Microeconomic Sources of Aggregate Productivity Growth in the Chilean Manufacturing Industry

Ana Paula Cusolito
World Bank

Alvaro Garcia-Marin
Universidad de Chile

William F. Maloney
World Bank

May 2016

[Preliminary and Incomplete]

Abstract

A large literature documents the existence of aggregate productivity gains after the occurrence of events triggering changes in competitive pressure –such as trade liberalizations and pro-market reforms–, and most of these gains come from reallocation of resources within of the economies (Pavcnik, 2002, among others). However, most of these results rely on revenue-based productivity measures, which may hinder a substantial part of within-plant efficiency gains. In this paper we study micro-level productivity dynamics in the Chilean manufacturing industry. We first evaluate the relevance of the reallocation mechanism compared to the alternative, within-plants mechanism, when using efficiency measures that are not affected by prices. In the spirit of Garcia Marin and Voigtänder (2016), we show that a significant part of what the previous literature identified as between, and within (revenue-based) efficiency, gains are driven by markups variation. Thus, the within-plant efficiency gains mechanism is by far more relevant than what previously has been thought, while a significant portion of the reallocation mechanism actually reflects market share gains by high-markup plants. After establishing the predominant role of within-plants efficiency gains, in the second part of the paper we focus in exploring the determinants of the alternative, within-plants efficiency gains. In particular, we explore the role of demand (i.e., marketing expenditure) and supply factors (investment in technology) in explaining the observed patterns for TFPR and TFPQ.

JEL: D24, F10, F14, L25, L60

Keywords: Physical productivity, Markups, Demand, Reallocation, Chile

1 Introduction

A large literature documents large and persistent differences in measured productivity across producers, even within narrowly defined sectors. This suggest that aggregate productivity growth could be achieved by simply reallocating resources from the least to the most productive establishments within each industry (Melitz, 2003; Hsieh and Klenow, 2009). The reallocation mechanism has proved to be quantitatively relevant: after events triggering changes in competitive pressure –such as trade liberalizations and pro-market reforms–, about two-thirds of the related aggregate productivity gains are due to the reallocation mechanism (Pavcnik, 2002, among others). However, most of these studies rely on revenue-based productivity measures, which may hinder a substantial part of within-plant efficiency gains. Indeed, as recent research shows, revenue-based productivity measures are downward biased if efficiency gains are pass on to customers in the form of lower prices (Foster et al., 2008; Garcia Marin and Voigtänder, 2016). Thus, to have a full understanding on the role of reallocation forces, it is important to use efficiency measures that are immune to the action of prices.

In this paper we study micro-level productivity dynamics in the Chilean manufacturing industry. The paper is divided in two main parts. We first evaluate the relevance of the reallocation mechanism compared to the alternative, within-plants mechanism, when using efficiency measures that are not affected by prices. We begin by verifying the usual result on the predominant role of the reallocation mechanism when using revenue-based total factor productivity (TFPR). We use two alternative decompositions in this exercise: the standard Olley and Pakes (1996) decomposition, and the more recent decomposition developed by Melitz and Polanec (2015) (which explicitly accounts for the role of plant entry and exit). Then, we study whether the result derived with revenue-based measures holds when using physical total factor productivity (TFPQ). Physical productivity is constructed using input and output quantities, and is thus not affected by changes in prices. Intuitively, since TFPR reflects a smaller portion of efficiency gains when output prices respond to a producer's efficiency, revenue-based productivity measures are most likely to underestimate within-plants efficiency gains, while the reallocation mechanism –which is mostly based on changes in the market shares of the establishments– should not be significantly affected. [1]

If revenue-productivity does not fully reflect quantity-based efficiency gains, then what do represent differences in TFPR? To complete the accounting exercise, we derive plant-level markups according to the method pioneered by Loecker and Warzynski (2012). In the spirit of Garcia Marin and Voigtänder (2016), we show that a significant part of what the previous literature identified as

[1] Ex-ante, it is unclear whether the role of reallocation mechanism will be larger when using TFPQ, because it will ultimately depend on the interaction between TFPR and TFPQ in plants experiencing changes in their market shares.

between, and within (revenue-based) efficiency gains are driven by markups variation. Thus, the within-plant efficiency gains mechanism is by far more relevant than what previously has been thought, while a significant portion of the reallocation mechanism actually reflects market share gains by high-markup plants. Thus, the within-plant efficiency gains mechanism is by far more relevant than what previously has been thought, while a significant portion of the reallocation mechanism actually reflects market share gains by high-markup plants.

