Do less productive firms catch up with the more productive ones? Evidence from a firm-level panel data

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Abstract

This paper studies the productivity dynamics of the Spanish manufacturing firms during the 1990s by analyzing the productivity transition matrix and by applying the classical convergence tests. The paper makes a direct use of the fact that firms are interested in their productivity growth with respect to the other firms by studying the determinants of firms' mobility within the productivity distribution. We find that the more innovative is a firm and the more experience it has the likelier it becomes to appear at higher quintiles. We also find that firms with better technology and larger participation of foreign capital has larger probability of improving their relative position.

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"A company can't outgrow its competitors unless it can out-innovate them"

Gary Hamel and Gary Getz, in Funding Growth in an Age of Austerity. Harvard Bussines Review, July 2004.

1 Introduction

The paper analyzes the productivity dynamics of the Spanish manufacturing firms during the 1990s with two main interests in mind. First, like most of papers that have studied the productivity dynamics, we try to answer the following questions: How does the productivity dispersion evolve over time? Is there a tendency for plants to converge, in their productivity characteristics? Bartelsman and Doms (2000) present an excellent survey of the studies that have used micro level data to analyze the productivity dynamics. The paper contribute to this literature by presenting evidence for an economy different than the U.S. or U.K.

Second, we are interested in to identify the determinants of the mobility of firms within the cross sectional productivity distribution. From the best of our knowledge, this question has not been analyzed. Most of the papers explain the mean productivity level or the mean productivity growth rate. Those studies are very important from a "macro" perspective because they allow to understand, for example, the way in which is possible to obtain more goods with the same quantity of inputs. However, from the point of view of the firm, they do not tell the complete story. Most of the time, firms are interested in becoming more productive than the other firms and not only more productive. The paper contribute to the literature by estimating the probability that a firm improves its relative position, in terms of productivity, as a function of its experience, technological usage, the innovation it realizes and the spillovers it receives. The firm's position in the productivity distribution depends on the position of the other firms therefore we consider all variables as deviations from the industry mean.

Traditionally, productivity dynamics is studied by analyzing the transition matrix. This approach has been followed by Baily, Hulten, and Campbell (1992) who analyzed the productivity dynamics in the U.S. manufacturing plants during the 1970s and 1980s. The transition matrix is helpful to understand the mobility of firms within the productivity distribution but it is not informative about the evolution of the productivity dispersion. The classical convergence literature developed by Barro and Sala-i-Martin (1991, 1992) provides simple methods to evaluate both the evolution of the productivity dispersion (σ-convergence test) and the mobility of firms within the productivity distribution (β-convergence test). There are some authors that have use these tools to study convergence in productivity across firms. For example, Oulton (1998) found a decreasing dispersion of labor productivity across surviving U.K. firms and Fung (2005) found that U.S. firms of the chemical, computers and electrical industries converge to their own steady-state productivity which is conditional on the firm's R&D effort and the spillovers that the firm receives. For the Spanish manufacturing firms Vivero (2005) have tested for convergence in productivity taking into account different productivity measures.

We use individual firm data from the "Encuesta sobre Estrategias Empresariales" (ESEE) over the period 1991-1999. This survey provides detailed information on the firms decisions that allows us to identify the variables driving changes in the relative position in terms of productivity. The sample is representative of the Spanish manufacturing firms classified by industry and size categories.

We find that the mobility of firms within the cross sectional productivity distribution and the productivity dispersion between firms belonging to the same industry is different in the first half of the decade. Until 1995 there is a reduction in the dispersion of productivity joint with higher mobility of firms within the productivity distribution. However, from 1995 to 1999 the dispersion of productivity increases and the mobility within the distribution is lower. The increase in the dispersion of the second half of the decade does not compensate the initial reduction and overall effect is a reduction of the productivity dispersion between firms belonging to the same industry. What is interesting to note is that the period with the lower firms' mobility and in which the dispersion of productivity between firms in the same industry increases coincides with a deceleration in the productivity growth rate of the Spanish manufacturing sector.

With respect to the determinants of the firms' mobility within the cross sectional productivity distribution, we find that process innovation, experience, technology usage and foreign capital play an important role in the probability that a firm improves its relative position.

The rest of the paper is organized as follows. Section 2 describes the data set and the variables used in the analysis. Section 3 considers the methods applied to characterize the productivity dynamics and the methodology we propose to study the determinants of firms' mobility within the productivity distribution. Section 4 presents the empirical results. Finally, section 5 concludes.

2 Data and Variables

We use individual firm data from "Encuesta sobre Estrategias Empresariales" (ESEE) an annual survey which refers to a representative sample of Spanish manufacturing firms. In this survey, firms with more than 200 employees in the first year were asked to participate and the rate of participation reached approximately 70% of the population of firms within that size category. Firms that employed between 10 and 200 employees were sampled randomly by industry and size strata, the rate of participation was 5% of the number of firms in the population. An important characteristic of the survey is that in subsequent years the initial sample properties have been maintained. Newly created firms have been added annually with the same sampling criteria that as in the base year and there are exits from the sample, coming by both death and attrition. Therefore due to this entry and exit process, the data set is an unbalanced panel of firms.

