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Learning by Doing and Spillovers:

Evidence from Firm-Level Panel Data

por

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Abstract

We extend the Bahk and Gort (1993) approach of testing for the impact of learning by doing (LBD) on firm productivity using data on a panel of Spanish manufacturing firms over the 1990-1998 period. While our results indicate evidence in support of the role of LBD, we show that this hinges on controlling for unobservable time invariant firm specific effects. Our results also suggest that spillovers from the accumulated experience within an industry can enhance firms' productivity, especially for established firms. Moreover, the level of embodied technology can improve the learning experience of some firms but only through firms' experience.

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1. Introduction

Economists have long taken an interest in the ability of firms to learn by experience, a process commonly referred to as learning by doing (LBD), as it is often viewed as a major source of technical change and productivity growth. Accordingly, as firms age, they are likely to improve in their productive efficiency over time by 'learning' from their experience of operating in the market. Understanding how this process takes place not only allows one to understand how productivities of firms change and industries evolve over time, but may also provide a key for explaining why even within narrowly defined industries, firms' productivities appear to differ so widely.

Although attempts at empirically quantifying the importance of LBD for firms' productive efficiency can be traced back to the early part of the last century, the actual logistics of it are, however, still very much under scrutiny and unresolved[1]. The earlier empirical studies on LBD took a rather stringent view of the process by implicitly or explicitly assuming that the level of technology was the same across firms, so that firms benefited relatively only from differences in their accumulated experience in the market, but not from relative advantages in their embodiment of general technology and know-how. Clearly, however, sunk costs and barriers to access will prevent some firms from instantaneously adopting the latest know-how and technology. Bahk and Gort (1993) using data on US manufacturing firms have since provided evidence that even after allowing for difference in the embodied technology of physical and human capital across firms, LBD is still important. In addition, Jensen et al. (2001) show using similar data that both factors, older firms' greater experience and the adoption of the newest technology by new entrants, are important determinants of productivity within industries. The previous authors also show that both elements push productivity to converge between old and new plants. Moreover, evidence from the literature on firm survival seems to indicate that firms' growth dynamics may be contingent on the state of technology and level of innovative activity within their industry. In particular, Audretsch (1991 and 1995) shows that firm survival and post-entry growth strongly depend on industry's conditions and particularly on the existing state of technology and the dynamics of innovative activity. That is, in highly innovative industries firms need to be especially innovative to have any chance of success.

As a consequence, one can naturally argue that the learning process derived from the accumulated experience of operating in the market may not just be

[1] See for example Arrow (1962) and Sheshinski (1967) for an overview of the first empirical studies on LBD.

internal, as such knowledge may 'spill' across firms' boundaries, so that the importance of internal LBD may be overestimated. Specifically, as experience within an industry rises, firms may be able to some extent to 'imitate' experiences of other firms rather than gain it solely through their own history. There are few recent case-studies that have attempted to disentangle such spillover effects from internal LBD although the evidence remains inconclusive. For instance, Thornton and Thompson (2001) studying wartime shipbuilding in the US find that learning spillovers were a significant source of productivity growth. Similarly, Gruber (1998) concluded that positive cross-firm spillovers were important in the production of erasable programmable read only memories. In contrast, Irwin and Klenow's (1994) study of the production of dynamic random memory chips find little evidence of LBD spillovers. Nevertheless, if there are spillovers then not controlling for them may bias the estimates of internal LBD.

In this paper we study the various facets of LBD using a panel data set of Spanish manufacturing firms. Our contributions to the literature are several. Firstly, we extend the approach by Bahk and Gort (1993) by also allowing for spillover effects of LBD. Secondly, we control for unobserved time invariant factors that could arguably have been biasing previous estimates of LBD, an aspect that appears to have not yet been addressed in the literature. Finally, we also allow for LBD to depend on the level of embodied technological change of a firm. Our results indicate that all of these factors are potentially important aspects to consider in trying to understand LBD.

The remainder of the paper is organized as follows. In the next section we outline Bahk and Gort's (1993) approach to measuring LBD. In Section III we describe our data set and provide summary statistics. Section IV contains our econometric analysis of measuring LBD. The final section concludes.