After establishing the predominant role of within-plants efficiency gains, in the second part of the paper we explore different explanations commonly cited in the literature as triggers of changes in measured productivity. The focus in this section lies in examining whether these factors could help in explaining the observed patterns for (and especially the divergences between) TFPR and TFPQ. To organize the analysis, we categorize the explanations in two broad sets. One set involves explanations based on demand, such as marketing expenditure in gaining new customers (Arkolakis, 2010; Drozd and Nosal, 2012). Notice that these type of explanations will most likely act through markups, thus, they will most likely affect TFPR but not TFPQ. The second set involves factors under the influence of the plant that affect their supply. Within them, we will explore the role of investment in technology (Bustos, 2011; Aw et al., 2011), changes in the the organization of labor within the firm (Caliendo, Mion, Opromolla, and Rossi-Hansberg, 2015), and learning by doing.

Understanding if most of aggregate productivity growth occurs due to the reallocation mechanism or not is not only relevant from an academic but also from a policy perspective. If the reallocation mechanism explains most of most of aggregate productivity growth, then the focus should be on promoting policies that foster competition, greasing the wheels for firm entry and exit, and the reallocation of resources across existing firms. In contrast, if within-plant efficiency gains is the predominant force, the focus should be in shedding light on policies and regulatory constraints on good firm performance.

Chile is an interesting case of study, as it applied several significant pro-market reforms in the 1980s and 1990s. Following these reforms, productivity experienced unprecendented rates of growth, leading the country to doubling it per-capita GDP between 1986 and 1998. Available empirical evidence confirms the positive effect of these reform on aggregate productivity growth. Moreover, and in line with the mechanisms I study in this paper, these studies show that the effect comes predominantly from the reallocation mechanism.[2]

After 1998, aggregate productivity growth slowed down in Chile (Fuentes, Larraín, and Schmidt-Hebbel, 2006). Available evidence suggest that the manufacturing sector has been one of the most

[2]See Pavcnik (2002) and Bergoeing and Repetto (2006) for the cases of trade liberalization, and structural reforms in general, respectively.

affected industries, lending support to the approach taken in this paper of studying the microeconomic sources of the productivity slowdown in this industry. Up to date, several explanations has been given for the productivity downturn (most of them only verified with macroeconomic data). The general conclusion suggest that there is no immediate cause for the deceleration; instead, the sources of the productivity slowdown seem to be multi-causal (Syverson, 2014).

Relative to the existing literature, this paper makes several contributions. First, the paper provides evidence on the relative importance of the reallocation mechanism once prices (and markups) are considered. This study thus complements a substantial literature studying the role of reallocation (and misallocations), as in Hsieh and Klenow (2009). Second, as in Garcia Marin and Voigtänder (2016), we show that a substantial part of what previous literature identified as 'within' and 'between' plants components of aggregate productivity growth, corresponds to dispersion in plant-level markups. Third, we provide evidence on the relation between revenue- and quantity-based measured efficiency gains and alternative mechanisms related to the demand (i.e., marketing expenditure) and supply side (investment in new technology). Fourth, we provide evidence on the microeconomic sources of the Chilean productivity slowdown occurred after 1998.

The rest of the paper is structured as follows. The section that follows the introduction discuss theoretical underpinnings and presents the decompositions we use to assess the relative importance of reallocation vs. within-plant efficiency gains to explain aggregate productivity growth. Section 3 presents the data we use in this paper. Section 4 establishes the main empirical fact in this paper: when using efficiency gains not affected by prices, the within-between decomposition reveals a by far more relevant role of within-plants productivity gains in accounting for aggregate productivity gains. Section 5 explore the impact of different demand and supply factors in explaining the different patterns when measuring efficiency gains with revenue vs. quantity-based productivity measures. Finally, section 6 presents the main conclusions.