We have aggregated firms in eleven industries according to the NACE classification[1]. Firms that change from one industry to another were excluded from

[1]We consider the following aggregation: 1.- Ferrous and Non-Ferrous Metals and Metal Products (NACE 27 and 28); 2.- Non-Metallic Products (NACE 26); 3.- Chemical Products (NACE 23, 24 and 25); 4.- Machinery (NACE 29); 5.- Office Machines and Electrical Goods (NACE 30, 31, 32 and 33); 6.- Transport Equipment (NACE 34 and 36); 7.- Food, Beverages and Tobacco (NACE 15 and 16); 8.- Textile, Leather and Shoes (NACE 17, 18 and 19); 9.- Wood Products and Furniture (NACE 20 and 36.1); 10.- Paper and Printing Products (NACE 22); and 11.-

the sample because productivity in different moments is not comparable for those firms. In total 293 observations were excluded because of that reason. We also exclude 73 observations because the firm reports an incomplete exercise in a year different than the one in which the firm leaves the market. After removing these observations the sample is an unbalanced panel of 2400 firms and 11007 observations between 1991 and 1999.

The productivity measure we consider is a modified Solow (1957) residual that allows for imperfect competition and variable capacity utilization (see Hall, 1988, 1990). We assume constant cost shares by industry and over time. We have carried out some robustness exercises to deviations from this assumption and confirmed that results do not change. We also assume constant returns to scale. Under these assumptions, if firm i belongs to industry j, the log of its productivity is given by

$$\log P_{it} = \log Y_{it} - s^c_{L_j} \log L_{it} - s^c_{M_j} \log M_{it} - s^c_{K_j} \left(\log K_{it} + \log \kappa_{it}\right) \qquad (1)$$

where κ is the yearly average capacity utilization rate reported by each firm, $s^c_{X_j} = \frac{1}{TN_j} \sum_{t=0}^{T} \sum_{i \in j} s^c_{X_{it}}$ is the cost share of input $X = L, M$ and K of firm i in period t. The output variable, Y, is the goods and services production in real terms. The nominal output is deflated by a firm's specific price index. This price index is a Paasche type price index computed with the price variation that each firm reports. L is the total effective worked hours obtained by multiplying the hours of work per employee by the number of employees. The materials, M, correspond to the intermediate consumption deflated by a materials price index. Like in the case of output, this is a Paasche-type price index computed with the variation in the price of purchased materials, energy and services reported by the firms. The capital, K, is recursively estimated by the equipment investment actualized by a price index of capital goods and using sectoral estimates of the depreciation rate. The capital usage cost, r, is the weighted sum of long term interest rate with banks and other long term debt plus a 15% depreciation rate minus the investment deflator.

To estimate productivity in levels, like we are doing here, it is necessary to assume a parametric functional form for the production function. Equation (1)

Other manufactured products (NACE 36, except 36.1).

assumes a Cobb-Douglas production function for each industry. When cost shares are constant over time, equation (1) gives the log of total factor productivity (TFP) without assuming any parametrical functional form for the production function.

The alternative to estimate the Solow residual in levels is to estimate the productivity growth rate and obtain the level of productivity by applying recursively the formula $\log P_{i,t} = \log P_{i,t-1} + \Delta \log P_{it}$ taking some consistent estimate of the initial level of productivity P_{i0}. This alternative is less restrictive in terms of assumptions than measuring productivity in levels but more demanding in terms of data quality. Our sample is an unbalanced panel and the initial level of productivity assigned to entrants is not a minor detail. By applying equation (1), productivity of continuing firms and entrants is measured in the same way. Escribano and Guasch (2005) present deeper discussion of this issue.

Although the mark-up does not appear explicitly in (1), this expression allows for imperfect competition in the output market because it is constructed using cost shares instead of revenue shares, as in the original Solow residual.

The ESEE provides the necessary information to evaluate the effect of process innovation, experience, exports, imports, foreign capital and the spillovers that a firm receives on the firm's mobility within the productivity distribution. We consider these variables because previous studies for the Spanish manufacturing firms have found that they are important to explain the productivity. For example, Delgado, Fariñas, and Ruano (2002) have found that the productivity of exporting firms is larger than the productivity of those firms that attend only the domestic market. With respect to investment, Huergo and Jaumandreu (2004) have found a positive relationship between productivity growth and process innovation. The technological diffusion have been studied by Ornaghi (2006) she found that the more spillovers receives a firm the more productive it becomes. Barrios and Strobl (2004) have studied the effect of experience on the firm productivity.

Innovation is a dummy variable that takes the value one when the firm declare that has introduced a process innovation. We consider only process innovation by assuming that is the only type of innovation that is relevant to increase productivity.

Following Hall and Mairesse (1995), the knowledge capital of firm i is measured by

$$KN_{it} = (1-\delta)KN_{i,t-1} + R_{i,t-1} \tag{2}$$

where δ is the depreciation rate of the knowledge capital and $R_{i,t-1}$ is the R&D expenditures of firm i in period $t-1$. We take δ equal to 0.15 which is the value suggested in Hall and Mairesse (1995). The initial value of the knowledge capital is also estimated like Hall and Mairesse (1995) by adding up the R&D expenditures and assuming a constant growth rate of these expenditures. However, the ESEE provides information about the firm's age and therefore we can add up only until the year in which the firm has born. This is an important advantage of this data base since it allows us to obtain a better approximation of the initial value of the knowledge capital. Previous papers does not use this information and assume that all firms have born many years ago. Let $year[1]_i$ be the first year that firm i appears in our sample and $born_i$ the year in which firm i has born then $n_i = year[1]_i - born_i$ is the age of firm i at the moment of entering in our sample. Then the initial knowledge capital of firm i is estimated by

