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 examines a large number of Spanish manufacturing firms during the 1990s. We find that less productive firms have had a higher productivity growth rate than the more productive ones. Moreover, examining the dynamics of the productivity distribution, we find an important fraction of firms that started at the bottom of the productivity distribution and end up at the top of the distribution. By using this fact, we propose a simple econometric procedure to evaluate the way in which innovation, experience and technological diffusion affect the mobility of firms within the productivity distribution. In particular, we estimate the probability that a firm achieves a higher quintile as a function of its experience, innovation and the spillovers it receives. We find that the more innovative and the more spillovers the firm receives the more likely achieves higher quintiles.

JEL classification: C23, D24, L16 ,L60.
Keywords: Manufacturing Sector, Productivity dynamics, Innovation, Diffusion.

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1 Introduction

In this paper we analyze the evolution of productivity in a large number of Spanish manufacturing firms during the 1990s with two main interests in mind: the evolution of the productivity distribution and the movements of firms within the cross sectional distribution of productivity.

The literature that has studied the dynamics of plants productivity has mainly tried to answer questions like: Why is the productivity dispersion so large? How does this dispersion evolve over time? Is there a tendency for plants to converge, in their productivity characteristics, either towards the best or worst practice plants, or towards the mean? For example, Baily, Hulten, and Campbell (1992) analyzed the productivity dynamics in the U.S. manufacturing plants over the period 1972-1988. They proposed four possible statistical models that can explain the patterns for plant dynamics. Answering the previous questions helps to understand which of the statistical models represents better the patterns of productivity evolution. By studying a similar date base, Bartelsman and Dhrymes (1998) found that the productivity dynamics vary by industry and plant age.

Most of the papers interested in productivity dynamics rely on the study of transition matrices. These transition matrices show the probability that a plant that was in a certain productivity quantile in an earlier period moves to other productivity quantile in a later period. However, it is also possible to study the productivity dynamics through the classical convergence tests developed by Barro and Sala-i-Martin (1991, 1992) or the convergence approach proposed by Quah (1993a,b). In this branch of the literature are the papers by Oulton (1998), Girma and Kneller (2005), Fung (2005), Nishimura, Nakajima, and Kiyota (2005) and Vivero (2005). However, the convergence results should be interpreted carefully. As Sala-i-Martin (1996) pointed out, the classical beta and sigma convergence test are related but they capture different aspects of the convergence process. On the one hand, \( \sigma \)-convergence relates to whether or not the distribution of productivity across firms shrinks over time; on the other hand, \( \beta \)-convergence relates to the mobility of different firms within the cross section productivity distribution. Therefore, we use the \( \sigma \)-convergence test to study how the productivity distribution evolves over time and the \( \beta \)-convergence test to evaluate the mobility of firms within the productivity distribution.

This paper contributes to productivity dynamics’ literature in two ways. First, by presenting new evidence from another economy different from the U.S. or U.K. and,
secondly, by presenting an econometric method to evaluate the role played by experience, process innovation and technology diffusion in the mobility of firms within the productivity distribution.

The econometric procedure we propose rests on the estimation of the probability that a firm change its relative position as a function of its process innovation, experience, the spillovers it receives and its previous position in the distribution.

We use individual firm data from the "Encuesta sobre Estrategias Empresariales" (ESEE) over the period 1990-1999, obtaining a sample which is representative for the Spanish manufacturing sector. The productivity measure we consider modifies the Solow residual in order to allow for imperfect competition in the goods markets and variable capacity utilization following the approach developed by Hall (1988, 1990).

The descriptive part of the paper can be summarized in the following sentence: The productivity distribution does not shrinks over time but there is considerable mobility within the distribution. This finding is common in the productivity literature that uses micro level data (see Bartelsman and Doms, 2000). We find that the mobility of firms within the distribution is higher in the first half of the decade. However, we can not reject the hypothesis of constant variance of productivity across firms over time for any of the two considered subperiods. What is interesting to note is that the period with the lower mobility coincide with a deceleration in the productivity growth rate of the Spanish manufacturing sector.

Baily, Hulten, and Campbell (1992) claim that the statistical model that describe the productivity dynamics is a mixture between a model with a deterministic trend plus a random shock and a model with permanent plant heterogeneity. The first model leads to no persistence in the productivity distribution and the last one to strong persistence in plant relative productivity. We find that there is persistence in the firms’ productivity distribution; however, there are some firms that change their relative position. We find that process innovation and the spillovers that a firm receive play an important role in the probability that a firm achieve a better relative position in the productivity distribution.