2 Theoretical Framework

2.1 TFPR, and its relationship with Markups and TFPQ

Productivity is commonly measured in empirical studies as a residual term between total output and the estimated contribution of production factors. Ideally, total output should be computed in terms of physical units of the final good. However, data on physical quantities is generally scarce and have only recently become available for some countries. As a result, the majority of studies use revenue as output variable for measuring productivity. From hereafter, we denote revenue productivity by TFPR, to differentiate from its quantity-based counterpart, which we denote by

TFPQ.

As shown in previous research, TFPR is a downward based measured of TFPQ (Foster et al., 2008; Garcia Marin and Voigtänder, 2016). The intuition for this result can be illustrated using the definition $TFPR = P \cdot TFPQ$. If firms pass part of the efficiency gains to customers in the form of lower prices, then TFPR will only show a fraction of the change in TFPQ.[3] For instance, if preferences are CES and there is constant returns to scale, any efficiency gain in TFPQ is transmitted into proportional changes in prices, so that TFPR will show no change in efficiency. Thus, TFPR is in general, a downward-biased measure of TFPQ. In empirical studies, this price bias is commonly tackled by deflating revenues with industry price indexes. However, *within* industries the bias does not disappear, and cross-sectional differences in TFPR will reflect the difference between individual plants' prices and the corresponding industry price index.

If revenue-productivity does not fully reflect quantity-based efficiency gains, then what do represent differences in TFPR? For simplicity, assume for now a Cobb-Douglas production function, where $\gamma = \alpha_L + \alpha_M + \alpha_K$ denotes the degree of returns to scale, with the subscripts L, M, and K denoting labor, material inputs, and capital, respectively. Total and marginal costs are then given by:

$$TC = \left(\frac{Q}{A}\right)^{\frac{1}{\gamma}} \left[\gamma \cdot w_L^{\frac{\alpha_L}{\gamma}} w_M^{\frac{\alpha_M}{\gamma}} w_K^{\frac{\alpha_K}{\gamma}} \left(\frac{1}{\alpha_K^{\alpha_K} \alpha_M^{\alpha_M} \alpha_L^{\alpha_L}}\right)\right] \quad (1)$$

$$MC = \left(\frac{Q^{1-\gamma}}{A}\right)^{\frac{1}{\gamma}} \left[w_L^{\frac{\alpha_L}{\gamma}} w_M^{\frac{\alpha_M}{\gamma}} w_K^{\frac{\alpha_K}{\gamma}} \left(\frac{1}{\alpha_K^{\alpha_K} \alpha_M^{\alpha_M} \alpha_L^{\alpha_L}}\right)\right] \quad (2)$$

where w_i denotes the price of input i and Q is physical output volume. Assuming that the plants does not affect input prices, then it can be shown that>

$$\Delta TFPR = \Delta\mu + \left(\frac{\gamma - 1}{\gamma}\right)(\Delta A - \Delta Q) \quad (3)$$

where we use $\triangle$ to denote percentage percentage changes. With constant returns ($\gamma = 1$), this implies that $\Delta TFPR = \Delta\mu$: TFPR does not reflect efficiency gains – unless plants raise markups when TFPQ increases. In the more general case with non-constant returns to scale ($\gamma \neq 1$), any differences between $\Delta TFPR$ and $\Delta\mu$ reflect deviations in the growth of TFPQ and output Q. In particular, when quantity increases more rapidly than TFPQ ($\Delta Q > \Delta A$), increasing returns imply that $\Delta TFPR < \Delta\mu$.

[3] As we show below, there is an important exception where TFPR fully reflects TFPQ: under constant returns to scale, if inputs prices do not change with efficiency gains and plants change markups in the same proportion than the change in TFPQ.

