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Productivity, Markups, and Trade: Evidence from Mexican Manufacturing Industries*

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Abstract: This paper applies a structural framework to estimate production function coefficients, obtain firm-level markup estimates, and evaluate the impact of the trade liberalization that took place in Mexico in the period 1984-1990 on the profitability of the firms operating in the domestic market and exporters. Quantitatively, the results show no evidence of substantial productivity growth, but some evidence of trade discipline on the price-cost margins. A markup premium is however identified for intensive exporters. Qualitatively, these results suggest that the effectiveness of trade policies crucially depends on adequately implementing complementary reforms aimed at improving the competitiveness and the efficiency in the allocation of resources in the internal market.

Keywords: Production function estimation; Productivity; Markups; Trade liberalization; Mexican manufacturing industries.

JEL Classification: D22, D24, F14, L11, L60.

Resumen: En este documento, se aplica un marco estructural para estimar los coeficientes de la función de producción, se obtienen estimaciones de márgenes precio-costo (markups) a nivel empresa y se evalúa el impacto de la liberalización comercial que ocurrió en México en el periodo 1984-1990 sobre la rentabilidad de las empresas que operan en el mercado nacional y la de los exportadores. Cuantitativamente, los resultados no muestran evidencia de un crecimiento sustancial de la productividad, pero sí cierta evidencia de la presencia de disciplina comercial en los márgenes de rentabilidad. Sin embargo, se observa una prima sobre los markups para los exportadores intensivos. Cualitativamente, estos resultados sugieren que la efectividad de las políticas comerciales depende fundamentalmente de la implementación adecuada de reformas complementarias que mejoren la competencia y la eficiencia en la asignación de los recursos en el mercado interno.

Palabras Clave: Estimación de la función de producción; Productividad; Markups; Liberalización comercial, Industrias manufactureras mexicanas.

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1 Introduction

To evaluate the effects of any policy or answer economic relevant questions it is of primary importance to accurately quantify the variables and the parameters that may be involved with the policy or the questions. Since production functions are a fundamental component of all economics, oftentimes it is hard to even formulate a question appropriately without considering production functions and embedding them in the framework. This is because much of economic theory provides testable implications that are directly related to technology and optimizing behavior. Production functions relate productive inputs to outputs and applied economists started to worry since the early 1940s about the issues confronting their estimation because of the potential correlation between optimal input choices and unobserved firm-specific determinants of production. The rationale behind this concern is intuitive. Firms that experience higher productivity shocks are likely to respond increasing their input usage, therefore classical estimation methods as, for example, ordinary least squares (OLS) will yield biased coefficient estimates and biased estimates of productivity. Consequently, any further analysis or evaluation based on those biased estimates will be necessarily unreliable.

In the literature many alternatives to OLS have been proposed, from relatively simple instrumental variables and fixed effects solutions to more complex and sophisticated techniques like dynamic panel data estimators and structural empirical models.¹ This study relates to this more recent structural estimation strand of the literature by relying on the original insight of Olley and Pakes (1996) and attempting to correctly estimate production function parameters and productivity using an observable proxy, either investment or intermediate inputs, to control for the correlation between input levels and the unobserved productivity shock. The essential assumption for successfully applying this methodology is that productivity and investment (or intermediate inputs) are linked through a unique monotonic relation so that observed investment (or intermediate inputs) choices contain valuable information about the productivity shock and can be used to consistently estimate production function coefficients. I take this empirical framework to a rich panel dataset including information on production and trade characteristics for over 2,000 Mexican manufacturing firms between 1984 and 1990.

With the unbiased production function estimates in hand, I further derive firm-level price-

¹For a successful application of duality and instrumental variables in the context of production function estimation see the contribution by Nerlove (1963). For examples of fixed effects in production function estimation see Hoch (1955), Hoch (1962), or Mundlak (1961). For dynamic panel data techniques see Chamberlain (1982) and, more recently, Blundell and Bond (2000). For structural empirical model of production function estimation see the pioneering contribution of Olley and Pakes (1996) and the successive extensions by Levinsohn and Petrin (2003) and Akerberg, Cavez, and Frazer (2015) with exogenous productivity and Doraszelski and Jaumandreu (2013) with endogenous productivity.

cost margins relying on a structural approach in which markups are given by the wedge between the cost share of factors of production and their revenue share. This approach has the advantage of being very general and flexible as it does not impose any strong restrictions on the underlying production function and it does not require to specify how firms compete in the market. I then compare these plant-level markup estimates with industry-level markups obtained through a simpler dual approach in order to verify the extent to which using micro-level information and directly controlling for unobserved firm-level productivity is important in correctly evaluating market power. In this dimension, my contribution connects to the literature on estimating markups using production data that dates back to R. Hall, Blanchard, and Hubbard (1986) and to the renewed debate regarding whether very disaggregated data (i.e. at the firm level) are necessary to obtain more accurate estimates of market power.²

During the period covered in the data the Mexican economy tried to find its way out of a deep recession undergoing major structural reforms such as reduction in government expenditure, privatization of state-owned companies, elimination of subsidies, deregulation of financial markets, liberalization of foreign investment, and a dramatic re-orientation of trade policy. The trade policy reforms were perhaps the most striking leading Mexico to become one of the most open economy in the world in less than a decade. Therefore, the Mexican economic environment in those years is particularly suitable to analyze the effects of trade exposure on the Mexican manufacturing firms. More specifically, in order to investigate whether the outward looking trade reforms lowered the profitability of the domestic firms by boosting competition, I test the relation between markups and measures of import liberalization in a regression framework. In addition, I combine the markups and the productivity estimates to verify the prediction of several recent international trade models that exporters are more productive and thus able to charge higher markups.³

Quantitatively, the main findings of my contribution can be summarized as follows. First, controlling for unobserved productivity with the investment proxy corrects for the simultaneity bias in the production function parameter estimates. Second, the markups estimated at the firm level are more reasonable and significantly higher than the ones estimated at the industry level, demonstrating that exploiting micro-level data and taking into account differences in

²See De Loecker and Warzynski (2012) for how to estimate markups with firm-level production data. For insights on the extent to which the level of (dis)aggregation in the data impacts and potentially biases the estimation of markups see R. Hall (2018) as well as De Loecker and Eeckhout (2017) and De Loecker and Eeckhout (2018).

³Bernard, Eaton, Jensen, and Kortum (2003) and Melitz and Ottaviano (2008) are examples of models where higher levels of productivity explain the ability of certain firms to both become exporters and charge higher markups.

productivity is important to assess the extent of market power. Third, there is no evidence that productivity grew substantially during the period of trade liberalization analyzed even though there is a lot of heterogeneity and reshuffling across firms. There is however evidence that allocative efficiency had a perverse effect in many industries with productive resources being reallocated toward less productive firms. Fourth, the industry-level analysis on the impact of trade liberalization on the profitability of the Mexican manufacturing industries provides some evidence of import discipline, but this result is not confirmed at the plant level. Lastly, the markup premium for exporters—the additional percentage markup granted to firms that export—is significant only for intensive exporters, i.e. firms exporting a high percentage of their output. Qualitatively, all these results point to a crucial lesson for the Mexican economy that is particularly insightful in times of great economic uncertainty. The effectiveness of trade policies crucially depends on the ability of implementing complementary reforms aimed at the internal market that promote competition, eliminate distortions in the allocation of resources, and stimulate investments in innovation and growth. These policy implications connect my study to a wave of recent papers that focus on productivity in developing countries and find that the low productivity that too often afflicts the developing world can be attributed to lack of competition (Bloom and Van Reenen (2007) and Bloom and Van Reenen (2010)) or the presence of policy distortions that result in a misallocation of resources across firms (Hsieh and Klenow (2009)).

The remainder of the paper is organized as follows. Section 2 provides an overview of the main issues regarding production function estimation and illustrates in detail the empirical methodology used to estimate the production function parameters as well as the markups. Section 3 briefly characterizes the main features of the Mexican trade liberalization and illustrates some simple models suitable to relate markups and trade exposure. The data and the sample selection criteria are described in Section 4. Sections 5 and 6 present the results of the production function estimation and price-cost margins analysis, respectively. Section 7 offers some concluding remarks.

2 Empirical Methodology

2.1 Issues with Correctly Estimating Production Function Parameters

Production functions are an essential component in both theoretical and empirical economic models and their estimation has a long history in applied economics, starting in 1800. However, researchers are actually interested in estimating production functions because, in most

cases, it is a tool for answering other questions, only partially related to the production function itself. Oftentimes it is hard to even formulate a question appropriately without considering production functions and embedding them in the framework. For example, a researcher may be interested in the presence of economies of scale in production, in whether productivity differences depend upon differences in the quality of labor or differences in R&D, in whether the marginal product of factors are equal to factor prices, in what the market structure is in different industries and how this is related to the profitability of the firms. All these questions require reliable estimates of cost or production functions and are so important and interesting in economics that it is worth trying to answer them, even though the estimation framework used for these purposes may be quite problematic.⁴

Econometric production functions, as we know them today, essentially relate productive inputs (e.g. capital and labor) to outputs and have their roots in the work of Cobb and Douglas (1928) who proposed production function estimation as a tool for testing hypotheses on marginal productivity and competitiveness in labor markets. Criticism to their approach came soon with Marschak and Andrews (1944) being the first to explicitly identify simultaneity as one of the main reasons why production function estimation is problematic noting that, in fact, the production function is only one part of a system of functional relationships known to the firm but mostly unknown or unobserved by the econometrician.⁵

The earliest responses to the concerns about the necessity of considering the endogeneity issues in production function estimation came through the increasing availability of panel data and developed, traditionally, along two main directions: fixed effects and instrumental variables. The problem with these two alternative approaches is that they are not a comprehensive solution to the problem at hand. When including fixed effects, one needs to be willing to assume that the firm-specific unobservable factors that are driving firm's choices are fixed over time. Productivity would be a perfect example of such a factor, yet the implausibility of considering it as fixed over time demonstrates how restrictive this assumption is. Regarding instrumental variables, the problem is that proper and valid instruments are very hard to come by. Input prices would be an obvious instrumental choice, but they are usually not reported by firms at the required level of detail and, even when they are, they do not reflect only exogenous

⁴For a detailed and comprehensive review of production function estimation issues and techniques see Akerberg, Benkard, Berry, and Pakes (2007).

⁵In Marschak and Andrews (1944)'s words: "*Can the economist measure the effect of changing amounts of labor and capital on the firm's output —the 'production function'— in the same way in which the agricultural research worker measures the effect of changing amounts of fertilizers on the plot's yield? He cannot because the manpower and capital used by each firm is determined by the firm, not by the economist. This determination is expressed by a system of functional relationships; the production function, in which the economist happens to be interested, is but one of them.*"

differences in input market conditions as they often capture some component of unmeasured input quality as well. In addition, the task of selecting valid price instruments is extremely challenging because individual input choices do not depend solely on the price of one input but most likely depend on the prices of all inputs of production. Furthermore, fixed effects and instrumental variables do not control for another crucial endogeneity issue, i.e. the fact that both input choices and exit decisions are endogenous and depend on factors that are known to the firm but unobservable to the econometrician.

In recent years, the increasing availability of firm-level data opened the door to more structural approaches for identifying production function coefficients controlling for simultaneity and selection problems. The key contribution of these approaches is to recognize that firms base their optimal production decisions on an unobservable factor, productivity, that is heterogeneous across firms, is likely to vary but be correlated over time, determines input choices, and affects the decision of exiting the market. Therefore, productivity, or a proxy for it, needs to be explicitly taken into account in the production function estimation.

2.2 A Structural Framework to Estimate Production Function Coefficients

2.2.1 The Empirical Model

To address the simultaneity problem, I rely on the insight of Olley and Pakes (1996), who propose to include directly in the production function estimation a proxy for productivity. This proxy is derived from a structural dynamic model of firm behavior that allows for firm-specific productivity differences, characterized by idiosyncratic changes over time, and specifies the information available to the firm when input decisions are made. Specifically, consider a firm j in industry i at time t (to simplify notation the industry subscript is omitted for now) producing output Q_{jt} according to the production function technology

$$Q_{jt} = F(X_{jt}, K_{jt}, \beta) \exp(\omega_{jt}) \quad (2.1)$$

where X_{jt} is a set of variable inputs, K_{jt} is capital stock, and β is a common set of technology parameters that governs the transformation of inputs to units of output in industry i . ω_{jt} is a firm-specific, Hicks-neutral productivity shock. Define value added as $Y_{jt} = Q_{jt} - M_{jt}$, with M_{jt} being intermediate inputs such as material and energy. Allowing for measurement error and for unanticipated shocks to production, the observed value added is given by $Y_{jt}\eta_{jt}$ and

the value added industry-specific production function is

$$y_{jt} = \beta_l l_{jt} + \beta_k k_{jt} + \beta_{ll} l_{jt}^2 + \beta_{kk} k_{jt}^2 + \beta_{lk} l_{jt} k_{jt} + \omega_{jt} + \eta_{jt} \quad (2.2)$$

where lower cases denote natural logarithms of the variables. Capital is a state variable accumulated accordingly to the deterministic dynamic investment process $k_{jt} = (1 - \delta)k_{jt-1} + i_{jt-1}$. Note that this particular formulation of the capital accumulation process implies that period t capital stock was actually determined at time $t - 1$. On the other hand, labor is assumed to be a perfectly variable input decided either at time t , when production takes place, or at time $t - b$, after capital but before production decisions occur.⁶ The importance of these assumptions regarding the timing of input choices is related to the identification of the production function coefficients and will become clear shortly. The error in (2.2) is assumed to be additively separable in the transmitted productivity component ω_{jt} and in the i.i.d. component η_{jt} . The main difference between these two components is that the former is assumed to be known by the firm when making optimal input choices while the latter is not so that η_{jt} simply represents a random optimization error. Note also that (2.2) is a translog production function but it easily allows to recover the Cobb-Douglas specification by dropping the higher order terms $(\beta_{ll} l_{jt}^2, \beta_{kk} k_{jt}^2)$ and the interaction term $(\beta_{lk} l_{jt} k_{jt})$.

In order to obtain consistent estimates of the production function coefficients, I directly control for unobserved productivity shocks, which are potentially correlated with labor and capital choices, adopting, again, the approach proposed by Olley and Pakes. Specifically, I use the investment function to proxy for productivity under the assumption that a firm's optimal investment demand, $i_{jt} = h_t(k_{jt}, \omega_{jt})$, is a strictly increasing function of its current productivity. The investment demand function contains all current state variables for the optimizing firm, i.e. its current level of capital and its current productivity. Conversely, labor does not enter the state space because it is a non-dynamic input and values of ω_{jt} prior to period t do not enter the state space either because the evolution of ω_{jt} is assumed to be governed by a first-order Markov process of the form $p(\omega_{jt} | \omega_{jt-1})$. Furthermore, the h function is only indexed by t (and not jt) since variables such as input prices and demand shifters, which may be also part of the state space, are allowed to vary only across time but not across firms as it is plausible to assume that firms operate in the same inputs market and under the same demand conditions. Given that the investment function is strictly monotonic

⁶For a comprehensive discussion on the decision timing assumptions required to identify production function coefficients associated with different inputs see also Akerberg et al. (2015).

in ω_{jt} , it can be inverted to obtain

$$\omega_{jt} = h_t^{-1}(k_{jt}, i_{jt}) \quad (2.3)$$

Following the same reasoning and maintaining the same assumptions on the evolution of the productivity process and the static/dynamic nature of the inputs, I also use the approach suggested by Levinsohn and Petrin (2003). They observe that investment levels are, in many cases, zero or very lumpy and propose to control for unobserved productivity using the intermediate input demand function as a proxy, instead. In this case, if the optimal expenditure level in intermediates, $m_{jt} = f_t(k_{jt}, \omega_{jt})$, is assumed to be a strictly increasing function of the current productivity, it can be inverted to generate

$$\omega_{jt} = f_t^{-1}(k_{jt}, m_{jt}) \quad (2.4)$$

2.2.2 Estimation Procedure

Equations (2.3) and (2.4) show that investment or, alternatively, intermediate input demand can be substituted into the production function as a proxy for the unobserved productivity term ω_{jt} , so that the estimating equation in (2.2) becomes

$$y_{jt} = \beta_l l_{jt} + \beta_k k_{jt} + \beta_{ll} l_{jt}^2 + \beta_{kk} k_{jt}^2 + \beta_{lk} l_{jt} k_{jt} + h_t^{-1}(k_{jt}, i_{jt}) + \eta_{jt} \quad (2.5)$$

or

$$y_{jt} = \beta_l l_{jt} + \beta_k k_{jt} + \beta_{ll} l_{jt}^2 + \beta_{kk} k_{jt}^2 + \beta_{lk} l_{jt} k_{jt} + f_t^{-1}(k_{jt}, m_{jt}) + \eta_{jt} \quad (2.6)$$

The estimation of (2.5) or (2.6) consists of two stages. The first stage serves the purpose of obtaining an estimate of the expected value added ϕ_{jt} and an estimate of η_{jt} alternatively running the following regressions:

$$y_{jt} = \phi_t(l_{jt}, k_{jt}, i_{jt}) + \eta_{jt} \quad (2.7)$$

or

$$y_{jt} = \phi_t(l_{jt}, k_{jt}, m_{jt}) + \eta_{jt} \quad (2.8)$$

where in (2.7) $\phi_{jt} = \phi_t(l_{jt}, k_{jt}, i_{jt}) = \beta_l l_{jt} + \beta_k k_{jt} + \beta_{ll} l_{jt}^2 + \beta_{kk} k_{jt}^2 + \beta_{lk} l_{jt} k_{jt} + h_t^{-1}(k_{jt}, i_{jt})$, while in (2.8) $\phi_{jt} = \phi_t(l_{jt}, k_{jt}, m_{jt}) = \beta_l l_{jt} + \beta_k k_{jt} + \beta_{ll} l_{jt}^2 + \beta_{kk} k_{jt}^2 + \beta_{lk} l_{jt} k_{jt} + f_t^{-1}(k_{jt}, m_{jt})$.