$$\begin{aligned} KN_{i,year[1]_i} &= \frac{R_{i,year[1]_i}}{1-\delta} \sum_{j=1}^{n_i} \left(\frac{1-\delta}{1+g}\right)^j \\ &= \frac{R_{i,year[1]_i}}{1-\delta} \left[\frac{\left(\frac{1-\delta}{1+g}\right)^{n_i+1} - 1}{\frac{1-\delta}{1+g} - 1} - 1 \right] \end{aligned} \tag{3}$$

where g is the growth rate of R&D. We take a value of g equal to 0.07 which is the average growth rate of R&D expenditures in the Spanish manufacturing sector during the period 1986-2001. To calculate this growth rate we use data from the Spanish statistical office, Instituto Nacional de Estadísticas (INE), who publishes the expenditures in R&D by year and industry.

The spillovers that a firm receives are measured by the capital knowledge of the industry to which the firm belongs. We take two different measures of the knowledge capital of the industry. First, we add up the firm level data. That is, if firm i belongs to industry k, then the spillovers are defined by $s_{it} = \log S_{it}$ where

$$S_{i,t} = \sum_{j \in k; j \neq i} KN_{j,t} \tag{4}$$

The effect of spillovers on productivity growth depends on the firm's absorptive capability. Ornaghi (2006) found that firm's absorptive capability for the Spanish manufacturing firms is a function of its size and therefore defines weights according to firms' size. To capture this effect we use interactions between the size group and the spillover.

Second, we use the data published by INE. The knowledge capital of the industry is estimated by applying the same procedure than the one applied to the firms' knowledge capital. The only difference is that in this case we follow Hall and Mairesse (1995) closer in the sense that we considered the infinity sum to obtain the initial knowledge capital.

Experience or learning by doing can be measured by the cumulative output of each firm or by the firm's age (see Bahk and Gort, 1993). We use the cumulative output of each firm, therefore experience is estimated by $e_{it} = \log E_{it}$ where E_{it} is given by

$$\begin{aligned} E_{i,t} &= \sum_{k=born_i}^{t} Y_{i,k} \\ &= \sum_{k=born_i}^{year[1]_i - 1} Y_{i,k} + \sum_{k=year[1]_i}^{t} Y_{i,k} \end{aligned} \tag{5}$$

The first term in equation (5) is the output cumulated by firm i before entering to our sample and the second term is the cumulated output since it enter to the sample. Because most of the firms were born before they were incorporated to the sample, the first term needs to be estimated. To estimate it we follow a similar approach than the applied by Hall and Mairesse (1995) to estimate the knowledge capital of firms. That is, we assume a constant output growth rate (r) and we add up the firms' output backward until the born year of each firm. Therefore, the first term of equation (5) is estimated by

$$\begin{aligned}\sum_{k=born_i}^{year[1]_i-1} Y_{i,k} &= Y_{i,year[1]_i} \sum_{j=1}^{n_i} \frac{1}{(1+r)^j} \\ &= Y_{i,year[1]_i} \left(1 - \frac{1}{(1+r)^{n_i}}\right) \frac{1}{r} \end{aligned} \tag{6}$$

We take r equal to 0.0366 which is the average growth rate of the Spanish industrial production for the period 1890-1999. To compute this value we use data from Table 5.2 page 364 in Carreras (2005). This is a better measure of experience than the one obtained by assuming that all firms have born many years ago or the one obtained by ignoring (6) and treating it as an individual unobserved effect. The later alternative is particularly problematic in our case because we are planning to estimate a probit model and the fixed effects estimates does not give consistent estimates. The measure we propose avoids that problem because does not introduce an individual unobserved effect.

3 Productivity Dynamics

3.1 Characterizing the Dynamics

Traditionally, the productivity dynamics is characterized by the transition matrix. Firms belonging to the same industry are ranked by their productivity in each year and then placed into the corresponding quantile. The transition matrix gives the fraction of firms that make each of the alternative movements among quantiles and therefore is an indicator of the mobility of firms within the productivity distribution. A more direct way to study the evolution of the productivity dispersion across firms is through the traditional σ-convergence test developed by Barro and Sala-i-Martin (1991, 1992).

We say that there is σ-convergence if the dispersion of firms' productivity tends to decrease over time.

The null hypothesis of no convergence states that "the variance of productivity in period T is equal to the variance of productivity in period 0" ($H_0 : \sigma_T^2 = \sigma_0^2$). We test this hypothesis against the alternative of convergence ($H_1 : \sigma_T^2 < \sigma_0^2$) through the statistics proposed by Caree and Klomp (1997). Under the null hypothesis of no convergence these statistics are given by

$$T_2 = (N - 2.5) \ln \left(1 + 0.25 \frac{(\hat{\sigma}_0^2 - \hat{\sigma}_T^2)^2}{\hat{\sigma}_0^2 \hat{\sigma}_T^2 - \hat{\sigma}_{0T}^2} \right) \xrightarrow{d} \chi^2(1) \tag{7}$$

and

$$T_3 = \frac{\sqrt{N}(\hat{\sigma}_0^2 / \hat{\sigma}_T^2 - 1)}{2\sqrt{1 - \hat{\pi}^2}} \xrightarrow{d} N(0, 1) \tag{8}$$

where σ_{0T} is the covariance of productivity in the first period (p_0) and productivity in the last period (p_T) and $\hat{\pi}$ is the estimate of π in $p_{iT} = \pi p_{i0} + e_i$.