2.2 Within/Between Decompositions

The two methodologies we use to analyze the relative importance of within-plant efficiency gains and the reallocation mechanism are based decomposing aggregate productivity at time t (Ω_t), which is a weighted average of firm productivity ω_{it}:

$$\Omega_t = \sum_i \theta_{it}\omega_{it} \tag{4}$$

where θ_{it} is the ratio of plant i's sales in period t and total industrial sales in period t and $\sum_i \theta_{it} = 1$.

Olley and Pakes's Decomposition

Olley and Pakes (1996) decompose the level of aggregate productivity in two terms, reflecting (i) average productivity growth, and (ii) reallocation of resources from less productive to more productive plants. Denoting $\bar{\omega}_t$ and $\bar{\theta}_t$ to the unweighted productivity and shares averages, then OP decomposition can be expressed as:

$$\Omega_t = \bar{\omega}_t + \sum_i \Delta\theta_{it}\Delta\omega_{it} \tag{5}$$

where $\Delta\omega_{it} = \omega_{it} - \bar{\omega}_t$ and $\Delta\theta_{it} = \theta_{it} - \bar{\theta}_t$. The first term in (6) represents average within-plant productivity, while the second term represents the contribution to the aggregate weighted productivity resulting from reallocation of market shares and resources across plants of different productivities.

Melitz and Polanec's Decomposition

The second decomposition, extends OP work by including the contribution of entrants and exitors to aggregate productivity growth. In contrast to the OP decomposition, MP gives a decomposition for the change in aggregate productivity:

$$\Omega_t = (\bar{\omega}_t^S - \bar{\omega}_{t-1}^S) + \sum_{i \in S} \Delta\theta_{it}^S \Delta\omega_{it}^S + \bar{\theta}_t^E(\bar{\omega}_t^E - \bar{\omega}_t^S) + \bar{\theta}_t^X(\bar{\omega}_{t-1}^S - \bar{\omega}_{t-1}^X) \tag{6}$$

2.3 Estimating Revenue Productivity (TFPR)

To compute TFPR, we first have to estimate the revenue production function. We specify a Cobb-Douglas production function with labor (l), capital (k), and materials (m) as production inputs. We estimate a separate production function for each 2-digit manufacturing sector (s).[4] with standard plant-level information:

$$q_{it} \quad = \quad \beta_l^s l_{it} + \beta_k^s k_{it} + \beta_m^s m_{it} + \omega_{it} + \varepsilon_{it} \tag{7}$$

where all lowercase variables are in logs; q_{it} are revenues of plant i in year t, ω_{it} is TFPR, k_{it} denotes the capital stock, m_{it} are material inputs, and ε_{it} represents measurement error as well as unanticipated shocks to output. We deflate all nominal variables (revenues, materials, wages) using 4-digit industry specific deflators provided by ENIA. Estimating (7) yields the sector-specific vector of coefficients $\boldsymbol{\beta}^s = \{\beta_l^s, \beta_k^s, \beta_m^s\}$.

When estimating (7) we follow the methodology by Ackerberg et al. (2015, henceforth ACF), who extend the framework of Olley and Pakes (1996, henceforth OP) and Levinsohn and Petrin (2003, henceforth LP). This methodology controls for the simultaneity bias that arises because input demand and unobserved productivity are positively correlated.[5] The key insight of ACF lies in their identification of the labor elasticity, which they show is in most cases unidentified by the two-step procedure of OP and LP.[6] We modify the canonical ACF procedure by specifying an endogenous productivity process that can be affected by export status and plant investment. In addition, we include interactions between export status and investment in the productivity process. This reflects the corrections suggested by Loecker (2013); if productivity gains from exporting also lead to more investment (and thus a higher capital stock), the standard method would overestimate the capital coefficient in the production function, and thus underestimate productivity (i.e., the residual). Accordingly, the law of motion for productivity is:

$$\omega_{it} \quad = \quad g(\omega_{it-1}, d^x_{it-1}, d^i_{it-1}, d^x_{it-1} \times d^i_{it-1}) + \xi_{it} \tag{8}$$

where d^x_{it} is an export dummy, and d^i_{it} is a dummy for periods in which a plant invests in physical capital (following Loecker, 2013).