In addition, the functions h_t^{-1} in (2.5) and f_t^{-1} in (2.6), are given by:

$$h_t^{-1}(k_{jt}, i_{jt}) = \bar{\beta}_k k_{jt} + \beta_i i_{jt} + \bar{\beta}_{kk} k_{jt}^2 + \beta_{ii} i_{jt}^2 + \beta_{ki} k_{jt} i_{jt} \quad (2.9)$$

and

$$f_t^{-1}(k_{jt}, m_{jt}) = \bar{\beta}_k k_{jt} + \beta_m m_{jt} + \bar{\beta}_{kk} k_{jt}^2 + \beta_{mm} m_{jt}^2 + \beta_{km} k_{jt} m_{jt} \quad (2.10)$$

Note that, due to the specification of (2.9) and (2.10), in the first stage the coefficients associated with capital and capital squared in (2.5) and (2.6), respectively, are not identified. These coefficients will be identified only in the second stage of the estimation using an appropriate set of moment conditions. Moreover, under the Cobb-Douglas specification with the investment demand or the intermediate inputs demand, i.e.

$$y_{jt} = \beta_l l_{jt} + \beta_k k_{jt} + h_t^{-1}(k_{jt}, i_{jt}) + \eta_{jt} \quad (2.11)$$

or

$$y_{jt} = \beta_l l_{jt} + \beta_k k_{jt} + f_t^{-1}(k_{jt}, m_{jt}) + \eta_{jt} \quad (2.12)$$

the coefficient associated with labor, β_l , can be identified and estimated in the first stage as well.

In the second stage, the (remaining) production function coefficients can be obtained relying on the Markov process assumption and the law of motion for productivity. More specifically, I model the productivity process non parametrically as a third degree polynomial of lagged productivity in the following way:

$$\omega_{jt} = \gamma_0 + \gamma_1 \omega_{jt-1} + \gamma_2 \omega_{jt-1}^2 + \gamma_3 \omega_{jt-1}^3 + \xi_{jt} \quad (2.13)$$

Using the estimated $\hat{\phi}_{jt}$ from the first stage, the value of productivity for any given vector of β , where $\beta = (\beta_l, \beta_k, \beta_{ll}, \beta_{kk}, \beta_{lk})$, can be computed as:

$$\omega_{jt}(\beta) = \hat{\phi}_{jt} - \beta_l l_{jt} - \beta_k k_{jt} - \beta_{ll} l_{jt}^2 - \beta_{kk} k_{jt}^2 - \beta_{lk} l_{jt} k_{jt} \quad (2.14)$$

By regressing $\omega_{jt}(\beta)$ on its lag $\omega_{jt-1}(\beta)$, it is possible to recover the innovation in productivity given by $\xi_{jt}(\beta)$. Specifically, denote $\beta Z_{jt} = \beta_l l_{jt} + \beta_k k_{jt} + \beta_{ll} l_{jt}^2 + \beta_{kk} k_{jt}^2 + \beta_{lk} l_{jt} k_{jt}$, then the productivity process in (2.14) can simply be rewritten as $\omega_{jt}(\beta) = \hat{\phi}_{jt} - \beta Z_{jt}$ and the term ξ_{jt}

in (2.13) is given by:

$$\begin{aligned} \xi_{jt}(\beta) = & \hat{\phi}_{jt} - \beta Z_{jt} - \gamma_0 - \gamma_1(\hat{\phi}_{jt-1} - \beta Z_{jt-1}) - \\ & \gamma_2(\hat{\phi}_{jt-1} - \beta Z_{jt-1})^2 - \gamma_3(\hat{\phi}_{jt-1} - \beta Z_{jt-1})^3 \end{aligned} \quad (2.15)$$

Equation (2.15) allows for calculating a $\xi_{jt}(\beta)$ term for every firm and every period which can be used in a GMM context to form appropriate moments in order to finally obtain estimates of the production function parameters.

More precisely, for the Cobb-Douglas specification, I carry on the estimate for β_l from the first stage and identify β_k using the moment condition on current capital

$$E[\xi_{jt}(\beta)k_{jt}] = 0 \quad (2.16)$$

The rationale behind the validity of this moment comes from the assumptions on the timing of input choices discussed before. Assuming that the optimal level of l_{jt} is chosen at time t , when also the innovation in productivity is known to the firm, implies that l_{jt} is correlated with ξ_{jt} and the coefficient on labor β_l needs to be identified in the first stage. Conversely, the optimal level of k_{jt} is assumed to be chosen at time $t - 1$, thus k_{jt} is not correlated with ξ_{jt} and the moment condition in (2.16) identifies the coefficient on capital β_k in the second stage of the estimation.

Regarding the translog production function I estimate the whole set of coefficients in the second stage relying on the moment conditions

$$E \left[\xi_{jt}(\beta) \begin{bmatrix} l_{jt-1} \\ k_{jt} \\ l_{jt-1}^2 \\ k_{jt}^2 \\ l_{jt-1}k_{jt} \end{bmatrix} \right] = 0 \quad (2.17)$$

These moments exploit the following assumptions on the timing of input choices. Once again, current capital is assumed to be decided one period ahead. Therefore, at time t , k_{jt} is not correlated with the innovation in productivity ξ_{jt} . Lagged labor is used to identify the coefficient on labor if current labor, l_{jt} , is expected to react to shocks to productivity and hence $E[\xi_{jt}(\beta)l_{jt}]$ is expected to be different from zero. Thus, the moment conditions in (2.17) identify the whole set of coefficients $(\beta_l, \beta_k, \beta_{ll}, \beta_{kk}, \beta_{lk})$ in the translog production function. The standard errors of the estimated coefficients are obtained by block-bootstrap which is a

special bootstrap technique designed to maintain the structure of the panel.⁷ Specifically, I bootstrap along the firm dimension, i.e. I randomly sample with replacement a number of firms equal to the number of firms present in each industry 400 times.

Two remarks regarding the estimation procedure are needed. First, I do not explicitly model entry and exit. This is because the panel I use is essentially closed given that, when a firm exited the sample, it was replaced by a similar firm and this new firm was assigned the same identifier as the exiting one. Consequently, it is not possible to keep track of entry and exit patterns and focus on selection issues. However, as Griliches and Mairesse (1995) and Levinsohn and Petrin (2003) note, the selection correction seems to make little difference once the simultaneity correction is in place. Second, I observe revenue instead of physical output, hence I actually estimate 'revenue' production function parameters deflating the sales with an industry-wide price index. This is an imperfect solution since, if the unobserved firm-specific output price index substantially differs from the industry price index, I am actually introducing a price error. Furthermore, if input decisions are correlated with the price error, the estimated coefficients of the production function may be biased downward because, as mentioned in the original contribution by Klette and Griliches (1996), more inputs will lead to higher output and decrease prices, *ceteris paribus*. Nonetheless, this imperfect solution appears to be the best possible solution, given the limitations in the available data

2.3 A Structural Approach to Derive Firm-level Markups

My second empirical goal is to derive markup estimates at the firm-level. To achieve this goal I follow the approach proposed by De Loecker and Warzynski (2012), which has the advantage of not depending on the availability of very detailed data. The data requirements, indeed, are limited to total expenditure on variable inputs (labor and materials), capital, investment and output at the firm-level. This approach is fairly direct from an economic theory perspective, since it relies on standard optimal input demand conditions that can be obtained from standard cost minimization. Moreover, it is straightforward to implement empirically, since the estimation is simply based on the insight that the cost share of factors of production are not equal to their output revenue share when markets are not perfectly competitive, so that the estimated markups can be interpreted as a measure of market power. Finally, this approach is flexible as it can be applied to a wide range of production functions and it is able to correct the markup bias by directly controlling for the firm-specific unobserved productivity.

⁷For more details about the block-bootstrap technique see Horowitz (2001).

To derive an expression for markups consider, once again, a firm j in industry i at time t (the industry subscript is again omitted for simplicity) producing output Q_{jt} using variable inputs $(X_{jt}^1, \dots, X_{jt}^V)$, which may include labor, materials, and energy, and capital K_{jt} as factors of production, and with productivity level ω_{jt} . This firm aims to minimize its cost of production by solving the problem

$$\begin{aligned} \min_{X_{jt}, K_{jt}} \quad & \sum_{v=1}^V P_{jt}^{X^v} X_{jt}^v + r_{jt} K_{jt} \\ \text{s.t.} \quad & Q_{jt} = Q_{jt}(X_{jt}^1, \dots, X_{jt}^V, K_{jt}, \omega_{jt}) \end{aligned} \quad (2.18)$$

where $P_{jt}^{X^v}$ denotes the price of any variable input and r_{jt} denotes the price of capital. The technology constraint takes a very general form and the only restriction imposed on $Q_{jt}(\cdot)$ is that it is continuous and twice differentiable with respect to its arguments. The Lagrangian associated with the minimization problem in (2.18) is given by:

$$\mathcal{L}(X_{jt}, K_{jt}, \lambda_{jt}) = \sum_{v=1}^V P_{jt}^{X^v} X_{jt}^v + r_{jt} K_{jt} + \lambda_{jt}(Q_{jt} - Q_{jt}(\cdot)) \quad (2.19)$$

with the first order condition with respect to each variable input being

$$\frac{\partial \mathcal{L}}{\partial X_{jt}^v} = P_{jt}^{X^v} - \lambda_{jt} \frac{\partial Q_{jt}(\cdot)}{\partial X_{jt}^v} = 0 \quad (2.20)$$

where λ_{jt} is the marginal cost of production.⁸

Rearranging terms, multiplying both sides of (2.20) by X_{jt}/Q_{jt} , and dividing by λ_{jt} yields

$$\frac{\partial Q_{jt}(\cdot)}{\partial X_{jt}^v} \frac{X_{jt}^v}{Q_{jt}} = \frac{1}{\lambda_{jt}} \frac{P_{jt}^{X^v} X_{jt}^v}{Q_{jt}} \quad (2.21)$$

(2.21) simply states that cost minimization requires the optimal input demand being satisfied when a firm equalizes the output elasticity of input X_{jt}^v to $\frac{1}{\lambda_{jt}} \frac{P_{jt}^{X^v} X_{jt}^v}{Q_{jt}}$.⁹

⁸The Lagrange multiplier λ_{jt} , in this context, measures the marginal cost of production since $\frac{\partial \mathcal{L}}{\partial Q_{jt}} = \lambda_{jt}$. Formally, λ_{jt} represents the shadow value of the constraint, i.e. the increase in cost generated by a marginal expansion in output.

⁹Note that, $\frac{1}{\lambda_{jt}} \frac{P_{jt}^{X^v} X_{jt}^v}{Q_{jt}}$ is not input X_{jt}^v 's cost share because, in general, $\lambda_{jt} Q_{jt}$ is not equal to the total cost of production. Only in the special case of constant marginal cost, given the interpretation of the Lagrange multiplier, (2.21) implies that, at the optimum, a firm equalizes the output elasticity of any variable input to its

Defining μ_{jt} as the the markup means that $\mu_{jt} = \frac{P_{jt}}{\lambda_{jt}}$ or, in a more compact way,

$$\mu_{jt} = \frac{\theta_{X_{jt}^v}}{\alpha_{X_{jt}^v}} \quad (2.22)$$

where $\theta_{X_{jt}^v}$ is the output elasticity with respect to the variable input X_{jt}^v and $\alpha_{X_{jt}^v}$ is the share of X_{jt}^v 's expenditure in total revenue.

As mentioned before, the technology constraint in (2.18) is very general and can easily encompass different specifications. Assuming that the technology takes the form of the value added production function in (2.2) (where labor is the only variable input) and estimating the production function parameters following the procedure illustrated in the previous section, the estimated output elasticity of labor is given by $\hat{\theta}_{L_{jt}} = \hat{\beta}_l + 2\hat{\beta}_{ll}l_{it} + \hat{\beta}_{lk}k_{it}$ under the translog, and by $\hat{\theta}_{L_{jt}} = \hat{\beta}_l$ under the Cobb-Douglas specification. Additionally, the expenditure share is $\alpha_{L_{jt}} = \exp(\hat{\eta}_{jt}) \frac{P_{L_{jt}}L_{jt}}{P_{jt}\tilde{Y}_{jt}}$, where \tilde{Y}_{jt} is observed value added, given by $Y_{jt} + \exp(\eta_{jt})$, allowing for measurement error. Note that the correction with the error term η_{jt} is important to eliminate any variation in the expenditure share that comes from variation in output not correlated with factor of production choices. Finally, with $\hat{\theta}_{L_{jt}}$ and $\alpha_{L_{jt}}$, the expression for the estimated markup for each firm in each period is derived as:

$$\hat{\mu}_{jt} = \frac{\hat{\theta}_{L_{jt}}}{\alpha_{L_{jt}}} \quad (2.23)$$

(2.23) emphasizes the rationale behind this approach for estimating markups, i.e. market power can be detected when the output elasticity of labor does not equalize the labor expenditure share.

2.4 A Simpler Dual Approach to Derive Industry-level Markups

The computational-intensive methodology illustrated so far allows for estimating firm-specific markups using disaggregated micro-level data. Here, I present a more parsimonious approach that can be applied to more aggregated data and is suitable to estimate industry-specific markups, under the assumption that all firms belonging to the same industry share the same price-cost margin. The purpose of exploring this alternative method is to have a benchmark

cost share. This is because the marginal cost can be constant only if it is equal to the average cost so that $\frac{P_{jt}^{X^v} X_{jt}^v}{\lambda_{jt} Q_{jt}}$ is, in fact, the input X_{jt}^v 's cost share, i.e. the expenditure on input X_{jt}^v , given by $P_{jt}^{X^v} X_{jt}^v$, over the total cost of production, given by $\lambda_{jt} Q_{jt}$.

for comparison between a simpler and less demanding (in terms of data requirements and computational burden) approach and a more structural and onerous one.

The basic idea behind this unsophisticated approach is that, under certain assumptions, total factor productivity can be calculated either as the residual of the production function or, alternatively, as the residual of the dual cost function. However, the correlation between these theoretically equivalent measures is hard to verify empirically. Roeger (1995) argues that this lack of correlation can be explained by the presence of a positive markup of prices over marginal costs. In fact, with imperfect competition, the difference in the growth rate of output and a weighted average of the input factors cannot be entirely attributed to technical change. This is because, if price exceeds marginal cost, the input shares per unit of output do not sum up to one, and are lower instead, because of the presence of a positive markup.

Formally, consider an industry i characterized by a linearly homogeneous production function. The value added for this industry at time t is given by $Y_{it} = \Theta_{it}F(L_{it}, K_{it})$ where L_{it} is labor, K_{it} is capital and Θ_{it} is an industry- and period-specific shock in production. Note that the productivity term Θ_{it} can be thought of as including an unanticipated and random element as well as an element that can be foreseen by all the firms in the industry. Carrying on the insight of R. E. Hall (1988), the decomposition of the Solow residual (SR) into a pure technology component and a markup component can be formulated as:

$$SR_{it} = \hat{Y}_{it} - \alpha_{it}\hat{L}_{it} - (1 - \alpha_{it})\hat{K}_{it} = \beta_{it} \left(\hat{Y}_{it} - \hat{K}_{it} \right) + (1 - \beta_{it})\hat{\Theta}_{it} \quad (2.24)$$

where the hat represents growth rates, P_{it}^L and P_{it}^Y are price of labor (i.e. wage) and price of output, respectively, and $\alpha_{it} = \frac{P_{it}^L L_{it}}{P_{it}^Y Y_{it}}$ is the labor expenditure share in total value added expressed in growth rates. In this context, market power can be recovered from the Lerner index $\beta_{it} = \frac{P_{it}^Y - c_{it}}{P_{it}^Y} = 1 - \frac{1}{\mu_{it}}$, with c_{it} denoting the marginal cost, and $\mu_{it} = \frac{P_{it}^Y}{c_{it}}$ the price-cost markup. While value added, input factor usage, and input shares can be easily observed in the data, the Lerner index and the productivity shock cannot. Hence, the estimation of β_{it} in (2.24) is problematic because $(\hat{Y}_{it} - \hat{K}_{it})$ and $\hat{\Theta}_{it}$ are positively correlated since optimal input decisions (in this case decisions concerning capital) are made taking into account the partially known productivity shock. A possible solution to this problem would require identifying appropriate instruments that are correlated with output, but are neither a consequence nor a cause of technological innovation. Yet, as it is well documented in the literature, finding such instruments is a difficult task.

To deal with this issue, Roeger derives the dual price-based Solow residual (SPR)

$$SPR_{it} = \alpha_{it} \hat{P}_{it}^L + (1 - \alpha_{it}) \hat{R}_{it} - \hat{P}_{it}^Y = -\beta_{it} (\hat{P}_{it}^Y - \hat{R}_{it}) + (1 - \beta_{it}) \hat{\Theta}_{it} \quad (2.25)$$

where R_{it} represents the rental rate of capital. Subtracting (2.24) from (2.25), the *net* Solow residual is given by:

$$\begin{aligned} SR_{it} - SPR_{it} &= (\hat{Y}_{it} + \hat{P}_{it}^Y) - \alpha_{it} (\hat{L}_{it} + \hat{P}_{it}^L) - (1 - \alpha_{it}) (\hat{K}_{it} + \hat{R}_{it}) \\ &= \beta_{it} \left[(\hat{Y}_{it} + \hat{P}_{it}^Y) - (\hat{K}_{it} + \hat{R}_{it}) \right] \end{aligned} \quad (2.26)$$

(2.26) can be further rewritten to obtain a direct measure of the price-cost markup, i.e.

$$(\hat{Y}_{it} + \hat{P}_{it}^Y) - (\hat{K}_{it} + \hat{R}_{it}) = \mu_{it} \left[\alpha_{it} \left((\hat{L}_{it} + \hat{P}_{it}^L) - (\hat{K}_{it} + \hat{R}_{it}) \right) \right] \quad (2.27)$$

Note that (2.27) simply states that the markup captures the difference between the net change in nominal value added and the net change in nominal labor payments weighed by the labor share in value added, where net means that the change in nominal capital has been netted out from both variables. Also note that the term $(1 - \beta_{it}) \hat{\Theta}_{it}$, causing the endogeneity issue in (2.24) and, potentially, in (2.25), does not appear in (2.27) so that this equation can be consistently estimated without using instrumental variables. Moreover, (2.27) provides a way of estimating markups indirectly controlling for (i.e. netting out) productivity. From (2.27) it is also clear that markup estimates at the industry-level can be easily obtained using only aggregated data on the nominal value added (calculated as the nominal value of sales minus the nominal value of materials), the total labor remuneration in nominal terms, and the nominal value of capital (calculated as the product between the real capital stock and the nominal interest rate).

