# What determines productivity dynamics at the firm level? Evidence from Spain

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**Abstract**

The current literature on firm dynamics considers the mobility of firms within the productivity distribution to be determined by exogenous random shocks. This paper evaluates human capital and learning by doing as possible factors determining the mobility once the exogenous shocks have taken place. The main contribution of the paper is to provide evidence on the endogenous mobility of firms within the productivity distribution.

**JEL Classification:** C51; D24; L60.
**Key words:** Productivity dynamics; Human Capital; Learning by Doing.

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# 1 Introduction

A recent study by Stucchi and Escribano (2007) finds mobility in the relative positions of productivity levels among Spanish manufacturing firms during the 1990s. This finding is important because changes in the distribution of individual productivity levels affects not only aggregate productivity, but also firm's entry and exit decisions. In the current literature on firm dynamics (see Jovanovic, 1982; Hopenhayn, 1992), changes in the relative positions of productivity levels are the result of random productivity shocks. Firms face individual productivity shocks and based on these shocks they decide to enter or exit the market. In this paper I find that the mobility of firms within the productivity distribution depends on firms' characteristics and strategic decision variables. In particular, I find that human capital and learning by doing affect the mobility within the productivity distribution, even after controlling for size, age, entry, exit, merger, scission, year and region. This finding is important not only from an empirical point of view. It also implies that theoretical models of firm dynamics should endogenize changes in the distribution of productivity among firms.

The closest empirical attempt that deal with the determinants of firms' mobility within the productivity distribution is Bartelsman and Dhrymes (1998). These authors analyze the transition matrix of plants' productivity for different groups of firms and find that older and larger plants tend to be more stable in the sense that they do not change their relative position in terms of productivity as much as newer and smaller plants. In this paper I go further and propose an econometric procedure to evaluate the way in which human capital and learning by doing affect the mobility of firms within the productivity distribution.

The rest of the paper is organized as follows. Section 2 explains the empirical methodology. Section 3 presents the results. Finally, section 4 concludes.

# 2 The empirical strategy

The mobility of firm $i$ within the productivity distribution depends on its productivity relative to the productivity of other firms. Therefore I consider variables in deviation from the industry mean. Thus, if firm $i$ belongs to industry $j$ I consider $\tilde{z}_{it} = z_{it} - \bar{z}_{jt}$ where $\bar{z}_{jt} = 1/N_{jt} \sum_{i \in j} z_{it}$. Let $p_{it}$ be the Total Factor Productivity (TFP) of firm $i$ in period $t$ in logs. The relevant variable to study firms' mobility within the productivity distribution is the change in $\tilde{p}_{it}$, $\Delta\tilde{p}_{it}$. Positive (negative) values of $\Delta\tilde{p}_{it}$ reflect that firm $i$ improved (worsen) its relative position. Therefore, the mobility of firms within the industry productivity distribution and its determinants can be analyzed by

$$\Delta\tilde{p}_{it} = \alpha'_{Mz}\tilde{\mathbf{z}}_{i,t-1} + \alpha_{Mp}\tilde{p}_{i,t-1} + \alpha'_{Mc}\mathbf{c}_{it} + \varepsilon_{it}, \tag{1}$$

where $\tilde{\mathbf{z}}_{i,t-1}$ is a vector that includes human capital (HC), learning by doing (LBD), and age, all in deviations from the industry mean and lagged one period. In Appendix A I present and discuss the definition of each variable. The use of predetermined explanatory variables is justified because the change in the firm's relative position in period $t$ is the result of decisions taken in previous periods.

The lag of the productivity deviation with respect to the industry mean captures the persistence in firms' relative position. The vector $\mathbf{c}_{it}$ is a set of control variables that includes dummies for entry, exit, merger, scission, size, year and region. Notice that industry dummies are not needed because variables are in deviations from the industry mean.