Our results are in line with the previous papers that have studied the Spanish manufacturing firms’ productivity. Huergo and Jaumandreu (2004) find a positive relationship between productivity growth and process innovation and Ornaghi (2006) find that the more spillovers receives a firm the more productive it becomes. Barrios and Strobl (2004) find that technological diffusion is more important than individual experience in order to
explain productivity levels in Spanish manufacturing firms during the 1990s. The main difference between our results and the above mentioned evidence is that we find that the effects of innovation and the spillovers that a firm receives are sufficiently important to make firms more likely to change their 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 firm’s mobility within the productivity distribution. Section 4 presents the empirical results together with robustness checks. Finally, section 5 concludes.

2 Data and Variables

We use individual firm data from the "Encuesta sobre Estrategias Empresariales" (ESEE). The reference population are the manufacturing firms with 10 or more employees. The sample is representative for the Spanish manufacturing sector (see Farinas and Jaimanoudeu, 1999). The filtered sample is an unbalanced panel of 1893 firms and 10941 observations between 1990 and 1999 (for more details see appendix A).

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. This is not a very restrictive assumption and allows to reduce the volatility of the cost shares. We have also 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, the modified Solow residual is

\[
\Delta p_{it} = \Delta y_{it} - s_c^{L_j} \Delta l_{it} - s_c^{M_j} \Delta m_{it} - s_c^{K_j} (\Delta k_{it} + \Delta \kappa_{it})
\]

where \( \kappa \) is the log of the capacity utilization rate, \( s_{X_j}^c = \frac{1}{TN_j} \sum_{t=0}^T \sum_{i \in j} s_{X_{it}}^c \) being \( s_{X_{it}}^c \equiv \frac{w_{x_it} X_{it}}{TC_{it}} \) the cost share of input \( X = L, M \) and \( K \) of firm \( i \) in period \( t \); \( TC_{it} \) is the total cost of firm \( i \) in period \( t \) and \( j \) is the industry to which firm \( i \) belongs to.

Although the mark-up does not appear explicitly in (1), it 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. It is possible to distinguish two sources

\[\text{Productivity levels are obtained by applying the recursive formula } p_{it} = p_{i,t-1} + \Delta p_{it} \text{ with } p_{i0} = y_{i0} - s_c^{L_j} l_{i0} - s_c^{M_j} m_{i0} - s_c^{K_j} (k_{i0} + \kappa_{i0}).\]
in heterogeneity across firms: differences in technology and differences in efficiency. We assume no differences in efficiency by controlling for variable capital utilization.

We are interested in evaluating the effect of process innovation, experience and the spillovers that a firm receives on the firm’s mobility within the productivity distribution.

Innovation is a dummy variable that takes the value one when the firm declare that in the previous year 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.

Experience or learning by doing is the measured by the firm’s age. The alternative of age is the cumulative output of each firm (see Bahk and Gort, 1993; Barrios and Strobl, 2004). The problem with cumulative output is that it can change by other reasons than experience e.g. by changes in the demand.

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

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

where $\delta$ is the depreciation rate of the knowledge capital (15%) and $R_{i,t-1}$ is the R&D expenditures of firm $i$ in period $t - 1$. For the initial value of the knowledge capital we consider $KN_{i0} = \bar{R}_i / (g + \delta)$ where $g$ is the growth rate of R&D (5%) and $\bar{R}_i$ is the time average of firm’s $i$ R&D expenditure.

The spillovers that a firm receives are measured by the weighted capital knowledge of the industry to which firm belongs. If firm $i$ belongs to industry $k$, then the spillovers are defined by $s_{it} = \log S_{it}$ where

$$ S_{it} = \sum_{j \in k; j \neq i} \omega_{ijk} KN_{jt} $$

$\omega_{ijk}$ denotes the weight assigned to firm $j$ knowledge capital stock in the spillover pools available to firm $i$. 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 therefore he defines weights according to firms’ size. We use the same weights as Ornaghi (2006). Table 1 shows the weighting scheme and can be read as follows. Consider the first row; when firm $i$ has less than 20 employees (group 1) can benefit from the entire knowledge capital of other firms in the same size-group (group 1), from half of the knowledge capital of other firms in size-group 2 and from a quarter of the knowledge capital of firms in size-group 3; this
Table 1: Spillovers: Weighting matrix

<table>
<thead>
<tr>
<th>Firm $i$ size group</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.- Less than 21 employees</td>
<td>1</td>
<td>0.5</td>
<td>0.5</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2.- 21 to 50 employees</td>
<td>1</td>
<td>1</td>
<td>0.5</td>
<td>0.5</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3.- 51 to 100 employees</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.5</td>
<td>0.5</td>
<td>0</td>
</tr>
<tr>
<td>4.- 101 to 200 employees</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>5.- 201 to 500 employees</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.5</td>
</tr>
<tr>
<td>6.- More than 500 employees</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Source: Ornaghi (2006), Table 1.2.