3 Trade Exposure and Price-Cost Margins

3.1 The Mexican Case

From the early 1950s until the early 1980s Mexico,¹⁰ like many other developing countries, adopted a growth strategy based on import substitution. Relying on protection measures

¹⁰The following data on the Mexican economy as well as the main features of the trade reform are taken from Kehoe (1995).

against world competition and on government intervention in the domestic economy, this strategy encouraged investment in industry, suppressed agricultural prices and expanded government enterprises. Between 1960 and 1981 Mexico experienced an average increase of real GDP of 7 percent per year - even accounting for the high rate of population growth over the that period, this translated into an average increase of GDP per capita of 4 percent per year. During the 1970-1982 period, however, the import substitution policy began to be less effective as policies of deficit spending and monetary expansion financed by public sector borrowing from international banks were implemented. As a result, Mexico experienced rising inflation which, together with a fixed nominal exchange rate, led to substantial real exchange rate appreciation and growing current account deficit. Despite the substantial economic imbalances, the Mexican economy continued to expand on an average growth rate of real GDP of 6.2 percent over 1970-1982.

In 1982 the import substitution policy, and the Mexican economy with it, fell apart. Faced with a massive public debt owned by foreign banks, sharply rising international interest rates, and falling oil prices due to the worldwide recession, Mexico could not meet its debt obligations. The peso collapsed, the government nationalized banks and implemented strict exchange rate controls and the economy entered a deep recession. In late 1982, under newly elected President Miguel de la Madrid Hurtado, Mexico embarked on its first steps on the long road to recovery. During the 1983-85 period, with the financial support of the International Monetary Fund, the new administration implemented a series of policies designed to cut the public sector deficit and turn the large trade deficit into a surplus. These policies included reduction in government expenditures, increases in taxes and in the prices of public services, elimination of many subsidies and closure of some public enterprises, enforcement of license requirements for all imports, and the abolition of the exchange rate controls. Although this program was successful in creating a trade surplus and in partially lowering inflation, it was not enough to prevent another crisis. In late 1985 fiscal discipline began to waver, IMF funding ended, an earthquake in Mexico City caused disruption and imposed significant costs, and the oil prices started on a steep decline that continued until 1987.

The 1985-87 period was characterized by falling output and accelerating inflation. It was during this period, however, that Mexico began some of the policy reforms that were crucial in bringing deficit and inflation rate to acceptable levels and restoring economic prosperity during the 1987-93 period. Major initiatives included privatization of state-owned companies, deregulation of financial markets, liberalization of foreign investment, and a dramatic re-orientation of trade policy.

The trade policy reforms were perhaps the most striking. In 1985 the process of *apertura*,

openness to foreign trade and investment, began and between 1982 and 1994 Mexico went from being a relatively closed economy, even for developing countries' standards, to being one of the most open in the world. In 1982 tariffs were as high as 100 percent and there was substantial dispersion in tariff rates. Licenses were required for importing any good and, as a general rule, foreigners were restricted to no more than 49 percent ownership of Mexican enterprises. In 1982 import licenses, not tariffs, were Mexico's most significant trade barriers. Starting in late 1983 quantitative restrictions were replaced with tariffs. The portion of tariff items subject to license requirements fell from 100 percent in 1983 to 65 percent in 1984 and reached 10 percent in 1985. By 1992 it was just 2 percent. Even so, the portion of the value of imports subject to license requirements fell more slowly: from 100 percent in 1983 to 83 percent in 1984, to 35 percent in 1985, to 11 percent in 1992. As import licenses were replaced by tariffs as the major tool of trade policy, average tariffs initially rose and then fell. The average tariff went from 23.2 percent in 1983 to 25.4 percent in 1985, to 13.1 in 1992. The trade-weighted average tariff went from 8.0 percent in 1983 to 13.3 percent in 1985, to 11.1 percent in 1992. Equally effective with the change in average tariff rates was the simplification of the tariff schedule. These measures were major steps in making the Mexican trade policy less protective and more transparent. They were accompanied by a number of other supporting policies: in 1986 Mexico acceded the GATT, adopting the Harmonized Commodity Description and Coding System, the Foreign Trade Law and the GATT Anti-Dumping Code. In short, in about five years Mexico dramatically liberalized its trade regime. The liberalization process was almost complete by the end of 1987, although the impact on the flow of imports was softened by real devaluations. The reforms helped to promote exports. In terms of both import penetration and export rates, the manufacturing sector became substantially open as a consequence.

3.2 Relating Markups and Measures of Trade Liberalization

Prior to the liberalization that begun in 1983, trade accounted for a small share of manufacturing production in most Mexican industries. Both the ratio of imports over domestic consumption and the ratio of exports over domestic production were below 10 percent. Nonetheless, as a consequence of the rapid and dramatic process of foreign trade and investment liberalization, in merely a decade Mexico became one of the most open economies in the world. In order to investigate whether this outward-looking reform generated import discipline—a decreased in profitability, measured through markups, due to the removal of trade protections—I rely on two simple models that allow for quantifying the impact of trade liberalization on the

price-cost margins. The first model is a variant of Domowitz, Hubbard, and Petersen (1986) and is suitable for a industry-level analysis on the markups. Consider the relation:

$$\mu_{it} = f(H_{it}, TRADE_{it}, H_{it} \times TRADE_{it}, KQ_{it}, I_i, T_t) \quad (3.1)$$

where the explanatory variables include a measure of industry structure, the Herfindahl index H_{it} , a measure of trade liberalization, the industry-level capital-output ratio KQ_{it} , as well as industry I_i and time T_t controls. Regarding the measure of trade exposure I alternatively use the share of total industrial output falling into commodity categories subject to import licenses ($QUOTA_{it}$), and the production-weighted official tariff rate ($TARIFF_{it}$). When the industry dummies are not included, most of the variation occurs across industries and the Herfindahl index and the capital-output ratio should identify variations in technology and the degree of competition among domestic producers. If a pro-competitive effect of trade exposure exists, it should manifest as a negative correlation between measures of trade liberalization and markups. Moreover, if highly-concentrated industries do not operate under perfect competition, they should be relatively more sensitive to foreign competition, therefore the interaction term between the Herfindahl index and the trade indicator should reflect the same negative relation between trade openness and price-cost margins. With panel data it is possible to further control for persistent differences across industries in technology and market structure by including industry dummy variables. In this case, the estimated coefficient reflect only temporal variation in the data and, since measures of trade policy change through time, price-cost margins regressions including industry dummies are better suited to capture the disciplining effect of trade liberalization.

The second model, proposed by Schmalensee (1985), aims at explaining the extent of competition within a given industry by studying firm-level margins. The rationale behind this second exercise is to detect whether cross-firm variations are due to industry-wide effects or to firm-specific market shares. In general, more efficient firms should be larger and have higher profits, therefore a positive relation between market shares and price-cost margins is usually expected and it is not necessarily an indication of market power, as emphasized by Demsetz (1973) in his famous critique. However, if the degree of market power differs across industries, industry dummies should capture this source of variation in firm-level profitability. If industry dummies are not significantly different across industries, the evidence suggests absence of heterogeneity in market power. For the purpose of verifying the effect of trade

liberalization on profitability at the firm level consider the following specification:

$$\mu_{jit} = f \left(S_{jit}, S_{jit}^2, TRADE_{it}, S_{jit} \times TRADE_{it}, KQ_{jit}, KQ_{jit}^2, I_i, T_t \right) \quad (3.2)$$

where the price-cost margin μ_{jit} of firm j in industry i in year t depends on its share of output in total domestic manufacturing production, S_{jit} and S_{jit}^2 , on the capital-output ratio KQ_{jit} , on an industry-specific measure of trade exposure, $TRADE_{it}$, as well as industry and year dummy variables.

3.3 Relating Markups and Export Status

The two previous models relate markups with trade exposure using trade indicators that mainly capture the extent of import liberalization. In fact, both the quota coverage and the average tariff rate measure protective restrictions on imports. A number of recent models of international trade, however, emphasize the implications of trade openness, productivity and profitability for exporters. More specifically, these models generate the result that more productive firms are more profitable because they can charge higher markups. The higher profitability allows these firms to pay an export entry cost and become exporters, thus exporters have usually higher markups. In the literature two main reasons for this positive relation between markups and firm's export status have been identified. Bernard et al. (2003), as well as Melitz and Ottaviano (2008) attribute the source of the markup premium for exporters to differences in productivity. Both contributions essentially predict that exporters will charge higher markups because they are more productive than their domestic rivals and this productivity wedge allows them to be more profitable and more competitive.¹¹ On the other hand, Kugler and Verhoogen (2011) and Hallak and Sivadasan (2013) explore the role of quality differences between exporters and non exporters assuming that, if exporters produce

¹¹It is important to note that not all the recent models of international trade imply that exporters, who are assumed to be more productive than non-exporters, are more profitable because they are able to charge higher markups. For example, with an isoelastic demand system, like the CES demand system in Melitz (2003), exporters are more productive and more profitable but do not charge higher markups. Their additional profitability comes from the fact that higher levels of productivity allow them to have lower marginal costs so that the point where the marginal revenue equalizes the marginal cost is further down the demand schedule granting them more sales. Conversely, exporters are able to charge higher markups in Melitz and Ottaviano (2008)'s model because the demand system is linear with horizontal product differentiation and markups are endogenous and depend on the size of a market and the extent of its integration through trade. In Bernard et al. (2003)'s model imperfect competition is the mechanism leading to variable markups. Specifically, with Bertrand competition producers who are more efficient tend to have a greater cost advantage over their closest competitors, set higher markups and appear more productive. More efficient producers are more likely to beat rivals in foreign markets and this is the reason why exporters tend to be more productive than non-exporters.

higher quality goods while using higher quality inputs, they can charge higher markups, all other things equal.

Given that with the structural approach I can estimate firm-level markups, I can easily relate a firm's markup to its export status in a regression framework as follows:

$$\ln(\mu_{jt}) = \psi_0 + \psi_1 E_{jt} + z_{jt}\rho + \varepsilon_{jt} \quad (3.3)$$

where μ_{jt} is the markup for firm j at time t and E_{jt} is a dummy variable that takes the value of one when firm j is an exporter. Thus, the coefficient associated with this dummy, ψ_1 , measures the percentage markup premium for exporters. In addition, z_{jt} is a set of variables including capital and labor use that control for differences in size and factor intensity, as well as year- and industry-specific dummy variables that control for aggregate trends in markups. The vector ρ collects the coefficients associated with the whole set of controls. After obtaining an estimate for ψ_1 , it is possible to recover the level markup difference, denoted as μ_E , by calculating the percentage difference with respect to the constant term ψ_0 , which captures the markup average for domestic firms. Specifically, $\mu_E = \psi_1 \exp(\psi_0)$. A positive and significant μ_E would imply that there is in fact a markup premium for exporters with respect to domestic producers.

4 Data

My entire analysis is conducted using plant-level panel data collected through Mexico's Annual Industrial Survey by the Mexican statistical agency INEGI. These data were made available by Mexico's Secretariat of Commerce and Industrial Development (SECOFI), (now Secretariat of Economy) and includes a sample of active Mexican manufacturing plants during the period 1984-1990.¹²

For a typical industry, the sample is representative of about 80 percent of the total output in that industry therefore, even if the smallest plants were excluded, the sample can be considered fairly representative. Note that, because of the way the data are reported, it is not possible to

¹²Note that the analysis has been conducted for the period 1984-1990 and cannot be extended in an immediate and straightforward way to more recent years for the following reasons. First, accessing more recent production data would now require being granted access to the Laboratorio de Microdatos at INEGI. Second, the production and trade data used in this paper were specifically matched to obtain measures of trade liberalization at the firm level based on the import/export composition of each firm. This level of accuracy and precision in the matching is not easily replicable given that disaggregated production and trade data are currently housed in different places (INEGI and Banco de México, respectively) and cannot be merged for confidentiality reasons.

identify which plants belong to the same firm. Therefore, even if there are certainly multi-plant firms in the sample, I formally treat a plant as a firm and do not try to capture the extent to which multi-plant firms may have a different strategic production behavior due to their multi-plant nature. For this reason the words *firm* and *plant* are used interchangeably, as it is not possible to make a meaningful distinction between these concepts in my data. Furthermore, as mentioned before, when a firm exited the sample, it was replaced with a firm with similar production characteristics and the new firm was assigned the same identifier as the exiting one. Thus, the panel can be considered essentially closed as it is not possible to keep track of entry and exit patterns. The panel is however unbalanced since a (marginally) decreasing number of firms is included in the sample over the years.

For each plant in each year it is possible to observe data on value of production, revenue, input expenditure, labor remunerations, value of fixed capital, investment, inventories, and input costs. Each plant can be traced and uniquely identified over time using a combination of industry (RAMA), class (CLASE) and plant (FOLIO) identity codes. The dataset also contains price indices at the industry level for output and intermediate inputs, as well as sector-wide deflators for machinery and equipment, buildings and land. Moreover, the dataset contains detailed information about imports, exports, and commercial policy features like coverage of import license and tariff rates at the industry level. This information is particularly useful to describe the Mexican trade liberalization process and to verify its effects on the price-cost margins.

4.1 Data Preparation: Relevant Variables and Sample Selection Criteria

The original sample consisted of 22,526 observations on 3,218 plants during the period 1984-1990. All the variables used in the analysis are reported in table 1, the monetary variables were converted to millions of 1980 Mexican pesos using specific deflators.

In addition, I use some of the original variables present in the dataset to construct new variables useful for the analysis. These variables, their description and the calculation details are reported in table 2. First, the expenditure in intermediates was calculated without taking into account inventories. This choice was dictated by the fact that in 1985 the variables characterizing inventories presented many missing observations thus, following one of the sample selection criteria (described in detail below) of withdrawing incomplete series, to consider inventories would have caused the elimination of half of the plants from the analysis. Second, total capital stock for each plant was calculated as the sum of replacement cost of capital and the capitalized value of the rents with a 10 percent discount rate. Third,

the variables involved in the calculation of the value added and the value added itself were corrected in order to account for the measurement error in the intermediate inputs expenditure for the *maquiladoras*.¹³ Specifically, the value added was corrected adding the income from subcontracting and subtracting the cost of subcontractors. The gross value of output, which suffers from the same bias, was corrected under the assumption that the ratio between value added and output and between primary materials and total inputs are constant through time and among plants running the following regression:¹⁴ $CORGVO = GVO + b\left(\frac{INSEMAQ}{PM} - \frac{GASTMAQU}{PM}\right)$. The value of the b ¹⁵ parameter used in the correction was estimated at a two-digit national accounts classification level (RAMA) using only the plants that did not conduct *maquila* activities. Finally, the corrected value of expenditure in intermediates was simply calculated by subtracting the corrected value added from the corrected value of gross output.

Around 20 percent of the original observations were eliminated discarding those that for at least one year had negative, zero, and missing values of the following variables: total employment, total hours worked, capital stock, gross value of output, corrected gross value of output, value added, corrected value added, intermediates, corrected intermediates, and labor remunerations. This process resulted in the elimination of 4,234 observations. Among the remaining 18,292 observations, additional 4,924 observations were eliminated dropping the incomplete series. That is, all the observations pertaining to plants that were discarded for at least one year because of one or more of the above reasons were completely eliminated from the sample in order to include only plants for which complete information for all the years was available. The final sample used in the analysis contained 13,368 observations on 2,088 plants. Moreover, in order to carry on the structural production function estimation using the investment as a proxy for productivity, 2,092 observations were further dropped in order to create the investment series. Finally, two sectors, Tobacco and Nonferrous metals, were dropped because the extremely low number of plants left after the sample selection was not adequate to perform a meaningful empirical analysis in those two industries.

¹³The *maquiladora* is a firm-concept very common in Mexico. *Maquiladoras* are manufacturing firms that are allowed to import materials and equipment on a duty-free and tariff-free basis for assembling or manufacturing and then either sell the assembled or manufactured products to the domestic firm which commissioned the *maquila* service or re-export the products outside the Mexican border. The *maquiladoras* generate measurement error because the Mexican accounting system attributes to the firm that order the subcontracting service the expenditure in intermediates actually used by the subcontractor.

¹⁴See table 2 for a detailed description of the variables involved in this regression.

¹⁵The average value of b is 1.47 with standard deviation 0.12.

4.2 Sample Characteristics

Table 3 reports in detail the industrial classification codes aggregated into each sector, the average number of plants in each sector, as well as some other characteristics that describe the relative importance of each sector in the total manufacturing output and the openness to trade. As shown in table 3 there is substantial heterogeneity in all these characteristics among the Mexican manufacturing industries considered in the analysis.

Table 4 summarizes the data by presenting the number of plants and various indicators of plant size pooling all the manufacturing plants during the period 1985-1990. Except for 1986, average plant growth is positive whether measured by gross output, value added, or total employment and it is particularly high in the last 2 years included in the sample. Average capital stock per plant decreases from 1985 to 1986, probably as a consequence of the physical destruction caused by the earthquake of 1985 and the low level of net investment during the recession of 1986. Its upward trend after 1987 is consistent with the recovery of the economy and the exit from the sample of small firms, which occurs mainly in 1989-1990. Capital productivity is characterized by ups and downs during the entire period and this may reflect underutilization of capacity and delays in replacing old equipment. Finally, investment follows also a very irregular pattern with sharp drops in 1986 and 1988 which are also likely picking up the adverse effects of the earthquake and the recession. Additional variables that are used in the regression models and further help to characterize the Mexican manufacturing environment are reported in table 6.

