Human Capital and Productivity Dynamics: Evidence from Spanish manufacturing firms

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Human capital and productivity dynamics: Firm level evidence from Spanish manufacturing firms [1]

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Abstract

This paper uses firm level data from Spanish manufacturing firms to provide evidence on the effect of human capital on the mobility of firms within the productivity distribution. We find that while larger and older firms are more prone to stay in the same relative position, human capital is an important factor driving upward mobility both for incumbents and newly created firms. In fact, firms with higher proportion of engineers and workers with a university degree are more likely to reach the top of the productivity distribution.

JEL Classification: C51; D24; L60.

Keywords: Productivity dynamics; Human Capital

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1. Introduction

Although several studies found that human capital is an important determinant of the level of firms' productivity–see, for example, Abowd et al. 1999, Abowd et al 2005, Haskel et al. 2005, or Fox et al 2011[4]—the way in which it affects the dynamics of productivity is a less explored issue. Understanding the role of human capital on the dynamics of firms' productivity is important both for firms and policy makers. From the firm perspective, knowing the determinants of this dynamic might help them to develop their strategy toward becoming more productive. From the policy maker perspective, this information might help them to design more effective policies aimed at increasing productivity. In fact, in developing countries several policies provide incentives for firms to hire workers with advanced degree because by doing this it is expected to transfer knowledge to firms and therefore to increase their productivity. At the macro level, the dynamic of firms' productivity is also important; it affects the aggregate productivity of the economy and therefore the level of output and welfare of the population. In spite of the importance of the determinants of the mobility of firms within the productivity distribution, most of the literature studying the dynamics of firms' productivity has focused on the effect of entrants and exiting firms (see, for example, Foster et al 1998 or Foster et al 2008). Fariñas and Ruano (2005) and López-Garcia (2008) presented evidence on the dynamics of firms productivity in Spain focusing on entrant and exiting firms. Fariñas and Ruano (2005) studied the implications of Hopenhayn's (1992) model of firm dynamics using nonparametric techniques and the same dataset we use in this paper. They find that the productivity

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[4] Fox et al. 2011 show that accounting for human capital and the wage bill decreases the productivity ratio of the 90th to the 10th productivity quintiles from 3 to 2.5.

distribution of continuing firms stochastically dominates the distribution of entrants and exiting firms. At the same time, they find that the productivity of entrants grows at higher rates implying upward mobility in the productivity distribution. An early attempt to deal with the determinants of firms' mobility within the productivity distribution is Bartelsman and Dhrymes (1998) who studied the transition matrix of US manufacturing plants' productivity over the period of 1972-1986. Considering different groups of plants, they 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.

We extend previous literature in two directions. First, we consider both categorical and continue variables. Our approach is therefore more flexible than the one used in Bartelsman and Dhrymes (1998) who focused on the transition matrix for different group of firms. Second, we focus on the effect of human capital on the mobility of firms within the productivity distribution controlling for firm specific characteristics like age or size, and whether the firm entered o exited the market during the 1990s.

Using data from the Survey on Business Strategies (*Encuesta sobre Estrategias Empresariales, ESEE*), which provides a representative sample of the Spanish manufacturing sector between 1991 and 1999, we find that: (i) Larger and older firm are more prone to stay in the same relative position. This finding corroborates the findings in Bartelsman and Dhrymes (1998). (ii) Entrants have higher productivity growth than incumbents. This finding confirms that Fariñas and Ruano (2005) findings are valid even after controlling for firms' characteristics. (iii)

Human capital is an important factor driving upward mobility in the productivity distribution both for incumbents and newly created firms.

The rest of the paper is organized as follows. Section 2 describes the dataset and presents some descriptive statistics. Section 3 explains the empirical methodology. Section 4 presents the results. Finally, section 5 concludes.