In the first stage of the ACF routine, a consistent estimate of expected output $\hat{\phi}_t(\cdot)$ is obtained

[4]The 2-digit product categories are: Food and Beverages, Textiles, Apparel, Wood, Paper, Chemicals, Plastic, Non-Metallic Manufactures, Basic and Fabricated Metals, and Machinery and Equipment.

[5]We follow LP in using material inputs to control for the correlation between input levels and unobserved productivity.

[6]The main technical difference is the timing of the choice of labor. While in OP and LP, labor is fully adjustable and chosen in t, ACF assume that labor is chosen at $t-b$ $(0 < b < 1)$, after capital is known in $t-1$, but before materials are chosen in t. In this setup, the choice of labor is unaffected by unobserved productivity shocks between $t-b$ and t, but a plant's use of materials now depends on capital, productivity, and labor. In contrast to the OP and LP method, this implies that the coefficients of capital, materials, and labor are all estimated in the second stage.

from the regression

$$q_{it} \quad = \quad \phi_t(l_{it}, k_{it}, m_{it}; \boldsymbol{x}_{it}) + \varepsilon_{it}$$

We use inverse material demand $h_t(\cdot)$ to proxy for unobserved productivity, so that expected output is structurally represented by $\phi_t(\cdot) = \beta^s_l l_{it} + \beta^s_k k_{it} + \beta^s_m m_{it} + h_t(m_{it}, l_{it}, k_{it}, \boldsymbol{x}_{it})$.[7] The vector $\boldsymbol{x}_{it}$ contains other variables that affect material demand (time and product dummies, reflecting aggregate shocks and specific demand components). Next, we use the estimate of expected output together with an initial guess for the coefficient vector $\boldsymbol{\beta}^s$ to compute productivity: for any candidate coefficient vector $\tilde{\boldsymbol{\beta}}^s$, productivity is given by $\omega_{it}(\tilde{\boldsymbol{\beta}}^s) = \hat{\phi}_t - \left(\tilde{\beta}^s_l l_{it} + \tilde{\beta}^s_k k_{it} + \tilde{\beta}^s_m m_{it}\right)$. Finally, we recover the productivity innovation ξ_{it} for the given candidate vector $\tilde{\boldsymbol{\beta}}^s$: following (8), we estimate the productivity process $\omega_{it}(\tilde{\boldsymbol{\beta}}^s)$ non-parametrically as a function of its own lag $\omega_{it-1}(\tilde{\boldsymbol{\beta}}^s)$, prior exporting and investment status, and the plant-specific probability of remaining single-product.[8] The residual is ξ_{it}.

The second stage of the ACF routine uses moment conditions on ξ_{it} to iterate over candidate vectors $\tilde{\boldsymbol{\beta}}^s$. In this stage, all coefficients of the production function are identified through GMM using the moment conditions

$$\mathbb{E}\left(\xi_{it}(\boldsymbol{\beta}^s)\mathbf{Z}_{it}\right) = 0 \tag{9}$$

where $\mathbf{Z}_{it}$ is a vector of variables that comprises lags of all the variables in the production function, as well as the current capital stock. These variables are valid instruments – including capital, which is chosen before the productivity innovation is observed. Equation (9) thus says that for the optimal $\boldsymbol{\beta}^s$, the productivity innovation is uncorrelated with the instruments $\mathbf{Z}_{it}$.

Given the estimated coefficients for each product category s (the vector $\boldsymbol{\beta}^s$), TFPR $\hat{\omega}_{it}$ can be calculated at the plant level:

$$\hat{\omega}_{it} = q_{it} - (\beta^s_l l_{it} + \beta^s_k k_{it} + \beta^s_m m_{it}) \tag{10}$$

where q_{it} are total plant revenues, and the term in parentheses represents the estimated contribution of the production factors to total output in plant i. Note that the estimated production function allows for returns to scale ($\beta^s_l + \beta^s_k + \beta^s_m \neq 1$), so that the residual $\hat{\omega}_{it}$ is not affected by increasing or decreasing returns.