4.3 Trade Statistics

The trade data on imports and exports, used to calculate the statistics at the industry level reported in the last three columns of table 3, came from the Commodity Trade database of the United Nations Statistical Office, which provides information at the four-digit level ISIC classification and categorizes products by end of use. These data were merged with the Mexico's Annual Industrial Survey, which, on the other hand, categorizes products by production technology, trying to achieve a reasonable match relying on detailed product codes available in the industrial survey. Also, since the trade data are reported in US dollars, they were first converted into 1980 US dollars and then into Mexican pesos using the 1980 exchange rate in order to render the figures comparable removing the exchange rate fluctuations.

In addition, the data on commercial policies were provided by the SECOFI and were already harmonized with the classification scheme of the industrial census. These data,

summarized by industry and time sub-periods in table 5, clearly demonstrate that most of the changes in commercial policy took place between 1985 and 1988.

5 Production Function Estimation Results

In this section I exploit the structural framework described in section 2.2 to estimate production function parameters controlling for endogenous productivity for eighteen Mexican manufacturing sectors. I estimate several models under different production technology specifications (Cobb-Douglas and translog) with both the Olley and Pakes and Levinson and Petrin approaches. The estimation results suggest that the Cobb-Douglas specification with the investment function used as a proxy for productivity (Olley and Pakes method) is the most adequate to fit the data, therefore I provide all the main results on production function parameters and productivity adopting this specification. At the end of the section I report and comment on robustness check results obtained with alternative models.

5.1 Production Function Parameters

I begin by presenting the production function estimates for the whole sample comparing the structural estimation results with the ones obtained using more standard OLS and fixed effects estimation techniques. I then test whether there is statistically significant evidence that the production function coefficients change during the period considered.

5.1.1 Comparing Different Estimators

The last two columns of table 7 report the results obtained estimating a Cobb-Douglas production function using the investment as a proxy for productivity (Olley and Pakes approach). Specifically, in the first stage equation (2.11) is estimated with OLS. The results of the first stage estimation, i.e. $\hat{\phi}_{jt}$ and $\hat{\eta}_{jt}$, are carried through the second stage where the residual ξ_{jt} of the productivity process from equation (2.13) is again obtained by OLS. Finally, equation (2.15) is estimated by GMM exploiting the moment condition on capital in (2.16). Note that, since the coefficient on labor β_l is identified and estimated in the first stage, I rely on one moment condition to identify the only remaining parameter, β_k , in the second stage. Thus, the system is just identified and the identity matrix is the optimal weighting matrix used in the GMM objective function.

In almost all sectors, with the exception of Food (1) and Glass (11), the coefficient associated

with labor is significant and ranges from 0.15 in Chemicals (9) to 0.96 in Leather and Footwear (6). The coefficient on capital, on the other hand, is significant for only twelve out of eighteen sectors and ranges from 0.36 in Plastic and Rubber (10) to 0.74 in Nonelectrical machinery (17). As expected, there are significant differences in the production function parameters, thus in technology, across sectors. In particular, some sectors like Clothing and Apparel (5), and Plastic and Rubber (10) are more labor intensive, while other sectors like Pulp and Paper (8), Chemicals (9), and Transportation equipment (19) are more capital intensive.

The comparison between the results from the structural estimations and those obtained with a simple OLS regression yields a well established empirical evidence. First, the coefficients on labor and capital are highly statistically significant across all sectors. Second, focusing only on the coefficients that are significant in the structural estimation, the OLS coefficient on labor is always larger while the coefficient on capital is always smaller than its structural counterpart. This pattern is well documented in the literature and is determined by the correlation structure between the transmitted productivity shock and the production inputs. More precisely, the variable input labor is supposed to be positively correlated with the unobserved productivity, thus the OLS coefficient on labor is likely to be biased upward. On the other hand, if current capital is not correlated with the current productivity shock, as it is decided one period ahead, or if capital is much less correlated with productivity than labor, the OLS estimate on capital is likely to be biased downward.

Finally, looking at the estimates obtained using plant-level fixed effects (third and fourth column of table 7), it is clear that, at least for labor, this approach partially mitigates the bias discussed above, i.e. the fixed effect coefficient on labor is always significant and smaller than the OLS one. However, the estimation of the capital parameter under fixed effects appears more problematic with some insignificant values and an unclear pattern with respect to the magnitude of the coefficient, which is higher than its OLS counterpart in some cases but smaller in some other cases. Nonetheless, the fixed effects estimates still remain higher for labor and lower for capital than those obtained with the structural approach. This is because the former is just an indirect way of controlling for unobserved productivity, whereas the latter fully and explicitly accounts for transitory productivity shocks.

With Cobb-Douglas technology, the production function coefficients represent the elasticity of output with respect to the inputs and their sum can be interpreted as returns to scale. Table 8 reports the estimated returns to scale, i.e. $\beta_l + \beta_k$. With OLS in most of the industries the sum of the two coefficients is very close to one but the constant returns to scale hypothesis is statistically verified only for half of the industries. The within estimator (plant-level fixed effects) delivers returns to scale that are in general below one and overall lower than in the

OLS case. However, for fourteen industries constant returns to scale are statistically verified. Finally, the returns to scale estimated with the structural procedure are mostly in between the OLS and FE results and, again, in thirteen out of eighteen industries the constant returns to scale hypothesis cannot be rejected. Since the structural approach, and to some extent also the FE, should deliver more credible estimates as they control (directly or indirectly) for productivity shocks, the empirical evidence seems to support the presence of constant returns to scale in the majority of the Mexican manufacturing industries.

5.1.2 Testing for a Structural Change in the Production Function Parameters

In order to verify whether the trade liberalization process generated factor reallocation phenomena across the Mexican manufacturing industries by modifying the factor intensity, I re-estimate the structural model dividing the sample into two sub-periods, the first from 1985 to 1987 and the second from 1988 to 1990. This choice is dictated by the fact that in the first three years (1985-1987) the most dramatic reforms took place, while the last three years (1988-1990) can be mainly considered a consolidation period. In order to carry out the test I modify (2.11) and (2.13) in the following way:

$$y_{jt} = \beta_l l_{jt} + \tilde{\beta}_l D_t l_{jt} + \beta_k k_{jt} + \tilde{\beta}_k D_t k_{jt} + \bar{\beta}_k k_{jt} + \tilde{\beta}_k D_t k_{jt} + \beta_i i_{jt} + \tilde{\beta}_i D_t i_{jt} + \beta_{kk} k_{jt}^2 + \tilde{\beta}_{kk} D_t k_{jt}^2 + \beta_{ii} i_{jt}^2 + \tilde{\beta}_{ii} D_t i_{jt}^2 + \beta_{ki} k_{jt} i_{jt} + \tilde{\beta}_{ki} D_t k_{jt} i_{jt} + \eta_{jt} \quad (5.1)$$

$$\omega_{jt} = \gamma_0 + \tilde{\gamma}_0 D_t + \gamma_1 \omega_{jt-1} + \gamma_2 \omega_{jt-1}^2 + \gamma_3 \omega_{jt-1}^3 + \xi_{jt} \quad (5.2)$$

where D_t is a dummy variable taking the value of one from 1988 on and zero otherwise. Note that in (5.2) only the constant, i.e. the average productivity, is allowed to change between the two sub-periods. The intuition behind (5.1) is simply that there is evidence of a structural change in the production function parameters if $\tilde{\beta}_l$ and $\tilde{\beta}_k$ are significantly different from zero.

Table 9 shows that, reasonably, in almost all the cases the estimated coefficients for the two sub-periods can be considered as an upper and lower bound for the coefficients estimated using the whole sample (reported in the last two columns of table 7). However, the first two columns of table 9 demonstrate that, especially for the capital coefficient, the division of the sample compromises the significance of the estimates. Moreover, regarding capital, the coefficient associated with the dummy variable is never significant meaning that there is no evidence that the capital parameter changed in the second part of the sample. As for labor, a significant structural change occurs after 1987 for just five industries: Beverages (2), Textiles (4), Chemicals (9), Plastic and Rubber (10), and Nonmetal minerals (13), with the

labor coefficient always increasing in the second sub-period. Nonetheless, since only in the Chemicals industry the capital coefficient is significant in the first sub-period and does not change between the two sub-periods, I conclude that, overall, the factor intensity remained fairly constant during the trade liberalization process for the majority of the industries with the exception of the Chemicals sector which became more labor-intensive. The coefficient associated with the dummy variable in (5.2), not reported here, is insignificant in every industry suggesting that the average productivity did not change from the first sub-period to the second.

5.2 Productivity Analysis

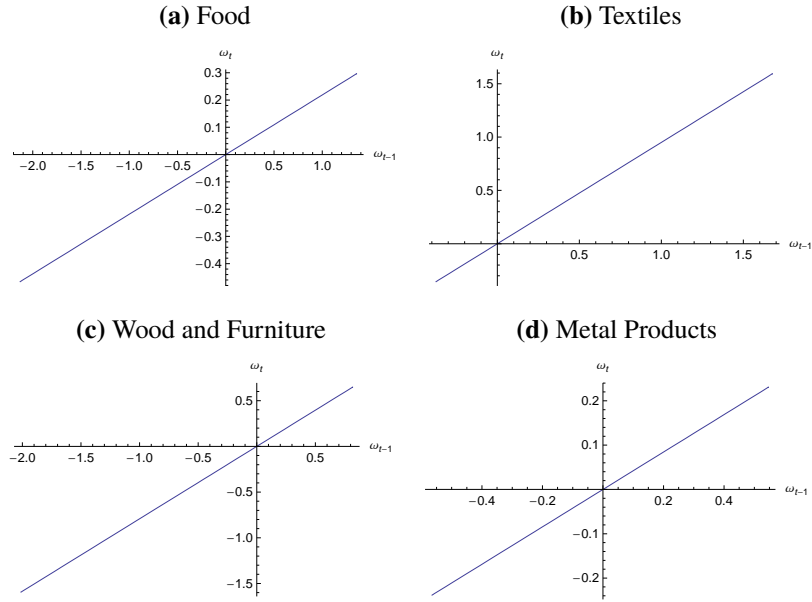
The structural framework illustrated in section 2.2 is suitable for obtaining a characterization of the technology in each industry through the production function coefficients, as well as an estimate of the productivity process for each firm in each year. Specifically, with a Cobb-Douglas technology, the productivity process can be recovered, after estimating β_l and β_k , as $\hat{\omega}_{jt} = \hat{\phi}_{jt} - \hat{\beta}_l l_{jt} - \hat{\beta}_k k_{jt}$. Furthermore, recall that the first-order Markov productivity process is modeled as a third degree polynomial of lagged productivity of the form: $\omega_{jt} = \gamma_0 + \gamma_1 \omega_{jt-1} + \gamma_2 \omega_{jt-1}^2 + \gamma_3 \omega_{jt-1}^3 + \xi_{jt}$.

The empirical evidence suggests that, since for almost all the industries the γ_0 , γ_2 , and γ_3 coefficients are statistically insignificant, the productivity process can be actually approximated by the AR(1) process $\omega_{jt} = \gamma_1 \omega_{jt-1} + \xi_{jt}$. Therefore, the current productivity depends only linearly on the value of the previous productivity. Moreover, the γ_1 coefficient is estimated to be always below one (except for the Cement industry (12)) meaning that the productivity process is stationary. Figure 1 depicts the productivity process for four industries chosen for illustrative purposes.

For two of these four industries, figure 2 shows the smoothed plots for capital and investment. Specifically, in each panel the vertical axis measures the estimated productivity shock, while the horizontal axis running left measures investment levels and the horizontal axis running right measures capital usage. The structural estimation procedure is based on a crucial monotonicity assumption regarding productivity and investment, i.e. the investment level should increase in productivity, conditioning on any observed levels of capital usage. As demonstrated in figure 2 this monotonicity condition appears to hold.

The ability of obtaining a direct estimate of the productivity process allows for analyzing the growth in productivity for each firm from one year to the next. In fact, knowing ω_{jt} , the growth in productivity can be easily calculated as $\Delta\omega_{jt} = \omega_{jt} - \omega_{jt-1}$. Table 10 displays

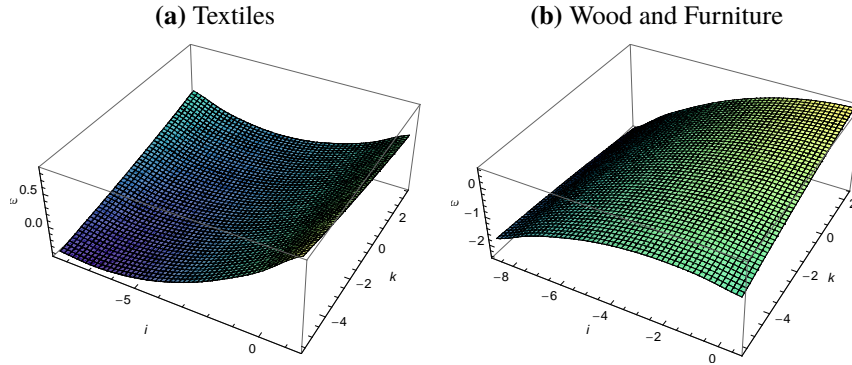
Figure 1: Productivity process



Note: Based on author's own estimations.

the mean and the standard deviation of the productivity growth by sector between 1986 and 1990. The average annual growth in productivity is relatively small, below 0.1 percent, for the majority of the industries and for six of them (Wood and Furniture (7), Pulp and Paper (8), Chemicals (9), Cement (12), Nonmetal minerals (13), and Iron and Steel (14)) the average growth is negative. The standard deviation, however, is relatively high suggesting that there are significant differences among firms in each industry with respect to productivity growth performances. The last column of table 10 shows the percentage of firms that have moved across the quartiles of the productivity growth distribution. The figures are always above 60 percent demonstrating that in each industry there is a lot of heterogeneity and reshuffling across firms. This results can be observed further in Figure 3 where the frequency and the kernel approximated distribution of productivity growth is depicted for three industries in 1986 (left panel) and 1990 (right panel). It is easy to see that, even if the distribution is always centered around zero, its shape considerably changes between the first and the last year in each of the three industries. Furthermore, in the Beverage sector the distribution is fairly symmetric although much more concentrated about the mean in both the first and last year. In the Chemicals sector the distribution is skewed to the right in 1986 but skewed to the left in 1990 and strongly concentrated about the mean in both years. In the Nonelectrical machinery sector the distribution is skewed to the right and concentrated about the mean in both 1986

Figure 2: Productivity as a function of capital and investment



Note: Based on author's own estimations.

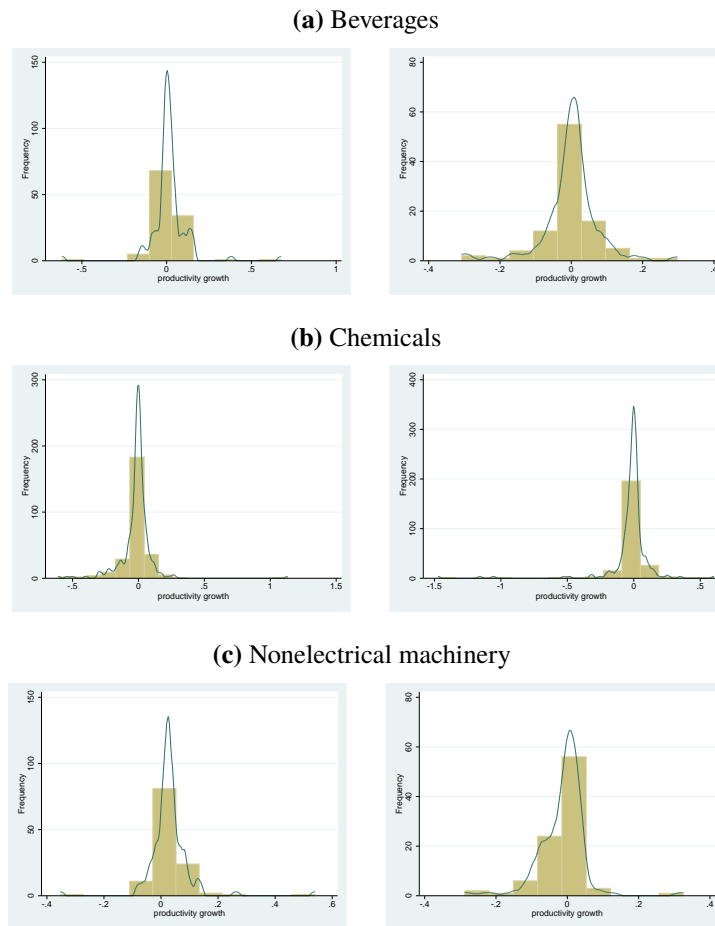
and 1990 but both skewness and kurtosis are lower in the last year. In conclusion in none of the sectors the distribution of productivity growth seems normal.

Together with a method for estimating the productivity process, Olley and Pakes (1996) also propose a decomposition that is insightful to analyze the dynamics of aggregate productivity. Specifically, define $\bar{\Omega}_t = \sum_j \omega_{jt} s_{jt}$ as the aggregate productivity in year t in each industry, where ω_{jt} is the firm-specific productivity process and s_{jt} is the share of firm j in the total value added of its industry. Also, define $\bar{\omega}_t = \frac{1}{N} \sum_{j=1}^N \omega_{jt}$ and $\bar{s}_t = \frac{1}{N} \sum_{j=1}^N s_{jt}$ as the average productivity and the average value added share in each industry, respectively. Then, the Olley and Pakes decomposition is given by:

$$\begin{aligned} \bar{\Omega}_t &= \bar{\omega}_t + \sum_{j=1}^N (\omega_{jt} - \bar{\omega}_t)(s_{jt} - \bar{s}_t) \quad \forall \{s_{jt}, \omega_{jt}\} \\ &= \bar{\omega}_t + \Gamma_t^{OP} \end{aligned} \tag{5.3}$$

The identity in (5.3) holds for growth levels as well (i.e. $\Delta \bar{\Omega}_t = \Delta \bar{\omega}_t + \Delta \Gamma_t^{OP}$) and implies that aggregate productivity can be decomposed into two distinct parts: one reflecting the effect of average productivity and the other reflecting allocative efficiency. Intuitively, the decomposition assumes that aggregate productivity in an industry can evolve and grow because the average productivity of the firms in that industry grows and/or because productive resources (capital and labor measured through value added) are reallocated to the most productive firms within that industry. Table 11 presents the industry averages of firm productivity growth, aggregate productivity growth weighed by share of value added, and changes in allocative efficiency. The interesting insight that emerges from these figures is that aggregate productivity

Figure 3: Distribution of productivity growth in 1986 (left panel) and 1990 (right panel)



Note: Based on author's own estimations.

growth is negative in more than half of the industries and this is mostly due to the fact that the change in allocative efficiency within these industries seem to have occurred in the opposite direction, i.e. toward the less productive firms.