To evaluate the movements of firms within the productivity distribution, together the transition matrix, we apply the classical β-convergence test. In this case, we say that there is absolute β-convergence if less productive firms' productivity tends to grow faster than productivity of the more productive firms.

The β-convergence hypothesis is tested using the following equation

$$g_{i,T} = a + bp_{i,0} + \mathbf{x}_{i,0}\delta + u_{i,T} \tag{9}$$

where $g_{i,T} = T^{-1}(p_{i,T} - p_{i,0})$ is the average growth rate between period T and period 0, T is a fixed horizon, $\mathbf{x}_{i,0}$ is the vector of control variables. Testing for β-convergence is equivalent to test whether b is negative.

Special attention needs to paid to the exiting firms. When the exiting firms are less productive than survival ones, the estimates of equation (9) are biased due to an endogenous selection problem. We control for this bias by applying the conventional Heckman's (1979) sample selection procedure. The selection equation gives the firms' survival probability. Following Olley and Pakes (1996) we estimate the survival probability as a function of age, capital and productivity. Adding the selection equation to equation (9) we get the model

$$g = \mathbf{x}_1\beta_1 + u \tag{10a}$$

$$s = \mathbf{1}[\mathbf{x}\delta + v > 0] \tag{10b}$$

Subindexes has been omitted to simplify notation. $(\mathbf{x}, s)$ is always observed; g is observed only when firm i survive between period 0 and period T ($s = 1$) and $\mathbf{1}[\cdot]$ is the indicator function. As is well known, in this model

$$\mathbb{E}(g|\mathbf{x}, s = 1) = \mathbf{x}_1\beta_1 + \gamma\lambda(\mathbf{x}\delta) \tag{11}$$

where $\lambda(\cdot) = \phi(\cdot)/\Phi(\cdot)$ is the inverse Mills ratio. Consistent estimates of β_1 and γ can be obtained by the standard two step procedure.

3.2 The Productivity Race: What the winners tell us?

As we mention in previous section, the transition matrix and the β-convergence test give us a measure of the mobility of firms within the cross section productivity distribution. Now, we are interested in the determinants of this mobility.

Bartelsman and Dhrymes (1998) extended the study by Baily, Hulten, and Campbell (1992) they found that the mobility of firms within the productivity distribution vary across industries and plants' age. We go further and try to evaluate the effect of process innovation, experience, exports, imports, foreign capital and technological diffusion on the mobility of firms within the productivity distribution.

Let $q_{it} = 1, 2, 3, 4, 5$ be the quintile to which firm i belongs to in period t. We define $w_{it} = \mathbf{1}[q_{it} - q_{i,t-1} > 0]$, this is variable takes the value 1 if firm i moves to a higher quintile between t and t-1 and therefore we call it "advance".

The movements across quintiles depends on: (a) the productivity of the firm, (b) the productivity of other firms, and (c) the quantity of firms in the sample. To take into account (a) and (b) we consider the difference between the value of each variable and the industry mean. That is, if firm i belongs to industry j we consider $\tilde{z}_{it} = z_{it} - z_{jt}$ where $z_{jt} = 1/N_{jt} \sum_{i \in j} z_{it}$. To take into account the effect of the quantity of firms in the sample we consider two variables: the quantity of entrants by sector and year and the quantities of exits by sector and year. These variables reflects entry and exit from the sample and not necessary from the industry.

We are interested in estimating

$$\mathbb{P}(w_{it} = 1|\mathbf{x}_{it}, s_{it} = 1) \tag{12}$$

The vector $\mathbf{x}_{it}$ include those variables that make firms likelier to appear in higher quintiles (lagged one period) and the control variables. We consider lagged explanatory variables because the dependent variable represents the change from one year to another in the relative position and that change is the result of the decisions taken by the firms in the previous year.

We expect that the more innovative is a firm, the more experience it has and the more spillover it receives the likelier it appears in higher quintiles. Therefore $\mathbf{x}_{it}$ includes innovation, experience and spillovers, all of them evaluated at t-1.

Firms that make use of new technologies, products or inputs are likelier to appear at higher quintiles. The quantity of imports with respect to sales could be a good indicator of the technology or inputs that the firm uses therefore we include this ratio in $\mathbf{x}_{it}$.

We also include the proportion of foreign capital because firms with a higher proportion of foreign capital could become more productive than the rest, for example, because they could receive spillovers from the firms to which they are affiliated or because they could have better know-how. There could also be a self selection effect because foreign investors may be interested in buying the more productive firms.

The region at which the firms belongs it is another important variable to take into account because some regions can have, for example, better infrastructure. Region can be also a measure of market size or market density. Syverson (2004) found that the more concentrated is the market the more productive are the firms.

The probability of moving to a higher quintile also depends on the previous position. The more extreme example are the firms belonging to the fifth quintile (the most productive firms), they never advance. To indicate the previous position we use the dummies variables $qk_{i,t} = \mathbf{1}[q_{it} = k]$ with $k = 1, 2, 3, 4, 5$.

In all the cases we control by size, industry and year. We also include dummy variables reflecting entry, exit, merger and scission.

$s_{it} = 1$ means that firm i survives between $t-1$ and t.

We do not include an unobserved time invariant individual effect because w_{it} is like the difference in productivity between period t and period t-1 and therefore removes any time invariant individual effect.

