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PRODUCT MIX CHANGES AND PERFORMANCE IN CHILEAN PLANTS

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Abstract

A recent theoretical literature has given relevance to the study of the relationship between product mix changes and firm productivity. In this paper, taking advantage of a rich dataset for manufacturing plants in Chile during the period 1996-2000, we use matching techniques and a difference in difference approach to estimate the causal impact of product mix changes on productivity and other plant-specific outcomes. Our results suggest a positive and increasing impact of product mix changes on total factor productivity and labor productivity after two years the product mix changes are introduced. We also find positive effects on employment and sales. Nevertheless, this positive effect is mainly driven by firms that add and drop products at the same time. Our results are in line with recent theoretical developments on the study of productivity determinants on multiproduct firms and illustrate how products creation and destruction are a source of within-firm productivity growth.

Key Words: multiple products, product switching, productivity

1. Introduction

The literature suggests that total productivity explains a relevant part of the differences in income per capita and economic growth across countries. Hall and Jones (1999) show that close to one half of those differences between countries are explained by differences in total factor productivity. Additionally, the innovation literature at the firm level has been able to link up to 75% of the differences in productivity to innovative activities, once industry spillovers are considered (Griliches, 1995). Another literature suggests that aggregate productivity growth is mainly driven by the reallocation of resources from low to high productivity firms resulting from policy changes, such as trade liberalization (Pavcnick, 2002; Bernard, et al., 2003). In contrast, recent evidence by Bartelsman et al. (2009), using a sample of 16 developing and developed countries, finds that a significant source of productivity growth comes from within-firm productivity increases.

Nevertheless, the precise source of these increases in productivity is not well understood. Recently, with the increased availability of firm-product level data a new literature has emerged for analyzing how within-firm resources reallocation can increase productivity. Bernard, et al. (2010) and Goldberg, et al. (2010) analyze the extent of product mix changes and their contribution to total output in manufacturing in the US and India, respectively. Navarro (2012) presents a similar exercise for Chile. These studies suggest that product mix changes are an important margin by which firms can move resources from less to more efficient uses. They also suggest that product mix changes are associated to productivity increases, but they do not address the causality issue. That is, it is not clear if this positive correlation between product

mix changes and productivity is due to the ex-ante productivity advantage of the firms that change their product mix or not.

In this paper, we empirically analyze precisely whether changes in plants' product mix can be a potential source of within-firm productivity growth. In particular, we exploit product level information for Chilean manufacturing plants during the period 1996-2000 and analyze whether product mix changes have affected total factor productivity and other measures of firm performance such as employment, sales and wages. Our motivation is to understand how the firms' products dynamics has an impact on several measures of firm performance.

Today, firms as Apple, Samsung and Sony dispute in the collective imaginary which company is the most innovative and dynamic. The three companies do release and kill products every year, but what do we know about the overall impact of these changes on firm's productivity? Less is known about this dynamic in the manufacturing industry in less developed countries. Hence, the case of Chile can be relevant for learning whether manufactures in developing countries are also part of this dynamic of product creation and destruction or this is an exclusive feature of high-technology firms in advanced countries. Moreover, the Chilean data is even more relevant for developing countries considering that an important part of our sample are small and medium size firms, in a sector that has been declining during the last decade, mainly driven by the competition from other developing countries, most importantly China among them (Alvarez and Opazo, 2011). Thus, our results are of particular importance for the developing world as these two characteristics are common among these countries.

We are also motivated by recent theoretical models in which firms endogenously sort across products and show that changes in the product mix have important quantitative effects on firm and aggregate productivity (Bernard et al., 2010). In these models firms experience productivity increases as a result of new arrangements in their product mix for which they have an already exogenously predefined productivity. The rearrangement of the product mix occurs as a result of policy changes as opening to trade that change trade costs (Bernard et al., 2011) or exposure to different competitive pressures (Mayer et al., 2011). In these cases firms react by increasing production of their most productive and hence higher-profits goods that allows them to survive to the new environment of either higher wages as a result of openness to trade, or tougher competition. Thus, by investigating the impact of product mix changes on productivity; our research tries to fill the gap in the empirical evidence supporting these types of models.

This paper is also related to the empirical literature looking at the impact of product innovation on productivity. Most of the empirical works in the innovation literature, however, use self-reported information on product innovation activities by firms and they do not rely on direct measures of how firms change their product mix (See Crepon, et al., 1998 Griffith et al., 2006, and Hall et al., 2008 among others)¹. Indeed, in the handbooks of innovation edited by Hall and Rosenberg (2010), Fagerberg, et al. (2006) and Stoneman (1995) there is almost no discussion on how changes in output mix can affect productivity, but only on the relationship between product innovation and productivity.

¹ For Latin American countries Crespi and Zuñiga (2011) show a positive relationship between innovation and productivity, but they rely on self-reported measures of innovation. See Alvarez et al. (2010) for a similar study using Chilean data and Chudnovsky et al. (2006) for Argentina.