[7] We approximate the function $\hat{\phi}_t(\cdot)$ with a full second-degree polynomial in capital, labor, and materials.

[8] Following Levinsohn and Petrin (2003), we approximate the law of motion for productivity (the function $g(\cdot)$ stated in (8)) with a polynomial.

2.4 Plant-Level Price Indexes

Estimating TFPQ is demanding from a data perspective. Outputs and inputs need to be observed in terms of physical quantities, and in general, this information is not available in typical plant or firm-level datasets. But even if this information is observed, an additional challenge remains for multi-product plants. For them, inputs and outputs need to be aggregated at the plant-level, which may be difficult if inputs and outputs are in different units or correspond to different products.[9] One way to circumvent these issues is to construct plant-level input and output price indexes, and then deflate plants' sales and input expenditures to obtain inputs and outputs in physical units.[10]

In this paper, we compute Tornqvist price indexes. The advantage of this type of index over other alternatives is that it gives a lower weight to outliers. We start by defining the log-change in plant-level prices Δp_{it} for plant i in period t as:

$$\Delta p_{it} = \sum_{v \in \Phi_v} \phi_{iv} (\ln P_{ivt} - \ln P_{iv,t-1}) \tag{11}$$

where Φ_v denotes the subset of outputs (inputs) sold (used) by plant i, and ϕ_v is the average share of input/ouput v between periods t and $t-1$. Once the price change is obtained, the level for the price index can be computed recursively:

$$\ln P_{it} = \ln P_{i,t-1} + \Delta p_{it} \tag{12}$$

A typical approach to compute price indexes is to normalize the price index in a given year for all plants. This method, however, makes impossible to identify cross-sectional price differences in the base year (González and Miles-Touya, 2016). To avoid such complication, for the first year of each plant in the sample, we follow the following procedure.[11] First, for each output/input we compute its log difference with the average industrial price for all plants with outputs/inputs in the same product category. Second, we aggregate outputs/inputs using the shares ϕ_v, but now computed for the initial period. Thus, given the level for the initial plant-level price, and using the recursion 12, the complete series for plant-level price indexes can be recovered.

[9] One special case where this issues are not a problem is for single-product plants producing with a single input. However, this subset of plants represents an small fraction of the universe of plant-year observations –less than ++5%++ of the total.

[10] A shortcoming of this more aggregate approach is that plant-level output price indexes do not account for differences in product scope Hottman, Redding, and Weinstein (2016).

[11] This procedure follows the literature computing Tornqvist TFP indexes, see Aw, Chen, and Roberts (2001).

3 Data

The main dataset we use in this paper is the *Encuesta Nacional Industrial Anual* (Annual National Industrial Survey – ENIA) for the years 1996–2005. Data for ENIA are collected annually by the Chilean National Institute of Statistics (INE), with direct participation of Chilean manufacturing plants. ENIA covers the universe of manufacturing plants with 10 or more workers. It contains detailed information on plant characteristics, such as sales, spending on inputs and raw materials, employment, wages, investment, and export status. ENIA contains information for approximately 4,900 manufacturing plants per year with positive sales and employment information. Out of these, about 20% are exporters, and 70% of exporters are multi-product plants. Within the latter (i.e., conditional on at least one product being exported), exported goods account for 79.6% of revenues. Therefore, the majority of production in internationally active multi-product plants is related to exported goods. Finally, approximately two third of the plants in ENIA are small (less than 50 workers), while medium-sized (50-150 workers) and large (more than 150 workers) plants represent 20 and 12 percent, respectively.

In addition to aggregate plant data, ENIA provides rich information for every good produced by each plant, reporting the value of sales, its total variable cost of production, and the number of units produced and sold. Products are defined according to an ENIA-specific classification of products, the *Clasificador Unico de Productos* (CUP). This product category is comparable to the 7-digit ISIC code.[12] The CUP categories identify 2,169 different products in the sample. These products – in combination with each plant producing them – form our main unit of analysis. In the following, we briefly discuss how we deal with inconsistent product categories, units of output, and other issues of sample selection.