To analyze upward and downward mobility I follow a similar approach to the one used by Jianakoplos and Menchik (1997) in their study of wealth mobility. Let $T_{it}$ be a dummy variable that take value one if firm $i$ moves to quintile 5 (Top quintile) in period $t$ and $B_{it}$ a dummy variable that takes value 1 if firm $i$ moves to quintile 1 (Bottom quintile) in period $t$. Quintiles are defined within each industry. The following probit models determine the probability that a firm moves to the top and bottom quintiles, respectively:

$$\begin{aligned} P(T_{it} = 1|\tilde{\mathbf{z}}_{i,t-1}, \mathbf{q}_{i,t-1}, \mathbf{c}_{it}) &= \Phi(\alpha'_{Tz}\tilde{\mathbf{z}}_{i,t-1} + \alpha'_{Tq}\mathbf{q}_{i,t-1} + \alpha'_{Tc}\mathbf{c}_{it}), \quad (2) \\ P(B_{it} = 1|\tilde{\mathbf{z}}_{i,t-1}, \mathbf{q}_{i,t-1}, \mathbf{c}_{it}) &= \Phi(\alpha'_{Bz}\tilde{\mathbf{z}}_{i,t-1} + \alpha'_{Bq}\mathbf{q}_{i,t-1} + \alpha'_{Bc}\mathbf{c}_{it}), \quad (3) \end{aligned}$$

where $\Phi(\cdot)$ is the normal cumulative distribution function, $\mathbf{q}_{i,t-1}$ is a vector that includes dummies for the quintile in which firm $i$ was in period $t-1$. Both equations include dummies for quintile 2, 3, and 4. Equation (2) does not include quintile 5 because firms in top do not move to top. Because of the same reason, equation (3) does not include quintile 1.

# 3 Empirical Results

I use individual firm data from the "Survey on Business Strategies" (ESEE) which is an annual survey of a representative sample of Spanish manufacturing firms conducted by Fundación SEPI.[1] The time period considered is 1991-1999. The number of firms in the sample is 2,338 and the number of observations is 12,828.[2]

The literature (see Bartelsman and Doms, 2000) has documented high persistence in firms' productivity and the Spanish manufacturing firms are not the exception. Table 1 shows that around 40% of the firms remain in the same quintile one year later. Moreover, persistence at the extremes of the distribution is even higher. One year before exiting the market, these firms were mainly at the bottom quintile of the productivity distribution. Similarly, new entrants enter the market with with lower productivity that incumbents. These results confirm the findings in Fariñas and Ruano (2005) who applied non parametric techniques to evaluate the implications of Hopenhayn's (1992) model of firm dynamic.

The question I want to address in the paper is whether human capital and learning explain part of the mobility of firms within the productivity distribution. Figure 1 provides an intuitive answer. This figure depicts the cumulative distribution (cdf) of the residual term of equation (1) estimated

[1]See *http://www.funep.es/esee/ing/i_esee.asp* for details.

[2]I follow five rules for dropping firms or observations: (i) firms that change from one industry to another; (ii) observations with negative value added or negative intermediate consumption, (iii) observations with ratios labor cost to sales or material cost to sales larger than one, (iv) observations in which the firm reports an incomplete exercise and is not the year in which the firm leaves the market, and (v) observations for which is no possible to compute productivity (or was possible only for one year) because the firm does not report all the necessary information.

Table 1: Within industries transition matrix

| | | Quintile t+1 | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | Exit |
| Quintile t | 1 | 0.531 | 0.224 | 0.069 | 0.043 | 0.032 | 0.102 |
| | 2 | 0.220 | 0.367 | 0.228 | 0.078 | 0.041 | 0.066 |
| | 3 | 0.077 | 0.221 | 0.344 | 0.230 | 0.071 | 0.058 |
| | 4 | 0.030 | 0.092 | 0.227 | 0.421 | 0.178 | 0.052 |
| | 5 | 0.033 | 0.035 | 0.072 | 0.178 | 0.619 | 0.063 |
| | Entry | 0.086 | 0.043 | 0.039 | 0.023 | 0.044 | |