2. Model and econometric issues

The LBD hypothesis suggests that firms take advantage of their experience in the market. We follow the approach proposed by Bahk and Gort (1993) and simplify the analysis by considering LBD as an aspect of disembodied technical change, whether such change takes the form of change in production process or change in product quality. In considering how LBD affects a firm, Bahk and Gort (1993) derive a simple production function from a Cobb-Douglas specification, while allowing for both embodied input-augmenting technical change and LBD. Accordingly, the output of a firm i at time t is a function of the following:

$$Y_{it} = A(t)\, G(V_{it}, X_{it}) L_{it}^{\beta_l} W_{it}^{\beta_w} K_{it}^{\beta_k} \quad (1)$$

where *Y* is gross value added, *i.e.,* sales net of variation in stock of final output and of intermediate products used, *L* represents the number of employees, *K* is the stock of capital consisting both of machinery and buildings, and *A* is a Solow-type productivity shift parameter. A firm's output is additionally assumed to depend on *X*, the firm's accumulated specific knowledge acquired through learning by doing. We shall go back to this variable later on in order to explain it in detail. Let consider before the variables *V* which is the weighted average vintage of the capital stock with values inversely related to the age of capital, and *W,* the average wage level in the firm, to control for embodied input-augmenting technical change of capital and human capital respectively. These latter two variables can be justified on a number of grounds. In terms of vintage capital, both empirical and theoretical findings suggest that vintage capital can affect growth through embodied technological progress and improvement in productive efficiency. Previous studies, such as Bahk and Gort (1993) and Doms et al. (1995), show empirically that plants using advanced technologies grow faster and are more likely to survive. In addition, Boucekkine et al. (1998) show theoretically that the vintage capital model may play a crucial role in explaining economic fluctuations and growth. The rationale of using W as an indicator of the quality in human capital rests on the assumption by Becker (1964), according to which workers are able to capture any returns to human capital through higher wages.

We estimate (1) by considering its logarithmic form as follows:

$$\ln(Y_{it}) = \beta_a + \beta_v V_{it} + \beta_l \ln(L_{it}) + \beta_w \ln(W_{it}) + \beta_k \ln(K_{it}) + \beta_x \ln(X_{it}) + \beta_t t + \varepsilon_{it} \quad (2)$$

where *Y, V, L, W, K*, and *X* are defined as above and *t* is chronological time in years intended to control for aggregate productivity shifts, and hence economy-wide LBD. In choosing an appropriate proxy for *X*, Bahk and Gort (1993) suggest using a plant's age or, alternatively, its cumulative output since birth, although the former, due to its obvious colinearity with the input variables, cannot be included simultaneously with *t*. Using simple OLS on the life cycle of plant births observed in their data set, the preceding authors find strong evidence supporting firm specific LBD using both plant age and cumulative output, but no evidence for economy wide learning. Additionally, their results imply that embodied input-augmenting technical change of both physical and human capital, as represented by V and W, respectively, is important for a firm's productivity.

As mentioned previously, the time trend variable *t* is intended to capture the influence of technological progress and economy-wide learning as in a classical

Solow-type specification. With such a specification, all firms are supposed to equally benefit from common technological progress. Equation (2) thus allows for only two channels for LBD, namely the firm-specific and economy-wide LBD. Such hypothesis is hardly sustainable once one considers the possible influences of conditions within an industry, such as the intensity of competition, the state of technology and the diffusion of knowledge between firms within the same sector. One may assume that in some industries such factors are likely to partly determine the way firms innovate and/or adapt to competitive pressure. More specifically, the role played by firms' experience is likely to not only influence their own productive efficiency but also that of their more direct competitors. We take account of this by including the weighted sectoral means of X_{it}, where weights (w_{it}) are firms' shares in total employment of the industry j to which the firm i belongs. This specification is similar to the one employed in macro or sector studies such as Hall (1988,1990) and Caballero and Lyons (1990, 1992), amongst others, although in a very different context. In a more related context, Thornton and Thompson (2001) use unweighted experiences of other shipyards to investigate the possibility of learning spillovers within the wartime shipbuilding industry. Including external learning spillovers in (2) gives:

$$\ln(Y_{it}) = \beta_a + \beta_v V_{it} + \beta_l \ln(L_{it}) + \beta_w \ln(W_{it}) + \beta_k \ln(K_{it}) + \beta_x \ln(X_{it}) + \beta_t t + \beta_s \ln(\sum_{i,\, i \in j} w_{it} X_{it}) + \varepsilon_{it} \quad (3)$$

where the term w_{it} is the weight corresponding to firm i as defined above while β_s measures the effect of LBD spillovers. Thus, while we use equation (2) to compare our results with Bahk and Gort (1993), equation (3) intends to test the role played by spillovers.