Regarding the relationship between productivity and trade liberalization, the analysis conducted so far does not show improvements in productivity during the period of substantial trade exposure considered in the paper. As verified in the previous section, the average productivity remained constant throughout the entire sample period, despite the fact that the first part of this period was characterized by more aggressive trade reforms than the second part. Also, average productivity growth seems to be very modest and the aggregate productivity growth is negative in many of the industries considered. To further investigate

the relationship between trade openness and productivity gains,¹⁶ I calculate the Spearman rank correlation coefficients between measures of productivity growth and measure of trade liberalization displayed in table 12.¹⁷ Several patterns are worth noting. First, focusing on aggregate productivity growth is more appropriate than focusing on average productivity growth because aggregate productivity is a more insightful measure as it takes into account the share of each firm in the total value added of its industry. Second, changes in trade openness are negatively correlated with changes in aggregate productivity and allocative efficiency, implying that an increase in trade openness (which corresponds to a decrease in quotas and tariffs) is associated with increases in both aggregate productivity and allocative efficiency. This result seems to suggest that trade liberalization had a positive effect on the productivity of the Mexican manufacturing firms. However, as the correlations between changes in productivity and trade measures is significant but very small and the productivity analysis conducted so far provided limited evidence of productivity gains, the positive effect is indeed quite modest.

5.3 Robustness Checks with Alternative Models

In this section I compare the production function coefficient estimates obtained applying the structural approach to alternative models. In particular, I estimate the following additional specifications:

- i. Value added with translog technology using the investment as a proxy for productivity (Olley and Pakes method) and estimating all the production function coefficients in the second stage relying on the moment conditions in (2.17).
- ii. Value added with Cobb-Douglas technology using the demand for intermediate inputs as a proxy for productivity (Levinson and Petrin method), estimating the coefficient on labor in the first stage and the coefficient on capital in the second stage relying on the moment condition in (2.16).
- iii. Value added with translog technology including intermediate inputs in the production function (Levinson and Petrin method) and estimating all the production function coefficients in the second stage relying on the moment conditions in (2.17).

¹⁶See also Krishna and Mitra (1998) and Pavcnik (2002) for empirical contributions studying the effects of trade liberalization on firm productivity in other developing countries.

¹⁷A similar table is presented in Tybout and Westbrook (1995) who use the same Mexican data utilized in this paper to study changes in efficiency induced by the trade liberalization reform.

- iv. Gross output with Cobb-Douglas technology including intermediate inputs in the production function (Levinson and Petrin method) and relying on the moment conditions of lagged labor, lagged intermediate inputs, and current capital to identify the coefficients associated with labor, intermediate inputs, and capital, respectively, in the second stage.

The results for the specifications ii. and iv. are omitted here because the estimation of these models was particularly problematic. The solving algorithm could not find a solution satisfying the optimization criteria and the resulting production function parameters were in many cases zero, which implies that, since I imposed the restriction for the β s to be nonnegative, this constraint was often binding. The results for specifications i. and iii. are presented in tables 13, 14, and 15, respectively. In particular, I estimate specification iii. twice, using the entire sample first and then using a subsample excluding the *maquiladoras*. This is because the Mexican accounting system includes in the books of the firm that orders a subcontracting service the value of expenditure in intermediate inputs used by the subcontractor, generating a measurement error problem with the intermediate inputs.

The results in tables 13, 14, and 15 demonstrate that, even if the translog specification allows for a more flexible way of modeling technology, the overall significance of the estimates is much lower because the higher order and interaction terms potentially generate collinearity issues. Moreover, the interpretation of the coefficients and returns to scale is complicated with translog production functions because the sign and the magnitudes of the coefficients do not have a straightforward meaning as they capture more elaborated and complex interactions between inputs. The lack of significance is exacerbated when the intermediate inputs demand is used as a proxy for productivity, as confirmed by the results reported in tables 14 and 15. The cause of this problem is likely to be the measurement error in intermediate inputs, originated by the peculiar way of recording expenditure in intermediates for the *maquiladoras*,¹⁸ which does not appear to be resolved even when these firms are excluded. In fact, a crucial requirement for the Levinson and Petrin method to be successfully applied is the absence of measurement error in intermediate inputs expenditure.

6 Price-Cost Margins Results

In this section I present the results on the industry-level markups estimated with the simple dual approach outlined in Section 2.4. I then compare these with the plant-level markups derived

¹⁸The way of recording expenditure in intermediates for the *maquiladoras* affects both the production accounts of the *maquiladoras* and the firms that subcontract the *maquila* services.

by plugging into equation (2.23) the production function parameters previously obtained within the structural framework. Finally, with the results of the markup estimations in hand, I investigate the relation between price-cost margins and trade openness.

6.1 Industry-level Markups

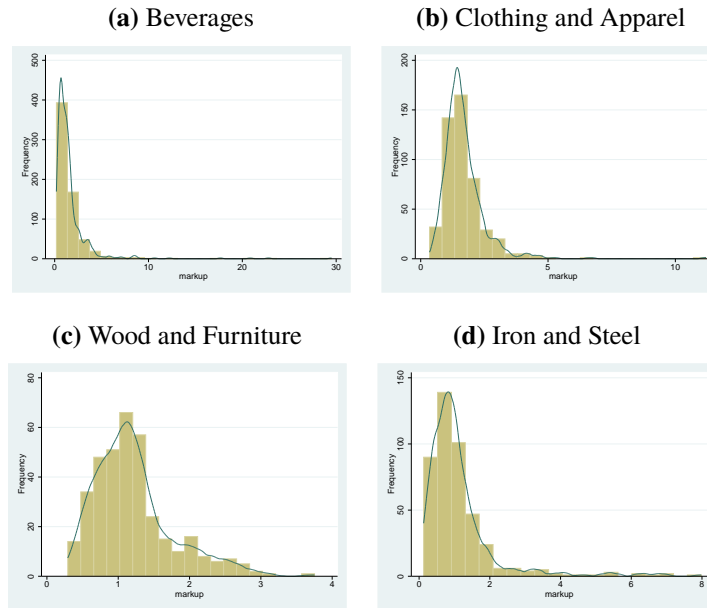
Table 16 reports the mean, median, and standard deviation of the year- and industry-specific markups recovered by estimating (2.27) by OLS. Note that with this procedure it is only possible to estimate one markup for each industry in each year, therefore the variation is along the cross-sectional (industry) dimension. The average markup ranges between 0.24 for Chemicals (9) and 2.69 for Cement (12) and in almost all the industries the mean and the median are different, with the mean being usually higher than the median, implying that the distribution of the markups is not symmetric. Moreover, the standard deviation is high indicating that in every industry the markups vary consistently across years. In many industries the magnitude of the markups is quite unreasonable (significantly lower than one) and the significance of the estimates is fairly poor. Overall this simple estimation procedure delivers very imprecise and unreliable results and it does not appear to be a valid alternative to the structural approach.

6.2 Plant-level Markups

Table 17 summarizes the plant-level markups recovered combining the output elasticity with respect to labor $\hat{\beta}_l$, obtained estimating (2.11), i.e. a Cobb-Douglas production function with the investment as a proxy for productivity, and data on labor expenditure and value added as described in (2.23). For sixteen out of eighteen industries the average markup is significantly different than zero and above or very close to one. Once again the mean is higher than the median implying that the markups distribution is positively skewed in almost all the industries. This result is confirmed in figure 4 where the distribution of the markups for some representative industries is plotted. The same figure shows also that the distribution of the markups is asymmetric, as expected. This is because markups are supposed to be bigger than or equal to one as they represent the ratio between price and marginal cost, therefore their distribution should be truncated around one. The standard deviation is very high indicating a substantial variation in markups across firms in each manufacturing sector.

The comparison between the results in table 16 and those in table 17 clearly highlights that the plant-level markups obtained with the structural approach are usually higher than the ones

Figure 4: Distribution of plant-level markup estimates



Note: Based on author's own estimations.

estimated at the industry level using the simplified approach. This is because the industry-level markups are estimated in first differences which usually leads to a downward bias. At the plant level, the highest significant markup, 2.20, is estimated for the Cement industry (12) while the lowest significant markup, 0.82, is estimated from the Chemical industry (9) and this results is the same at the industry level. Nonetheless, the correlation between the industry-level average markups and the plant-level average markups is merely 0.10.

Table 19 shows the markups estimated at the plant level using different specification for the production functions, i.e. the alternative models i. and iii. described before. The plant-level markups with translog technology are confirmed to be higher than the industry-level ones in almost all the sectors under any specification. However, the significance of these results is much lower than the significance of the plant-level markups obtained with Cobb-Douglas technology and this is mainly due to the fact that the Cobb-Douglas specification fits the data better and delivers more precise and reliable estimates of the production function parameters and, therefore, of the markups as well. Furthermore, I conduct a test to verify whether the average and median markups are statistically bigger than one. In fact, since the markup in this context is defined as price over marginal cost, a meaningful markup should be equal to or greater than one. For almost all the industries and under any specification I cannot reject the

null hypothesis that the markups are statistically bigger than one at a 5 percent significance level. This result, though, needs to be considered cautiously because the confidence intervals obtained by block-bootstrap used for inference are not very tight.

In conclusion, the striking differences between the industry-level and plant-level markup estimates, as summarized in table 18, highlight the following important point. Relaxing the constant markup assumption across firms and allowing for time varying and heterogeneous productivity shocks leads to more precise and substantially higher markups.

6.3 Markups, Trade Liberalization, and Export Status

In this section I study in detail the linkages between markups and trade. First, I rely on the models described in section 3.2 to analyze the impact of trade liberalization on the price-cost margins at the industry and plant level. Then, I focus on characterizing the relation between markups and export status. Moreover, since the structural framework allows for estimating both markups and productivity at the plant level, I further explore the role of productivity in the profitability of the Mexican manufacturing plants.

6.3.1 Industry-Level Analysis

To perform the industry-level analysis I use the results of the markups estimation presented in section 6.1 obtained with the simple dual approach and the results obtained with the structural approach estimating a Cobb-Douglas technology and using investment as a proxy for productivity. In fact, only these two sets of results are directly comparable since one of the requirements to estimate (2.27) is for the production function to be linearly homogeneous and the test on the returns to scale of the Cobb-Douglas production function in (2.11) confirmed that there is statistically significant evidence of constant returns to scale in most of the industries. Recall that the markups obtained with the simple dual approach are directly estimated at the industry-level. On the other hand, the price-cost margins obtained with the structural approach are estimated at the plant level, thus, in this part of the analysis, I collapse these results to the annual average markup in each industry. The other explanatory variables included in (3.1), i.e. Herfindahl index, capital-output ratio and measures of trade exposure, are constructed by aggregating and averaging across individual firms in each sector in each year. Models 1 and 2, which include industry-specific dummy variables, should explain the temporal variation within each industry while models 3 and 4, with only year dummy variables, are supposed to capture the variation between sectors. Note also that the measures of trade exposure reflect the extent of trade liberalization, i.e. a decrease in the quota coverage

or in the tariff rate implies an increase in trade openness and foreign competition. Therefore, a positive coefficient associated with these trade indicators describes a negative effect of the trade reforms on the markups and is expected in the presence of import discipline. The regression results are reported separately for each type of trade liberalization instrument in tables 20-23.

Tables 20 and 21 report the regression results obtained estimating (3.1) by OLS and using the industry-level markups recovered with the simple dual approach as a dependent variable. It is easy to see that, using either the quota coverage or the average tariff rate as trade indicators, very few coefficients in these regressions are significant and this result is exacerbated in models 3 and 4 which include only year dummy variables. The lack of significance is further confirmed by the adjusted R^2 which is quite low, although all the models are globally significant as verified by the F -statistic.

In both cases, with quota and tariff, one of the few significant coefficients is the one associated with the capital-output ratio in models 1 and 2. The sign of this coefficient is unexpectedly negative. However, since only the temporal variation is picked up in the model with industry dummy variables, this result may be reflecting underutilization of installed capacity during the recession, which was prevalent for most of the sample period. As for the measures of trade exposure, the coefficient associated with the tariff rate (table 21, model 3) is positive and highly significant indicating that the markups tend to be lower the more the openness to trade is. The coefficient on the interaction term between the trade indicator and the capital-output ratio in model 2 is also consistently significant with both quota and tariff. Its positive sign is again evidence of trade discipline and suggests that industries with a higher capital-output ratio are more likely to experience a reduction in margins as a consequence of trade liberalization. Nonetheless, because of the overall very low explanatory power, the regression results reported in tables 20 and 21 cannot be viewed as strong evidence of an impact of trade on the markups. In addition, these results confirm that the simple dual approach used to obtain the markups at the industry level is inadequate since the markup estimates are imprecise, and in many cases insignificant, and this compromises any further analysis conducted with those estimates.

I now turn to the regressions reported in tables 22 and 23 whose results are also obtained estimating (3.1) by OLS with the annual average markup in each sector, recovered from the structural plant-level estimation, as dependent variable. First, note that in these regressions the level of significance is substantially higher, especially when the industry dummy variables are included (models 1 and 2). Thus, even if aggregated at the industry level, the markups coming from the structural estimation appear to perform much better. However, a substantial

part of the explanatory power comes from industry effects as demonstrated by the R^2 which greatly increases from models 3 and 4 to models 1 and 2. This outcome possibly reflects sector-specific industrial characteristics, policies, entry barriers or technological differences that are not captured by the other explanatory variables considered. The year effects are always negative, with both quota and tariff, in model 1 and 2 and are also negative in models 3 and 4 for the majority of the years considered. This result may capture the fact that during the period of analysis the Mexican economy faced difficult challenges that negatively impacted firm profitability. The industry dummy variables, when included, are significant in many industries and their sign are consistent across all the specifications.

When quota is used as a trade indicator, the coefficient on the capital-output ratio has the expected positive sign in every model and in model 3 and 4 it is also highly significant, implying that industries with a higher capital share of output have higher price-cost margins. On the other hand, when tariff is used as a measure of trade exposure, this coefficient is still positive and significant when industry dummies are left out, but turns negative, although insignificant, when industry effects are controlled for. The coefficient associated with the Herfindahl index, when significant (model 3 with both quota and tariff) is positive confirming a higher rate of profitability in more concentrated industries. The coefficients on quota coverage and tariff rate are both positive and significant in model 3 indicating that price-cost margins decrease as trade protections are removed. In model 1, however, the same coefficients are not significant, suggesting that differences in the level of protection across sectors seem to be more relevant than variation over time. Adding interaction terms reveals a more complex picture. The net impact of quota coverage and tariff rate as well as their interaction with the Herfindahl index and the capital-output ratio are not significant in explaining the temporal variation (model 2), but the interaction between quota and Herfindahl index (table 22, model 4) and the interaction between tariff and capital-output ratio (table 23, model 4) are significant. Specifically, the interaction term for quota coverage and Herfindahl index is positive and significant implying that the profitability of the most concentrated industries is likely to decrease when trade is liberalized. Conversely, the interaction term for tariff rate and capital-output ratio is negative and highly significant suggesting that the trade reforms have a negative impact on the margins of the industry with the lowest capacity.

In summary, the industry-level analysis provides some evidence of import discipline, i.e. lower protection generated lower profitability in the Mexican manufacturing industries. This pattern is clearly established across sectors but not as clearly over time. Moreover, the importance of using reliable estimates (in this case markups) to correctly evaluate economic policies is emphasized by the much better performance of the markups estimated within the

structural framework with respect to the ones estimated relying on the simpler dual approach.

6.3.2 Plant-Level Analysis

To examine the intra-sectoral variation in price-cost margins I estimate (3.2) by OLS using the plant-level markups as the dependent variable. Recall that these markups were recovered from the structural estimation of my preferred specification, i.e. Cobb-Douglas technology with investment as a proxy for productivity. The explanatory variables are also calculated at the plant level with the exception of the trade indicators, quota coverage in model 1 and average tariff rate in model 2, which are only available at the industry level. The regression results are reported in table 24.

First note that the plant-level models are globally significant as indicated by the F -statistic, but explain only a small fraction of the plant-level variation in price-cost margins as confirmed by the relatively low value of the adjusted R^2 (approximately 0.13). This is nonetheless a common outcome of regressions performed on large micro-level dataset as the one used here. The year dummy variables are always negative but insignificant while the industry dummy variables are significant in many cases with both positive and negative signs.

The coefficient associated with market share is positive and highly significant suggesting that a rise in its market share increases the price-cost margin of a plant but at a decreasing rate, since the coefficient on the squared share is negative and significant, conversely. The coefficient on capital-output ratio is positive and highly significant in both models implying that, as expected, an increase in capacity has a positive effect on the profitability of a plant, however this effect becomes marginal when the capacity is large, as demonstrated by the very small magnitude of the coefficient on the squared capital-output ratio. As for the trade indicators, the coefficients on quota coverage and tariff rate are both insignificant, implying that there is no evidence that the trade reforms affected the price-cost margins of the Mexican manufacturing plants.¹⁹

I also estimate the same regressions with the plant-level markups obtained under different specifications, i.e. translog technology with both investment and intermediate inputs demand as proxies for productivity, as dependent variable. The results, not reported here, are in line with those presented in table 24. However, the overall significance of the models is lower, presumably because, as already mentioned, the translog production function specification delivers imprecise and noisy markup estimates.