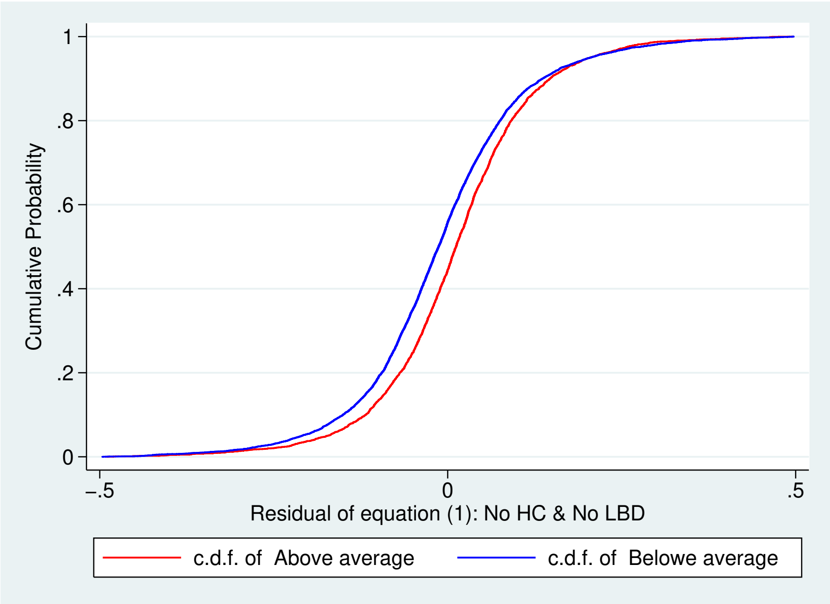
(i) The transition matrix is the average of the transition matrix of each year weighted by the quantity of firms in each year.
(ii) The fraction of exiting firms is with respect to the number of firms in t-1 and the fraction of entering firms is with respect to the number of firms in period t.

without including human capital and learning by doing as explanatory variables.[3] These residuals show the mobility that is not explained by size, age, entry, exit, merger, scission, year or region. Figure 1 compares four groups of firms: Panel (a) compares the cdf of the residual term of firms with higher human capital than the industry mean with the cdf of the residual term of firms lower human capital than the industry mean, and Panel (b) does the same for firms with higher or lower learning by doing than the industry mean. The cdf of the firms with above-average human capital is to the right of the cdf of the firms with below-average human capital (i.e., there is first-order stochastic dominance). This means that after controlling for age, size, entry, exit, merger, scission, year and region, human capital still plays a role in explaining the mobility of firms within the productivity distribution. Panel (b), by contrast, does not exhibit first-order stochastic dominance,[4] so it seems to show that the effect of learning by doing is concentrated in the lower tail of the mobility distribution.

[3]This regression is not displayed in Table 2.

[4]The cdf of above-average LBD crosses the cdf of below-average LBD.

Panel (a): Human Capital.




Panel (b): Learning by doing.

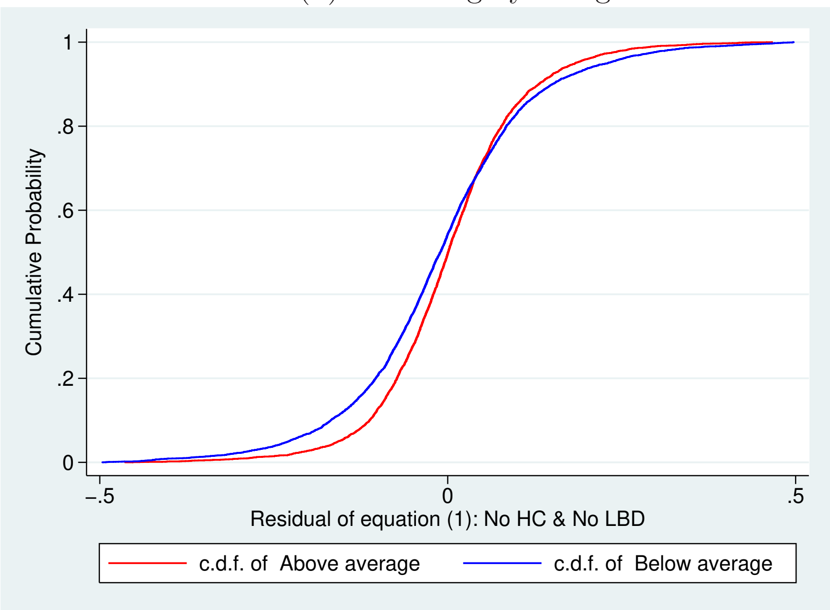



Figure 1: The mobility effect of human capital and learning by doing.

