *0.883** | |
| License coverage 4 dig. 1989 | | | 0.598* |
| | | | *0.579** |

Notes: Spearman rank correlation coefficient *in italics.* * and ** represent significance at 5 and 10% levels, respectively

Table 5 Impact of Lagged Trade Policy on Productivity

| Regressors | OLS (1) | OLS (2) | OLS (3) | F.Effects (4) | F.Effects (5) | OLS (6) | OLS (7) | OLS (8) | F.Effects (9) | F.Effects (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Nominal tariff 3-digit | -0.164 * | -0.112 * | -0.108 * | -0.059 * | -0.074 * | | | | | |
| | (0.011) | (0.026) | (0.026) | (0.015) | (0.016) | | | | | |
| Nominal tariff 4-digit | | | | | | -0.193 * | -0.29 * | -0.112 * | -0.061 * | -0.081 * |
| | | | | | | (0.01) | (0.018) | (0.025) | (0.015) | (0.016) |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects 3-digit | | Yes | | | | | Yes | | | |
| Industry effects 4-digit | | | Yes | | Yes | | | Yes | | Yes |
| N. observations | 57861 | 57861 | 57861 | 57861 | 57861 | 54501 | 54501 | 54501 | 54501 | 54501 |
| R-squared | 0.009 | 0.340 | 0.368 | 0.035 | 0.053 | 0.011 | 0.355 | 0.377 | 0.034 | 0.051 |

Notes: Productivity is obtained nonparametrically and by GMM with materials controlling for endogeneity.
Robust standard errors are in parenthesis. * and ** indicate significance at 5% and 10% levels, respectively.
All regressions include a constant.
Years included are 1977, 1979, 1981, 1984-1989. One period lagged tariff measures are used.

Table 6 Impact of Lagged Trade Policy on Productivity Including Age and Exit

| Regressors | OLS | OLS | OLS | F.Effects | F.Effects | OLS | OLS | OLS | F.Effects | F.Effects |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Nominal tariff 3-digit | -0.116 * | -0.112 * | -0.109 * | -0.056 * | -0.07 * | | | | | |
| | (0.011) | (0.027) | (0.026) | (0.015) | (0.016) | | | | | |
| Nominal tariff 4-digit | | | | | | -0.132 * | -0.112 * | -0.111 * | -0.058 * | -0.077 * |
| | | | | | | (0.012) | (0.027) | (0.027) | (0.015) | (0.016) |
| Age | 0.005 * | 0.003 * | 0.003 * | 0.006 * | 0.006 * | 0.005 * | 0.004 * | 0.003 * | 0.007 * | 0.007 * |
| | (0.0004) | (0.0004) | (0.0004) | (0.001) | (0.001) | (0.0004) | (0.0004) | (0.0004) | (0.001) | (0.001) |
| Age squared | -0.00002 * | -0.00002 * | -0.00002 * | -0.0001 * | -0.0001 * | -0.00003 * | -0.00002 * | -0.00002 * | -0.0001 * | -0.0001 * |
| | (0.00001) | (0.00001) | (0.00001) | (0.00001) | (0.00001) | (0.00001) | (0.00001) | (0.00001) | (0.00001) | (0.00001) |
| Exit indicator | 0.011 | -0.008 | -0.007 | -0.029 * | -0.028 * | 0.013 | -0.007 | -0.008 | -0.03 * | -0.029 * |
| | (0.01) | (0.009) | (0.009) | (0.005) | (0.005) | (0.01) | (0.009) | (0.009) | (0.006) | (0.006) |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects 3-digit | | Yes | | | | | Yes | | | |
| Industry effects 4-digit | | | Yes | | Yes | | | Yes | | Yes |
| R-squared | 0.015 | 0.344 | 0.370 | 0.036 | 0.054 | 0.016 | 0.356 | 0.380 | 0.036 | 0.052 |
| N. observations | 57861 | 57861 | 57861 | 57861 | 57861 | 54501 | 54501 | 54501 | 54501 | 54501 |

Notes: Productivity is obtained nonparametrically and by GMM with materials controlling for endogeneity.
Robust standard errors are in parenthesis. * and ** indicate significance at 5% and 10% levels, respectively.
All regressions include a constant.
Exit indicator is equal to 1 in the last year of plant presence in the sample.
Years included are 1977, 1979, 1981, 1984-1989. One period lagged tariff measures are used.