A firm cannot take advantage of the research efforts undertaken by large firms (groups 4, 5 and 6).

3 Productivity Dynamics: Methods

3.1 Characterizing the Dynamics

Baily, Hulten, and Campbell (1992) and Bartelsman and Dhrymes (1998) used transition matrices to study productivity dynamics. Firms belonging to the same industry can be ranked by their relative productivity in each year and placed into the corresponding quintiles. Then the transition matrix gives the fraction of firms that make each of the alternative movements among quintiles. We make use of the transition matrices to evaluate productivity dynamics but we also apply the traditional convergence tests developed by Barro and Sala-i-Martin (1991, 1992).

Two comments with respect to the convergence test are necessary. First, it is important to realize that the convergence definition involved in each of these tests is different. As Sala-i-Martin (1996) pointed out, even though the classical beta and sigma convergence test are related, they capture different aspects of the convergence process. In effect, $\sigma$-convergence relates to whether or not the distribution of productivity across firms shrinks over time; and on the other hand, $\beta$-convergence relates to the mobility of different firms within the cross section productivity distribution. Secondly, in our setup it is sensible to ask whether firms should converge in productivity and if so, which kind of convergence we should expect? Jovanovic and MacDonald (1994) present a competi-
tive diffusion model in which under certain conditions follower’s productivity grow faster than leader’s productivity ($\beta$-convergence). The forces that push the population of firms towards convergence in their model are the following: (i) the diffusion of technology that results from the followers’ efforts to imitate the leaders and, (ii) the harder technological search effort by technological followers when they are as efficient as the leaders in finding better technologies.

Barro and Sala-i-Martin (1991, 1992) show that $\sigma$-convergence imply $\beta$-convergence. That is, $\beta$-convergence is a necessary (but not sufficient) condition for $\sigma$-convergence. Therefore we can start by testing $\sigma$-convergence. The convergence definition in this case is the following:

**Definition 1 ($\sigma$-convergence)** There is $\sigma$-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

$$T_2 = (N - 2.5) \ln \left(1 + 0.25 \frac{\sigma_0^2 - \sigma_T^2}{\sigma_0^2 \sigma_T^2 - \sigma_0^2 \sigma_T^2} \right) \xrightarrow{d} \chi^2(1)$$

and

$$T_3 = \sqrt{N} \frac{\sigma_0^2 / \sigma_T^2 - 1}{2 \sqrt{1 - \hat{\pi}^2}} \xrightarrow{d} N(0,1)$$

where $\sigma_{0T}$ 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 $\pi$ in $p_{iT} = \pi p_{i0} + e_i$.

To evaluate the movements of firms within the productivity distribution we apply the $\beta$-convergence test. The convergence definition in this case is the following:

**Definition 2 ($\beta$-convergence)** There is absolute $\beta$-convergence if less productive firms’ productivity tends to grow faster than productivity of the more productive firms.

The convergence hypothesis is tested using the following equation

$$g_{i,T} = a + b p_{i,0} + x_{i,0} \delta + u_{i,T}$$
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 convergence is equivalent to test whether \( b \) is negative. The speed of convergence is given by \( \beta = -\log(1 + bT)/T \).

When there are no controls, \( \mathbf{x}_{i,0} \), a negative \( b \) means that all firms move toward the same steady-state productivity level (absolute convergence). On the other hand, when the controls \( \mathbf{x}_{i,0} \) are present a negative value of \( b \) means that each firm converges to its own steady-state productivity level (conditional convergence).

Special attention needs to paid to the exiting firms. To take into account the effect of these firms we can consider the analysis in Jovanovic (1982), Olley and Pakes (1996) or Syverson (2004). The productivity growth in these models is due to selection across firms. Less productive firms are pushed out of the market. This mechanism is very different than the one operating in Jovanovic and MacDonald’s model in which productivity growth is due to learning.\(^2\)

When the exiting firms are less productive than survival ones, the estimates of equation (6) 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. To estimate this equation we follow Olley and Pakes (1996) and estimate the survival probability as a function of age and capital. Adding the selection equation to equation (6) we get the model

\[
\begin{align*}
g & = \mathbf{x}_1 \beta_1 + u \quad (7) \\
s & = 1[\mathbf{x}\delta + v > 0] \quad (8)
\end{align*}
\]

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 \( 1[\cdot] \) is the indicator function. As is well known, in this model

\[
\mathbb{E}(g|\mathbf{x}, s = 1) = \mathbf{x}_1 \beta_1 + \gamma \lambda(\mathbf{x}\delta) \quad (9)
\]

where \( \lambda(\cdot) = \phi(\cdot)/\Phi(\cdot) \) is the inverse Mills ratio. Consistent estimates of \( \beta_1 \) and \( \gamma \) can be obtained by the standard two step procedure.