One important concern with simple regressions between productivity and changes in product mix is that this last variable is endogenous. As shown by Bernard et al. (2010), firms select products depending on their abilities and the fixed costs of producing goods. In this case, there are factors that can affect both productivity and the probability of changing the product mix introducing a positive correlation between both variables. To deal with this issue we employ the methodology of differences-in-differences with propensity score matching taken from the impact evaluation literature. The main idea behind difference-in-differences is to use repeated observations on firms to account for time-invariant differences among them. This estimator is a measure of the difference between the before and after change in productivity, employment and sales for firms introducing a new product (or dropping an existing) and the corresponding change for firms that do not. The propensity score matching methodology is used for pairing firms introducing (dropping) new products with the most similar members of the control group on the basis of their observable characteristics.

We also deal with recent concerns on using industry-deflators for computing firm productivity. Recent literature on firm productivity has analyzed whether productivity measures are biased due to using industry-wide price indexes instead of firm-specific prices indexes to deflate sales. Under this procedure the error term in the estimations of productivity would be correlated with input demands thereby biasing the estimations of total factor productivity (De Loecker, 2011). In terms of our study, given the unique characteristics of our dataset we are able to properly deal with this bias.

Our results show that product mix changes have a positive impact on total factor productivity (TFP) and labor productivity. These positive effects are increasing over two years

after the plant product innovation and they are found especially for plants introducing a new product and simultaneously dropping products in a given year. To consider broad indicators of firm performance, we also estimate the impact of product mix changes on sales, employment and wages. Our results suggest a positive impact of product mix changes on sales and employment growth, but not on wages.

The paper is structured as follows. In the second section, we describe the data. In the third section, we describe the methodology. In the fourth section, we show our results. The fifth section concludes.

2. Data Description

We use data from the national annual manufacturing survey (Encuesta Nacional Industrial Anual, ENIA) managed by the official Chilean statistics agency (INE). The unit of observation is a plant with ten or more employees and there are on average more than 3,300 plants per year in the sample. Thus, our dataset contains plant-product level information for more than 26,000 observations from 1996 to 2003. We match the information on plant characteristics with the data on plants products. The latter information is contained in “Formulario Número 3” of the survey (Form 3, from now on, F3) and allows us to identify the specific goods that the plants produce. It should be noted that more than 95% of the plants produce for single-plant firms in 1996, the only year with firm and plant level information available. For this reason we will use the terms firm and plants interchangeably.

The information on plant products is available up to 2003 but there was a change in products classification in 2001. Even though there are harmonization tables for the two product classifications, the product mix changes that would result for 2001 seem too high to be reliable.

For this reason, we consider plants that have introduced product mix changes only during the period 1996-2000, but we evaluate the effects on these changes on measures of firm performance up to 2003, the final year of the original sample. To avoid the bias associated with plants that have introduced changes with the new classification, we exclude them from the analysis. Then, our sample contains plants that have not introduced product mix change during the whole period 1996-2003 and those that changed product in the period with homogenous product classification: 1996-2000.

Products are defined according to local classifications denoted by CUP (Unique Products Classification). The product information is more disaggregated than a seven-digit Second Revision International Standard Industry Classification (ISIC). Hereafter we will refer to the more disaggregated definition of a product as "product" or "ENIA product". It is possible to assign the products to different seven-digit and more aggregate ISIC categories. We will refer to two-digit ISIC categories as "sectors" and four-digit ISIC categories as "industries". There are ten sectors, 87 industries, 246 five-digit ISIC categories, 566 six-digit ISIC categories and 1987 ENIA products in the pooled 1996-2000 sample.² Table 1 presents information on the number of plants and products per year under alternative product aggregations for the sample used in this study.

We need to obtain a measure of total factor productivity (hereafter, TFP) for the analysis. TFP is a residual of an estimated production function. We estimate value added production functions at the two digit ISIC level following the Levinsohn and Petrin (2003) technique. In this process we drop around 3,000 plant observations for which we cannot obtain measures of TFP³.

² As shown in Navarro (2012) the distribution of products by sector is highly heterogeneous.

³ This is the case of plants for which there is missing information on some of the inputs of the production function or plants which are not active for consecutive years.

One advantage of our dataset is that we can compute firm-specific price deflators avoiding potential biases associated with using industry-specific deflators for nominal variables.

The data on plants' products by year allows us to identify changes in the product mix due to the creation and destruction of a product over time. Then, our definition of product creation (adding) considers the case of firms producing a product in year t , which it was not produced in $t-1$. Similarly, product destruction (dropping) refers to a product that was produced in $t-1$, but not produced in t . Given that there are also cases of firms that add and drop products in the same year, we consider these separately. Then we have four groups of firms: (i) those that introduce products (add), (ii) those that drop products (drop), (iii) those that introduce and drop products in the same year (both), and finally, (iv) those that keep their product mix intact between two consecutive years.