Table 7 Impact of the Real Exchange Rate and Lagged Trade Policy on Productivity

| Regressor | OLS | F.Effects | OLS | OLS | F.Effects | OLS | OLS | F.Effects | OLS | OLS | F.Effects |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| Traded 3-digit Industries | -0.126 * | -0.217 * | | | | | | | | | |
| | (0.05) | (0.025) | | | | | | | | | |
| Traded 4-digit Industries | | | -0.069 * | -0.179 * | -0.184 * | | | | | | |
| | | | (0.052) | (0.042) | (0.025) | | | | | | |
| RER | -0.002 * | -0.002 * | -0.002 * | -0.002 * | -0.002 * | -0.001 * | -0.0003 | -0.0004 * | -0.001 * | -0.00004 * | -0.0004 * |
| | (0.0002) | (0.0001) | (0.0002) | (0.0002) | (0.0001) | (0.0003) | (0.0002) | (0.0001) | (0.0003) | (0.002) | (0.0001) |
| RER*Traded Ind. | 0.001 * | 0.002 * | 0.001 * | 0.001 * | 0.001 * | | | | | | |
| | (0.0003) | (0.0001) | (0.0003) | (0.0002) | (0.0001) | | | | | | |
| Trend | -0.024 * | -0.024 * | -0.025 * | -0.018 * | -0.025 * | -0.007 * | -0.0003 | -0.009 * | -0.007 * | 0.002 | -0.01 * |
| | (0.002) | (0.001) | (0.003) | (0.002) | (0.001) | (0.004) | (0.003) | (0.002) | (0.004) | (0.003) | (0.002) |
| Trend*Traded Ind. | 0.019 * | 0.015 * | 0.018 * | 0.01 * | 0.014 * | | | | | | |
| | (0.003) | (0.001) | (0.003) | (0.002) | (0.001) | | | | | | |
| Nominal Tariff 3-digit | | | | | | -0.049 * | -0.127 * | -0.122 * | | | |
| | | | | | | (0.011) | (0.02) | (0.011) | | | |
| Nominal Tariff 4-digit | | | | | | | | | -0.093 * | -0.243 * | -0.109 * |
| | | | | | | | | | (0.01) | (0.017) | (0.011) |
| Age | | | | | | 0.004 * | 0.003 * | 0.006 * | 0.004 * | 0.003 * | 0.006 * |
| | | | | | | (0.001) | (0.0004) | (0.001) | (0.001) | (0.0004) | (0.001) |
| Age squared | | | | | | -0.000005 | -0.000002 | -0.0001 * | -0.00001 | -0.000003 | -0.0001 * |
| | | | | | | (0.00001) | (0.00001) | (0.00001) | (0.00001) | (0.00001) | (0.00001) |
| Exit indicator | | | | | | 0.013 | -0.007 * | -0.017 * | 0.016 * | -0.006 | -0.017 * |
| | | | | | | (0.012) | (0.011) | (0.006) | (0.013) | (0.011) | (0.006) |
| Industry effects 3-digit | | | | Yes | | | Yes | | | Yes | |
| N. observations | 77423 | 77423 | 72651 | 72651 | 72651 | 45304 | 45304 | 45304 | 42630 | 42630 | 42630 |
| R-squared | 0.014 | 0.011 | 0.025 | 0.361 | 0.012 | 0.009 | 0.366 | 0.006 | 0.009 | 0.381 | 0.005 |

Notes: Productivity is obtained nonparametrically and by GMM with materialscontrolling for endogeneity.
Robust standard errors are in parenthesis. * and ** indicate significance at 5% and 10% levels, respectively.
The omitted category are nontraded industries.
Increase in the RER value is a real appreciation of the Colombian peso (IMF definition).
In columns (1)-(5), Petroleum Derivatives and Iron and Steel are excluded as their export data has irregularities, therefore the classication according to trade orientation is not defined.
Exit indicator is equal to 1 in the last year of plant presence in the sample.
In columns (1), (2) interactions refer to 3-digit traded industries, whereas in columns (3)-(5) they refer to 4-digit traded industries.
Years included in columns (1)-(5): 1980-1991. In columns (6)-(11): 1981, 1983, 1984-1989. One period lagged tariff measures are used.

**Table 8 Impact of Lagged Trade Policy on Productivity Differentiated by Size (Average Employment)**

| Regressor | OLS<br>(1) | OLS<br>(2) | OLS<br>(3) | OLS<br>(4) | OLS<br>(5) | OLS<br>(6) |
|---|---|---|---|---|---|---|
| Small | -0.004 | 0.096 * | 0.032 * | 0.019 * | 0.158 * | 0.04 * |
| | (0.008) | (0.013) | (0.024) | (0.009) | (0.011) | (0.024) |
| Large | 0.337 * | 0.443 * | 0.377 * | 0.308 * | 0.451 * | 0.337 * |
| | (0.015) | (0.018) | (0.027) | (0.015) | (0.016) | (0.026) |
| Nominal tariff 3-digit*Small | -0.035 * | -0.019 | -0.012 | | | |
| | (0.012) | (0.027) | (0.026) | | | |
| Nominal tariff 3-digit*Large | -0.451 * | -0.358 * | -0.356 * | | | |
| | (0.024) | (0.033) | (0.032) | | | |
| Nominal tariff 4-digit*Small | | | | -0.086 * | -0.18 * | -0.036 |
| | | | | (0.012) | (0.019) | (0.025) |
| Nominal tariff 4-digit*Large | | | | -0.392 * | -0.4 * | -0.266 * |
| | | | | (0.022) | (0.024) | (0.03) |
| Year effects Small Large | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects 3-digit | | Yes | | | Yes | |
| Industry effects 4-digit | | | Yes | | | Yes |
| N. observations | 57861 | 57861 | 57861 | 47415 | 47415 | 47415 |
| R-squared | 0.0269 | 0.3618 | 0.3875 | 0.0265 | 0.374 | 0.3957 |