Table 2 shows the results of estimating equations (1), (2) and (3). For each equation I consider two models: (i) one with human capital and learning by doing (Benchmark model); and (ii) another, excluding learning by doing (No LBD model). Column [1] in Table 2 shows the Benchmark model. The firms that improve their relative position are those with larger human capital and learning by doing than the average firm in their industries. Larger and older firms show lower mobility confirming Bartelsman and Dhrymes' (1998) findings.

The estimates of equations (2) and (3) (columns [3] and [5]) show that human capital increases the probability of moving to the top and does not reduce the probability of falling to the bottom. By contrast, learning by doing reduces the probability of falling to the bottom and does not increase the probability of moving to the top. The last finding confirms the intuition behind Panel (b) in Figure 1 in the sense that learning by doing produces upward mobility by reducing the probability of falling at the bottom of the productivity distribution.

The effect of human capital on mobility is clear. Firms with larger human capital may easily adopt new technologies and therefore increase their productivity which lead them to move up in the productivity distribution and eventually achieve the top of the productivity distribution. The result that shows that human capital does not reduce the probability of falling to the bottom could be the consequence of large heterogeneity in firms' data.[5]

The effect of learning by doing is less clear and deserves special attention.

[5]Note that the coefficient of human capital in equation (3) is negative but statistically not significant.

Table 2: The mobility of firms within the productivity distribution

| | Equation (1) | | Equation (2)$^{(a)}$ | | Equation (3)$^{(a)}$ | |
|---|---|---|---|---|---|---|
| | **Benchmark** | **No LBD** | **Benchmark** | **No LBD** | **Benchmark** | **No LBD** |
| | [1] | [2] | [3] | [4] | [5] | [6] |
| Human Capital in t-1$^{(b)}$ | 0.222*** | 0.267*** | 0.161*** | 0.155*** | -0.031 | -0.104** |
| Learning by Doing in t-1$^{(b)}$ | 0.013*** | | -0.002 | | -0.016*** | |
| Age in t-1$^{(b)}$ | -0.000*** | 0.000*** | 0.000 | 0.000 | 0.000*** | -0.000*** |
| Medium | -0.001 | 0.021*** | 0.005 | 0.001 | 0.003 | -0.022*** |
| Large | -0.014*** | 0.023*** | -0.006 | -0.012** | 0.002 | -0.039*** |
| Exit | -0.025** | -0.027*** | 0.018 | 0.019 | 0.047*** | 0.051*** |
| Entry | 0.014*** | 0.004 | 0.021** | 0.023*** | -0.004 | 0.009 |
| Merger | 0.019** | 0.019* | 0.018 | 0.019 | -0.011 | -0.010 |
| Scission | -0.044* | -0.040* | 0.076* | 0.075* | 0.077** | 0.071 |
| Productivity in t-1$^{(b)}$ | -0.399*** | -0.388*** | | | | |
| Quintile 2 in t-1 | | | 0.055*** | 0.055*** | 0.268*** | 0.264*** |
| Quintile 3 in t-1 | | | 0.112*** | 0.111*** | 0.131*** | 0.121*** |
| Quintile 4 in t-1 | | | 0.256*** | 0.253*** | 0.070*** | 0.061*** |
| Observations | 10295 | 10295 | 10295 | 10295 | 10295 | 10295 |
| $R^2$ (or pseudo $R^2$) | 0.22 | 0.21 | 0.14 | 0.14 | 0.19 | 0.18 |

All regressions include a constant and year and region dummies. Robust standard errors.
Significance levels: $*$: 10% $**$ : 5% $***$: 1%
Notes:
(a) The reported estimates for Equation (2) and Equation (3) are the marginal effects.
(b) Deviation from the industry mean.