In Table 2, we present information on the percentage of plants that add; drop and both add and drop products between two consecutive years in the period 1997-2000⁴. It shows that nearly 70% of the plants do not introduce changes in their product mix. According to these figures, the most prevalent change is dropping a product (17% of the plants), followed by adding a product (15%). Only about 9% of the plants introduce and drop products at the same time. It can also be appreciated that these plants do not represent a disproportionate proportion of output. On average, plants changing their product mix adding a product, dropping a product or doing both represent 20%, 16%, and 9% of total output, respectively. This is different to similar results for

⁴ Given that we define a change respect to the previous year, 1997 is the first year when an introduction or dropping a product is observed.

the U.S. reported by Bernard et al. (2010), where the percentage of firms reporting adding and dropping of products represent 25% of the total firms, but 68% of total output.

In Table 3 we show the incidence and relevance of product mix changes across industries averaged for the period 1997-2000. In general, for most of the sectors, we find that product mix changes are important both in terms of the number of the plants and the output involved. These figures show that the incidence and relevance of product mix changes is higher for some sectors such as Wood and Wood Products, but lower in Food and Beverages. Moreover, as shown in Bernard et al. (2010) for the U.S and in Navarro (2012) for Chile, the correlation of adding and dropping is positive across industries. Those industries with higher incidence and relevance of adding are those also with higher dropping rates.

Table 4 provides information about differences in characteristics between plants introducing product mix changes between two consecutive years and those that do not during the period 1997-2000. We run a separate regression of the log of the plant characteristic on a dummy variable for each of the three groups defined above⁵. The base category corresponds to plants that have not introduced any changes in the product mix between two consecutive years. All regressions are OLS except for the probability of export which is a probit (marginal effects reported) and they all include year and industry fixed effects. In most of the cases the coefficients are statistical significant at the 1% level. The results indicate that, in general, plants introducing changes in their product mix are larger, more productive and more likely to export than plants that do not change their product mix. There are some differences depending on the

⁵ In this case, given that the dummy variables must to be mutually exclusive groups, add and drop are defined as plants that only add and only drop products.

type of change in the product mix. For plants introducing a product, the results show a positive correlation with all the plants characteristics, indeed with wages. In the case of plants dropping products, we only find a significant relationship with size (employment and output), but not with productivity, exporting and wages. Finally, adding and dropping simultaneously is significant related with size, productivity and the probability of exporting, but not with wages.

A question that emerges from these results is whether product mix change is a result of selection, i.e. larger and more productive plants that are more likely to introduce and drop products, or if the decision to change their product mix has any further effects on plant performance. This is indeed the central question that we address in the next sections.

3. Methodology

To identify the causal effect of product mix changes on plant performance, we need to deal with the endogeneity of introducing and dropping products. Even if product mix changes are correlated with positive performance (increase in TFP, for example), it is still not clear if more productive plants are more likely to change products or if product mix changes lead to TFP increases. An important problem in the estimation of the causal effect of product mix changes on plant performance is how to deal with this endogeneity problem.

Ideally one would like to know what would have been the performance of the plants if they had not changed their product mix. There are two main problems. First, the endogeneity of product mix changes. Second, we only observe the outcomes of plants when they change the product mix, but not the outcomes of the same plants if they did not change their product mix. We have instead to create a proper counterfactual for those plants. Different techniques can be used to deal with this issue. In our case we implement the propensity score matching (PSM)

method (Rosenbaum and Rubin, 1983) to select a control group and then we apply a differences-in-differences estimation for evaluating the impact of product mix changes on TFP and other outcomes among Chilean plants.⁶

Given that we have three treated groups, we follow the literature on multiple treatments. The multiple treatments exist when there are more than one alternative, in this case, the plant can decide between either not introducing changes in the product mix or choosing some of the other three alternatives: add, drop or both. However, using a multinomial Probit or Logit estimation could violate the assumption of independence among the relevant alternatives (Caliendo and Kopeinig, 2008). We estimate three separate Probit models for selecting the appropriate control sample for each group, as suggested by Lechner (2001)⁷.

The treatment is then a dummy variable A_{ijt} which takes a value of 1 if the plant i introduced a product ($j=1$), dropped a product ($j=2$), or did both ($j=3$) at time t , and zero if the plant did not change its product mix at all during the sample period. For the case of our study the control group includes only plants that maintained exactly the same production structure over the period 1996-2003. One problem with the definition of the treatment considered is that it can be the case that the plant continues creating or dropping products in subsequent years. For this reason, it can be the case that the detected impact of the product mix change is contaminated by the effect of posterior changes in their product mix. However, this effect is

⁶ There are other studies that used the PSM methodology with plant level data for manufacturing. See, for example, De Loecker (2007), Serti and Tommasi (2008), Fyrges and Wagner (2008), and Gorg et al. (2008).