Notes: Productivity is obtained nonparametrically and by GMM with materials controlling for endogeneity.
Robust standard errors are in parenthesis. * and ** indicate significance at 5% and 10% levels, respectively.
Small plants have on average less than 50 employees across the sample period.
Years included are 1977, 1979, 1981, 1984-1989. One period lagged tariff measures are used.

Table 9 Impact of Lagged Trade Policy on Productivity Differentiated by Size (Market Share)

| Regressor | OLS | OLS | OLS | F.Effects | F.Effects | OLS | OLS | OLS | F.Effects | F.Effects |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Market share 3-digit | 10.67 * | 12.28 * | 11.72 * | 9.91 * | 10.56 * | 9.44 * | 10.63 * | 9.89 * | 10.16 * | 10.78 * |
| | (0.675) | (0.745) | (0.714) | (0.473) | (0.482) | (0.625) | (0.713) | (0.72) | (0.494) | (0.505) |
| M. share squared | -15.97 * | -20.73 * | -18.95 * | -12.68 * | -13.18 * | -14.31 * | -19.02 * | -17.49 * | -13.07 * | -13.39 * |
| | (2.371) | (3.002) | (2.814) | (0.785) | (0.786) | (2.328) | (2.969) | (2.853) | (0.802) | (0.803) |
| Nominal tariff 3-digit | -0.104 * | -0.1 * | -0.095 * | -0.056 * | -0.07 * | | | | | |
| | (0.011) | (0.026) | (0.026) | (0.015) | (0.016) | | | | | |
| Nom.tariff3*M.share | -7.714 * | -5.799 * | -6.029 * | -0.001 | -0.011 | | | | | |
| | (1.109) | (0.903) | (0.848) | (0.008) | (0.008) | | | | | |
| Nominal tariff4-digit | | | | | | -0.13 * | -0.217 * | -0.105 * | -0.056 * | -0.077 * |
| | | | | | | (0.011) | (0.018) | (0.025) | (0.015) | (0.016) |
| Nom.tariff4*M.share | | | | | | -6.234 * | -2.692 * | -2.186 * | 0.019 | -1.038 |
| | | | | | | (0.012) | (0.858) | (0.86) | (0.819) | (0.822) |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects 3-digit | | Yes | | | | | Yes | | | |
| Industry effects 4-digit | | | Yes | | Yes | | | Yes | | Yes |
| N. observations | 57861 | 57861 | 57861 | 57861 | 57861 | 47415 | 47415 | 47415 | 47415 | 47415 |
| R-squared | 0.033 | 0.377 | 0.399 | 0.052 | 0.071 | 0.033 | 0.389 | 0.406 | 0.053 | 0.069 |

Notes: Productivity is obtained nonparametrically and by GMM with materials controlling for endogeneity.
Robust standard errors are in parenthesis. * and ** indicate significance at 5% and 10% levels, respectively.
Years included are 1977, 1979, 1981, 1984-1989. One period lagged tariff measures are used.

Table 10 Impact of Lagged Trade Policy on Productivity Differentiated by Degree of Domestic Competition (Herfindahl Index, Turnover Rate)