\(^2\)The productivity growth mechanism suggested by Jovanovic and MacDonald is close to Schmitz (2005) findings. Schmitz find that, after an increase in competition, the iron ore producers more than double their productivity level. He also finds that this increase in productivity is due to a change in work practices and not due to selection across mines.
3.2 The mobility of firms within the productivity distribution

Bartelsman and Dhrymes (1998) extend the study by Baily, Hulten, and Campbell (1992) finding that the mobility of firms within the productivity distribution vary across industries and age. We go further and try to evaluate the effect of process innovation and technological diffusion on the mobility of firms within the distribution.

We study the way in which process innovation and technological diffusion affect the probability that a firm achieves a higher quintile. Therefore we are interested in estimating

$$P(w_{it} = 1|x_{it}, s_{it} = 1, c_{i}) = \Phi(x_{it}\gamma + c_{i})$$ (10)

where \(w_{it} = 1\) if firm \(i\) moves to a higher quintile in period \(t\). The vector \(x_{it}\) include innovation, experience, spillovers and the previous position of the firm. \(s_{it} = 1\) means that firm \(i\) survives between \(t - 1\) and \(t\).

We allow for an unobserved individual effect, \(c_{i}\), because it could capture managerial capability.

To estimate equation (10) we assume that \(x_{it}\) is strictly exogenous conditional on \(c_{i}\) and \(c_{i}|x_{it} \sim N(\psi + \bar{x}_{i}\xi, \sigma_{a}^2)\) where \(\bar{x}_{i}\) is the average of \(x_{it}\), \(t = 1, 2, \ldots, T\) and \(\sigma_{a}^2\) is the variance of \(a_{i}\) in the equation \(c_{i} = \psi + \bar{x}_{i}\xi + a_{i}\). Under this assumptions we have the Chamberlin’s Random Effects Probit model. As is well known in this model, the consistent estimates of \(\psi_{a}\), \(\gamma_{a}\) and \(\xi_{a}\) can be obtained by a pooled probit of \(y_{it}\) on \(1, x_{it}, \bar{x}_{i}\) with \(\bar{x}_{i} = \sum_{t=1}^{T} x_{it}\).

We test the strict exogeneity of \(x_{it}\) by adding \(x_{i,t+1}\) in equation (11 and checking that the coefficients of \(x_{i,t+1}\) are statistically no significant. Another way to test for the strict exogeneity assumption is applying an incremental Sargan test in the linear probability model.

The Chamberlin’s Random Effect Probit Model have some features that are relevant in our study. First, the assumptions needed to obtain consistent estimators are weaker than the needed in the traditional random effects probit model. Second, it allows for a particular correlation between the unobservable individual effect and the explanatory variables. Finally, it is computationally simple, only involves the estimation of a pooled probit model of \(y_{it}\) on \(1, x_{it}, \bar{x}_{i}\).
4 Empirical Results

4.1 Characterizing the Productivity Dynamics

The heterogeneity in productivity across firms even within narrowly defined industries 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 produces 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 and Textiles or 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 four industries (the other industries show a similar pattern). For example, firms with productivity level less than L1 belongs to the first quintile; firms with productivity level between L1 and L2 to the second quintile and so forth.
Table 2: $\sigma$-Convergence Test