⁷ We actually performed a multinomial estimation of the model as well and the results are similar to the separate Probit estimations we report.

likely to be reduced by the fact that at least two thirds of the plants in our matched samples changed their product mix only once in the sample period.⁸

Ignoring the type of treatment and time subscripts for expositional purposes, the values of A_i determine the assignment of plants to the treatment and control groups. Let Y_{is}^1 be the outcome of plant i evaluated s periods after treatment. The causal effect of product mix changes on the outcome after treatment is then $Y_{is}^1 - Y_{is}^0$ where Y_{is}^0 is the outcome evaluated in case of no changes in products ($A_i = 0$). Clearly, Y_{is}^0 is not observable.

It is standard to define the average effect on outcome as

$$E(Y_{is}^1 - Y_{is}^0 | A_i = 1) = E(Y_{is}^1 | A_i = 1) - E(Y_{is}^0 | A_i = 1).$$

While the first term is observed the second term is not. An estimator of this counterfactual widely used in the evaluation literature is

$$E(Y_{is}^0 | A_i = 1) = E(Y_{is}^0 | P(X), A_i = 1) = E(Y_{is}^0 | P(X), A_i = 0)$$

where $P(X)$ is the probability of changing products conditional on a set of observable characteristics X . Note that the average value of the outcome should be independent of the treatment indicator (conditional independence). We also need to consider a range for $P(X)$ such that the comparison of expected values between the control and treatment groups is feasible (common support).

Accordingly, we first estimate a Probit model for the probability of changing the product mix (propensity score) conditional on a set of observables X . We need then to find a control

⁸ As a robustness test we performed all the experiments with a sample of firms that changed their product mix only once in the whole sample period. The results are similar to the reported here though with reduced statistical significance given the smaller sample sizes.

group very similar to the treatment group in terms of its predicted probability of changing the mix of products, defined by p_i . This requires choosing a set X of variables that are not influenced by the treatment (Todd, 1999), i.e. characteristics prior to the product mix change. For our study, the elements of X should include variables that are thought to affect the probability of introducing or dropping a product.

According to Todd (2008), there is no theoretical basis on how to choose X and which variables are included in X can have important implications for the estimator's performance. Rosenbaum and Robin (1983) propose as a specification (balancing) test to choose a set X such that there are no differences in X between the two groups after conditioning for $P(X)$. We include as predictors of changing product mix the following variables: TFP growth, the number of products, a dummy variable for exporters, the share of the plant in industry output, three size dummy variable, and industry and years dummy variables.

Once we have estimated the propensity scores we match the groups using the method of the nearest neighbor. That is, for each innovating plant with propensity score p_i , we select the plant k from the control group such that its propensity score p_k is as close as possible to p_i . We implement the methodology following the procedure developed by Leuven and Sianesi (2003).

In Table 5, we show the Probit results. We find that average TFP growth in the previous two year affects negatively the probability of changing products, though the impact is not significant at high enough confidence levels. This might be an indication that firms decide to adjust their extensive margin of production when productivity falls. It is also observed in the table that the number of products affects the probability of introducing changes in the product

mix positively. This is consistent with the idea that multi-product firms are more likely to drop and add products (Bernard et al., 2010). We find also the plant's market share is positively associated with the probability of changing products. In the case of size, all else equal larger firms (those employing more than 200 employees) are less likely to introduce changes in their product mix. The results show that there are not significant differences between exporters and non-exporters in terms of their probability of adding and/or dropping products. Finally, the estimation reveals differences across sectors and over time. Compared to the year 2000, during 1999 plants were more likely to add and drop products. In the case of industries, there are some such as wood and metallic products where the prevalence of products mix changes is higher than the rest of the industries.

Before turning to the results, it is important then to evaluate the quality of the matching procedure. For this purpose, for each variable in X it was computed the average for the treated and control groups of the matched and unmatched samples and tested for differences in their respective means. This information is summarized in Table 6 for each of the multiple treatments. This table reports the standardized differences in the means of all the variables included in the X vector. For each variable, the first row displays the mean differences between the treatment and the control groups before matching and their statistical significance.

Additionally, the second row shows the same information computed with the sub-sample of matched observations. Indeed, it can be noticed in Table 6 that for some variables such as export status, market share and percentage of firms in certain size, sector and year categories there are significant differences in means between treated and control firms before matching that were successfully eliminated with the matching procedure. As a result, for all but only just one of the

variables (dummy for size between 101 and 200 employees in the experiment with product drops) there are no differences in the first moments of the characteristics between treated and controls.

We also performed an overall test of balance of the matching procedure. In the bottom of Table 6 it is presented the R-squared of a regression of the propensity score for each treatment with the matched and unmatched samples, respectively. As shown in the table, the explanatory power of the determinants of product mix changes is significantly reduced to a number not statistically different from zero in the matched samples. This can be seen as an indication of an acceptable quality of the matching procedure.