| Regressor | OLS (1) | OLS (2) | OLS (3) | OLS (4) | OLS (5) | OLS (6) | OLS (7) | OLS (8) |
|---|---|---|---|---|---|---|---|---|
| Herfindahl Index 3-digit | 0.579 * | 0.148 | | | | | | |
| | (0.123) | (0.119) | | | | | | |
| Nominal tariff 3-digit | -0.106 * | | -0.209 * | -0.126 * | | | -0.917 * | |
| | (0.014) | | (0.014) | (0.027) | | | (0.057) | |
| Nom.tariff3*Herf.3 | -3.559 * | | | | | | | |
| | (0.298) | | | | | | | |
| Nominal tariff 4-digit | | -0.153 * | | | -0.222 * | -0.292 * | | -0.863 * |
| | | (0.014) | | | (0.014) | (0.02) | | (0.046) |
| Nom.tariff4*Herf.3 | | -2.206 * | | | | | | |
| | | (0.277) | | | | | | |
| Herfindahl Index 4-digit | | | -0.373 * | -0.143 ** | -0.231 * | -0.001 | | |
| | | | (0.065) | (0.08) | (0.075) | (0.094) | | |
| Nom.tariff3*Herf.4 | | | 1.081 * | 0.361 * | | | | |
| | | | (0.138) | (0.164) | | | | |
| Nom.tariff4*Herf.4 | | | | | 0.638 * | 0.026 | | |
| | | | | | (0.146) | (0.168) | | |
| Turnover rate 3-digit | | | | | | | -0.247 * | -0.429 * |
| | | | | | | | (0.1) | (0.101) |
| Nominal tariff3*Turnover3 | | | | | | | 2.428 * | |
| | | | | | | | (0.207) | |
| Nominal tariff4*Turnover3 | | | | | | | | 2.415 * |
| | | | | | | | | (0.185) |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects 3-digit | | | | Yes | | Yes | | |
| N. observations | 57861 | 54501 | 57861 | 57861 | 54501 | 54501 | 57861 | 54501 |
| R-squared | 0.014 | 0.0149 | 0.0096 | 0.3402 | 0.0113 | 0.3551 | 0.015 | 0.017 |

Notes: Productivity is obtained nonparametrically and by GMM with materials controlling for endogeneity.
Robust standard errors are in parenthesis. * and ** indicate significance at 5% and 10% levels, respectively.
Years included are 1977, 1979, 1981, 1984-1989. One period lagged tariff measures are used.

**Table 11 Impact of Lagged Trade Policy on Productivity, Effective Rates of Protection**

| Regressors | OLS | OLS | OLS | OLS | OLS | OLS | F.Effects | F.Effects | F.Effects | F.Effects |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (1') | (2) | (2') | (3) | (3') | (4) | (4') | (5) | (5') |
| Nominal tariff 3-digit | | -0.091 * | | -0.176 * | | -0.174 * | | -0.122 * | | -0.132 * |
| | | (0.013) | | (0.029) | | (0.029) | | (0.018) | | (0.019) |
| ERP 3-digit | 0.025 * | | 0.006 | | 0.007 | | 0.027 * | | 0.026 * | |
| | (0.006) | | (0.014) | | (0.014) | | (0.009) | | (0.009) | |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects 3-digit | | | Yes | Yes | | | | | | |
| Industry effects 4-digit | | | | | Yes | Yes | | | Yes | Yes |
| N. observations | 32456 | 32456 | 32456 | 32456 | 32456 | 32456 | 32456 | 32456 | 32486 | 32486 |
| R-squared | 0.004 | 0.004 | 0.359 | 0.359 | 0.386 | 0.387 | 0.022 | 0.024 | 0.046 | 0.048 |

Notes: Productivity is obtained nonparametrically and by GMM with materials controlling for endogeneity.
Robust standard errors are in parenthesis. * and ** indicate significance at 5% and 10% levels, respectively.
All regressions include a constant.
Nominal tariffs at a 3-digit level are from a different source than nominal tariffs in Tables 10-14.
Years included are 1980, 1984, 1985, 1990, 1991. One period lagged ERP and tariff measures are used.

**Table 12 Impact of Lagged Trade Policy on Productivity Differentiated by Size (Average Employment, Market Shares), Effective Rates of Protection**

**Part A**

| Regressor | OLS (1) | OLS (1') | OLS (2) | OLS (2') | OLS (3) | OLS (3') |
|---|---|---|---|---|---|---|
| Small | -0.083 * | -0.02 * | 0.047 * | 0.124 * | -0.018 | 0.044 ** |
| | (0.008) | (0.008) | (0.017) | (0.013) | (0.026) | (0.024) |
| Large | 0.227 * | 0.258 * | 0.389 * | 0.42 * | 0.298 * | 0.332 * |
| | (0.015) | (0.016) | (0.022) | (0.019) | (0.029) | (0.026) |
| ERP 3 digit*Small | 0.1 * | | 0.074 * | | 0.066 * | |
| | (0.007) | | (0.022) | | (0.014) | |
| ERP 3-digit*Large | -0.135 * | | -0.155 * | | -0.135 * | |
| | (0.012) | | (0.017) | | (0.017) | |
| Nominal tariff 3-digit*Small | | 0.018 | | -0.082 * | | -0.082 * |
| | | (0.015) | | (0.03) | | (0.03) |
| Nominal tariff 3-digit*Large | | -0.327 * | | -0.382 * | | -0.376 * |
| | | (0.028) | | (0.037) | | (0.036) |
| Year effects Small Large | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects 3-digit | | | Yes | Yes | | |
| Industry effects 4-digit | | | | | Yes | Yes |
| N. observations | 32456 | 32456 | 32456 | 32456 | 32456 | 32456 |
| R-squared | 0.027 | 0.024 | 0.388 | 0.382 | 0.409 | 0.408 |