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<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
</tr>
<tr>
<td>All Industries</td>
<td>2.593</td>
<td>1.105</td>
<td>3.510$^\dagger$</td>
<td>1.301$^\dagger$</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Metals and Metals Products</td>
<td>1.234</td>
<td>1.485$^\dagger$</td>
<td>6.023$^\ast$</td>
<td>3.621$^{**}$</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Non-Metallic Minerals</td>
<td>8.478$^{**}$</td>
<td>8.378$^{**}$</td>
<td>12.20$^{**}$</td>
<td>8.003$^{**}$</td>
<td>-</td>
<td>-</td>
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<tr>
<td>Chemical Products</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Agricultural and Ind. Machinery</td>
<td>-</td>
<td>-</td>
<td>1.708</td>
<td>1.609$^\dagger$</td>
<td>0.655</td>
<td>0.899</td>
</tr>
<tr>
<td>Office Mach. and Elect. Goods</td>
<td>-</td>
<td>-</td>
<td>0.063</td>
<td>0.268</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Transport Equipment</td>
<td>1.567</td>
<td>1.943$^\ast$</td>
<td>0.094</td>
<td>0.344</td>
<td>11.42$^{**}$</td>
<td>4.798$^{**}$</td>
</tr>
<tr>
<td>Food, Beverages and Tobacco</td>
<td>1.224</td>
<td>1.307$^\dagger$</td>
<td>2.375</td>
<td>1.680$^\ast$</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Textile, Leather and Shoes</td>
<td>7.177$^{**}$</td>
<td>3.435$^{**}$</td>
<td>1.989</td>
<td>1.616$^\dagger$</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Timber and Furniture</td>
<td>5.171$^\ast$</td>
<td>6.915$^{**}$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Paper and Printing Products</td>
<td>-</td>
<td>-</td>
<td>0.850</td>
<td>1.205</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

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

When $\hat{\sigma}_T^2 > \hat{\sigma}_0^2 ; H_1 : \sigma_T^2 > \sigma_0^2$ ($\sigma$-Divergence Test) these cases are represented by "-".

Significance levels: $\dagger$: 10% $^\ast$: 5% $^{**}$: 1%

Figure 1 shows that the productivity distribution does not shrink over time. This result is confirmed by testing for a reduction in the variance ($\sigma$-convergence). Some authors criticize this kind of test arguing that the sample variance can increase or decrease depending on the starting point. We test for a reduction in the variance of productivity across firms for the complete period (1990-1999), and for two sub periods (1990-1994 and 1995-1999).

Table 2 shows the T2 and T3 statistics for the complete manufacturing sector and by industry. Table 2 shows the test statistics only for those industries that display a reduction in the sample variance. In general, Table 2 shows no significant reduction of the variance in any of the considered periods. Only Non-Metallic Minerals, Textile, Leather and Shoes and Timber and Furniture show a decreasing variance for the complete period. Moreover, there are sectors that show divergence. Office Machinery and Electronic Goods shows divergence for the complete decade (stronger for the second half).
Table 3: β-Convergence Test

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<td></td>
<td>OLS</td>
<td>Heckman 2S</td>
<td>OLS</td>
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<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>$p_0$</td>
<td>-0.080**</td>
<td>-0.080**</td>
<td>-0.154**</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.006)</td>
<td>(0.010)</td>
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<tr>
<td>$\lambda(x\delta)$</td>
<td>-</td>
<td>0.003</td>
<td>-</td>
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<tr>
<td></td>
<td>(0.022)</td>
<td>(0.043)</td>
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Selection:

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<tbody>
<tr>
<td>$k$</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td>0.066†</td>
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<tr>
<td></td>
<td>(0.045)</td>
<td>(0.046)</td>
<td></td>
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<td></td>
<td>(0.037)</td>
</tr>
<tr>
<td>age</td>
<td>-0.003</td>
<td></td>
<td>0.003</td>
<td></td>
<td>-0.004†</td>
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<tr>
<td></td>
<td>(0.003)</td>
<td></td>
<td>(0.003)</td>
<td></td>
<td>(0.002)</td>
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<tr>
<td>$p_0$</td>
<td>-0.080</td>
<td></td>
<td>-0.382†</td>
<td></td>
<td>-0.285</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.216)</td>
<td></td>
<td>(0.219)</td>
<td></td>
<td>(0.192)</td>
<td></td>
</tr>
</tbody>
</table>

Number of Obs. 222 599 425 599 725 1192

Implied β 0.149 0.150 0.255 0.218 0.086 0.087

Notes: Regressions include a constant. Controls: size, industry, region ;
Standard errors in brackets.
Significance levels: †: 10%  *: 5%  **: 1%

Now we focus on the mobility of firms within the productivity distribution. Table 3 shows the results of the β-convergence test.