¹⁹A similar result is found in Grether (1996).

6.3.3 Markups for Exporters

To characterize the relation between markups and export status I first estimate (3.3) by OLS using the logarithms of the plant-level markups estimated using my preferred specification, i.e. Cobb-Douglas technology with investment as a proxy for productivity, as the dependent variable. The explanatory variables are capital and labor use, a full interaction of year and industry dummy variables, and, of course, a dummy variable indicating export status. After obtaining an estimate for the coefficient associated with the exporter dummy ψ_1 , and the constant term ψ_0 , I perform a test on the significance of the nonlinear combination of the parameters $\psi_1 + \exp(\psi_0)$ which captures the level markup difference for exporters. Finally, I re-estimate (3.3) adding the estimated productivity ω_{jt} in order to directly control for differences in productivity and verify whether there is still evidence of a markup premium for exporter. Specifically, the second regression is given by: $\ln(\mu_{jt}) = \psi_0 + \psi_1 E_{jt} + \psi_2 \omega_{jt} + z_{jt} \rho + \varepsilon_{jt}$.

In both cases, with and without the additional productivity control, I obtain that the level markup difference $\mu_E = \psi_1 + \exp(\psi_0)$ is positive, 0.019 not controlling for productivity and 0.016 controlling for productivity, respectively, but insignificant. However, since the number of exporting firms in the Mexican manufacturing industries is not very high in the years considered and, most importantly, the extent of exporting is quite limited for the majority of the exporters, I try to verify whether the markup premium exists for intensive exporters, i.e. firms that export a high percentage of the value of their output. To do so I calculate for each exporter the ratio of exports value over output value and substitute the export dummy in (3.3) with another dummy, $E_{H_{jt}}$, that indicates export intensity. Specifically, $E_{H_{jt}}$ is equal to one if firm j is in the 75th or above percentile of the export-output ratio distribution, i.e. if firm j is an intensive exporter. Table 25 shows the results obtained estimating the modified version of (3.3) by OLS with the export intensity dummy, not controlling (model 1) and controlling for productivity (model 2).

First, the coefficient associated with the export intensity dummy variable is always positive and significant, with and without including productivity in the regression, suggesting that exporting has a positive impact on price-cost margins. Also, the coefficient associated with productivity in model 2 is positive and highly significant, meaning that productivity contributes to firms' profitability. In addition, the level markup difference for intensive exporters μ_{E_H} is positive and significant in both models. More precisely, I obtain a significantly estimated μ_{E_H} of 0.0588 in model 1 which implies that intensive exporters have a level markup premium of approximately 6 percent. In model 2 the estimated μ_{E_H} is significant and equal to 0.0539, meaning that, even controlling for productivity, the intensive exporter have a

level markup premium of approximately 5.4 percent. Note that controlling for productivity in this context means to control for differences in marginal costs, if ψ_2 (the coefficient on productivity) picks up cost heterogeneity fully, so that the coefficient on the intensive exporter dummy picks up the variation in average prices between intensive exporter and the other firms (low exporters and non exporters). However, because the productivity used in this regression was estimated as the residual of a value added production function, it may not contain only differences in costs but also unobserved quality differences in both inputs and output, as well as others market power effects. Nonetheless, it is important to emphasize that an intensive exporter effect is still present, even once differences in productivity are accounted for. This result is therefore consistent with the recent international trade literature predicting a positive relation between markups and exports status, especially in the case of intensive exporters.

6.3.4 Reconciling Industry- and Plant-level Evidence

As already mentioned, the exercise performed in this paper demonstrates the importance of relying on accurate and precise estimates when evaluating the effects of a policy. For this reason, the results reported in tables 20 and 21 are not to be trusted because they are based on implausible and insignificant markup estimates. However, even considering only firm-specific markups, the analysis conducted at the plant level delivers different results than the analysis at the industry level. How can this evidence be reconciled to understand and assess the effectiveness of trade liberalization in reducing market power in the Mexican manufacturing industries? Specifically, what can rationalize the fact that trade liberalization did not significantly reduce price-cost margins at the plant level but seems to have affected them at the industry level? Moreover, why are intensive exporters different?

Possible answers to these questions lie in the selection mechanism characterized in recent trade models.²⁰ The key insight of these models is that, if trade exposure does not change the behavior of the single firm, but simply the selection of the firms that are able to stay in the market, a direct effect of trade liberalization at the firm level would not be observed, but it could be observed at the industry level because of changes in the intra-industry composition. In this case, the lack of trade discipline evidence at the plant level is consistent with the idea that Mexican firms were not prompted to charge lower markups as a consequence of trade liberalization. Nonetheless, if the substantial decrease in protection from foreign competition generated intra-industry selection among firms forcing those that were charging higher markups to exit, and possibly be substituted by lower-profitability firms, the effect of

²⁰See Melitz (2003).

trade liberalization would manifest in lower industry-level markups. In addition, the selection process works through the productivity channel inducing the most productive firms to become exporters, which, as discussed before, are able to enjoy a markup premium. Since exporters, and especially intensive exporters, represent a very small fraction of the total firms considered in the analysis, it is reasonable to observe that their higher-profitability status is relevant and significant, yet not enough to offset the overall effect determined by the intra-industry selection of low-profitability firms.

7 Conclusions

In this contribution I focus on the importance of correctly estimating production function parameters and price-cost margins in order to assess differences in technology, productivity, and market power among eighteen Mexican manufacturing firms and evaluate the impact of trade liberalizing policies on their profitability.

I estimate production function parameters relying on a structural framework that corrects for the simultaneity bias using investment or intermediate inputs as a proxy for unobserved productivity. My results confirm the well established empirical evidence that production function coefficients obtained with OLS are biased and support the argument that controlling for firm-specific productivity shocks corrects this bias. In fact, compared to OLS, the structural estimation delivers a much lower labor parameter and a higher capital parameter. I also find evidence of constant returns to scale in the majority of the industries analyzed.

The second step in my empirical investigation consists of using the production function estimates to recover firm-level markups adopting a structural approach in which markups are derived from cost minimization first order conditions and can be interpreted as the wedge between the cost share of production factors and their revenue share. I test the validity of this approach by comparing the firm-level markup estimates with industry-level markups obtained through a less sophisticated dual estimation approach. The price cost-margins estimated at the plant level are more reasonable in terms of magnitude and significantly higher than their industry-level counterparts. This result demonstrates that explicitly taking into account differences in productivity is crucial in assessing the extent of market power.

Finally, I exploit the fact that the sample spans over a period of dramatic reforms in the Mexican economy to quantify the impact of trade exposure on the markups. I conduct an industry-level as well as a plant-level analysis relating price-cost margins and measures of import liberalization. The industry-level evidence seems to support the hypothesis of import

discipline, i.e. the removal of trade protections negatively affected the profitability of domestic firms, but this evidence is not confirmed in the plant-level analysis. In addition, I test the prediction that larger firms are likely to be more productive, thus can charge higher markups and afford to pay a sunk cost to become exporters. In the case of Mexican exporters I find a statistically significant markup premium only for intensive exporters, i.e. firms that export a high percentage of their output, and for these firms the premium persists even after netting out the effect of productivity. This evidence is consistent with recent international trade models predicting that trade exposure does not necessarily change the behavior of the single firm but induces a selection of firms modifying the intra-industry composition. Productivity is certainly an important channel through which the selection mechanism works allowing the most productive firms to become exporters and to be, on average, more profitable.

Since the trade liberalization of the late 1980s analyzed in this paper, Mexico has become even more open and integrated in production value chains by joining the North American Free Trade Agreement (NAFTA) in 1994. NAFTA created one of the world's largest free trade zones and was supposed to lay the foundations for strong economic growth and rising prosperity for its members. While the period after the enactment of NAFTA, and before China's admission to the World Trade Organization, was associated with an above-average GDP growth in Mexico, it is difficult to determine the extent to which this was the result of firms becoming more productive. The exposure to trade should have boosted competition and created greater incentives for innovation and productivity improvements, yet the evidence of such improvements is limited. In addition, in more recent years, Mexico's exporting performance has been impressively strong, especially to the United States, but the overall economy has experienced a rather sluggish GDP growth. All these considerations suggest that the effectiveness of trade policies crucially depends on the ability of implementing complementary reforms aimed at the internal market that promote competition, eliminate distortions in the allocation of resources, and stimulate investments in innovation and growth. Especially in times of great uncertainty, such as the current ones regarding the future of NAFTA, focusing on building a solid, competitive, and productive domestic economy is of paramount importance for Mexico's prosperity.

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Table 1: Variables from the original dataset used in the analysis

Variable	Description
<i>Labor force</i>	
TOTREMUN ¹	total labor remunerations
TOHHOM ¹	total hours worked
TOPEOC	total employment
<i>Inputs costs</i>	
TOTMASUM ⁵	total material cost
GTRENALQ ¹	rent and leasing costs
VAENELCN ⁶	value of electricity consumed
GASTMAQU ¹	cost of subcontractors
<i>Value of output</i>	
VALPROEL ²	value of output
<i>Revenue</i>	
INSERMAQ ¹	income from subcontracting
<i>Fixed capital</i>	
V68 ⁴	machinery and equipment valued at replacement cost
V92 ⁴	machinery and equipment produced for own use
V69 ³	construction and installation valued at replacement cost
V93 ³	construction and install assets produced for own use
V70 ¹	land valued at replacement cost
V71 ⁷	transportation equipment valued at replacement cost
V94 ⁷	transportation equipment assets produced for own use
V72 ¹	other assets valued at replacement cost
V95 ⁴	other asset produced for own use
<i>Trade indicators</i>	
TAI630	average tariff on input (June 30)
TAI1230	average tariff on input (Dec. 30)
TAQ630	average tariff on output (June 30)
TAQ1230	average tariff on output (Dec. 30)
LCI630	license coverage on input (June 30)
LCI1230	license coverage on input (Dec. 30)
LCQ630	license coverage on output (June 30)
LCQ1230	license coverage on output (Dec. 30)
<i>Price indices</i>	
¹ PM	wholesale price index
² PPP	producer price index
³ PKE	construction price index
⁴ PK	machinery price index
⁵ PMP1	raw materials price index
⁶ PEMP	electricity price index
⁷ PKT	transportation price index

Note: Based on variable codes from INEGI's Annual Industrial Survey provided by the former Mexican Secretariat of Commerce and Industrial Development.

Table 2: Variables constructed

Variable	Description	Calculation
GVO	Gross value of output	$GVO=(VALPROEL/PPP)+(V92/PKM)+ (V93/PKE)+(V94/PKT)+(V95/PKM)$
INT	Intermediates	$INT=(TOTMASUM/PMP1)+(VAENELCN/PEMP)$
VA	Value added	$VA=GVO-INT$
CORVA	Corrected value added	$CORVA=VA+(INSERMAQ/PM)- (GASTMAQU/PM)$
CORGVO	Corrected gross value of output	$CORGVO=GVO+(b*((INSERMAQ/PM)- (GASTMAQU/PM)))$
CORINT	Corrected intermediates	$CORINT=CORGVO-CORVA$
TRCK	Total replacement cost of capital	$TRCK=(V68/PKM)+(V69/PKE)+(V70/PM)+ (V71/PKT)+(V72/PM)$
KSTOCK	Capital stock	$KSTOCK=TRCK+((GTRENALQ/PM)/0.10)$
INVEST	Investment	$INVEST=KSTOCK_t - 0.9*KSTOCK_{t-1}$
TLPM	Deflated total labor remunerations	$TLPM=TOTREMUN/PM$
TLMPH	Labor remunerations per hour	$TLMPH=TLPM/TOHHOM$

Note: Based on variable codes from INEGI's Annual Industrial Survey provided by the former Mexican Secretariat of Commerce and Industrial Development and calculations developed by the author.

Table 3: Industry-specific indicators

Rama	Sector	Industry	# of plants	Share of output	Share of imports	Share of exports	% of plants exporting
11-19	1	Food	226	11.66	7.24	3.09	0.20
20-22	2	Beverages	108	8.42	2.59	2.64	0.22
	23	Tobacco	6	1.35	2.58	0.22	0.10
24-26	4	Textiles	103	2.25	10.00	8.17	0.24
	27	Clothing and Apparel	81	0.82	19.22	2.29	0.10
	28	Leather and Footwear	19	0.18	1.62	58.00	0.38
29-30	7	Wood and Furniture	61	0.64	3.42	5.25	0.13
31-32	8	Pulp and Paper	117	4.80	15.22	1.82	0.13
33-40	9	Chemicals	277	15.72	12.54	11.27	0.42
41-42	10	Plastic and Rubber	159	3.21	14.54	4.51	0.21
	43	Glass	22	3.07	6.90	15.73	0.62
	44	Cement	27	2.71	2.05	9.06	0.39
	45	Nonmetal Minerals	95	1.22	9.68	3.01	0.13
	46	Iron and Steel	73	10.58	3.10	4.88	0.24
	47	Nonferrous Metals	6	3.68	2.77	48.68	0.51
48-50	16	Metal Products	106	2.87	14.34	8.80	0.32
	51	Nonelectrical Machinery	116	1.85	28.80	26.14	0.29
52 -55	18	Electrical Machinery	109	5.49	20.52	8.60	0.41
56-58	19	Transport Equipment	116	19.06	19.54	39.94	0.44
	59	Other Manufacturing	46	0.54	16.92	4.14	0.20

Note: Based on author's own calculations with data from INEGI's Annual Industrial Survey provided by the former Mexican Secretariat of Commerce and Industrial Development. The share of output is reported as average over the sample period. The shares of imports and exports are calculated as shares of total sectoral imports and exports, respectively, over sectoral output and are reported as averages over the sample period.

Table 4: Production characteristics

Variable	1985	1986	1987	1988	1989	1990
Numbers of Plants	1,949	1,972	1,953	1,919	1,873	1,614
Gross Value of Output ^a	465.01	439.07	453.21	473.80	554.19	619.88
Value Added ^b	415.56	243.88	247.99	259.75	304.36	361.79
Δ Gross Value of Output ^c		7.81	6.66	4.76	21.27	15.09
Δ Value Added ^d		-2.20	53.45	98.89	61.86	42.65
Capital Stock ^e	3.14	2.92	2.99	2.94	3.05	3.22
Capital Productivity ^f	4.59	4.70	4.74	4.35	4.56	4.56
Investment ^g	24.94	13.38	37.03	19.17	36.64	36.53
Total Employment	369.29	348.28	343.33	350.20	802.02	409.50
Δ Total Employment ^h		7.64	1.62	2.40	17.82	44.55

Note: Based on author's own calculations with data from INEGI's Annual Industrial Survey provided by the former Mexican Secretariat of Commerce and Industrial Development. ^aIn millions of 1980 pesos; ^bIn millions of 1980 pesos; ^cPercentage; ^dPercentage; ^eIn millions of 1980 pesos; ^fAverage plant-level gross value of output/capital stock; ^gIn millions of 1980 pesos; ^hPercentage.

Table 5: Average annual change in trade protection

	Δ Import coverage		Δ Average tariff rate	
	1985-1988	1988-1990	1985-1988	1988-1990
Food	-24.34	-11.46	-22.97	-5.97
Beverages	-33.09	-29.63	-34.73	-7.33
Tobacco	3.17	-0.17	-26.57	-8.46
Textiles	-49.56	-25.70	-24.89	-12.37
Clothing and Apparel	-41.60	-47.83	-25.16	-11.93
Leather and Footwear	-56.32	-40.18	-25.44	-11.01
Wood and Furniture	-71.98	-31.37	-25.50	-12.99
Pulp and Paper	-53.11	-45.68	-33.80	-10.98
Chemicals	-53.08	-23.34	-21.31	-7.23
Plastic and Rubber	-70.13	-30.21	-21.95	-12.12
Glass	-48.72	-4.71	-34.00	-11.14
Cement	-25.36	-0.81	-20.27	-6.93
Nonmetal Minerals	-50.98	-8.57	-24.12	-10.22
Iron and Steel	-42.95	-4.92	-18.71	0.15
Nonferrous Metals	-51.64	-6.68	-23.51	-8.04
Metal Products	-66.38	-19.88	-27.73	-9.74
Nonelectrical Machinery	-44.07	-14.83	-18.70	-3.20
Electrical Machinery	-72.64	-40.66	-22.54	-10.03
Transport Equipment	-44.31	-36.09	-24.39	-7.16
Other Manufacturing	-47.78	-17.44	-23.73	-9.60

Note: Based on author's own calculations with trade data provided by the former Mexican Secretariat of Commerce and Industrial Development. The change is expressed in percentage.