3. Data Description

We conduct our econometric test of the LBD hypothesis using firm-level data of the Spanish manufacturing industry over the period 1990-1998. Further information about the data set is provided in the appendix. Our data are different in two respects to most of the more recent studies of LBD. First, in general, studies on LBD have been conducted at the plant-level. The fact that we use firm-level data is not, however, necessarily an inconvenience. As a matter of fact, it is arguably unreasonable to assume that learning at the plant level is independent of other establishments linked to the same parent firm. In other words, knowledge acquired through experience by the parent firm or other plants within the same firm is likely to be transferred at least to some extent to other plants, old or new.[2]

The second important difference in our data set refers to the fact that previous studies have exclusively focused on following plants after observing their birth. Our data does not cover enough births to leave us with a reasonable sample size, and hence we also include firms whose birth occurred prior to the beginning of our sample period, which meant including firms of all ages, thus also much older plants than in the Bahk and Gort (1993) and Jensen et al (2001) studies. In order to verify that the inclusion of older plants is not driving any differences or similarities in our results, we also experiment with breaking up our sample into younger and older firms.

The consequence of not considering only firms from their birth is that, at least in the simple OLS specification, we can only use a firm's age as a proxy for its acquired experience. One should note, however, that the use of a panel fixed effects estimator allows us to nevertheless still use cumulative output as a proxy for experience given that we can thus set previous unobserved output at an arbitrary value since it is purged from the equation once fixed-effects are accounted for.

The case of the Spanish manufacturing industry proves to be particularly illustrative of the potential role played by LBD in explaining firms' productive efficiency. In effect, Spanish manufacturing has undergone profound structural changes over the time span considered here, that is, during the decade following Spain's accession to the European Community (EC). Spanish firms have long been characterised by low productivity level and competitiveness with respect to their more direct competitors from Western Europe. For example, Barrios and Strobl (2002) show that Spanish manufacturing firms' productivity was substantially lower than in the rest of Europe in the mid-80ies but have grown substantially in the aftermath of Spain's accession to the EC together with strong industrial restructuring in order to face growing foreign competition. Table 1 provides some descriptive statistics on the mean of productivity, the number of firms, size, age and the standard deviation of age by sector for 1990 and 1998. First one observes that productivity as well as the number of firms have grown substantially over the period under scrutiny. Non-reported results on the dispersion of productivity also reveal important disparities within sectors, a result in line with preceding studies, see Jensen et al. (2001). Descriptive data on firms' age reveal interesting features. While average age has generally grown during the 1990-98 period, the standard deviation of firms' age is very large denoting important differences in firms'

[2] This gives further support for using a fixed effects estimator, as we will argue later.

experience. Accordingly, if some credential is to be given on the LBD hypothesis, the large dispersion in firms' ages may explain in part the large dispersion in firms' productivity.

4. Econometric Results

In what follows we first present some general results of our test of the LBD hypothesis using equation (2) as benchmark. We draw some inference from using fixed-effect panel estimators and also consider possible non-linearity in LBD. Second we look more closely at the potential existence of spillovers linked to LBD using equation (3). We also consider possible interaction between LBD and technological progress through vintage capital.

4.1 General results

Inference from firm and sector-level fixed effects

Our estimation of (2) using simple OLS and a firm's age as a proxy for firm specific LBD is given in Table 2. One should note that, in contrast to Bahk and Gort (1993), we also included year specific time dummies in order to control for macro-economic factors that may have occurred over our sample period[3]. Given that we cannot, as previously mentioned, include an aggregate time trend simultaneously with firm age, these time dummies may to some extent also capture economy-wide LBD, although we cannot separate the effect of such from other macro-economic shocks. As can be seen, in contrast to Bahk and Gort (1993), we find no evidence of firm-specific LBD influencing output, whereas, in line with their study, our results do suggest that embodied technical change of physical capital, as proxied by V, acts to increase a firm's output.