4 Empirical Results

4.1 Characterizing the Productivity Dynamics

The first question that we address is how large is the heterogeneity in productivity across firms in the Spanish manufacturing sector. As Bartelsman and Doms (2000) have pointed out for other countries, even within narrowly defined industries the productivity heterogeneity across firms is large. The ratio between the maximum and the minimum productivity level in some industries is above 10. This means that, with the same quantity of inputs, the most productive firm produce 10 times more than the less productive firm. Because this ratio may be affected by extreme values, we also compare the ratio between the minimum productivity in the 10% more productive to the maximum productivity in the 10% less productive by year and sector. This is a very conservative heterogeneity measure because it ignores both the most and the least productive 10% of firms by year and industry. Even with this conservative measure, there are sectors like Non-Metallic Minerals; Agricultural and Industrial Machinery and Textiles, Leather and Shoes that in 1990 have ratios larger than 2.

Figure 1 shows the evolution of the average productivity and the levels of productivity that divide the productivity distribution into quintiles in the 10 considered industries. In general, the productivity distribution does not shrink over time.

We test for a reduction in the variance of productivity across firms for the complete period (1991-1999) and for two sub periods (1991-1994 and 1995-1999). We consider both the complete and the balanced panel to capture the effect of entrants and exiting firms on the productivity dispersion. The test should be carried by industry, however the quantity of observations by industry is small. Therefore we consider deviations from the productivity mean of each industry, if firm i belongs to industry k, we define $p'_{i,t} = p_{i,t} - \frac{1}{N_{k,t}} \sum_{j \in k} p_{j,t}$.

Table 1 shows the T2 and T3 statistics for the complete manufacturing sector both for p and p'. The dispersion of the productivity, both for the complete and balanced panel, does not show a significant variation in any of the considered subperiods. However, the dispersion of the deviation of productivity from the industry mean shows different behavior in each subperiod. The first half of the decade show a significant reduction in the dispersion (σ-convergence) but the second half of the decade shows a significant increase in the dispersion (σ-divergence). The overall effect is a reduction in the dispersion. The results does not change if we consider the balanced panel. Figure 2 shows the evolution of the variance of productivity. This figure confirm the previous results. Between 1991 and 1999 p is practically constant and p' describes an U-shaped trajectory with lower dispersion in 1999. The decrease of dispersion of the deviation of productivity with respect to the industry mean is higher for the firms belonging to the balanced panel. This result indicates that firms that belongs to the same industry and were at the beginning of the period and survive until the end have become more homogeneous in term of productivity.

Now we focus on the mobility of firms within the productivity distribution. Table 2 shows the results of the β-convergence test.

Columns (1), (3) and (5) report the OLS estimation of equation (9) for the complete period and for the two sub periods with $\mathbf{x}_{i,0}$ being the set of size, industry and region dummies. We reject the null hypothesis of no convergence for the three cases. That is, we find that productivity of the less productive firms has grown faster than productivity of the more productive ones. The industry, size and region dummies are significant. The implied speed of convergence for the period 1990-1994 is much higher than the speed of convergence for the period 1995-1999.

Columns (2), (4) and (6) shows the results of the Heckman's two step procedure to control for sample selection. As we anticipate in section 3, to estimate the survival probability we follows Olley and Pakes (1996) by assuming that this probability is a function of age, capital and productivity. We include a third order series approximation of the survival function. We also control for industry, size and region. The estimated coefficient for the initial level of productivity is basically the same than the estimated by OLS.

A common assumption in the literature is that exiting firms are less productive than the survival ones and therefore they drive convergence. We can test the convergence effect of exiting firms by considering their effect on the selection bias. The test for the convergence effect of exiting firm is $H_0 : \gamma = 0$ (Exiting firms do not have effect on the convergence). We have $\mathbb{V}(g|\mathbf{x}, s = 1) = \mathbb{V}(g|\mathbf{x}) = \mathbb{V}(u)$, and so homoscedasticity holds under H_0, moreover, the asymptotic variance of $\hat{\gamma}$ is not affected by $\hat{\delta}$ when $\gamma = 0$. Therefore, a standard t test on $\hat{\gamma}$ is a valid test of the null hypothesis of no selection bias. The coefficient of the inverse Mills ratio (γ) is significant for the complete period but no for any of the subperiods. These finding suggest that exiting firms does not affect the β-convergence results. Only the speed of convergence for the complete period suffer an upward bias of 4.1%.

Less productive firms have had a higher productivity growth rate in all the considered periods but the dispersion of productivity only shows a decrease until 1995. This could be because some followers overtake the original leaders. We see that this is the case by analyzing the transition matrices in Table 3. These transition matrices are constructed considering p'. The transition matrix shows the fraction of firms that make each of the alternative movements among quintiles from one year to another (transition matrix on the left) and between a period of five years (transition matrix on the right). The transition matrices in Table 3 are the average of the corresponding matrices, weighted by the quantity of firms in each year. Approximately 40% of the firms remain in the same quintile one year later and if the firm belongs to the top or bottom quintile these percentage is 10% higher. That is, persistence is higher at the extremes of the productivity distribution. After five years the proportion of firms that remains in the same quintile is smaller, approximately 15%.

Another interesting characteristic of our data is the exiting rate. After one year 12% of the firms exit from our sample (both for death and attrition) and after five years the exiting rate is 50%. Table 3 shows that the exiting firms are not mainly from the less productive firms (quintile 1).