3.1 Data Cleaning

We exclude plant-product-year observations that have zero values for total employment, demand for raw materials, sales, or product quantities. In addition, we only consider plants with non-missing observations for input and output prices between its first and last year of operation in the sample. This last requirement is necessary for computing the plant-level input and output indexes presented in section 2.4. After these adjustments, our sample consists of ++ plant-product-year observations.

[12] For example, the wine industry (ISIC 3132) is disaggregated by CUP into 8 different categories, such as "Sparkling wine of fresh grapes", "Cider", "Chicha", and "Mosto".

3.2 Estimated TFPQ, TFPR and Markups

Table 1 shows the estimated output elasticities and returns to scale for each 2-digit sector. The sum of output elasticities corresponds to returns to scale. We find that on average, the estimated coefficients point to constant returns to scale. In particular, when weighted by the number of plants in each sector, the sum of output elasticities is 1.009 in our baseline Cobb-Douglas case.

[++Add summary statistics for prices, TFPR, TFPQ and Markups. Show negative relation between TFPQ and prices, and positive correlation between TFPR and markups. Cross-sectional regressions on firms size, capital intensity, layers of management.++]

4 Reallocation vs. Within-Plant Productivity Gains

In this section we present our results for the OP and MP decompositions presented in section 2.2. We first present our results for TFPR, and then for TFPQ. Finally, we show that most of TFPR gains are related to markups gains.

[++ADD RESULTS++]

5 Within-Plant Efficiency Gains: Supply vs. Demand Factors

After establishing the predominant role of within-plants efficiency gains, in this section we explore different explanations commonly cited in the literature as triggers of changes in measured productivity. The focus in this section lies in examining whether these factors could help in explaining the observed patterns for (and especially the divergences between) TFPR and TFPQ. To organize the analysis, we categorize the explanations in two broad sets. One set involves explanations based on demand, such as marketing expenditure in gaining new customers (Arkolakis, 2010; Drozd and Nosal, 2012). Notice that these type of explanations will most likely act through markups, thus, they will most likely affect TFPR but not TFPQ. The second set involves factors under the influence of the plant that affect their supply. Within them, we will explore the role of investment in technology (Bustos, 2011; Aw et al., 2011), changes in the the organization of labor within the firm (Caliendo, Mion, Opromolla, and Rossi-Hansberg, 2015), and learning by doing.

6 Concluding Remarks

[++TO BE COMPLETED++]

References

Ackerberg, D. A., K. Caves, and G. Frazer (2015). Identification Properties of Recent Production Function Estimators. *Econometrica 83*(6), 2411–2451.

Arkolakis, C. (2010). Market Penetration Costs and the New Consumers Margin in International Trade. *Journal of Political Economy 118*(6), 1151 – 1199.

Aw, B. Y., X. Chen, and M. J. Roberts (2001). Firm-level evidence on productivity differentials and turnover in Taiwanese manufacturing. *Journal of Development Economics 66*(1), 51–86.

Aw, B. Y., M. J. Roberts, and D. Y. Xu (2011). R&D Investment, Exporting, and Productivity Dynamics. *American Economic Review 101*(4), 1312–44.

Bergoeing, R. and A. Repetto (2006). Micro Efficiency and Aggregate Growth in Chile. *Latin American Journal of Economics-formerly Cuadernos de Economía 43*(127), 169–192.

Bustos, P. (2011). Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms. *American Economic Review 101*(1), 304–40.

Caliendo, L., G. Mion, L. D. Opromolla, and E. Rossi-Hansberg (2015). Productivity and Organization in Portuguese Firms. Technical report, NBER WP 21811.

Drozd, L. A. and J. B. Nosal (2012). Understanding International Prices: Customers as Capital. *American Economic Review 102*(1), 364–95.