On should note that in estimating (2), Bahk and Gort (1993) adhere strictly to their model in (1) and hence are implicitly assuming that the explanatory variables fully capture a firm's production process. In reality, of course, this is unlikely to be the case as other factors may also determine a firm's productivity and/or the proxies used to capture the inputs specified above may be less than perfect than their intent. Specifically, if there are other unobservable (to the researcher) factors

[3] One should note that although an F-test supported the inclusion of time dummies, their exclusion did not qualitatively alter conclusions regarding our variables of interest.

that determine a firm's output, and we here assume that they are time invariant, then the error term in (2) may be specified as:

$$\varepsilon_{it} = \mu_i + \omega_{it}$$

where μ is the unobserved time invariant plant specific effect and ω is the remaining i.i.d error term. If μ is correlated with any of the regressors then simple OLS on (2) would render their estimates biased – a now standard result used to advocate panel data estimators if such data is available; see Greene (2000). For example, technological intensity not adequately captured by K or V, is likely to affect both output and the ability to learn by doing. One could similarly argue in terms of institutional arrangements within the firm. Moreover, such time invariant factors may also be at the sector level[4]. For instance, barriers to entry in a sector may both increase a firm's output, but also reduce its incentive to learn by doing.

Thus, as a next step, we first include industry specific time dummies in our OLS specification to determine whether the failure to control for unobservable time invariant industry specific effects may be biasing our estimates. However, although a simple F-test supports the joint significance of the industry dummies, the results in column (2) of Table 2 do not suggest that their inclusion significantly alters the previous results. There is still evidence of the importance of vintage capital, while there is no support for LBD taking place. Given that due to data restrictions our sample of firms also includes much older plants than in the Bahk and Gort (1993) sample for the US and thus this may feasibly be driving the difference in results, we also divided our sample into young and old firms. In choosing our cut-off point for this categorisation, we simply used the maximum age of plants included in the Bahk and Gort (1993) sample, namely 14 years of age, as a natural cut-off for a firm to be considered 'young'. The OLS results of this exercise, including industry dummies, are given in the last two columns of Table 2. Accordingly, although there are some difference in the size of the coefficients for all variables, their direction and significance levels are consistent across both samples, hence suggesting that our inclusion of an older firm population cannot account for our lack of evidence of firm specific LBD.

As argued earlier, our OLS estimates may be biased even after we control for time invariant industry specific effects. We thus re-ran our base specification using a panel data fixed effects estimator, which allows us to purge any unobserved time invariant firm specific effects from our equation, the results of which are depicted

[4] As a matter of fact, in also examining 15 industries of their sample separately, Bahk and Gort (1993) find that in only 11 of these the LBD at the firm level still holds. Morever, the coefficient for the significant industries varies substantially.

in the first column of Table 3. As can be seen, the results are now strikingly different. While the vintage of capital is no longer a significant determinant of output, the positive and significant coefficient on age suggests strong evidence of firm specific LBD, a result that is now in line with Bahk and Gort (1993)[5]. The elasticity of our age variable is in fact larger than the one found by the previous authors. We find approximately a 6% output rise per year of age while the Bahk and Gort (1993) estimated the same elasticity to be only 1%. Moreover, as shown by our F-test of time invariant firm specific effects, these are important to take account of in the estimation of our equation, and hence support the fixed effects estimates rather than our earlier OLS results. As noted earlier, the use of a fixed effects estimator also allows us to circumvent our problem of not having explicit data on cumulated output for firms whose start-up occurred prior to the beginning of our sample period as an alternative proxy for firm specific LBD. The estimates including this alternative proxy, as well as an aggregate time trend, intended to proxy economy-wide increases in the stock of knowledge, are provided in the second column Table 3. Accordingly, this second proxy confirms our results from using firm age – there is evidence in support of firm specific LBD, but none for embodied technical change of physical capital[6]. Moreover, the insignificant coefficient on the time trend suggests that there is no evidence that aggregate increases in the stock of knowledge increase a firm's output.