4.2 The productivity Race

We are interested in estimating equation (12) which gives the probability that a firm moves to a higher quintile. As we mention before, we consider as explanatory variables: innovation, experience, spillovers, the ratios imports-sales and export-sales and the proportion of foreign capital. All these variables lagged one period and in deviations from the industry mean. We also include the interaction between the knowledge capital of the firm and the spillovers it receives. This interaction shows whether knowledge capital and spillovers are complementary or substitutes.

All the estimates include dummies indicating the quintile in the previous year, size, year and region.

The first two columns of Table 4 shows the coefficients and the marginal effects resulting from estimating equation (12) by a pooled Probit Model. There is a direct relationship between innovation, experience, imports, foreign capital and the probability of improving the relative position in terms of productivity. Small firms (firms with less than 200 employees) have larger probability of improving their relative position, this is consistent with the catching up process. An important finding is that the probability of improving the relative position in terms of productivity depends on the region. If a firm is located in Asturias, Cataluña, Madrid or Pais Vasco it has higher probability of improving its relative position; however if the firm is located in Murcia it has lower probability of improve it relative position.

Column (3) and (4) shows the results of estimating equation (12) by the linear probability model (LPM). The drawback of the LPM is that it assumes constant marginal effects and that it does not guarantee predicted probabilities in the [0,1] interval. The advantage is that it is easier to estimate when some of the regressors are endogenous. The results from estimating the LPM are qualitative the same as the obtained by the probit model.

Column (3) reports the OLS estimates of the LPM. From the comparison of columns (2) and (3) it is evident that the marginal effect of innovation, imports and foreign capital in the LPM are larger than the ones in the probit. The marginal effect of experience in the LPM is smaller than in the probit model.

We also estimate the LPM considering that innovation, experience, foreign capital and the ratio exports-sales are endogenous the results are shown in column (4). We tested for the endogeneity of these variables and at 5% of significance level we can not reject the exogeneity hypothesis however at 10% of significance we reject the null hypothesis of exogeneity. We instrument the endogenous variables with their lagged values and with the industry mean of each variable. When we estimate the LPM considering innovation, experience, exports and foreign capital as endogenous the marginal effect of experience and foreign capital decreases with respect to the one estimated by OLS and the marginal effect of innovation and imports increases.

The ratio export-sales, the spillovers that the firm receives and the interaction between those spillovers and the firm's knowledge capital have no statistically significant effect on the probability that a firm improves its relative position.

Summarizing, the more innovative is a firm the more likelier it appears in higher quintiles. An innovation in the previous year can increase the probability of moving to a higher quintile in 5%. The role of foreign capital is similar to that of innovation, an increase in the foreign capital of 1% (with respect to the industry mean) implies an increase in the probability of moving to a higher quintile in 4.6%. The effect of experience is smaller but significant, an increase in 1% in the experience with respect to the mean implies an increase in the probability of 1%. The spillovers that a firm receives, its interaction with knowledge capital as well as the export-sales ratio have no significant effect on the probability of moving to a higher quintile. The imports-sales ratio is a proxy for the technology usage or new inputs, the effect of this variable is large. An increase in 1% in the technological usage leads to an increase of around 10% in the probability of moving to higher quintiles.

5 Conclusions

We find large heterogeneity in productivity between firms even within narrowly defined industries. This heterogeneity is persistent, we find that there is no reduction in the variance of firms productivity in the manufacturing sector as a whole. However, once we study deviations from the industry mean we find a reduction in the productivity dispersion. We can distinguish two periods with different evolution of the productivity dispersion; from 1991 to 1994 the dispersion decreases and since 1995 there is an increase in the dispersion. We also find that less productive firms have had a larger productivity growth rate than the more productive ones. This result is robust to the sample selection originated by the exiting firms. Summarizing, until 1995 there is convergence in productivity across firms both in the sense of β and σ and since 1995 there is β-convergence and σ-divergence. These results are consistent with firms changing their relative position in the productivity distribution.

One of the main contributions of the paper is the study of firms' mobility within the productivity distribution. We find that process innovation, experience, foreign capital and the ratio imports-sales increase the probability that a firm improves its relative position. At the same time, we find that the spillovers that a firm receives and the export-sales ratio have no significant effect on that probability.

The paper also has policy implications. We found that the probability that a firm improves its relative position depends on the region in which the firm is located. This finding can be consequence of the market size or density and there could also be spatial spillovers. However, an important cause of these differences could be infrastructure. And therefore there could be place for public policy to improve the firms productivity. This finding also has implications for the firms location decision. Clearly, Asturias, Cataluña, Madrid and Pais Vasco have comparative advantages.

It could be interesting to analyze whether the productivity distribution in the service sector follows a similar pattern than the productivity distribution of manufacturing firms. It could be also interesting to study which are the variables that explain the the mobility of firms within the productivity distribution in the service sector. However with the data set we have these questions can not be addressed.

We find that foreign firms have higher probability of moving to higher quintiles however we do not specify why. There are several possible explanations: they could receive spillovers from the firm to which they are affiliated, there could be a self selection problem if foreign investors buy the most productive firms or simply they may have better know-how. The analysis of foreign firms and their know-how is part of ongoing research.