Table 6: Trade and performance variables for selected years

Industry	Average tariff rate			Quota coverage			Herfindal index			Capital-output ratio		
	1985	1988	1990	1985	1988	1990	1985	1988	1990	1985	1988	1990
Food	0.233	0.099	0.121	0.660	0.280	0.222	0.011	0.012	0.016	0.502	0.661	0.559
Beverages	0.541	0.148	0.163	0.879	0.233	0.129	0.036	0.042	0.044	1.249	2.259	2.119
Tobacco	0.432	0.166	0.178	0.803	0.879	0.877	0.237	0.256	0.240	0.892	0.728	0.826
Textiles	0.351	0.137	0.142	0.429	0.029	0.019	0.029	0.025	0.027	0.728	0.807	0.730
Clothing and Apparel	0.429	0.170	0.172	0.748	0.008	0.005	0.061	0.067	0.074	0.387	0.636	0.480
Leather and Footwear	0.437	0.176	0.178	0.826	0.004	0.003	0.051	0.059	0.087	0.358	0.587	0.369
Wood and Furniture	0.399	0.156	0.156	0.701	0.014	0.011	0.035	0.045	0.056	0.761	0.775	0.698
Pulp and Paper	0.343	0.078	0.103	0.513	0.029	0.010	0.035	0.036	0.042	0.920	1.215	0.703
Chemicals	0.227	0.105	0.122	0.558	0.056	0.041	0.012	0.014	0.013	0.715	0.791	0.992
Plastic and Rubber	0.304	0.139	0.142	0.552	0.010	0.008	0.053	0.061	0.067	5.185	0.806	0.798
Glass	0.459	0.129	0.143	0.541	0.048	0.047	0.065	0.079	0.074	1.097	1.063	0.812
Cement	0.183	0.084	0.098	0.491	0.132	0.131	0.059	0.056	0.057	1.818	2.007	3.091
Nonmetal Minerals	0.335	0.140	0.145	0.452	0.026	0.024	0.037	0.037	0.039	0.851	1.223	0.904
Iron and Steel	0.153	0.077	0.106	0.440	0.009	0.008	0.100	0.085	0.101	0.910	1.267	1.060
Nonferrous Metals	0.262	0.110	0.126	0.446	0.007	0.007	0.415	0.770	0.938	0.819	1.650	1.767
Metal Products	0.308	0.112	0.124	0.483	0.011	0.010	0.039	0.052	0.059	0.716	0.719	0.585
Nonelectrical Machinery	0.230	0.118	0.142	0.447	0.049	0.032	0.036	0.058	0.074	1.329	1.502	1.160
Electrical Machinery	0.331	0.147	0.153	0.534	0.009	0.006	0.025	0.047	0.088	0.536	0.758	0.598
Transport Equipment	0.266	0.109	0.127	0.652	0.109	0.054	0.056	0.056	0.065	0.641	0.862	0.541
Other Manufacturing	0.335	0.140	0.154	0.527	0.050	0.042	0.068	0.063	0.080	0.437	0.467	0.443

Note: Based on author's own calculations with data from INEGI's Annual Industrial Survey and trade data provided by the former Mexican Secretariat of Commerce and Industrial Development.

Table 7: Estimates of production function coefficient under different estimation methodologies

Industry	OLS		FE		Structural	
	β_l	β_k	β_l	β_k	β_l	β_k
1	0.7407***	0.2243***	0.5601***	0.3161***	0.0537	0.5749**
2	0.5873***	0.3654***	0.2402***	0.2492***	0.2751**	0.6385**
4	0.7115***	0.1243***	0.4717***	0.0845	0.4914**	0.0833
5	0.7949***	0.2067***	0.6128***	0.0364	0.5967**	0.2334
6	0.8408***	0.2353***	0.5624***	0.2017**	0.9606**	0.0086
7	0.7293***	0.2424***	0.5486***	0.3465***	0.4192**	0.0615
8	0.6923***	0.3273***	0.2629***	0.6271***	0.2320**	0.5934**
9	0.6454***	0.3251***	0.1343***	0.1500***	0.1545**	0.6202**
10	0.7943***	0.2525***	0.5239***	0.1128**	0.5108**	0.3617**
11	0.7291***	0.1906***	0.9015***	0.3534***	0.0475	0.6243**
12	0.8219***	0.1667***	0.4523***	-0.0043	0.4852**	0.8142
13	0.8143***	0.1804***	0.5834***	0.2179***	0.3992**	0.3970**
14	0.8039***	0.2285***	0.5298***	0.2009***	0.2622**	0.4180**
16	0.7238***	0.3396***	0.4642***	0.3298***	0.3432**	0.5092**
17	0.7454***	0.2758***	0.6412***	0.2909***	0.4699**	0.7388**
18	0.9131***	0.1723***	0.7183***	0.0440	0.2678**	0.6330**
19	0.6379***	0.4406***	0.3661***	0.3624***	0.3099**	0.7342**
20	0.9414***	0.0883***	0.4884***	0.0369	0.3188**	0.1178

Note: Based on author's own estimations. The stars indicate significance levels (** $p < 0.05$, *** $p < 0.01$). For the structural estimation the standard errors are obtained by block-bootstrap.

Table 8: Returns to scale
under different estimation methodologies

	OLS	FE	Structural
Industry	$\beta_l + \beta_k$	$\beta_l + \beta_k$	$\beta_l + \beta_k$
1	0.9650	0.8762	0.6286**
2	0.9527**	0.4894**	0.9136**
4	0.8358**	0.5562**	0.5747
5	1.0016	0.6492**	0.8301**
6	1.0761**	0.7641**	0.9692**
7	0.9717	0.8951	0.4807**
8	1.0196	0.8900**	0.8254
9	0.9705**	0.2843**	0.7747
10	1.0468**	0.6367**	0.8725
11	0.9197**	1.2549	0.6718**
12	0.9886	0.4566**	1.2994**
13	0.9947	0.8013**	0.7962**
14	1.0324	0.7307**	0.6802
16	1.0634**	0.7940**	0.8524**
17	1.0212	0.9321	1.2087**
18	1.0854**	0.7623**	0.9008**
19	1.0785**	0.7285**	1.0441**
20	1.0297	0.5253**	0.4366**

Note: Based on author's own estimations. The stars indicate that the constant returns to scale hypothesis $H_0 : \beta_l + \beta_k = 1$ cannot be rejected at a 5 percent significance level.

Table 9: Production function coefficients estimates for the sample divided in two sub-periods

Industry	1985-1987		1988-1990	
	β_l	β_k	$\beta_l + \tilde{\beta}_l$	$\beta_k + \tilde{\beta}_k$
1	0.0355	0.0002	0.0898	1.9850
2	0.1994**	0.6455	0.3573**	0.5397
4	0.4175**	0.2257	0.5968**	0.1530
5	0.5314**	0.0236	0.6527	0.3806
6	0.9343**	0.0000	0.9617	0.3746
7	0.4317**	0.2614	0.4083	0.5654
8	0.2109**	0.6516	0.2500	0.5409
9	0.0815**	0.6566**	0.2214**	0.5900
10	0.4031**	0.4216	0.6390**	0.3083
11	-0.0091	0.6738**	0.0415	2.0660
12	0.4614**	0.4091	0.5405	0.9828
13	0.3372**	0.5547	0.4672**	0.1800
14	0.2578**	0.5190	0.2643	0.1855
16	0.3263**	0.4570	0.3391	0.5750
17	0.4652**	0.2690	0.4961	1.2480
18	0.2274**	0.5754**	0.3053	0.6739
19	0.3630**	0.6670	0.2577	0.8071
20	0.2593**	1.3320**	0.4975	0.0154

Note: Based on author's own estimations. In the first two columns, the stars indicate that zero is not contained in the 95 percent confidence interval obtained by block-bootstrapping the sample. In the last two columns, the stars indicate that the coefficient is significantly different between the first and the second sub-period.

Table 10: Annual productivity growth

Industry	Mean	Std. Dev.	% Firms moving
1	0.0078	0.2392	73.29
2	0.0048	0.1110	78.57
4	0.0005	0.1082	73.78
5	0.0022	0.2607	74.50
6	0.0042	0.1154	70.75
7	-0.0049	0.2390	72.12
8	-0.0027	0.1285	74.56
9	-0.0039	0.1231	76.46
10	0.0006	0.1212	75.49
11	0.0079	0.3033	85.06
12	-0.0121	0.2199	78.85
13	-0.0001	0.1292	77.17
14	-0.0084	0.1186	67.41
16	0.0004	0.0959	70.93
17	0.0045	0.1164	67.20
18	0.0065	0.2574	80.98
19	0.0002	0.1728	74.89
20	0.0221	0.2660	71.35

Note: Based on author's own estimations. The last column reports the percentage of firms that during the period 1986-1990 have moved across the quartiles of the productivity growth distribution.

Table 11: Aggregate productivity growth decomposition

Industry	$\Delta\bar{\omega}_{jt}$	$\Delta\bar{\Omega}_t$	$\Delta\Gamma_t^{OP}$
1	0.0078	0.0137	0.0066
2	0.0048	0.0075	-0.0006
4	0.0005	-0.0125	-0.0191
5	0.0022	-0.0349	-0.0328
6	0.0042	0.0123	0.0072
7	-0.0049	0.0134	0.0191
8	-0.0027	-0.0277	-0.0244
9	-0.0039	-0.0029	-0.0001
10	0.0006	0.0053	0.0029
11	0.0079	0.0233	0.0200
12	-0.0121	-0.0099	0.0067
13	-0.0001	-0.0040	-0.0035
14	-0.0084	-0.0595	-0.0532
16	0.0004	-0.0018	-0.0007
17	0.0045	-0.0130	-0.0129
18	0.0065	0.0436	0.0432
19	0.0002	-0.0056	-0.0094
20	0.0221	0.0515	0.0273

Note: Based on author's own estimations. In growth levels the productivity decomposition is given by $\Delta\bar{\Omega}_t = \Delta\bar{\omega}_t + \Delta\Gamma_t^{OP}$ so that the number in the second column is (approximately) given by the sum of the numbers in the first and last column, for each industry.

Table 12: Cross-industry Spearman rank correlations among changes in productivity and trade exposure measures

	$\Delta\bar{\omega}$	$\Delta\bar{\Omega}$	$\Delta\Gamma^{OP}$	ΔQ	ΔT
$\Delta\bar{\omega}$	1.0000				
$\Delta\bar{\Omega}$	0.1003**	1.0000			
$\Delta\Gamma^{OP}$	0.0156	0.8967**	1.0000		
ΔQ	-0.0133	-0.0224**	-0.0469**	1.0000	
ΔT	-0.0832**	-0.0681**	-0.0444**	0.2402**	1.0000

Note: Based on author's own estimations. The productivity growth $\Delta\bar{\omega}$, the aggregate productivity growth $\Delta\bar{\Omega}$ and the change in allocative efficiency $\Delta\Gamma^{OP}$ are industry-year averages over the period 1986-1990. ΔQ and ΔT are the changes in quota and tariff coverage over the period 1985-1990. The stars indicate the significance level of the rank correlation (** $p < 0.05$).

Table 13: Estimates of production function coefficients, translog technology, Olley and Pakes method

Industry	β_l	β_k	β_{ll}	β_{kk}	β_{lk}
1	-0.5721**	0.8281**	-0.2091**	0.1178	-0.0163
2	-0.1930	0.7812**	-0.1736**	0.0080	0.1688
4	0.2847	0.2217**	-0.0709	0.0658	-0.0519
5	-0.0629	0.4851**	-0.1372	0.0439	0.0179
6	1.1807**	-0.9369**	0.4271	0.2104**	-0.8233**
7	-0.1161	0.4346	-0.2170	-0.0726	0.1719
8	0.0109	0.4832	-0.1031	0.0496	-0.0376
9	0.0249	0.5997**	-0.0522**	0.0461	-0.0056
10	0.1905	0.6011**	-0.1205**	0.0214	0.0960
11	-0.7413	1.1676	-0.3956	-0.1522	0.5748
12	-0.6070	0.9394	0.0396	-0.1361	0.4806
13	0.0622	0.3478**	-0.1197**	0.0199	0.0065
14	-0.2046	0.7527**	-0.2260	-0.0090	0.2257
16	-0.0524	0.4558**	-0.1157	0.1322	-0.1350
17	0.2323	0.6427	-0.0173	0.0281	-0.0093
18	-0.8505	1.3917**	-0.5748**	-0.1901	0.7524
19	0.3172**	0.7545**	0.0107	0.0715	-0.0268
20	-0.6517**	0.9863**	-0.3648**	-0.0030	0.2928

Note: Based on author's own estimations. The stars indicate significance levels (** $p < 0.05$), i.e. zero is not contained in the 95 percent confidence interval obtained by block-bootstrapping.

Table 14: Estimates of production function coefficients, translog technology, Levinson and Petrin method (full sample)

Industry	β_l	β_k	β_{ll}	β_{kk}	β_{lk}
1	0.1802	0.2095	-0.0513	0.0472	-0.0954
2	0.0427	0.5830**	-0.1206	0.0164	0.0997
4	3.4026	1.2897	0.4224	0.1580	-0.1516
5	-0.0905	0.1157	-0.1374	0.0480	0.0742
6	1.0747	-0.7804	0.3546	0.1824	-0.6245**
7	-0.3855	0.1080	-0.2711	-0.0653	0.2937
8	0.4332	0.2107	0.0085	0.0867	-0.1770
9	0.2912	0.4189	-0.0070	0.0442	-0.0515
10	0.8374	0.0504	0.1267	0.1365	-0.2883
11	0.0808	0.6522	0.0868	0.0135	0.0125
12	-0.6883	1.5939**	0.4354	-0.2522	0.3858
13	-0.1825	0.0699	-0.1802	0.0058	0.1736
14	0.5714**	0.2521	-0.0752	0.0166	0.0229
16	0.0089	0.4300	-0.1181	0.1094	-0.1072
17	-0.2529	-0.7824	-0.1235	-0.0594	0.1201
18	-0.0418	0.5842	-0.2297	0.0530	0.1067
19	0.4602**	0.5693**	0.0380	0.0830**	-0.0936
20	-0.7006	0.4892	-0.2989	0.0049	0.2461

Note: Based on author's own estimations. The stars indicate significance levels (** $p < 0.05$), i.e. zero is not contained in the 95 percent confidence interval obtained by block-bootstrapping.

Table 15: Estimates of production function coefficients, translog technology, Levinson and Petrin method (no *maquiladoras*)

Industry	β_l	β_k	β_{ll}	β_{kk}	β_{lk}
1	0.3688	0.0799	0.0246	0.0713	-0.2004
2	0.3015	0.4871**	0.0186	0.0313	-0.0108
4	1.9368	0.8479	0.2181	0.0842	-0.1069
5	-0.0888	0.0604	-0.1406	0.0232	0.0899
6	1.1008	-1.3294	0.3612	0.0915	-0.6068
7	-0.4666	0.0064	-0.2858	-0.0727	0.2973
8	0.3385	0.2600	-0.0135	0.0961	-0.1688
9	0.2820	0.3859	0.0008	0.0477	-0.0735
10	0.3165	0.5362	-0.0904	0.0070	0.0880
11	-0.5346	0.9487	-0.2968	-0.0829	0.3910
12	0.6469	0.6338	0.0770	-0.0684	0.0222
13	-0.2048	0.0895	-0.1775	0.0130	0.1527
14	0.1499	0.5091**	-0.2016	0.0056	0.1357
16	-4.8433	1.9756	-1.5002	-0.1237	0.7065
17	-0.1554	-0.7857	-0.0907	-0.0421	0.0681
18	-0.0285	0.4356	-0.1706	0.1099	-0.0467
19	0.4329**	0.5857**	-0.0032	0.0735	-0.0279
20	-0.7159	0.4555	-0.3246	-0.0238	0.3011

Note: Based on author's own estimations. The stars indicate significance levels (** $p < 0.05$), i.e. zero is not contained in the 95 percent confidence interval obtained by block-bootstrapping.

Table 16: Industry-level markup estimates

Industry	Mean	Med.	St.D.
1	1.00	0.47	1.36
2	2.54	1.63	3.82
4	0.99	0.59	1.02
5	0.79	0.80	0.47
6	1.45	1.11	1.37
7	1.50	0.93	1.75
8	1.28	1.26	1.16
9	0.24	0.22	0.31
10	0.89	1.10	0.73
11	2.58	0.77	4.17
12	2.69	1.42	3.53
13	0.90	0.54	1.00
14	0.70	0.48	0.74
16	0.70	0.62	0.72
17	0.92	0.43	1.46
18	0.65	0.37	0.83
19	0.30	0.06	0.50
20	0.73	0.56	0.63

Note: Based on author's own estimations. Mean, median, and standard deviation of the markups are calculated for each industry pooling all the years.

Table 17: Plant-level markup estimates,
Cobb-Douglas technology

Industry	Olley&Pakes (full sample)		
	Mean	Med.	St.D.
1	0.40	0.28	0.55
2	1.61**	1.12**	2.17
4	1.04**	0.92**	0.60
5	1.68**	1.52**	0.85
6	2.19**	2.30**	0.35
7	1.21**	1.13**	0.56
8	0.96**	0.70**	4.27
9	0.82**	0.51**	3.11
10	1.13**	1.02**	0.86
11	0.29	0.26	0.21
12	2.20**	2.21**	1.12
13	1.25**	1.12**	0.65
14	1.13**	0.89**	1.04
16	0.93**	0.83**	0.53
17	0.99**	0.91**	0.50
18	0.82**	0.70**	0.59
19	1.37**	0.79**	2.78
20	1.08**	0.96**	0.57

Note: Based on author's own estimations. The stars indicate significance level (** $p < 0.05$), i.e. zero is not contained in the 95 percent confidence interval obtained by block-bootstrapping.

Table 18: Comparing industry- and plant-level markups

Industry	<i>Industry-level</i>		<i>Plant-level</i>	
	Mean μ	Median μ	Mean μ	Median μ
1	1.00	0.47	0.40	0.28
2	2.54	1.63	1.61**	1.12**
4	0.99	0.59	1.04**	0.92**
5	0.79	0.80	1.68**	1.52**
6	1.45	1.11	2.19**	2.30**
7	1.50	0.93	1.21**	1.13**
8	1.28	1.26	0.96**	0.70**
9	0.24	0.22	0.82**	0.51**
10	0.89	1.10	1.13**	1.02**
11	2.58	0.77	0.29	0.26
12	2.69	1.42	2.20**	2.21**
13	0.90	0.54	1.25**	1.12**
14	0.70	0.48	1.13**	0.89**
16	0.70	0.62	0.93**	0.83**
17	0.92	0.43	0.99**	0.91**
18	0.65	0.37	0.82**	0.70**
19	0.30	0.06	1.37**	0.79**
20	0.73	0.56	1.08**	0.96**

Note: Based on author's own estimations. The stars indicate significance level (** $p < 0.05$), i.e. zero is not contained in the 95 percent confidence interval obtained by block-bootstrapping.