Columns (1), (3) and (5) report the OLS estimation of equation (6) for the complete period and for the two sub periods with $x_{i,0}$ 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. In the selection equation, following Olley and Pakes (1996),
Table 4: Transition Matrix

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.59</td>
<td>0.24</td>
<td>0.09</td>
<td>0.04</td>
<td>0.04</td>
<td></td>
<td>1</td>
<td>0.42</td>
<td>0.27</td>
<td>0.15</td>
<td>0.10</td>
</tr>
<tr>
<td>2</td>
<td>0.22</td>
<td>0.40</td>
<td>0.24</td>
<td>0.09</td>
<td>0.05</td>
<td></td>
<td>2</td>
<td>0.29</td>
<td>0.30</td>
<td>0.23</td>
<td>0.11</td>
</tr>
<tr>
<td>3</td>
<td>0.09</td>
<td>0.23</td>
<td>0.37</td>
<td>0.23</td>
<td>0.08</td>
<td></td>
<td>3</td>
<td>0.13</td>
<td>0.27</td>
<td>0.24</td>
<td>0.25</td>
</tr>
<tr>
<td>4</td>
<td>0.04</td>
<td>0.08</td>
<td>0.23</td>
<td>0.43</td>
<td>0.23</td>
<td></td>
<td>4</td>
<td>0.04</td>
<td>0.06</td>
<td>0.24</td>
<td>0.43</td>
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<tr>
<td>5</td>
<td>0.04</td>
<td>0.04</td>
<td>0.08</td>
<td>0.21</td>
<td>0.62</td>
<td></td>
<td>5</td>
<td>0.03</td>
<td>0.07</td>
<td>0.14</td>
<td>0.21</td>
</tr>
</tbody>
</table>

we consider that survival probability is a function of capital, age and productivity. We also control for industry, size and region. The estimated coefficient for the initial level of productivity is basically the same than the OLS estimates.

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 $V(g|\mathbf{x}, s = 1) = V(g|\mathbf{x}) = V(u)$, 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 ($\gamma$) is no significant in any of the considered periods. These finding suggest that exiting firms does not affect the $\beta$-convergence results.

Less productive firms have had a higher productivity growth rate but there is no significative reduction in dispersion. This could be because some followers overtake the original leaders. We see that this is the case by analyzing the transition matrices in Table 4. The one year transition matrix shows the fraction of firms that make each of the alternative movements among quintiles from one year to another. The five year transition matrix shows the same movements but considering the average productivity in each half of the decade. They both present persistence; approximately 40% of the firms remain in the same quintile one year later and if the firm belongs to the extremes these percentage is 20% higher. However, there is a non negligible fraction of firms that move to other quintile.
Table 5: The mobility of firms within the productivity distribution.

<table>
<thead>
<tr>
<th>Model</th>
<th>Testing Exogeneity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameters</td>
<td>Marginal Effects</td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>innovation in t-1</td>
<td>0.095 *</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
</tr>
<tr>
<td>spillovers in t-1</td>
<td>0.127 **</td>
</tr>
<tr>
<td></td>
<td>(0.042)</td>
</tr>
<tr>
<td>age</td>
<td>0.018</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
</tr>
<tr>
<td>innovation in t</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>spillovers in t</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>8973</td>
</tr>
<tr>
<td>Pseudo $R^2$</td>
<td>0.175</td>
</tr>
</tbody>
</table>

Dependent variable: $w_{it} = 1$[if firm $i$ moves to a higher quintile in period $t$]

Robust standard errors in brackets.

Controls: Quintile in t-1, size, sector, year and $\bar{x}_i$.

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

4.2 Firms’ mobility within the productivity distribution

We are interested in the effect of process innovation, experience and spillovers on the probability that a firm achieves higher quintiles.

Table 5 shows the results of estimating equation (10) by the Chamberlin’s Random Effect Probit Model. We control by the quintile in the previous year, size, sector, year and region. This table shows that process innovation and the spillovers that a firm receives are important to improve the position in the productivity distribution. For example, if a firm introduces a process innovation, the probability of improving its relative position in the productivity distribution increases by 3%. The spillovers that a firm receives increase the probability of improving the relative position by 4%. The absorptive capability of the firm is implicit in the way in which the spillovers are measured.

These results are consistent with previous findings for the Spanish manufacturing
firms. For example, Huergo and Jaumandreu (2004) found that processes innovation increase the productivity growth and Ornaghi (2006) found that the more spillovers receives a firm the more productive it becomes. It is important to note, that our findings suggest that these effects are sufficiently large to make firms more likely to change their relative position.

Table 5 also shows that experience plays no role in achieving higher quintiles. This finding is also consistent with previous studies for the Spanish manufacturing firms. Barrios and Strobl (2004) find that the effect on the productivity growth of the spillovers that a firm receives are more important than that of the individual experience.

These findings helps to improve the understanding of the productivity dynamics. Baily, Hulten, and Campbell (1992) suggest that the statistical model that explain the productivity dynamics is a deterministic trend for productivity (that can vary across firms) plus a random shock. Table 5 shows that the statistical model also has to take into account innovation and spillovers.