4. Results

Table 7 presents the results of the estimations of the effect of product mix changes on two measures of productivity measures in logs: TFP and labor productivity, and for the three groups considered: introduce products (add), drop products (drop), and introduce and drop products at the same time (both). In Table 8 we report the results for plants that only add or drop product without any other change in their product mix structure. We present differences-in-differences estimations for the year in which the product mix change is introduced (t) and one ($t+1$) and two years ($t+2$) later, compared with the year before the product mix has been changed ($t-1$). Then, each coefficient is interpreted as the percentage change in productivity caused by variations in the product mix. All the regressions include year and industry dummy variables.

As displayed Table 7, most of the coefficients are positive, but they are only significant after two years the plants changed their product mix. These results hold for those firms either adding, dropping, and introducing and dropping products at the same time. The economic

magnitude is also relevant. We find positive effects of 17% on total factor productivity for adding products, 18% for dropping products, and 30% for firms adding and dropping products simultaneously. The significance, magnitude and timing are similar when considering the effects of product mix changes on labor productivity.

However, as we show in Table 8, when considering the effect of product creation or destruction in isolation from other product mix changes, the effects are not significant. These results can be interpreted as that the positive effect of product adds and drops do only occur when accompanied by another simultaneous product mix change. This explains why the effect of both adding and dropping products is the stronger. In such case, our results show that total factor productivity and labor productivity can increase 30% and 27%, respectively, after two years firms add and drop products jointly. Summarizing, our results suggest that only when the firm changes its products structure by adding “good” products and dropping the “bad” ones simultaneously, the effects on productivity are positive.

In terms of dynamics, it is worthy to note that these results suggest that the effect of product mix changes take time to materialize in productivity gains. We find consistently that only after two years the effect is positive and statically significant. Moreover, these findings reveal that productivity increments are not only associated to introducing a product, as the literature on productivity and innovation has shown, but also to dropping products. This is in line with recent theoretical models that show that multi-product firms can increase their productivity by dropping their low-productivity products (Bernard et al, 2010).

In Table 9, we show additional results looking at the effects of product mix changes on employment, sales and wages. Following the literature on multi-product firms, we would

expect that changes in the product mix, by rising productivity, will be associated with firm growth. Although the literature is not very explicit in terms on the effects of product mix changes on wages, we look also at the effects on this variable for analyzing how workers can be affected by these changes. This estimation is motivated by the literature on the effects of product innovation and skill composition that suggest that innovation would favor skilled workers. In such a case, we can expect a positive effect on average wages whenever product innovations increases the demand for skilled workers and change the labor composition within firms.

The results, in general, show a positive effect of product mix changes on sales with some differences across treatment groups. In the case of plants adding products, the impact is positive and significant only two years after the introduction of a product and ranging between 10% and 19%. In the case of dropping products, the effect on sales is positive and significant (12%) only two years after the products is dropped. Similarly, for plants that introduce and drop products simultaneously, we find an impact of 24% on sales two years after the product change. In the case of employment, the estimations show a positive and smaller effect. For average wage, all of the results show not significant parameters except for one at the 10% level, suggesting that product mix changes would in any case lead to a very slight reduction in wages.

Similarly to the results for productivity, we obtain that there is barely any effect on outcomes when restricting the analysis to firms that only added or dropped products with no other changes in their product mix (Table 10).

5. Conclusions

Recent theoretical models propose a novel mechanism in which changes in product mix affects overall firms' productivity despite the fact each firm product's productivity is exogenously predefined. The key fact underlying this change in productivity is the change in the selection of products that each firm produces. Thus, policy changes or changes in the level of competition can be linked to changes in firms' product mix and overall productivity. Nevertheless, there are few empirical investigations that support this relationship between products mix changes and firm performance. Thus, our research attempts to fill this gap in the existing empirical literature on the subject, and with a focus on developing countries for which the evidence is even scarcer.

We have use matched plant and products data coming from the Chilean official manufacturing survey for 1996-2003 and implement a propensity score matching technique combined with a difference in difference approach. We analyze the immediate and lagged impact of product mix changes on productivity and other firm outcomes. In our main exercise we find evidence of a robust effect of product mix changes on productivity in Chilean manufacturing. This effect is increasing up to two years after the product mix has changed.. Our results imply that changes in product mix generate an increasing impact on productivity that can go up to 30% two years after the mix change takes place. These increases in productivity are substantial and thus are not just statistically significant but economically meaningful. We also find a similar positive effect on sales and employment growth, but not on wages.

Our results also suggest that productivity gains occur only if there are simultaneous add and drop in of products. This would be consistent with the idea that low-productivity products

are replaced by new more productive or with greater demand ones. Thus, productivity gains are not only generated by product mix changes due to dropping products. It seems that joint product creation and destruction are the main sources of productivity gains.