2. Data and descriptive statistics

We use individual firm level data from the Survey on Business Strategies (*Encuesta sobre Estrategias Empresariales, ESEE*) which is an annual survey of a representative sample of the Spanish manufacturing sector conducted by Fundación SEPI. In this survey, all the firms with more than 200 employees in the first year (1990) were asked to participate and firms with 10 to 200 employees were sampled randomly by industry and size strata. The rate of participation reached approximately 70% and 5% of the population of firms within these size categories. Another important feature of the survey is that in the years after 1990 the initial sample properties have been maintained. Newly created firms have been added annually with the same sampling criteria as in the base year. Within the sample, exits could stem from either shutdown or non-reporting. Therefore, the data set is an unbalanced panel of firms. Even though the first year of the survey is 1990, we decided to use the information from 1991 to 1999 because the data corresponding to 1990 is not perfectly comparable with that of subsequent years. We classify firms in eleven industries according to the NACE classification. This classification gives a reasonable balance between homogeneity and the number of observations within each

industry (See Huergo and Jaumandreu 2004). The sample is an unbalanced panel of 2,110 firms and 12,238 observations.[5]

The main variable of interest in this paper is a firm's productivity. To compute the log of firm i's productivity in period t, p_{it}, we consider the most standard Total Factor Productivity (TFP) measure based on Solow's residuals, i.e.,

$$p_{it} = y_{it} - \alpha_l \, l_{it} - \alpha_m \, m_{it} - \alpha_k \, (k_{it} + \kappa_{it}), \tag{1}$$

where y is the log of output, l, m, and k are the log of labor, materials, and capital respectively, κ is the log of the annual average capacity utilization rate reported by each firm, and α_x ($x=l$, m, k) are input-output elasticities. Output is measured by the value of produced goods and services deflated using the industrial production price index. Labor input is measured by the total of hours worked, materials are measured by the value of intermediate consumption deflated using the industrial production price index, and capital by the firm's value of the capital stock deflated using the price index of investment in equipment goods. To measure the input-output elasticities we use industries' average cost shares over the total sample period.[6]

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[5] To select the sample for the empirical analysis we follow six rules. First, we exclude firms that change from one industry to another because productivity in different moments of time is not comparable for those firms. Second, we exclude firms with merger or scission. Third, we exclude observations with negative value added or negative intermediate consumption. Fourth, we exclude observations with ratios of labor cost to sales or material cost to sales larger than one. Fifth, we exclude the observation when the firm reports an incomplete exercise in a year different than the one in which it leaves the market. Finally, we exclude the observation when the firm does not report all the information needed to compute productivity or only provides that information for one year.

[6] Alternatively, the input-output elasticities can be obtained estimating the production function applying, for example, the methods proposed by Olley and Pakes (1996) and the following papers dealing with the structural identification of productivity (see, Levinsohn and Petrin 2003 and Ackerberg et al 2006). We do not follow this alternative because these methods assume that a firm's productivity follows an exogenous Markov process and in this paper we are interested in the determinants of this Markov process. Doraszelski and Jaumandreu (2012) extend

This productivity measure rests on two assumptions. The first one is of constant cost shares by industry and over time. This is the same assumption used to estimate industries' production functions. The second assumption is constant returns to scale. We are confident of this assumption because several papers (see, Alonso and Sanchez 2001, Doraszelski and Jaumandreu 2012) tested it using the same dataset and did not find evidence against it.

Measuring productivity in this way provides us with a productivity measure that is general enough to allow for imperfect competition in the output market and variable capacity utilization. With respect to imperfect competition in the output market, although the mark-up does not appear explicitly in equation (1), it is constructed using cost shares and therefore does not assume perfect competition (Hulten 2001). With this measure we also control for the effect of variable capacity utilization on firms' productivities.

The other important variable in this paper is human capital. We measure human capital by the proportion of engineers and workers with a college degree as reported by firms. Table 1 shows the descriptive statistics of the variables we use in the analysis.

[Table 1 here]

A well-documented fact in the productivity literature is that a firm's productivity is highly persistent (Bartelsman and Doms 2000); this means that after one year, a large proportion of the firms remain in the same relative position in terms of productivity. Spanish manufacturing

the previous methods allowing for an endogenous Markov process. However, even in this much more flexible set up, only one productivity determinant is allowed.

firms are not the exception. Table 2 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 (10% higher at the bottom and 20% higher at the top of the distribution). This table also shows the relative position of entrants and exiting firms. As can be seen in the last column, one year before exiting the market, exiting firms were mainly at the bottom quintile of the productivity distribution. Similarly, the last row shows that new entrants entered the market with lower productivity than incumbents.