The estimates of Table 5 are only valid under the assumption of strict exogeneity of innovation, spillovers and experience. Experience is measured by age and therefore it is exogenous. The exogeneity test for innovation in t-1 and spillovers in t-1 consist in add one lead of these variables and check that these leads are statistically no significant. Column (3) and (4) of Table 5 show the estimated parameters and the marginal effects when we add a lead for innovation and spillovers. It is possible to note that, after controlling for the unobservable effect, both innovation and spillovers in period t are statistically no significant. Then, the estimates of equation (10) in column (1) and the corresponding marginal effects are consistent.

Another way to test the exogeneity of innovation in t-1 and spillovers in t-1 is through the linear probability model. First, estimate equation (10) by first difference GMM assuming that $x_{it}$ is predetermined and therefore using $(x_{it-2}, x_{it-3})$ as instruments. Second, assume that $x_{it}$ is exogenous and therefore it is also possible to include $x_{i,t-1}$ in the set of instruments. If the incremental Sargan test can not reject the hypothesis that $x_{i,t-1}$ is a valid instrument, then $x_{i,t}$ is exogenous. By applying this procedure we can not reject that innovation in t-1 and spillovers in t-1 are strictly exogenous in equation (10).

Summarizing, if a firm has introduced a process innovation in the previous year, it has larger probability of achieve a better position in the productivity distribution. The
spillovers that a firm receive also increase the probability of achieving better position. In
the firms’ mobility within the distribution experience is not as important as innovation
or technological diffusion.

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. However, we 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. These results are consistent with
firms changing their relative position in the distribution.

One of the main contributions of the paper is the method we propose to evaluate the
effect of innovation, experience and spillovers on the firm’s mobility within the produc-
tivity distribution. We find that process innovation increases by 3% the probability of
improving the relative position. The spillovers that a firm receives are also important
for improving the relative position, they increase the probability of achieving a higher
quintile by 4%.

A Data and Variable Definitions

A.1 Data Base and Sample Selection

We use individual firm data from the "Encuesta sobre Estrategias Empresariales" (ESEE).
The reference population are the manufacturing firms with 10 or more employees. The
sample is representative for the Spanish manufacturing sector (see Fariñas and Jaumand-
dreu, 1999). All the firms with more than 200 employees are requested to participate and
firms with more than 10 but less than 200 employees are sampled randomly by industry
and size strata. Exits from the sample are both by death and attrition.

Following Huergo and Jaumandreu (2004), who have used the same data set, we
aggregate firms in ten industries (see Table 6). Firms that change from activity sector
were eliminated from the sample because productivity in different moments it is not
comparable for these firms. We also restrict the sample to firms with observations in at
least three consecutive years. This is choice is standard in the literature. The cleaned
### Table 6: Industry definition

<table>
<thead>
<tr>
<th>Industry</th>
<th>ESSE classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Ferrous and Non-Ferrous Metals and Metal Products</td>
<td>1+4 Ferrous and Non-Ferrous Metals + Metal Products</td>
</tr>
<tr>
<td>2 Non-Metallic Minerals</td>
<td>2 Non-Metallic Minerals</td>
</tr>
<tr>
<td>3 Chemical Products</td>
<td>3+17 Chemical Products + Rubber and Plastic Products</td>
</tr>
<tr>
<td>4 Agricultural and Industrial Machinery</td>
<td>5 Agricultural and Industrial Machinery</td>
</tr>
<tr>
<td>5 Office and Data-Processing Machines and Electrical Goods</td>
<td>6+7 Office and Data-Processing Machines + Electrical Goods</td>
</tr>
<tr>
<td>6 Transport Equipment</td>
<td>8+9 Motor Vehicles + Other Transport Equipment</td>
</tr>
<tr>
<td>7 Food, Beverages and Tobacco</td>
<td>10+11+12 Meats, Meat Preparation + Food Products and Tobacco + Beverages</td>
</tr>
<tr>
<td>8 Textile, Leather and Shoes</td>
<td>13+14 Textiles and Clothing + Leather, Leather and Skin Goods</td>
</tr>
<tr>
<td>9 Timber and Furniture</td>
<td>15 Timber, Wooden Products</td>
</tr>
<tr>
<td>10 Paper and Printing Products</td>
<td>16 Paper and Printing Products</td>
</tr>
</tbody>
</table>

Source: Huergo and Jaumandreu (2004)

The sample is an unbalanced panel of 1506 firms and 8868 observations between 1990 and 1999.