Our selection model also gives some relevant evidence on which firms are more likely to introduce product mix changes. We find that multi-product firms and those with larger market share are more likely to introduce and drop products. In contrast, previous TFP growth and the export status are not significantly associated with changes in the product mix. We also find significant differences across industries, suggesting that even after controlling for firm-specific characteristics there are some industries in which changes in product mix are more prevalent. This can be due to demand or supply industry-specific shocks that we are not able to control for and also to differences in unobservable industry-specific differences in cost of creation and destruction of products.

This evidence contributes to a better understanding on the dynamics of product creation and destruction in the manufacturing industry for a less developed country. Our results reveal that relevant changes in product mix and its positive effect on productivity are not an exclusive feature of high-technology firms in advanced countries. This can have important implications for developing economies because policies oriented to facilitate the dynamics of product creation and destruction may be a relevant source of productivity growth in these countries.

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Table 1: Data

Year	Plants	Products	ISIC 6 digits	ISIC 5 digits
1996	3873	1641	524	235
1997	3676	1587	532	236
1998	3316	1542	518	234
1999	3037	1515	512	229
2000	2990	1599	520	226

Note: Matched plants and products observations after TFP estimations.

Table 2: Prevalence of Product Mix Changes

	Percent of Plants				Percent of Output			
	Add	Drop	Both	None	Add	Drop	Both	None
1997	13	17	7	69	20	19	9	65
1998	14	15	8	72	27	15	9	63
1999	18	20	14	65	18	17	10	65
2000	16	15	10	67	16	14	9	72
Average	15	17	9	68	20	16	9	66

Table 3: Prevalence of Product Mix Changes across Industries
(Average 1997-2000)

	Percent of plants				Percent of Output			
	Add	Drop	Both	None	Add	Drop	Both	None
Food and Beverage	7	8	3	59	14	14	8	55
Textile	12	13	7	52	11	12	6	54
Wood	24	24	18	38	31	32	25	37
Pulp and Paper	12	13	5	49	10	8	2	51
Chemicals	14	17	10	50	18	16	9	53
Non-metallic	10	10	6	53	7	9	3	61
Metallic	18	19	12	46	24	9	5	55
Machinery	13	15	8	49	12	11	6	58
Other Industries	15	13	8	53	22	18	15	47

Table 4: Differences in Plant Characteristics

	Output	Employment	TFP	Labor Prod.	Exporter	Wage
Add	0.22 [3.92]***	0.17 [4.56]***	0.06 [1.88]*	0.05 [1.66]*	0.05 [3.19]***	0.05 [2.62]***
Drop	0.10 [1.94]*	0.12 [3.44]***	0.02 [0.55]	-0.02 [0.57]	0.02 [1.64]	0.00 [0.11]
Both	0.19 [3.96]***	0.12 [3.91]***	0.08 [3.32]***	0.06 [2.38]**	0.05 [3.67]***	0.02 [1.29]
Constant	13.12 [115.58]***	4.09 [54.11]***	9.24 [157.70]***	9.03 [168.53]***	0.12 [5.42]***	7.86 [254.83]***
Observations	11820	11817	10352	11817	11820	11816
R-squared	0.30	0.20	0.44	0.31	0.24	0.33

Note: Coefficients for fixed effects not reported. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels based on robust standard errors, respectively..

Tabla 5: Probit Regressions

	Add		Drop		Both	
	Coefficient	Z	Coefficient	z	Coefficient	Z
Lag TFP Growth	-0.142	-1.53	-0.124	-1.32	-0.062	-0.55
Lag Number of Products (log)	0.498	6.80	0.681	9.50	0.460	5.15
Lag Export Status	0.145	1.18	0.124	1.01	0.218	1.50
Lag Share Value of Output (log)	0.085	1.70	0.171	3.47	0.123	2.13
Size: 51-100	-0.083	-0.55	-0.213	-1.45	-0.134	-0.76
Size: 101-200	0.024	0.13	-0.265	-1.42	-0.045	-0.21
Size: >200	-0.493	-2.00	-0.865	-3.56	-0.919	-2.89
Textiles	0.273	1.95	0.142	0.99	0.170	0.99
Wood	1.414	9.01	1.391	8.81	1.545	8.99
Pulp & Paper	-0.115	-0.36	0.433	1.95	-0.339	-0.75
Chemicals	0.253	1.73	0.291	2.17	0.227	1.35
Non-metallic	0.450	1.97	0.224	0.91	0.299	1.06
Metallic	1.210	3.36	0.774	1.70	0.796	1.66
Machinery	0.328	2.27	0.121	0.79	0.098	0.53
Other industries	0.026	0.06	-0.117	-0.24	.	.
Year 1998	-0.036	-0.29	0.012	0.10	-0.158	-1.02
Year 1999	0.313	2.63	0.326	2.70	0.412	2.95
Constant	-1.305	-2.43	-0.451	-0.85	-1.057	-1.70
Observations	2069		2090		1940	
Pseudo R2	0.1528		0.1839		0.2066	