Non-linearity in LBD

In her study of the impact of age on US plant productivity, Powers (1995) discovered that after a certain threshold, firms' experience cease to exert a positive influence on productivity and, at best, have no influence on productivity once a certain level is reached. A similar result is also found by Bahk and Gort (1993). To allow for the possibility that a firm's capacity to learn by doing, as proxied by firm age, may similarly decrease in Spanish manufacturing we thus also experimented with allowing for a non-linear relationship between experience and productivity by additionally including the squared value of firm age as an explanatory variable. The insignificant coefficient on the squared value of firm age in the third column of Table 3, however, suggests that the relationship between productivity and LBD is linear in our case[7]. In addition, the coefficient on the firm-specific LBD remains fairly unchanged.

[5] Similarly, Thornton and Thompson (2001) find evidence of firm specific LBD in their estimation of the determinants of unit labor requirements in shipping yards.

[6] The elasticity found for cumulated production is around 30% as showed in column (2) of table 3. Here the coefficient tells that when a firm doubles its *cumulated production*, productivity rises by 30%.

[7] We also included higher polynomials, but in all cases these turned out to be insignificant.

4.2 Spillovers, learning by doing and vintage capital

Learning by doing and Spillovers

A firm's ability to learn by doing may arguably not be independent of other firm's accumulated experience from the same activity. A new firm may be able to learn from firms who have already accumulated greater experience, essentially benefiting from spillovers of sector-wide accumulated experience. As a matter of fact, studies by Hall (1988,1990) and Caballero and Lyons (1990,1992) among others provide support for the existence of positive externalities in productivity, although they do not explicitly focus on LBD spillovers. Moreover, Thornton and Thompson (2001) who explicitly study learning spillovers find strong support for such in the US wartime shipbuilding industry. One could also argue that other firms' accumulated experience may act to increase the competitive pressure and disadvantage in lack of experience of younger, less experienced firms. If these countervailing forces are, of course, fairly time invariant over shorter time periods, like the one represented by our data set, then they would be purged from (3) by the fixed effects estimator. However, in newer sectors or in sectors where there are exogenous influential technological or other undergoing structural changes this is unlikely to be the case. Under the latter scenario, our estimate of firm specific LBD could very well be biased, and, depending on the dominance of either of the just mentioned countervailing force, may under- or overestimated the impact of LBD on firms' productivity. To assess this possibility we thus calculated the weighted mean age of firms within a sector and included this variable as well as its squared term in (2) which gives us equation (3) as shown in section 2. The results of our estimations are given in column (4) of Table 3. As can be seen, the coefficient on the externality variable AGE_S is positive and significant. However, the coefficient on this variable is equal to 3%, that is, half the value obtained for the firm-specific LBD. This result is similar to those obtained in very different case-studies like Thornton and Thompson (2001) and Gruber (1998) in that these showed that even if externalities plays a significant role in explaining productive efficiency, their contribution is lower in magnitude to the role played by firm-specific learning. Finally we also find only weak evidence for non-linearity in the effect of spillovers, as indicated by the low absolute value its squared term in column (4) of Table 3.

Although our OLS estimates by age group did not appear to suggest that our inclusion of older firms, relative to the study by Bahk and Gort (1993) for the US, was driving our differences in results, it is still possible that the failure to control for time invariant observables may be obscuring any differences across age groups. We thus re-estimated the different specifications in Table 3 separately for the younger and older firms in our sample, respectively, in Tables 4 and 5. For younger firms, we find similarly to the overall sample that vintage capital does not play a significant role in explaining productivity. In contrast, firms specific LBD increases productivity, regardless of whether it is measured by age or accumulated output. Finally, we find no evidence that there is economy wide LBD nor that the vintage of capital affects the firm specific ability to learn by doing.

Limiting the sample to observations from those firms with at least 14 years experience in the market, as shown in Table 4, makes no exception to the finding that firm specific LBD is an important determinant of a firm's productivity. This again holds regardless of whether we measure LBD as firm age or accumulated output. However, we also discover that unlike younger firms, older firms benefit from economy wide LBD. This may be due to the likelihood that younger firms already embody much of the most recent technology and know-how when they start up. We also find that it is only older firms that benefit from the degree of experience present in a sector, as measured by the weighted average age in a sector. In this case, the coefficient for the externality variable is now equivalent to the one found for the firm-specific LBD, that is around 7% versus 6% for the firm-specific LBD. In other words, only older firms benefit from spillovers and the effect of such is similar to firm-specific LBD.