### A.2 Variables:

Output (Y): Goods and services production in real terms. The nominal output corresponds to sales plus the variation of inventories. They are deflated using the firm’s specific price index. This price index is Paasche type price index computed with the price variation that each firm reports.

Total effective worked hours (L): Obtained by multiplying the hours of work per employee by the number of employees.

Capital (K): Is recursively estimated from an estimated initial value and the equipment investment actualized by a price index of capital goods and using sectoral estimates of the depreciation rate. For more details see Martín-Marcos and Suárez (1997).

Capital usage cost (r): Weighted sum of long term interest rate with banks and other
Table 7: Quantity of observations by year and industry

<table>
<thead>
<tr>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Metals and Metals Products</td>
<td>68</td>
<td>110</td>
<td>131</td>
<td>136</td>
<td>148</td>
<td>157</td>
<td>152</td>
<td>187</td>
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<td>1414</td>
</tr>
<tr>
<td>Non-metallic Minerals</td>
<td>38</td>
<td>62</td>
<td>80</td>
<td>86</td>
<td>90</td>
<td>91</td>
<td>92</td>
<td>90</td>
<td>80</td>
<td>67</td>
<td>776</td>
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<td>Chemical Products</td>
<td>75</td>
<td>113</td>
<td>138</td>
<td>144</td>
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<td>155</td>
<td>175</td>
<td>162</td>
<td>135</td>
<td>1412</td>
</tr>
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<td>Agricultural and Ind. Machinery</td>
<td>34</td>
<td>47</td>
<td>57</td>
<td>61</td>
<td>64</td>
<td>67</td>
<td>72</td>
<td>80</td>
<td>75</td>
<td>66</td>
<td>623</td>
</tr>
<tr>
<td>Office Mach. and Elect. Goods</td>
<td>60</td>
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<td>104</td>
<td>102</td>
<td>100</td>
<td>105</td>
<td>98</td>
<td>114</td>
<td>100</td>
<td>88</td>
<td>959</td>
</tr>
<tr>
<td>Transport Equipment</td>
<td>46</td>
<td>66</td>
<td>82</td>
<td>81</td>
<td>76</td>
<td>74</td>
<td>70</td>
<td>79</td>
<td>70</td>
<td>65</td>
<td>709</td>
</tr>
<tr>
<td>Food, Beverages and Tobacco</td>
<td>109</td>
<td>145</td>
<td>181</td>
<td>196</td>
<td>193</td>
<td>196</td>
<td>193</td>
<td>191</td>
<td>176</td>
<td>149</td>
<td>1729</td>
</tr>
<tr>
<td>Textile, Leather and Shoes</td>
<td>98</td>
<td>153</td>
<td>189</td>
<td>192</td>
<td>195</td>
<td>183</td>
<td>189</td>
<td>206</td>
<td>191</td>
<td>165</td>
<td>1761</td>
</tr>
<tr>
<td>Timber and Furniture</td>
<td>39</td>
<td>64</td>
<td>84</td>
<td>89</td>
<td>87</td>
<td>72</td>
<td>74</td>
<td>91</td>
<td>86</td>
<td>76</td>
<td>762</td>
</tr>
<tr>
<td>Paper and Printing Products</td>
<td>32</td>
<td>62</td>
<td>77</td>
<td>85</td>
<td>88</td>
<td>90</td>
<td>93</td>
<td>100</td>
<td>93</td>
<td>76</td>
<td>796</td>
</tr>
<tr>
<td>Total</td>
<td>599</td>
<td>910</td>
<td>1123</td>
<td>1172</td>
<td>1199</td>
<td>1192</td>
<td>1188</td>
<td>1313</td>
<td>1207</td>
<td>1038</td>
<td>10941</td>
</tr>
</tbody>
</table>

long term debt plus a 15% depreciation rate minus the investment deflator.

Capacity utilization ($\kappa$): Yearly average rate of capacity utilization reported by firms.

Materials (M): Intermediate consumption deflated by a materials price index. This price index is a Paasche-type price index computed starting from the percentage variations in the price of purchased materials, energy and services reported by the firms.

Productivity: Explained in section 2.

Process Innovation: Explained in section 2.

Experience: Explained in section 2.

Spillovers: Explained in section 2.

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pa n i e s , ” O x f o r d E c o n o m i c P a p e r s , 5 0 ( 1 ) , 2 3 – 3 8 .

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Q u a h , D . ( 1 9 9 3 b ) : “ G a l t o n ’ s F a l l a c y a n d T e s t o f t h e C o n v e r g e n c e H y p o t h e s i s , ” S c a n d i-