Table 6: Matching Quality

Variable	Sample	Add			Drop			Both		
		Mean			Mean			Mean		
		Treated	Control	p> t	Treated	Control	p> t	Treated	Control	p> t
TFP Growth	U	-0.040	0.001	0.311	-0.043	-0.001	0.264	-0.020	-0.001	0.691
	M	-0.015	-0.003	0.841	-0.033	0.005	0.479	-0.010	-0.020	0.885
Products (log)	U	0.663	0.358	0.000	0.832	0.374	0.000	0.610	0.354	0.000
	M	0.628	0.640	0.875	0.768	0.820	0.495	0.581	0.595	0.883
Export Status	U	0.299	0.223	0.034	0.273	0.222	0.134	0.299	0.223	0.082
	M	0.286	0.293	0.893	0.262	0.331	0.200	0.295	0.375	0.266
Share (log)	U	-9.502	-9.897	0.004	-9.471	-9.901	0.001	-9.515	-9.891	0.024
	M	-9.571	-9.583	0.947	-9.513	-9.353	0.357	-9.519	-9.493	0.906
Size: 51-100	U	0.150	0.132	0.535	0.155	0.134	0.443	0.144	0.132	0.736
	M	0.165	0.195	0.525	0.159	0.145	0.744	0.159	0.170	0.84
Size: 101-200	U	0.163	0.091	0.004	0.137	0.089	0.043	0.175	0.090	0.005
	M	0.128	0.128	1.000	0.110	0.214	0.017	0.159	0.205	0.437
Size: >200	U	0.075	0.091	0.508	0.068	0.091	0.328	0.041	0.093	0.084
	M	0.075	0.083	0.821	0.076	0.083	0.829	0.045	0.011	0.175

Table 6: Matching Quality (continued)

Variable	Sample	Add			Drop			Both		
		Mean			Mean			Mean		
		Treated	Control	p> t	Treated	Control	p> t	Treated	Control	p> t
Textiles	U	0.156	0.178	0.51	0.124	0.176	0.096	0.124	0.182	0.146
	M	0.173	0.180	0.873	0.138	0.131	0.864	0.136	0.205	0.231
Wood	U	0.245	0.038	0.000	0.224	0.036	0.000	0.340	0.038	0.000
	M	0.188	0.195	0.877	0.172	0.131	0.328	0.273	0.261	0.866
Pulp & Paper	U	0.014	0.033	0.191	0.050	0.034	0.289	0.010	0.034	0.200
	M	0.015	0.000	0.157	0.055	0.055	1.000	0.011	0.000	0.319
Chemicals	U	0.150	0.138	0.691	0.205	0.141	0.027	0.165	0.142	0.522
	M	0.158	0.188	0.518	0.193	0.262	0.162	0.182	0.159	0.691
Non-metallic	U	0.041	0.035	0.706	0.031	0.034	0.832	0.031	0.035	0.821
	M	0.045	0.053	0.777	0.034	0.028	0.736	0.034	0.011	0.315
Metallic	U	0.034	0.006	0.000	0.012	0.005	0.243	0.021	0.005	0.063
	M	0.023	0.015	0.653	0.014	0.007	0.563	0.023	0.034	0.652
Machinery	U	0.143	0.134	0.768	0.099	0.133	0.227	0.093	0.135	0.237
	M	0.158	0.113	0.284	0.110	0.145	0.381	0.102	0.102	1.000
Other Ind.	U	0.007	0.020	0.253	0.006	0.019	0.237	0.000	0.000	1.000
	M	0.008	0.008	1.000	0.007	0.007	1.000	0.000	0.000	1.000
Year 1998	U	0.327	0.391	0.123	0.354	0.392	0.337	0.237	0.383	0.004
	M	0.331	0.331	1.000	0.352	0.379	0.627	0.250	0.364	0.103
Year 1999	U	0.483	0.319	0.000	0.472	0.318	0.000	0.588	0.321	0.000
	M	0.466	0.466	1.000	0.462	0.476	0.815	0.557	0.477	0.294
Year 2000	U	0.190	0.290	0.010	0.174	0.289	0.002	0.175	0.297	0.010
	M	0.203	0.203	1.000	0.186	0.145	0.345	0.193	0.159	0.555
Overall Balance Test	Sample	Pseudo R2	LR chi2	p>chi2	Pseudo R2	LR chi2	p>chi2	Pseudo R2	LR chi2	p>chi2
	U	0.153	162.09	0.000	0.184	208.63	0.000	0.207	159.15	0.000
	M	0.008	3.03	1.000	0.033	13.25	0.719	0.040	9.580	0.845

Table 7: Effects of Product Mix Changes on Productivity Growth
(with respect to t-1)