Learning by doingand vintage capital

As argued before, a firm's ability to learn by doing may also be affected by the level of its embodied technology. For example, more recent levels of technology may also allow firms to adapt to changes in their environment, and hence benefit from experience. To investigate this we included an interaction term between vintage capital and a firm's age in our model, the results of which are reported in the last column of Table 3. The negative and significant coefficient on the interaction term in conjunction with the persistent insignificance of the vintage capital variable on its own indicates that embodied technological change only affects productivity through a firm's learning experiences. In other words, firms with more outdated levels of embodied technology are less likely to gain from LBD.

In addition, the results reported in last column of table 4 also show that once we allow for the interaction between vintage capital and firm age, vintage capital has a significant positive effect on productivity. The estimated elasticity of vintage capital is equal to 2.8%, being very similar to the elasticity found by Bahk and Gort (1993) who estimated it around 2.5 and 3%. In our case, this suggests that updating capital stock to incorporate the newest of technology is more important for older firms, whose equipment is likely to become outdated after some years of use. It also implies that the underlying assumption in the analysis by Jensen et al (2001) that post-entry investments are dominated by initial investment is not necessarily appropriate for older firms.[8]

5. Summary and Conclusion

The present paper provides evidence on firm-level learning by doing (LBD) using data for the Spanish manufacturing industry over the 1990-98 period. In contrast to previous studies, we use panel estimation techniques and show that not taking account of time invariant firm-specific effects greatly affects the nature of the results. Once we control for firms' specific effects, we find a positive and significant effect of LBD, whether represented by firm age or cumulated production. However, we find no significant relationship between firms' productivity and vintage capital. As a matter of fact, we find that the relationship between vintage capital and productivity is more subtle: embodied technological change affects productivity only *through* firms' experience, although only for older firms. This result is in line with studies such as, amongst others, De Long and Summers (1991) that have documented the leading role played by investment equipment for economic growth and business cycles patterns. Old firms are also more likely to benefit from economy wide LBD. Finally, we also find that sectoral LBD spillovers is an important factor in explaining the productivity of firms, as has been found by Gruber (1998) and Thornton and Thompson (2001) although this result is limited to old firms. Unlike the previous authors, however, the contribution of spillovers is found to be at least as important as firm-specific LBD.

[8] Jensen et al (2001) were restricted to this assumption given the unavailability of data on the vintage of capital.

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Table 1: Summary statistics for total factor productivity, the number of firms, the average size and age by sector, 1990-98

	TFP		# firms		Size		age		Std. dev. age	
Sector	1990	1998	1990	1998	1990	1998	1990	1998	1990	1998
Ferrous and Non-F. Met.	-0.57	0.68	50	69	653.8	515.2	28.7	32.7	22.6	24.2
Non-Metalic Mineral Products	0.30	0.92	161	204	165.6	213.4	23.4	28.8	26.0	25.4
Chemicals	0.59	1.44	153	191	381.3	309.9	33.4	40.6	24.2	25.2
Metal Products	0.54	2.46	233	362	139.7	121.2	21.5	23.5	22.5	21.2
Industrial Machinery	0.64	2.93	125	171	253.1	179.8	23.0	26.8	21.3	20.5
Computing	2.63	3.46	24	36	369.9	349.1	18.5	25.8	15.5	18.0
Electrical Machinery	1.00	2.74	201	274	416.6	284.6	19.2	24.0	18.8	18.3
Vehicles	0.58	1.36	74	116	1338.9	959.6	22.3	23.6	16.8	17.8
Other Transport industry	-0.38	1.60	52	72	860.5	784.8	29.2	34.0	31.0	31.1
Meat and Preserved Food	-0.05	1.09	61	83	237	215.5	18.3	22.0	14.8	15.4
Food and Tobacco	0.58	1.00	228	286	242.3	249.5	25.9	30.6	25.0	25.5
Beverages	0.07	0.82	52	63	351.3	332	46.3	57.3	42.8	50.0
Textiles	1.13	2.15	248	357	173.2	145.7	18.6	23.3	21.7	22.9
Leather and Footwear	2.53	3.51	77	124	64.9	34.1	14.6	16.5	24.5	21.0
Wood and Furniture	0.30	2.33	141	208	53.2	57.7	13.6	17.5	14.5	13.9
Paper and Printing	0.70	1.85	164	233	174.7	157.9	22.6	26.2	27.7	26.7
Rubber and Plastics	1.04	1.56	96	159	131.8	118.2	19.0	21.8	12.6	15.2
Other Manufacturing	3.15	2.30	48	64	83.5	82.0	20.5	26.3	22.3	21.4