Table 19: Plant-level markup estimates, translog technology

Industry	Olley&Pakes (full sample)			Levinson&Petrin (full sample)			Levinson&Petrin (no <i>maquiladoras</i>)		
	Mean	Med.	St.D.	Mean	Med.	St.D.	Mean	Med.	St.D.
1	2.98	2.07	4.04	3.89	2.99	7.12	3.51**	2.51	4.84
2	2.37**	1.63	2.79	2.61	1.87	3.03	1.62	1.22	2.72
4	1.27**	1.11**	0.80	4.89**	4.42**	3.60	3.16**	2.71**	2.50
5	2.17**	2.20**	1.20	1.76**	1.61**	1.25	2.01**	1.91**	1.22
6	2.35**	1.88**	3.15	1.84**	1.39**	2.25	1.79**	1.33**	2.50
7	2.17**	2.16**	1.22	1.83**	1.43**	2.42	1.87**	1.54**	2.50
8	4.90	1.35**	94.62	0.89	1.52	17.36	0.96	1.43	8.32
9	1.06**	0.51**	3.51	1.61	1.03	3.36	1.53	0.91	3.34
10	1.45**	1.42**	0.71	1.44	1.34	0.66	1.46	1.33	0.96
11	2.74	1.82	3.78	0.63	0.55	1.74	1.17	0.65	2.01
12	3.10	2.89	3.45	1.26	1.57	5.18	3.31	3.28	1.68
13	2.22**	2.37	1.17	1.87**	1.65**	1.60	1.90**	1.71**	1.63
14	2.12	1.60	2.72	3.49**	2.97**	3.22	3.11**	2.57**	3.68
16	1.24	1.57**	1.47	1.45	1.62	1.80	1.52	1.47	8.82
17	0.69	0.60	0.45	0.44	0.22	0.89	0.48	0.27	1.13
18	1.85	1.22	3.33	2.53	1.45	8.21	2.43	1.27	7.53
19	1.20	0.75	2.27	1.13	0.97**	1.90	1.66**	1.12**	2.15
20	2.61**	2.69	2.23	1.48**	1.22**	1.81	1.50	1.27	1.95

Note: Based on author's own estimations. The stars indicate significance level (** $p < 0.05$), i.e. zero is not contained in the 95 percent confidence interval obtained by block-bootstrapping.

Table 20: Regression estimates at the industry level with industry-level markup as the dependent variable and quota coverage as the trade liberalization indicator

Variable	Model 1	Model 2	Model 3	Model 4
<i>Independent</i>				
Intercept	1.394 (1.952)	2.791 (2.016)	0.267 (0.626)	0.324 (0.806)
H	-11.228 (23.00)	-21.935 (23.53)	4.422 (7.586)	5.710 (10.19)
QUOTA	-0.460 (1.757)	-3.081 (3.106)	1.385 (1.197)	1.331 (2.366)
KQ	-0.531 (0.314)*	-1.608 (0.549)***	0.177 (0.231)	0.016 (0.402)
H*QUOTA		8.967 (41.13)		-7.001 (37.36)
KQ*QUOTA		2.847 (1.211)**		0.531 (1.062)
<i>Year dummy</i>				
1985	2.497 (1.143)**	2.132 (1.168)*	1.637 (0.841)**	1.581 (0.855)*
1986	-0.606 (0.705)	-0.674 (0.691)	-0.796 (0.598)	-0.773 (0.607)
1987	0.225 (0.610)	0.345 (0.600)	0.009 (0.563)	0.059 (0.578)
1988	0.250 (0.572)	0.217 (0.560)	0.315 (0.547)	0.333 (0.554)
1989	0.068 (0.561)	-0.044 (0.552)	0.213 (0.545)	0.219 (0.552)
<i>Industry dummy</i>				
1	-0.171 (1.643)	-0.416 (1.675)		
2	2.294 (1.277)*	2.461 (1.277)*		
4	-0.061 (1.347)	-0.251 (1.321)		
5	0.171 (0.958)	0.365 (0.942)		
6	0.742 (0.954)	0.872 (0.937)		
7	0.868 (1.075)	1.168 (1.062)		
8	0.479 (1.191)	0.555 (1.166)		
9	-0.916 (1.566)	-1.179 (1.540)		
10	0.598 (1.024)	0.376 (1.009)		
11	2.244 (0.935)**	2.707 (0.936)***		
12	2.875 (1.143)***	3.911 (1.202)***		
13	0.098 (1.179)	0.219 (1.155)		
14	0.603 (1.064)	1.404 (1.095)		
16	-0.139 (1.039)	-0.164 (1.017)		
17	0.464 (1.028)	0.933 (1.026)		
18	-0.183 (1.037)	-0.154 (1.020)		
19	-0.166 (0.977)	0.098 (0.962)		
N. of Observations	108	108	108	108
Root MSE	1.573	1.539	1.623	1.638
Adjusted R^2	0.256	0.288	0.208	0.194
F -statistic	2.480	2.600	4.510	3.570
Prob > F	0.001	0.000	0.000	0.000

Note: Based on author's own estimations. The stars indicate significance levels (** $p < 0.05$, *** $p < 0.01$). Model 1 includes year and industry dummy variables. Model 1 includes year and industry dummy variables as well as the interactions between quota and Herfindahl index and quota and capital-output ratio. Model 3 includes only year dummy variables. Model 4 includes year dummy variables and the interactions between quota and Herfindahl index and quota and capital-output ratio.

Table 21: Regression estimates at the industry level with industry-level markup as the dependent variable and average tariff rate as the trade liberalization indicator

Variable	Model 1	Model 2	Model 3	Model 4
<i>Independent</i>				
Intercept	-1.516 (2.041)	1.962 (2.314)	-0.884 (0.727)	-0.941 (1.280)
H	-3.121 (21.78)	-30.882 (27.64)	1.989 (7.288)	0.193 (18.63)
TARIFF	14.372 (4.391)***	1.822 (7.155)	8.699 (2.863)***	8.908 (6.504)
KQ	-0.464 (0.294)	-2.850 (0.859)***	0.342 (0.230)	0.494 (0.623)
H*TARIFF		99.348 (106.5)		9.179 (98.80)
KQ*TARIFF		9.085 (3.128)***		-0.665 (2.552)
<i>Year dummy</i>				
1985	-0.329 (0.989)	-0.557 (0.955)	0.682 (0.771)	0.680 (0.792)
1986	-2.857 (0.870)***	-3.023 (0.836)***	-1.916 (0.701)***	-1.932 (0.715)***
1987	-0.727 (0.613)	-0.734 (0.589)	-0.515 (0.573)	-0.530 (0.581)
1988	0.495 (0.543)	0.470 (0.521)	0.409 (0.527)	0.401 (0.534)
1989	0.133 (0.528)	-0.052 (0.510)	0.209 (0.525)	0.208 (0.531)
<i>Industry dummy</i>				
1	1.070 (1.553)	0.437 (1.515)		
2	1.809 (1.084)*	2.251 (1.069)**		
4	0.249 (1.269)	0.130 (1.247)		
5	-0.596 (0.880)	-0.454 (0.851)		
6	0.005 (0.880)	0.164 (0.846)		
7	0.615 (1.010)	0.634 (0.991)		
8	1.099 (1.136)	0.988 (1.108)		
9	0.373 (1.525)	-0.076 (1.480)		
10	0.910 (0.968)	0.732 (0.948)		
11	1.915 (0.885)***	1.994 (0.849)**		
12	4.119 (1.135)***	6.055 (1.265)***		
13	0.436 (1.113)	0.433 (1.085)		
14	1.876 (1.069)*	2.994 (1.118)***		
16	0.548 (0.997)	0.472 (0.974)		
17	1.289 (0.999)	1.772 (0.986)*		
18	-0.011 (0.977)	0.091 (0.968)		
19	0.489 (0.926)	0.773 (0.899)		
N. of Observations	108	108	108	108
Root MSE	1.480	1.420	1.563	1.580
Adjusted R ²	0.394	0.208	0.265	0.251
F-statistic	3.220	3.580	5.830	4.580
Prob> F	0.000	0.000	0.000	0.000

Note: Based on author's own estimations. The stars indicate significance levels (** $p < 0.05$, *** $p < 0.01$). Model 1 includes year and industry dummy variables. Model 2 includes year and industry dummy variables as well as the interactions between tariff and Herfindahl index and tariff and capital-output ratio. Model 3 includes only year dummy variables. Model 4 includes year dummy variables and the interactions between tariff and Herfindahl index and tariff and capital-output ratio.

Table 22: Regression estimates at the industry level with industry-average markup as the dependent variable and quota coverage as the trade liberalization indicator

Variable	Model 1	Model 2	Model 3	Model 4
<i>Independent</i>				
Intercept	1.283 (0.163)***	1.278 (0.175)***	0.593 (0.180)***	0.700 (0.225)***
H	-2.051 (1.923)	-2.044 (2.055)	7.254 (2.173)***	3.667 (2.868)
QUOTA	-0.019 (0.147)	-0.026 (0.266)	1.076 (0.346)***	0.443 (0.663)
KQ	0.025 (0.026)	0.031 (0.048)	0.164 (0.067)**	0.295 (0.114)**
H*QUOTA		0.288 (3.459)		18.843 (10.24)*
KQ*QUOTA		-0.015 (0.106)		-0.438 (0.298)
<i>Year dummy</i>				
1985	-0.119 (0.095)	-0.115 (0.100)	-0.593 (0.243)**	-0.534 (0.241)**
1986	-0.121 (0.058)**	-0.120 (0.059)**	-0.231 (0.173)	-0.269 (0.171)
1987	-0.056 (0.050)	-0.057 (0.051)	-0.113 (0.163)	-0.186 (0.163)
1988	-0.036 (0.048)	-0.036 (0.048)	0.022 (0.158)	-0.013 (0.156)
1989	-0.057 (0.047)	-0.057 (0.047)	0.011 (0.158)	-0.013 (0.155)
<i>Industry dummy</i>				
1	-0.800 (0.138)***	-0.795 (0.144)***		
2	0.447 (0.106)***	0.448 (0.109)***		
4	-0.143 (0.112)	-0.142 (0.114)		
5	0.599 (0.080)***	0.598 (0.082)***		
6	1.101 (0.080)***	1.102 (0.081)***		
7	0.070 (0.090)	0.069 (0.092)		
8	-0.183 (0.099)*	-0.183 (0.100)*		
9	-0.381 (0.131)***	-0.379 (0.134)***		
10	-0.012 (0.085)	-0.010 (0.087)		
11	-0.803 (0.078)***	-0.805 (0.081)***		
12	1.037 (0.095)***	1.032 (0.103)***		
13	0.081 (0.099)	0.080 (0.100)		
14	0.074 (0.089)	0.070 (0.096)		
16	-0.202 (0.087)**	-0.202 (0.088)***		
17	-0.155 (0.086)*	-0.157 (0.088)*		
18	-0.312 (0.087)***	-0.311 (0.088)***		
19	0.247 (0.081)***	0.246 (0.083)***		
N. of Observations	108	108	108	108
Root MSE	0.131	0.133	0.470	0.462
Adjusted R^2	0.933	0.931	0.147	0.175
F -statistic	60.70	54.85	3.300	3.280
Prob> F	0.000	0.000	0.000	0.000

Note: Based on author's own estimations. The stars indicate significance levels (** $p < 0.05$, *** $p < 0.01$). Model 1 includes year and industry dummy variables as well as the interactions between quota and Herfindahl index and quota and capital-output ratio. Model 3 includes only year dummy variables. Model 4 includes year dummy variables and the interactions between quota and Herfindahl index and quota and capital-output ratio.

Table 23: Regression estimates at the industry level with industry-average markup as the dependent variable and average tariff rate as the trade liberalization indicator

Variable	Model 1	Model 2	Model 3	Model 4
<i>Independent</i>				
Intercept	1.335 (0.179)***	1.421 (0.217)***	0.448 (0.223)**	-0.144 (0.360)
H	-2.194 (1.928)	-3.245 (2.595)	6.367 (2.238)***	3.801 (5.109)
TARIFF	-0.259 (0.387)	-0.624 (0.661)	1.615 (0.883)*	4.399 (1.817)**
KQ	0.025 (0.026)	-0.019 (0.082)	0.188 (0.071)***	0.914 (0.178)***
H*TARIFF		4.860 (9.502)		9.583 (26.67)
KQ*TARIFF		0.160 (0.299)		-3.202 (0.733)***
<i>Year dummy</i>				
1985	-0.083 (0.087)	-0.087 (0.089)	-0.335 (0.237)	-0.376 (0.223)*
1986	-0.086 (0.077)	-0.090 (0.078)	-0.275 (0.216)	-0.375 (0.201)*
1987	-0.042 (0.054)	-0.043 (0.054)	-0.133 (0.177)	-0.200 (0.164)
1988	-0.041 (0.048)	-0.041 (0.048)	0.050 (0.163)	0.015 (0.151)
1989	-0.058 (0.047)	-0.062 (0.047)	0.014 (0.162)	0.013 (0.150)
<i>Industry dummy</i>				
1	-0.828 (0.137)***	-0.838 (0.141)***		
2	0.447 (0.095)***	0.460 (0.099)***		
4	-0.147 (0.112)	-0.144 (0.115)		
5	0.609 (0.078)***	0.607 (0.080)***		
6	1.110 (0.078)***	1.113 (0.079)***		
7	0.074 (0.090)	0.079 (0.092)		
8	-0.194 (0.100)*	-0.191 (0.102)*		
9	-0.405 (0.135)***	-0.412 (0.138)***		
10	-0.018 (0.085)	-0.017 (0.088)		
11	-0.798 (0.078)***	-0.797 (0.079)***		
12	1.012 (0.100)***	1.052 (0.118)***		
13	0.075 (0.099)	0.080 (0.101)		
14	0.052 (0.095)	0.083 (0.105)		
16	-0.213 (0.088)**	-0.211 (0.090)**		
17	-0.170 (0.088)*	-0.156 (0.091)*		
18	-0.315 (0.087)***	-0.308 (0.090)***		
19	0.232 (0.082)***	0.241 (0.083)***		
N. of Observations	108	108	108	108
Root MSE	0.131	0.132	0.484	0.447
Adjusted R^2	0.933	0.932	0.094	0.228
F -statistic	61.04	55.51	2.380	4.160
Prob > F	0.000	0.000	0.000	0.000

Note: Based on author's own estimations. The stars indicate significance levels (** $p < 0.05$, *** $p < 0.01$). Model 1 includes year and industry dummy variables. Model 2 includes year and industry dummy variables as well as the interactions between tariff and Herfindahl index and tariff and capital-output ratio. Model 3 includes only year dummy variables. Model 4 includes year dummy variables and the interactions between tariff and Herfindahl index and tariff and capital-output ratio.

Table 24: Regression estimates at the plant level with plant-level markup as the dependent variable

Variable	Model 1	Model 2
<i>Independent</i>		
Intercept	1.0684 (0.1175)***	1.1154 (0.1485)***
SHARE	1.6139 (0.2531)***	1.3719 (0.3773)***
SHARE ²	-0.2433 (0.1261)*	-0.2219 (0.1275)*
KQ	0.1659 (0.0057)***	0.1658 (0.0057)***
KQ ²	-1.8e ⁻⁴ (8.3e ⁻⁶)***	-1.8e ⁻⁴ (8.3e ⁻⁶)***
QUOTA	-0.0048 (0.2349)	
TARIF		-0.2925 (0.5565)
SHARE*QUOTA	0.6111 (0.5275)	
SHARE*TARIFF		1.9790 (1.6234)
<i>Year dummy</i>		
1985	-0.1134 (0.1370)	-0.0654 (0.1126)
1986	-0.1257 (0.0771)*	-0.0908 (0.1012)
1987	-0.1004 (0.0649)	-0.0848 (0.0707)
1988	-0.0603 (0.0617)	-0.0614 (0.0619)
1989	-0.0602 (0.0619)	-0.0596 (0.0618)
<i>Industry dummy</i>		
1	-0.7805 (0.1311)***	-0.7909 (0.1254)***
2	0.2169 (0.1489)	0.2269 (0.1331)*
4	-0.1105 (0.1321)	-0.1115 (0.1318)
5	0.5857 (0.1432)***	0.5990 (0.1396)***
6	1.1255 (0.1833)***	1.1399 (0.1806)***
7	0.0333 (0.1454)	0.0415 (0.1460)
8	-0.2394 (0.1295)**	-0.2496 (0.1304)**
9	-0.3969 (0.1189)***	-0.4125 (0.1236)***
10	-0.0451 (0.1244)	-0.0510 (0.1249)
11	-1.1191 (0.1938)***	-1.1326 (0.1943)***
12	0.6382 (0.1824)***	0.6229 (0.1889)***
13	0.0650 (0.1337)	0.0627 (0.1334)
14	-0.2687 (0.1421)*	-0.2924 (0.1533)*
16	-0.2190 (0.1316)*	-0.2299 (0.1327)*
17	-0.2457 (0.1296)*	-0.2601 (0.1329)**
18	-0.3643 (0.1309)***	-0.3699 (0.1308)***
19	-0.0406 (0.1330)	-0.0515 (0.1335)
N. of Observations	11205	11205
Root MSE	1.814	1.814
Adjusted R ²	0.127	0.127
F-statistic	59.48	59.49
Prob> F	0.000	0.000

Note: Based on author's own estimations. The stars indicate significance levels (** $p < 0.05$, *** $p < 0.01$). Model 1 includes quota as a trade liberalization indicator. Model 2 includes tariff as a trade liberalization indicator.

Table 25: Markups and export status

Variable	Model 1	Model 2
E_{Hjt}	0.0216 (0.0082)***	0.0198 (0.0076)***
ω_{jt}		0.3977 (0.0118)***
Linear restriction		
$\mu_{EH} = \psi_1 + \exp(\psi_0)$	0.0588 (0.0222)***	0.0539 (0.0208)***
N. of Observations	7929	7929
Root MSE	0.287	0.268
Adjusted R^2	0.871	0.887
F -statistic	590.8	669.4
Prob> F	0.000	0.000

Note: Based on author's own estimations. The stars indicate significance levels (*** $p < 0.01$). Model 1 includes only the export intensity dummy variable and the set of z_{jt} controls. Model 2 includes the export intensity dummy variable, the set of z_{jt} controls as well as productivity.