Add			Drop			Both		
<u>Total Factor Productivity</u>								
t	t+1	t+2	t	t+1	t+2	t	t+1	t+2
0.0646	0.0821	0.1744	0.0563	0.0536	0.1821	0.0438	0.07	0.2969
[0.0679]	[0.0674]	[0.0820]**	[0.0570]	[0.0625]	[0.0721]**	[0.0870]	[0.0963]	[0.0941]**
2055	2055	2055	2074	2074	2074	1931	1931	1931
0.08	0.09	0.13	0.08	0.1	0.14	0.08	0.1	0.15
<u>Labor Productivity</u>								
t	t+1	t+2	t	t+1	t+2	t	t+1	t+2
0.0799	0.0404	0.1932	0.0727	0.0261	0.1149	0.0988	0.0404	0.2672
[0.0578]	[0.0626]	[0.0670]**	[0.0478]	[0.0580]	[0.0645]*	[0.0718]	[0.0893]	[0.0849]**
2055	2055	2055	2074	2074	2074	1931	1931	1931
0.03	0.06	0.1	0.04	0.06	0.09	0.04	0.07	0.09

Table 8: Effects of Product Mix Changes on Productivity Growth
(with respect to t-1)

Add Only			Drop Only		
<u>Total Factor Productivity</u>					
t	t+1	t+2	t	t+1	t+2
0.1105	0.1431	0.0466	0.0183	-0.0245	-0.0044
[0.1085]	[0.0804]*	[0.1420]	[0.0628]	[0.0644]	[0.1035]
1861	1861	1861	1872	1872	1872
0.09	0.09	0.14	0.05	0.09	0.14
<u>Labor Productivity</u>					
t	t+1	t+2	t	t+1	t+2
0.057	0.0667	0.0624	-0.0206	-0.0667	-0.1142
[0.1016]	[0.0787]	[0.1031]	[0.0563]	[0.0624]	[0.0950]
1861	1861	1861	1872	1872	1872
0.04	0.07	0.11	0.04	0.07	0.08

Table 9: Effects of Product Mix Changes on Sales, Employment, and Wages Growth
(with respect to t-1)

Add			Drop			Both		
<u>Sales</u>								
t	t+1	t+2	t	t+1	t+2	t	t+1	t+2
0.1018	0.1112	0.1885	0.0298	0.0518	0.1184	0.0976	0.1053	0.2388
[0.0489]**	[0.0569]*	[0.0624]***	[0.0441]	[0.0472]	[0.0557]**	[0.0507]*	[0.0745]	[0.0830]***
2055	2055	2055	2074	2074	2074	1931	1931	1931
0.05	0.1	0.12	0.05	0.1	0.11	0.05	0.11	0.12
<u>Employment</u>								
t	t+1	t+2	t	t+1	t+2	t	t+1	t+2
0.0499	0.0999	0.0452	0.0203	0.0546	0.0268	0.0433	0.0889	0.0318
[0.0236]**	[0.0315]***	[0.0390]	[0.0216]	[0.0269]**	[0.0322]	[0.0317]	[0.0415]**	[0.0544]
2055	2055	2055	2074	2074	2074	1931	1931	1931
0.05	0.08	0.09	0.05	0.08	0.1	0.05	0.08	0.1
<u>Average Wage</u>								
t	t+1	t+2	t	t+1	t+2	t	t+1	t+2
-0.0192	-0.0445	-0.0345	0.0148	-0.0151	-0.0727	0.0107	-0.0564	-0.0081
[0.0282]	[0.0303]	[0.0376]	[0.0248]	[0.0279]	[0.0378]*	[0.0338]	[0.0391]	[0.0471]
2055	2055	2055	2074	2074	2074	1931	1931	1931
0.04	0.05	0.06	0.04	0.06	0.08	0.05	0.06	0.08

Table 10: Effects of Product Mix Changes on Sales, Employment, and Wages Growth
(with respect to t-1)

Add Only			Drop Only		
<u>Sales</u>					
t	t+1	t+2	t	t+1	t+2
0.1481	0.1709	0.1341	-0.039	-0.0259	-0.0124
[0.1100]	[0.0884]*	[0.0820]	[0.0746]	[0.0557]	[0.0685]
1861	1861	1861	1872	1872	1872
0.06	0.11	0.13	0.06	0.11	0.12
<u>Employment</u>					
t	t+1	t+2	t	t+1	t+2
0.0601	0.1308	0.1012	-0.0053	-0.0024	-0.0245
[0.0326]*	[0.0459]***	[0.0431]**	[0.0257]	[0.0345]	[0.0394]
1861	1861	1861	1872	1872	1872
0.06	0.1	0.11	0.05	0.09	0.1
<u>Average Wages</u>					
t	t+1	t+2	t	t+1	t+2
-0.078	-0.0481	-0.1058	0.0132	-0.0125	-0.1822
[0.0465]*	[0.0457]	[0.0609]*	[0.0349]	[0.0381]	[0.0604]***
1861	1861	1861	1872	1872	1872
0.05	0.06	0.08	0.05	0.07	0.1