**Part B**

| Regressor | OLS (1) | OLS (1') | OLS (2) | OLS (2') | OLS (3) | OLS (3') | FE (4) | FE (4') | FE (5) | FE (5') |
|---|---|---|---|---|---|---|---|---|---|---|
| Market share 3-digit | 10.64 * | 10.16 * | 11.81 * | 11.96 * | 10.97 * | 11.28 * | 10.51 * | 10.37 * | 10.77 * | 10.73 * |
| | (0.671) | (0.681) | (0.653) | (0.692) | (0.615) | (0.654) | (0.533) | (0.641) | (0.643) | (0.65) |
| M. share squared | -18.97 * | -18.07 * | -23.11 * | -23.17 * | -20.97 * | -21.11 * | -18.05 * | -17.98 * | -18.27 * | -18.32 * |
| | (1.673) | (1.576) | (1.722) | (1.733) | (1.59) | (1.616) | (1.449) | (1.451) | (1.455) | (1.456) |
| ERP 3-digit | 0.061 * | | 0.012 | | 0.012 | | 0.029 * | | 0.026 * | |
| | (0.006) | | (0.014) | | (0.014) | | (0.009) | | (0.009) | |
| ERP3*M.share | -3.232 * | | -1.929 * | | -1.755 * | | 0.281 | | 0.182 | |
| | (0.699) | | (0.578) | | (0.541) | | (0.413) | | (0.411) | |
| Nominal tariff 3-digit | | -0.04 * | | -0.162 * | | -0.161 * | | -0.122 * | | -0.132 * |
| | | (0.013) | | (0.029) | | (0.029) | | (0.018) | | (0.018) |
| Nom.tariff3*M.share | | -5.404 * | | -3.776 * | | -3.871 * | | 0.747 | | 0.4 |
| | | (1.319) | | (1.135) | | (1.059) | | (0.794) | | (0.789) |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects 3-digit | | | Yes | Yes | | | | | | |
| Industry effects 4-digit | | | | | Yes | Yes | | | Yes | Yes |
| N. observations | 32456 | 32456 | 32456 | 32456 | 32456 | 32456 | 32456 | 32456 | 32456 | 32456 |
| R-squared | 0.030 | 0.029 | 0.395 | 0.396 | 0.417 | 0.418 | 0.039 | 0.041 | 0.063 | 0.065 |

Notes: Productivity is obtained nonparametrically and by GMM with materials controlling for endogeneity.
Robust standard errors are in parenthesis. * and ** indicate significance at 5% and 10% levels, respectively.
In Part A, small plants have on average less than 50 employees across the sample period. In Part B, market shares are relative to 3-digit industry output.
Years included are 1980, 1984, 1985, 1990, 1991. One period lagged ERP and tariff measures are used.

**Table 13 Impact of Lagged Trade Policy on Productivity Differentiated by Degree of Domestic Competition (Herfindahl Index, Turnover Rate), Effective Rates of Protection**

| Regressor | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
|---|---|---|---|---|---|---|---|---|
| | (1) | (1') | (2) | (2') | (3) | (3') | (4) | (4') |
| Herfindahl Index 3-digit | 0.076 | -0.21 | | | | | | |
| | (0.14) | (0.149) | | | | | | |
| ERP 3-digit | 0.036 * | | 0.011 * | | 0.007 * | | -0.051 * | |
| | (0.008) | | (0.008) | | (0.015) | | (0.026) | |
| ERP3*Herf.3 | -0.963 * | | | | | | | |
| | (0.18) | | | | | | | |
| Nominal tariff 3-digit | | -0.094 * | | -0.244 * | | -0.198 * | | -0.866 * |
| | | (0.016) | | (0.013) | | (0.03) | | (0.068) |
| Nom.tariff3*Herf.3 | | -1.477 * | | | | | | |
| | | (0.372) | | | | | | |
| Herfindahl Index 4-digit | | | -0.067 * | -0.528 * | -0.004 * | -0.348 * | | |
| | | | (0.068) | (0.071) | (0.075) | (0.083) | | |
| ERP3*Herf.4 | | | 0.295 * | | -0.016 * | | | |
| | | | (0.071) | | (0.074) | | | |
| Nom.tariff3*Herf.4 | | | | 1.275 * | | 0.795 * | | |
| | | | | (0.147) | | (0.174) | | |
| Turnover 3-digit | | | | | | | -0.173 | -0.352 * |
| | | | | | | | (0.111) | (0.116) |
| ERP3*Turnover3 | | | | | | | 0.324 * | |
| | | | | | | | (0.112) | |
| Nom.tariff3*Turnover3 | | | | | | | | 2.576 * |
| | | | | | | | | (0.245) |
| Year effects | | | | | | | | |
| Industry effects 3-digit | | | | | Yes | Yes | | |
| N. observations | 32456 | 32456 | 32456 | 32456 | 32456 | 32456 | 32456 | 32456 |
| R-squared | 0.006 | 0.008 | 0.005 | 0.015 | 0.359 | 0.360 | 0.004 | 0.011 |