The benchmark model shows, as expected, that larger and older firms are less dynamic. Moreover, it also shows that older firms have larger probability of falling to the bottom of the distribution which is consistent with vintage capital models. However, when learning by doing is omitted (model No LBD in Table 2) the sign of age and the size dummies get reversed implying that mature and large firms are more dynamic and have lower probability of falling to the bottom.[6] These findings are counter intuitive and are in contrast with previous evidence (see Bartelsman and Dhrymes, 1998; Fariñas and Ruano, 2005). This suggest that the factor driving upward mobility and that reduces the probability of falling to the bottom of the productivity distribution is learning by doing and not size or age.

Table 1 shows that at the moment of entry, newly created firms have lower productivity than incumbents. However, the estimates in Table 2 point out that entrants show more mobility and have larger probability of moving to the top of the productivity distribution. Note that the entry dummy takes value 1 in all the years in which the firm is in the market and not only in the entry year. The definition of exit is analogous. Exiting firms have a larger probability of falling to the bottom of the productivity distribution. This confirm the finding in Table 1 that shows that one year previous to exit the market exiting firms were mainly in the bottom quintile. Scission increases both the probabilities of achieving the top and falling to the bottom. This means that scission take place between the more and less productive firms.

[6]The change in the sign is due to omission bias when excluding learning by doing since this variable is correlated with size and age.

## 4 Concluding remarks

The main contribution of the paper is to relate the mobility of firms within the productivity distribution to human capital and learning by doing. Bartelsman and Dhrymes (1998) find that the mobility of firms within the productivity distribution depends on firms' age and size. This paper confirms their findings and provides evidence that the mobility within the productivity distribution is also a function of firms' strategic decisions.

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# A Variable Definitions

**Total Factor Productivity:** Solow residual using cost shares and corrections for variable capacity utilization. If firm $i$ belongs to industry $j$, the log of its productivity is given by

$$\log P_{ijt} = \log Y_{ijt} - s^c_{L_j} \log L_{ijt} - s^c_{M_j} \log M_{ijt} - s^c_{K_j} \left(\log K_{ijt} + \log \kappa_{ijt}\right) \quad (4)$$

with $\kappa$ being the yearly average capacity utilization rate reported by each firm, $s^c_{X_j} = \frac{1}{TN_j} \sum_{t=0}^{T} \sum_{i \in j} s^c_{X_{it}}$ the cost share of input $X = L$ (labor), $M$ (materials) and $K$ (capital) of firm $i$ in period $t$. This measure rests on the following assumptions: (i) cost shares are constant over time and industry specific, and (ii) constant returns to scale.

**Human Capital:** Fraction of engineers and workers with a college degree.

**Age:** The age of the firm is the difference between the current year and the year of birth declared by the firm.

**Learning by doing:** Following Bahk and Gort (1993), as proxy for learning by doing I use the cumulative output of each firm. The difference with their measure is that I estimate the initial level of cumulative output of firms that have been born before entering the sample. The advantage of this approach is that it does not introduce a firm unobserved component. This advantage is particularly important because equations (2) and (3) are nonlinear and the fixed effect estimator is not consistent. In order to estimate the initial level I add up the previous production until the year of birth, assuming a constant output growth rate of 1.8%, which is the average growth rate of the Spanish industrial production over 1975-1999. I consider this period because the average age of firms in 1991 is 16.4 years.

**Entry:** Time invariant dummy variable that takes value 1 if the firm has entered the market after 1991.

**Exit:** Time invariant dummy variable that takes value 1 if the firm leads the market after 1991.

**Merger:** Dummy variable that takes value 1 when the firm is involved in a merger operation.

**Scission:** Dummy variable that takes value 1 when the firm is involved in a scission operation.

**Size:** There categories. Firms with more than 200 employees (Large firms) and firms with less than 200 but more that 50 employees (Medium size firms) and firms with less than 50 employees (Small firms).

**Industry:** Eleven industries according to NACE classification. This classification gives a reasonable balance between homogeneity and the number of observations within each industry (see Huergo and Jaumandreu, 2004).

**Region:** Five regions. Madrid, Catalonia, Basc Country, Valencia and rest of Autonomous Communities. This classification is according with the firms' headquarters. I also classified firms by region taking into account the number of employees and the results are robust because there are many one plant firms.