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Table 1: σ-Convergence Test

	p'			p		
	91-99	91-94	95-99	91-99	91-94	95-99
Complete Panel:						
σ_0^2	0.057	0.054	0.037	0.167	0.161	0.157
σ_T^2	0.042	0.044	0.046	0.158	0.156	0.165
N	349	675	714	349	675	714
T2	7.52***	9.48***	13.37***	0.54	0.43	2.05
T3	3.18***	3.39***	-3.54***	0.51	0.42	-0.84
Balanced Panel:						
σ_0^2	0.056	0.056	0.033	0.167	0.167	0.159
σ_T^2	0.041	0.032	0.041	0.158	0.151	0.158
N	349	349	349	349	349	349
T2	8.83***	32.5***	6.8***	0.54	2.62	0.01
T3	3.49***	7.5***	-2.55***	0.51	1.01	0.04

$H_0 : \sigma_T^2 = \sigma_0^2$; $H_1 : \sigma_T^2 < \sigma_0^2$

When $\hat{\sigma}_T^2 > \hat{\sigma}_0^2$; $H_1 : \sigma_T^2 > \sigma_0^2$ (σ-Divergence Test)

Significance levels: $*$: 10% $**$: 5% $***$: 1%

Table 2: β-Convergence Test

	1991-1999		1991-1994		1995-1999	
	OLS	Heckman 2S	OLS	Heckman 2S	OLS	Heckman 2S
	(1)	(2)	(3)	(4)	(5)	(6)
p_0	-0.101***	-0.100***	-0.168***	-0.168***	-0.074***	-0.074***
	(0.007)	(0.005)	(0.012)	(0.008)	(0.010)	(0.007)
$\lambda(\mathbf{x}\delta)$	-	-0.015**	-	0.002	-	0.008
		(0.007)		(0.018)		(0.012)
N	349	988	675	988	714	1210
Implied β	0.266	0.256	0.279	0.279	0.092	0.092

Notes: Regressions include a constant. Controls: size, industry, region ;
Robust standard errors in brackets.
β is the speed of convergence and is given by $-\log(1+bT)/T$.
Significance levels: $*$: 10% $**$: 5% $***$: 1%

Table 3: Transition Matrix

	One Year Transition Matrix							Five Year Transition Matrix					
	1	2	3	4	5	Exit		1	2	3	4	5	Exit
1	52.1	21.1	8.8	3.0	3.0	12.1	1	16.9	12.2	9.3	7.7	5.9	48.0
2	18.5	36.9	20.4	8.1	3.9	12.2	2	11.6	13.5	12.5	7.5	5.9	49.0
3	7.4	20.3	33.3	20.6	7.0	11.2	3	6.8	12.5	13.2	11.6	8.4	47.3
4	3.3	6.4	20.0	39.1	19.1	12.0	4	2.6	9.1	9.2	14.4	13.2	51.6
5	3.7	4.0	6.5	17.0	53.6	15.2	5	2.7	4.9	6.3	10.7	19.1	56.3

The transition matrices are the average of the corresponding transition matrices weighted by the quantity of firms in each year and are constructed from p'.

Table 4: The mobility of firms within the productivity distribution.

	Probit		Linear Probability Model	
Variable	Coeff	marginal	OLS	GMM
Innovation (t-1)	0.086**	0.009**	0.024**	0.052*
Experience (t-1)	0.043***	0.022***	0.012***	0.009*
Spillover (t-1)	0.134	0.014	0.038	-0.006
Knowledge captital*spillovers	0.000	0.000	0.000	0.000
Imports (t-1)	0.595***	0.061***	0.090***	0.101***
Exports (t-1)	0.104	0.011	0.037	0.020
Foreign capital (t-1)	0.210***	0.004***	0.058***	0.046**
Exit t	-0.006	-0.001	-0.005	0.000
Merger in t-1	0.115	0.013	0.024	0.026
Scission in t-1	0.303	0.040	0.083	0.087
Quantity of innovation (t-1)	0.004	0.000	0.001	0.002
Quantity of entrants (t-1)	-0.003**	-0.0003**	-0.001**	-0.002*
Quantity of exits (t-1)	-0.002	0.000	-0.001	-0.002
Less than 200 employees	0.229***	0.022***	0.060***	0.052***
Aragon	0.209*	0.025*	0.062*	0.061*
Asturias	0.480***	0.071***	0.126***	0.128***
Baleares	0.055	0.006	0.021	0.018
Canarias	-0.040	-0.004	0.011	0.007
Cantabria	0.148	0.017	0.037	0.025
Castilla-Leon	0.156	0.018	0.049	0.065*
Castilla-La Mancha	0.164	0.019	0.057	0.062
Cataluña	0.186**	0.021**	0.060**	0.065**
Extremadura	-0.097	-0.009	0.019	0.022
Galicia	-0.080	-0.008	-0.018	-0.025
Madrid	0.286***	0.035***	0.087***	0.087***
Murcia	-0.349**	-0.027**	-0.100**	-0.112**
Navarra	0.132	0.015	0.042	0.047
Pais Vasco	0.269***	0.033***	0.079***	0.087***
Rioja	0.247	0.031	0.078	0.101*
Valencia	0.029	0.003	0.013	0.025
N	7345	7345	7345	6023

Dependent variable: $w_{it} = \mathbf{1}$[if firm i moves to a higher quintile in period t]
Robust standard errors in brackets.
Controls: Dummies for quintile in t-1 (quintile 1, 2, 3 and 4), year.
Significance levels: $*$: 10% $**$: 5% $***$: 1%