Notes: Productivity is obtained nonparametrically and by GMM with materials controlling for endogeneity.
Robust standard errors are in parenthesis. * and ** indicate significance at 5% and 10% levels, respectively.
Years included are 1980, 1984, 1985, 1990, 1991. One period lagged ERP and tariff measures are used.

Table 14 Impact of Lagged Trade Exposure on Productivity

| Regressors | OLS | OLS | OLS | OLS | OLS | OLS | F.Effects | F.Effects |
|---|---|---|---|---|---|---|---|---|
| | (1) | (1') | (2) | (2') | (3) | (3') | (4) | (4') |
| Import penetration ratio 3-digit | 0.182 * | 0.165 * | 1.77 * | 1.78 * | 1.784 * | 1.792 * | 0.443 * | 0.442 * |
| | (0.01) | (0.01) | (0.078) | (0.078) | (0.076) | (0.076) | (0.024) | (0.024) |
| Age | | 0.003 * | | 0.002 * | | 0.002 * | | 0.007 * |
| | | (0.0004) | | (0.0003) | | (0.0004) | | (0.0009) |
| Age squared | | 0.000003 | | 0.000001 * | | -0.000001 | | -0.0001 * |
| | | (0.00001) | | (0.00001) | | (0.00001) | | (0.00001) |
| Exit indicator | | -0.01 | | -0.03 * | | -0.029 * | | -0.027 * |
| | | (0.009) | | (0.008) | | (0.008) | | (0.004) |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects 3-digit | | | Yes | Yes | | | | |
| Industry effects 4-digit | | | | | Yes | Yes | | |
| R-squared | 0.004 | 0.010 | 0.357 | 0.360 | 0.384 | 0.386 | 0.010 | 0.012 |
| N. observations | 71928 | 71928 | 71928 | 71928 | 71928 | 71928 | 71928 | 71928 |

| Regressors | OLS | OLS | OLS | OLS | OLS | OLS | F.Effects | F.Effects |
|---|---|---|---|---|---|---|---|---|
| | (5) | (5') | (6) | (6') | (7) | (7') | (8) | (8') |
| Import penetration ratio 4-digit | 0.075 * | 0.057 * | -0.036 * | -0.035 ** | 0.655 * | 0.658 * | 0.249 * | 0.248 * |
| | (0.009) | (0.009) | (0.018) | (0.018) | (0.052) | (0.052) | (0.019) | (0.019) |
| Age | | 0.004 * | | 0.002 * | | 0.002 * | | 0.007 * |
| | | (0.0004) | | (0.0003) | | (0.0003) | | (0.001) |
| Age squared | | -0.000003 * | | 0.000001 | | 0.0000003 | | -0.0001 * |
| | | (0.00001) | | (0.00001) | | (0.00001) | | (0.00001) |
| Exit indicator | | -0.01 | | -0.029 * | | -0.029 * | | -0.027 * |
| | | (0.009) | | (0.008) | | (0.008) | | (0.004) |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects 3-digit | | | Yes | Yes | | | | |
| Industry effects 4-digit | | | | | Yes | Yes | | |
| N. observations | 67687 | 67687 | 67687 | 67687 | 67687 | 67687 | 67687 | 67687 |
| R-squared | 0.001 | 0.008 | 0.365 | 0.369 | 0.391 | 0.393 | 0.007 | 0.009 |

Notes: Productivity is obtained nonparametrically and by GMM with materials controlling for endogeneity.
Robust standard errors are in parenthesis. * and ** indicate significance at 5% and 10% levels, respectively.
Exit indicator is equal to 1 in the last year of plant presence in the sample.
All regressions include a constant.
Years included are 1981-1991. One period lagged import penetration ratios are used.