[Table 2 here]

3. The empirical strategy

Studying the mobility of firms within the productivity distribution involves studying changes in a firm's relative position in terms of productivity. The relative position of firm i within the productivity distribution depends on its productivity and the productivity of the rest of the firms in the industry. Therefore, to measure the relative position we consider the deviation from the industry mean, i.e., if firm i belongs to industry j, its relative position in terms of productivity is given by

$$\tilde{p}_{it} = p_{it} - \bar{p}_{jt},\tag{2}$$

where p_{it} is the log of firm i's total factor productivity in period t defined in equation (1) and $\bar{p}_{jt}$, is the industry j's average of the log of firms' productivity in period t. Then, the relevant variable to study firms' mobility within the productivity distribution is the change from t-1 to t in $\tilde{p}_{it}$, $\Delta \tilde{p}_{it}$,. Positive (negative) values of $\Delta \tilde{p}_{it}$ reflect that firm i improved (worsened) its

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relative position. Therefore, the relationship between the mobility of firms within the industry productivity distribution and its determinants can be analyzed through the following simple regression model

$$\Delta \tilde{p}_{it} = \alpha'_{Mz} \tilde{z}_{i,t-1} + \alpha_{Mp} \tilde{p}_{i,t-1} + \alpha'_{Mc} c_{i,t-1} + \epsilon_{it} \qquad (3)$$

where $\tilde{z}_{i,t-1}$ is a vector that includes human capital and age, both in deviations from the industry mean and lagged one period. 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, $\tilde{p}_{i,t-1}$, captures the persistence in firms' relative position. The vector $\tilde{c}_{i,t-1}$ is a set of control variables that includes dummies for entry, exit, size, year and region, and the proportion of foreign capital. Notice that industry dummies are not needed because variables are in deviations from the industry mean.

As mentioned in the introduction, the closest approach to deal with the mobility of firms within the productivity distribution is Bartelsman and Dhrymes (1998) who analyze the transition matrix of different groups of plants. The main advantage of estimating equation (3) is that it allows a more ample consideration of variables as well as any kind of variables as determinants of firms' mobility within the productivity distribution.

In addition to the study of the mobility of firms within the productivity distribution, we are also interested in the characteristics of firms that achieve the top distribution and in the characteristics of firms that fall at the bottom. These are low probability events (6.18% of firms achieved the top and 6.71% fell at the bottom) however they have strong implications that make them worth studying. Becoming a firm at the top of the productivity distribution may imply improvements in the future market position. On the other hand, Table 2 shows that firms at the bottom of the productivity distribution have a higher probability of exiting the market. To analyze these events we 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 takes the 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:

$$P\big(T_{it} = 1 \big| \tilde{z}_{i,t-1}, q_{i,t-1}, c_{i,t}\big) = \Phi\big(\alpha'_{Tz}\tilde{z}_{i,t-1} + \alpha_{Tq}q_{i,t-1} + \alpha'_{Tc}c_{i,t}\big), \tag{4}$$

$$P\big(B_{it} = 1 \big| \tilde{z}_{i,t-1}, q_{i,t-1}, c_{i,t}\big) = \Phi\big(\alpha'_{Bz}\tilde{z}_{i,t-1} + \alpha_{Bq}q_{i,t-1} + \alpha'_{Bc}c_{i,t}\big), \tag{5}$$

where $\Phi(\cdot)$ is the normal cumulative distribution function, $q_{i,t-1}$ 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 (4) does not include quintile 5 because firms at the top do not move to top. Because of this same reason, equation (5) does not include quintile 1. Therefore,

the reference firms in equations (4) and (5) are those in the bottom and top quintile, respectively.

4. Empirical Results

4.1 The mobility of firms within the productivity distribution

Table 3 shows the results of estimating equation (3). Column [1] in Table 3 shows that the firms with larger human capital than the average firm in the industry improved their relative position in the productivity distribution.

Column [1] also shows that larger and older firms improved their position. This result is counterintuitive and contrary to previous evidence. To further understand the latter result we consider the effect of learning-by-doing; a variable that is highly correlated with age and size and omitted in this specification.

The literature has found that learning-by-doing, or firm experience, is also important for productivity (Syverson 2011). Benkard (2000), for example, shows that the number of worker hours an airplane manufacturer required to build an airplane was halved by the 30th plane, and again by the 100th. He also conveys that the experience stock is transient, with some "forgetting" plausible and steep learning curves with the introduction of new products.

[Table 3 here]

To measure learning-by-doing we follow a similar approach to Bahk and Gort (1993) who used the cumulative output from firm's birth to the current period. One challenge when measuring the cumulative output is to measure the cumulative output from birth to the first year in the sample for those firms who entered the sample after their first year. Bahk and Gort (1993) assumed that firms were born several years ago and they considered a constant growth of output and an infinite horizon to add past output until the first year in the sample. We refined their method by adding output only until the year of birth. In order to estimate the initial level of cumulative output we therefore 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. We consider this period because the average age of firms in 1991 is 16.4 years.