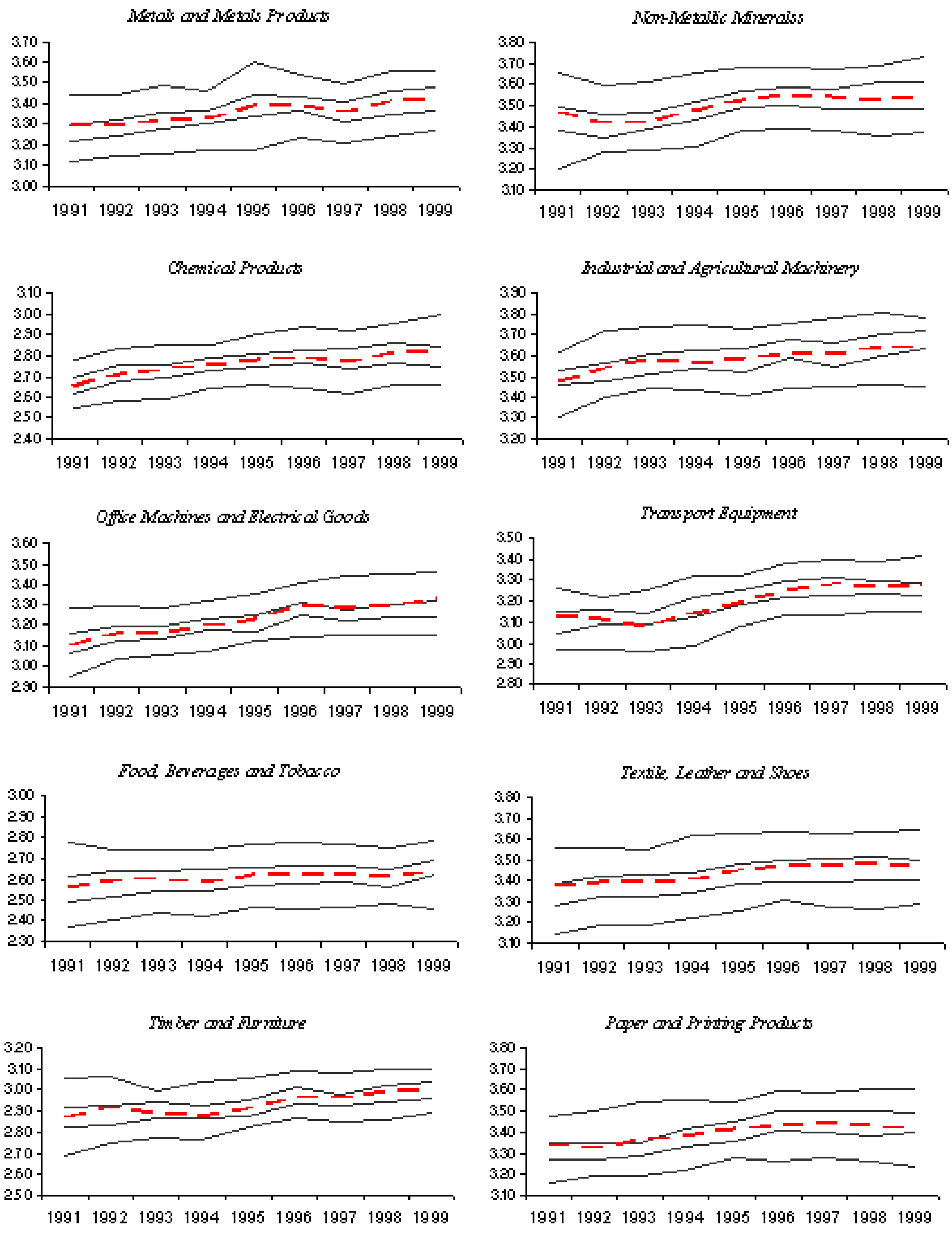

Figure 1: Productivity Evolution by Industry.

Continuous lines divide quintiles and dotted lines are the mean value of each industry.

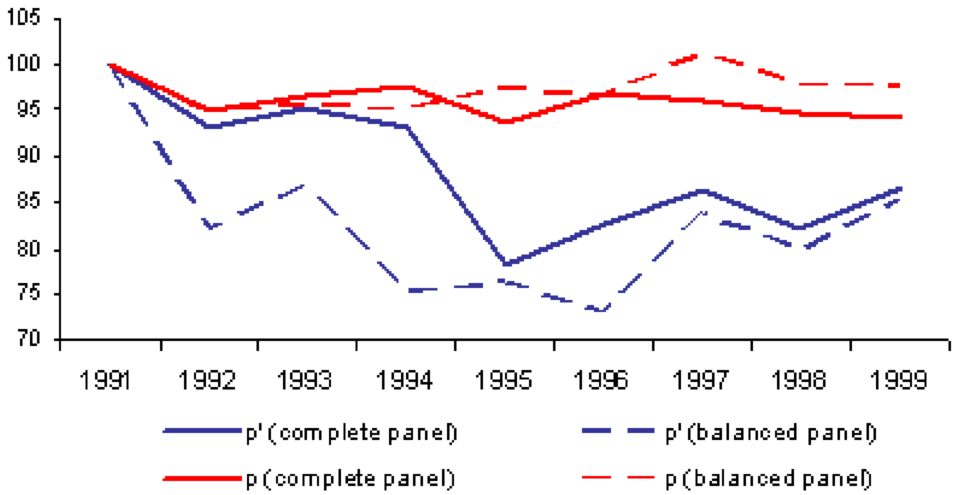

Figure 2: Variance of Productivity (1991=100)