**Table 15 Impact of Lagged Trade Exposure on Productivity Differentiated by Size (Average Employment)**

**Part A**

| Regressor | OLS | OLS | OLS | OLS | OLS | OLS |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Small | -0.079 * | -0.03 * | -0.093 * | -0.078 * | 0.058 * | -0.064 * |
| | (0.007) | (0.009) | (0.018) | (0.008) | (0.008) | (0.018) |
| Large | -0.007 | 0.072 * | 0.008 | 0.021 | 0.191 * | 0.061 * |
| | (0.014) | (0.014) | (0.02) | (0.014) | (0.014) | (0.02) |
| Import Penet.3-digit*Small | -0.012 | 1.554 * | 1.582 * | | | |
| | (0.011) | (0.074) | (0.072) | | | |
| Import Penet.3-digit*Large | 0.644 * | 2.187 * | 2.163 * | | | |
| | (0.02) | (0.076) | (0.074) | | | |
| Import Penet.4-digit*Small | | | | -0.053 * | -0.178 * | 0.542 * |
| | | | | (0.01) | (0.019) | (0.05) |
| Import Penet.4-digit*Large | | | | 0.373 * | 0.203 * | 0.916 * |
| | | | | (0.019) | (0.023) | (0.052) |
| Year effects Small Large | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects 3 digit | | Yes | | | Yes | |
| Industry effects 4 digit | | | Yes | | | Yes |
| N. observations | 71928 | 71928 | 71928 | 67687 | 67687 | 67687 |
| R-squared | 0.030 | 0.385 | 0.408 | 0.023 | 0.389 | 0.413 |

**Part B**

| Regressor | OLS | OLS | OLS | F.Effects | F.Effects | OLS | OLS | OLS | F.Effects |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Market share 3-digit | 7.28 * | 9.89 * | 9.19 * | 13.05 * | 13.73 * | 7.58 * | 10.18 * | 9.41 * | 13.66 * |
| | (0.274) | (0.261) | (0.253) | (0.426) | (0.429) | (0.279) | (0.263) | (0.26) | (0.448) |
| M. share squared | -16.98 * | -22.82 * | -20.73 * | -21.33 * | -22 * | -16.93 * | -22.78 * | -20.75 * | -22.86 * |
| | (1.035) | (1.168) | (1.078) | (0.973) | (0.971) | (0.997) | (1.124) | (1.072) | (0.996) |
| Import penet. 3-digit | 0.129 * | 1.751 * | 1.764 * | 0.414 * | 1.611 * | | | | |
| | (0.01) | (0.073) | (0.071) | (0.024) | (0.049) | | | | |
| Imp.penet.3*M.share | 3.888 * | 3.605 * | 3.544 * | -2.592 * | -2.937 * | | | | |
| | (0.714) | (0.597) | (0.534) | (0.717) | (0.727) | | | | |
| Import penet. 4-digit | | | | | | 0.048 * | 0.022 | 0.664 * | 0.226 * |
| | | | | | | (0.009) | (0.018) | (0.049) | (0.019) |
| Imp.penet.4*M.share | | | | | | 2.329 * | 2.437 * | 2.505 * | -1.409 ** |
| | | | | | | (0.77) | (0.604) | (0.573) | (0.733) |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects 3-digit | | Yes | | | | | Yes | | |
| Industry effects 4-digit | | | Yes | | Yes | | | Yes | |
| N. observations | 71928 | 71928 | 71928 | 71928 | 71928 | 67687 | 67687 | 67687 | 67687 |
| R-squared | 0.028 | 0.393 | 0.415 | 0.028 | 0.057 | 0.024 | 0.400 | 0.420 | 0.027 |

Notes: Productivity is obtained nonparametrically and by GMM with materials controlling for endogeneity.
Robust standard errors are in parenthesis. * and ** indicate significance at 5% and 10% levels, respectively.
In Part A, small plants have on average less than 50 employees across the sample period. In Part B, market shares relative to 3-digit industry output.
Years included are 1981-1991. One period lagged import penetration ratios are used.

Table 16 Impact of Lagged Trade Exposure on Productivity Differentiated by Degree of Domestic Competition (Herfindahl Index, Turnover Rate)

| Regressor | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Herfindahl Index 3-digit | -0.838 * | -0.855 * | | | | | | |
| | (0.051) | (0.052) | | | | | | |
| Import penet. 3-digit | 0.234 * | | 0.291 * | 1.656 * | | | -0.787 * | |
| | (0.016) | | (0.019) | (0.082) | | | (0.076) | |
| Imp.penet.3*Herf.3 | -0.041 | | | | | | | |
| | (0.22) | | | | | | | |
| Import penet. 4-digit | | 0.071 * | | | 0.1 * | -0.105 * | | -1.084 * |
| | | (0.014) | | | (0.016) | (0.026) | | (0.058) |
| Imp.penet.4*Herf.3 | | 0.889 * | | | | | | |
| | | (0.215) | | | | | | |
| Herfindahl Index 4-digit | | | 0.199 * | -0.118 * | 0.176 * | -0.148 * | | |
| | | | (0.028) | (0.032) | (0.033) | (0.04) | | |
| Imp.penet.3*Herf.4 | | | -1.076 * | 0.822 * | | | | |
| | | | (0.146) | (0.174) | | | | |
| Imp.penet.4*Herf.4 | | | | | -0.378 * | 0.623 * | | |
| | | | | | (0.126) | (0.149) | | |
| Turnover 3-digit | | | | | | | 0.003 * | 0.001 * |
| | | | | | | | (0.0004) | (0.0004) |
| Imp.penet.3*Turnover3 | | | | | | | 0.061 * | |
| | | | | | | | (0.004) | |
| Imp.penet.4*Turnover3 | | | | | | | | 0.07 * |
| | | | | | | | | (0.003) |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects 3-digit | | | | Yes | | Yes | | |
| N. observations | 71928 | 67687 | 71928 | 71928 | 67687 | 67687 | 71928 | 67687 |
| R-squared | 0.009 | 0.005 | 0.005 | 0.357 | 0.002 | 0.366 | 0.008 | 0.006 |