Our measure of learning-by-doing is correlated with firm age and size and therefore when it is not included in the estimation of equation (3) there is a bias due to omitted variables. After the inclusion of learning-by-doing in the estimation of equation (3) in column [2] the omitted variables bias is corrected and the results verify the expected findings by Bartelsman and Dhrymes (1998). Indeed, column [2] shows that larger and older firms are prone to stay in the same relative position and therefore they do show lower mobility.

4.2 The probability of reaching the top and falling at the bottom

Table 4 shows the estimates of equations (4) and (5). Column (1) shows that human capital increases the probability of moving to the top. This finding is robust to the inclusion of the additional learning-by-doing control, as seen in Column (2).

Moreover, the estimate of equation (5) in column [3] shows that human capital decreases the probability of falling to the bottom. However, this finding is not robust to the inclusion of the learning-by-doing control. Therefore, we can conclude that when a firm is trying to achieve the cutting-edge productivity that characterizes the top quintile the level human capital is most important. However, when considering what might prevent a firm from falling to the bottom experience, or learning-by-doing, is what matters most.

[Table 4 here]

4.3 The dynamics of entrants

Table 2 showed that at the moment of entry, newly created firms had lower productivity than incumbents. The estimates in Table 3, pointed out that while initial productivity is lower entrants do show higher productivity growth rates and they improve their relative position in the productivity distribution. Fariñas and Ruano (2005) find similar results analyzing the productivity growth distribution of entrants and incumbents. Similarly, Table 4 also showed

that entrants have larger probability of moving to the top of the productivity distribution and exiting firms of falling at the bottom of the productivity distribution.[7]

The dynamics of entrants is interesting and can be seen graphically. Figure 1 shows the location of entrants in the TFP distribution in the entry year, one, two, three and four years after entry (t0, t0+1, t0+2, t0+3 and t0+4). This figure shows the fraction of entrants that moved from the lower quintiles to the higher quintiles and the fraction of entrants that exit the market. In the entry year, entrants were less productive than incumbents; they were concentrated in lower quintiles. At the fourth year after entry, the percentage of entrants in quintiles 2, 3, 4 and 5 of the productivity distribution was almost equal and only quintile 1 have a larger proportion of entrants (5% more). This finding confirms Faniñas and Ruano (2005) in the sense that entrants increased their productivity at a higher rate than incumbents. We also did the same exercise in the size distribution. Interestingly, the fraction of entrants that moved from lower to higher quintiles was larger in the productivity distribution than in the size distribution. This means that entrants showed more persistence in terms of size than in terms of productivity. Survival of newly created firms was related to size and productivity. Entrants that failed were small or medium-sized firms. In the sample, none of the entrants that failed was large in terms of employment and only one was in the top quintile of sales.[8]

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[7] Entry and exit dummies take value 1 in all the years in which the firm is in the market and not only in the entry and exit year.

[8] The proportion of entrants that failed provides information on the level of competition in the industry. The industry in which there were more entrants that failed was textiles, an industry that faces strong foreign competition.

One important question for our paper is whether human capital also drives mobility of entrants. To answer this question we estimate equations (3), (4), and (5) on the subsample of firms that entered the market between 1991 and 1999. Table 5 shows the results of these estimations. This table shows that the effect of human capital –both in terms of mobility and probability of achieving the top and falling at the bottom—for entrants is similar than the effect for the rest of firms.

[Figure 1 here]

5. Conclusions

This paper studied the dynamics of the productivity of Spanish manufacturing firms and its main contribution is in relating the mobility of firms within the productivity distribution to human capital.

The main findings of the paper can be summarized as follows: (i) Human capital helps firms to improve their relative position in terms of productivity. (ii) Learning-by-doing also contributes to improve the relative position in terms of productivity. (iii) Age and size are negatively correlated to productivity dynamics. (iv) Human capital is important to achieve the top of the productivity distribution. (v) Experience helps firms to prevent them from falling to the bottom of the productivity distribution. (vi) Entrants are more dynamic than incumbents. (vii) Human capital also plays an important role on the dynamics of entrants.