Foster, L., J. Haltiwanger, and C. Syverson (2008). Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability? *American Economic Review 98*(1), 394–425.

Fuentes, R., M. Larraín, and K. Schmidt-Hebbel (2006). Sources of Growth and Behavior of TFP in Chile. *Latin American Journal of Economics-formerly Cuadernos de Economía 43*(127), 113–142.

Garcia Marin, A. and N. Voigtänder (2016). Exporting and Plant-Level Efficicnecy Gains: It's in the Measure. Technical report, UCLA and Universidad de Chile.

González, X. and D. Miles-Touya (2016). Estimating Production Functions when Prices are Partially Observed. Technical report, Manuscript, Universidad de Vigo.

Hottman, C., S. J. Redding, and D. E. Weinstein (2016). Quantifying the Sources of Firm Heterogeneity. *Quarterly Journal of Economics*. forthcoming.

Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and Manufacturing TFP in China and India. *The Quarterly Journal of Economics 124*(4), 1403–1448.

Levinsohn, J. and A. Petrin (2003). Estimating Production Functions Using Inputs To Control For Unobservables. *Review of Economic Studies 70*(2), 317–341.

Loecker, J. D. (2013, August). Detecting Learning by Exporting. *American Economic Journal: Microeconomics 5*(3), 1–21.

Loecker, J. D. and F. Warzynski (2012). Markups and Firm-Level Export Status. *American Economic Review 102*(6), 2437–71.

Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica 71*(6), 1695–1725.

Melitz, M. J. and S. Polanec (2015, 06). Dynamic Olley-Pakes productivity decomposition with entry and exit. *RAND Journal of Economics 46*(2), 362–375.

Olley, G. S. and A. Pakes (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica 64*(6), 1263–97.

Pavcnik, N. (2002). Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants. *Review of Economic Studies 69*(1), 245–276.

Syverson, C. (2014). An Analysis of Recent Productivity Trends in Chile. Manuscript, Interamerican Development Bank.

TABLES

Table 1: Output Elasticities and Returns to Scale in the Chilean Data

	Elasticities			Returns
	Labor	Capital	Materials	to Scale
	(1)	(2)	(3)	(4)
Food and Beverages	0.146	0.139	0.637	0.922
	(0.032)	(0.007)	(0.017)	(0.043)
Textiles	0.201	0.064	0.598	0.863
	(0.177)	(0.018)	(0.116)	(0.165)
Apparel	0.313	0.068	0.711	1.092
	(0.101)	(0.035)	(0.097)	(0.045)
Wood and Furniture	0.381	0.065	0.628	1.075
	(0.07)	(0.017)	(0.059)	(0.06)
Paper	0.338	0.071	0.65	1.06
	(0.053)	(0.025)	(0.042)	(0.024)
Basic Chemicals	0.168	0.181	0.754	1.103
	(0.07)	(0.027)	(0.056)	(0.046)
Plastic and Rubber	0.231	0.116	0.766	1.112
	(0.025)	(0.011)	(0.023)	(0.038)
Non-Metallic Manufactures	0.141	0.214	0.574	0.929
	(0.057)	(0.035)	(0.04)	(0.036)
Metallic Manufactures	0.287	0.098	0.655	1.04
	(0.045)	(0.016)	(0.031)	(0.061)
Machinery and Equipment	0.347	0.085	0.603	1.035
	(0.182)	(0.019)	(0.062)	(0.116)
Average (Unweighted)	0.255	0.110	0.658	1.023
Average (Weighted)	0.243	0.111	0.655	1.009

Notes: The table reports the estimated output elasticities for the baseline Cobb-Douglas production function, estimated for plants within 2-digit sectors. Columns 1-3 display the Cobb-Douglas elasticities with respect to each production factor (labor, capital, and material inputs). In column 4, we report the implied returns to scale, which are equal to the sum of the coefficients in columns 1-3. All variables are computed at the plant level. Standard errors are in parenthesis. The weighted average at the bottom of the table uses the number of plants in each sector as weights.