Notes: Productivity is obtained nonparametrically and by GMM with materials controlling for endogeneity. Robust standard errors are in parenthesis. * and ** indicate significance at 5% and 10% levels, respectively.
All regressions include a constant.
Years included are 1981-1991. One period lagged import penetration ratios are used.

Table 17 Impact of Lagged Trade Policy and Trade Exposure on Productivity Growth

| Regressors | OLS (1) | OLS (2) | OLS (3) | F.Effects (4) | F.Effects (5) | OLS (6) | OLS (7) | OLS (8) | F.Effects (9) | F.Effects (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Nominal tariff 3-digit | 0.03 * | -0.057 * | -0.057 * | -0.034 ** | -0.05 * | | | | | |
| | (0.007) | (0.018) | (0.018) | (0.019) | (0.02) | | | | | |
| Nominal tariff 4-digit | | | | | | 0.022 * | -0.029 * | -0.061 * | -0.046 * | -0.053 * |
| | | | | | | (0.006) | (0.014) | (0.017) | (0.018) | (0.019) |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects 3-digit | | Yes | | | | | Yes | | | |
| Industry effects 4-digit | | | Yes | | Yes | | | Yes | | Yes |
| N. observations | 45514 | 45514 | 45514 | 45514 | 45514 | 42884 | 42884 | 42884 | 42884 | 42884 |
| R-squared | 0.010 | 0.019 | 0.020 | 0.010 | 0.018 | 0.010 | 0.019 | 0.020 | 0.010 | 0.017 |

| Regressors | OLS (1') | OLS (2') | OLS (3') | F.Effects (4') | F.Effects (5') |
|---|---|---|---|---|---|
| ERP 3-digit | 0.009 * | -0.035 * | -0.035 * | -0.017 | -0.021 ** |
| | (0.004) | (0.009) | (0.009) | (0.01) | (0.01) |
| Year effects | Yes | Yes | Yes | Yes | Yes |
| Industry effects 3-digit | | Yes | | | |
| Industry effects 4-digit | | | Yes | | Yes |
| N. observations | 29274 | 29274 | 29274 | 29274 | 29274 |
| R-squared | 0.008 | 0.013 | 0.016 | 0.010 | 0.020 |

| Regressors | OLS (1'') | OLS (2'') | OLS (3'') | F.Effects (4'') | F.Effects (5'') | OLS (6'') | OLS (7'') | OLS (8'') | F.Effects (9'') | F.Effects (10'') |
|---|---|---|---|---|---|---|---|---|---|---|
| Import Penetration 3-digit | 0.016 * | 0.251 * | 0.251 * | 0.112 * | 0.308 * | | | | | |
| | (0.006) | (0.048) | (0.048) | (0.029) | (0.059) | | | | | |
| Import Penetration 4-digit | | | | | | 0.006 | 0.025 * | 0.068 * | 0.053 * | 0.098 * |
| | | | | | | (0.006) | (0.011) | (0.034) | (0.023) | (0.04) |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects 3-digit | | Yes | | | | | Yes | | | |
| Industry effects 4-digit | | | Yes | | Yes | | | Yes | | Yes |
| N. observations | 64238 | 64238 | 64238 | 64238 | 64238 | 60445 | 60445 | 60445 | 60445 | 60445 |
| R-squared | 0.008 | 0.014 | 0.015 | 0.006 | 0.014 | 0.008 | 0.013 | 0.014 | 0.006 | 0.013 |

Notes: Productivity growth rates are obtained for each plant as the difference between productivity (obtained nonparametrically and by GMM with materials controlling for endogeneity) at t and at productivity at t-1.

Robust standard errors are in parenthesis. * and ** indicate significance at 5% and 10% levels, respectively.

All regressions include a constant.

Years included are: for tariffs 1979, 1981, 1984-1989, for ERP 1980, 1984, 1985, 1990, 1991, for import penetration 1981-1991. One period lagged ERP, tariffs and import penetration ratios are used.