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Table 1: Descriptive statistics

	Mean	S.D.	Min	Max
Productivity	1.53	0.27	0.54	3.41
Human capital	0.03	0.06	0	0.88
Learning-by-doing (in logs)	11.47	2.35	4.84	19.07
Age in years	22.66	20.32	0	100
Size dummies				
Small firms	0.55	0.50	0	1
Medium-sized firms	0.16	0.36	0	1
Large firms	0.30	0.46	0	1
Region dummies				
Catalonia	0.26	0.44	0	1
Madrid	0.14	0.34	0	1
Basque country	0.07	0.26	0	1
Asturias	0.02	0.14	0	1
Other regions	0.51	0.49	0	1
Industry dummies				
Metals and metals products	0.13	0.34	0	1
Non-metallic minerals	0.07	0.26	0	1
Chemical products	0.12	0.33	0	1
Agricultural and industrial machinery	0.05	0.22	0	1
Office machinery and electrical goods	0.09	0.28	0	1
Transport equipment	0.06	0.24	0	1
Food, beverages and tobacco	0.16	0.37	0	1
Textile, leather, and shoes	0.15	0.36	0	1
Timber and furniture	0.06	0.24	0	1
Paper and printing products	0.08	0.26	0	1
Other manufactured products	0.02	0.15	0	1
Entry	0.15	0.35	0	1
Exit	0.06	0.23	0	1

Table 2: Transition matrix for firms' productivity

		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	0.043	0.023	0.044	

Notes: (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.

Table 3: The mobility of firms within the productivity distribution

	Equation (3)	
	[1]	[2]
Human capital in t-1 [(b)]	0.260***	0.213***
	[0.0402]	[0.0392]
Learning-by-doing in t-1 [(b)]	-	0.0118***
		[0.00148]
Age in t-1 [(b)]	0.00030***	-0.00023***
	[7.64e-05]	[8.73e-05]
Large firms	0.00874**	-0.0181***
	[0.00344]	[0.00435]
Exit	-0.0298***	-0.0264***
	[0.0100]	[0.00997]
Entry	0.00222	0.0132**
	[0.00536]	[0.00547]
R-squared	0.21	0.22
Number of observations	9,867	9,867

Notes: (i) All regressions include a constant, year and region dummies, and the proportion of foreign capital, (ii) Robust standard errors, (iii) Significance levels: *, **, and ***, 10, 5, and 1%, respectively.
(b) Deviation from the industry mean.

Table 4: The probability of achieving the top or falling to the bottom

	Equation (4)		Equation (5)	
	[1]	[2]	[3]	[4]
Human capital in t-1 (b)	0.159***	0.163***	-0.110**	-0.0381
	[0.0371]	[0.0375]	[0.0541]	[0.0462]
Learning-by-doing in t-1 (b)	-	-0.00119	-	-0.0148***
		[0.00178]		[0.00164]
Age in t-1 (b)	7.98E-05	0.000131	-0.000498***	0.000252*
	[0.000117]	[0.000138]	[0.000135]	[0.000139]
Exit	0.019	0.0186	0.0506***	0.0441***
	[0.0117]	[0.0117]	[0.0139]	[0.0131]
Entry	0.0215**	0.0202**	0.0112	-0.00173
	[0.00860]	[0.00878]	[0.00700]	[0.00577]
Large	-0.0151***	-0.0127**	-0.0241***	0.00741
	[0.00473]	[0.00590]	[0.00471]	[0.00725]
Quintile 2 in t-1	0.0565***	0.0566***	0.271***	0.274***
	[0.0106]	[0.0106]	[0.0145]	[0.0147]
Quintile 3 in t-1	0.113***	0.113***	0.118***	0.128***
	[0.0119]	[0.0119]	[0.0122]	[0.0128]
Quintile 4 in t-1	0.258***	0.260***	0.0640***	0.0728***
	[0.0145]	[0.0145]	[0.0110]	[0.0117]
Pseudo R-square	0.14	0.14	0.18	0.19
Number of observations	9,867	9,867	9,867	9,867

Notes: (i) Reported values are marginal effects evaluated at the mean (ii) All regressions include a constant, year and region dummies, and the proportion of foreign capital, (iii) Robust standard errors, (iv) Significance levels: *, **, and ***, 10, 5, and 1%, respectively.
(b) Deviation from the industry mean.

Table 5: The dynamics of entrants

	Equation (3)		Equation (4)		Equation (5)	
	[1]	[2]	[3]	[4]	[5]	[6]
Human capital in t-1 (b)	0.155**	0.139**	0.163**	0.169***	-0.173	-0.107
	[0.0690]	[0.0699]	[0.0653]	[0.0650]	[0.113]	[0.0908]
Learning-by-doing in t-1 (b)	-	0.00687	-	-0.0057	-	-0.0287***
		[0.00492]		[0.00520]		[0.00519]
Age in t-1 (b)	0.00188*	0.00111	0.00236***	0.00297***	0.00122	0.00393***
	[0.000978]	[0.00110]	[0.000863]	[0.00101]	[0.00111]	[0.00118]
Exit	-0.0313	-0.0297	0.0279	0.0276	0.0757*	0.0693*
	[0.0315]	[0.0313]	[0.0323]	[0.0324]	[0.0416]	[0.0408]
Large	0.0172	-0.00071	0.0467	0.0766	-0.0516***	-0.0191
	[0.0148]	[0.0182]	[0.0377]	[0.0555]	[0.0107]	[0.0281]
Productivity in t-1 (b)	-0.298***	-0.302***	-	-	-	-
	[0.0325]	[0.0339]				
Quintile 2 in t-1	-	-	0.0792***	0.0804***	0.377***	0.403***
			[0.0271]	[0.0273]	[0.0400]	[0.0415]
Quintile 3 in t-1	-	-	0.142***	0.148***	0.212***	0.256***
			[0.0332]	[0.0348]	[0.0384]	[0.0433]
Quintile 4 in t-1	-	-	0.258***	0.270***	0.145***	0.184***
			[0.0416]	[0.0435]	[0.0401]	[0.0457]
R-squared (or pseudo R-squared)	0.18	0.18	0.16	0.16	0.20	0.23
Number of observations	1,374	1,374	1,374	1,374	1,374	1,374

Notes: (i) Reported values are marginal effects evaluated at the mean (ii) All regressions include a constant, year and region dummies, and the proportion of foreign capital, (iii) Robust standard errors, (iv) Significance levels: *, **, and ***, 10, 5, and 1%, respectively.
(b) Deviation from the industry mean.

Figure 1: Productivity dynamics of entrants. Percentage of entrants between 1991 and 1995
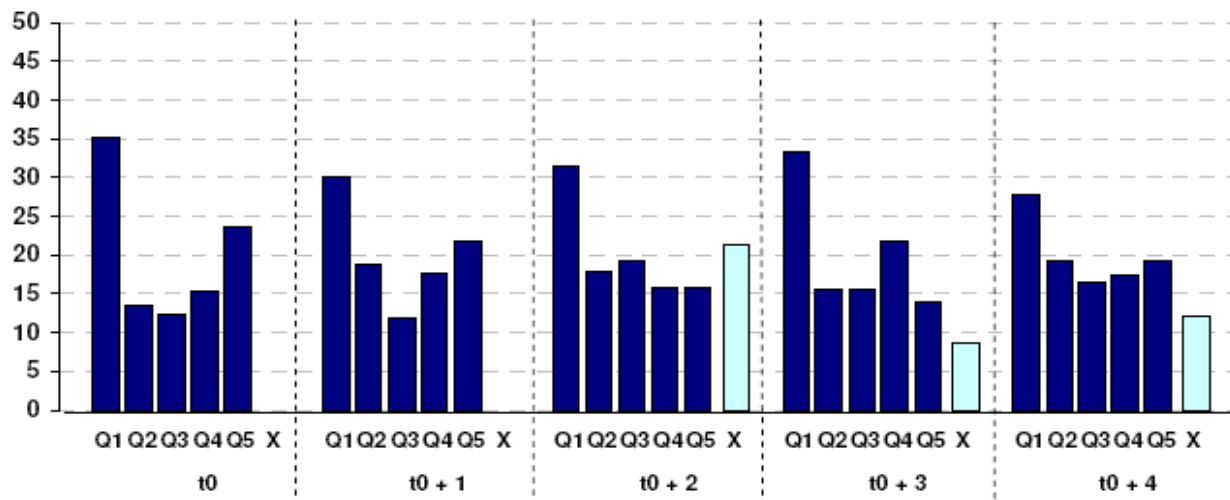
Notes: t0 is the entry year; Qi means quintile i; and X indicates exiting firms. In t0 and t0+1 there are no exits because a condition for being in the sample is providing information at least for two consecutive years.