Notes:

(1) TFP is equal to ln(va)-sk*ln(K)-sl*ln(L), where L and K represent the number of employees and the capital stock respectively while the sk and sl correspond to the share of capital and labor in value-added. TFP is measured as an index=1.00 for Electrical Machinery in 1990. Sources: ESEE and authors' computation

(2) Average number of employees by firm.

Table 2: OLS estimates

	(1)	(2)	(3)	(4)
log(L)	0.586***	0.612***	0.628***	0.603***
	(0.018)	(0.019)	(0.030)	(0.026)
Log(W)	0.649***	0.624***	0.548***	0.698***
	(0.034)	(0.037)	(0.055)	(0.051)
Log(K)	0.402***	0.389***	0.402***	0.391***
	(0.013)	(0.013)	(0.019)	(0.019)
V	0.020***	0.020***	0.029***	0.015***
	(0.003)	(0.003)	(0.005)	(0.003)
AGE_F	-0.000	-0.001	-0.004	-0.000
	(0.001)	(0.001)	(0.005)	(0.001)
Constant	-1.193***	-1.054***	-0.174	-2.022***
	(0.240)	(0.288)	(0.472)	(0.394)
Sample	All	All	Young	Old
Ind. Dummies	No	Yes	Yes	Yes
Observations	7442	7442	2943	4499
F-Test (β_i=0)	2546.53	1009.19	264.95	574.38
R-squared	0.79	0.79	0.72	0.78

Notes :
(1) ***, **, and * signify one, five, and ten per cent significance levels, respectively.
(2) All regressions include time dummies.
(3) Standard errors in parentheses.

Variables used:
L is the number of employees
W is the real wage rate
V is vintage capital
AGE_F is the age of the firm

Table 3: FE estimates – total sample

	(1)	(2)	(3)	(4)	(5)
log(L)	0.283***	0.238***	0.293***	0.284***	0.290***
	(0.062)	(0.065)	(0.062)	(0.062)	(0.062)
Log(W)	0.017	-0.101	0.022	0.019	0.029
	(0.075)	(0.078)	(0.075)	(0.075)	(0.075)
Log(K)	0.132***	0.121***	0.135***	0.132***	0.132***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
V	-0.001	-0.002	-0.001	-0.000	0.012
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)
AGE_F	0.064***		0.054***	0.066***	0.061***
	(0.009)		(0.012)	(0.009)	(0.009)
$\log(\Sigma Y)_F$		0.296***			
		(0.060)			
Trend		0.012			
		(0.016)			
AGE_F^2			0.000		
			(0.000)		
AGE_S				0.036**	
				(0.016)	
AGE_S^2				-0.000*	
				(0.000)	
AGE_F*V					-0.000**
					(0.000)
Obs.	7442	7440	7442	7442	7442
Firms	2203	2202	2203	2203	2203
F-test (β_j=0)	47.89***	74.22***	43.68***	40.39***	43.97***
F-test (μ_i=0)	3.24***	2.87***	3.23***	3.24***	3.22***
R-squared	0.08	0.08	0.08	0.08	0.08

Notes :
(1) ***, **, and * signify one, five, and ten per cent significance levels, respectively.
(2) All regressions include time dummies.
(3) Standard errors in parentheses.

Variables used:
L is the number of employees
W is the real wage rate
V is vintage capital
AGE_F is the age of the firm
AGE_S is the average age by sector
$\text{Log}(\Sigma Y)_F$ is firm's cumulated production

Table 4: FE estimates – old firms

	(1)	(2)	(3)	(4)	(5)
log(L)	0.517***	0.542***	0.526***	0.523***	0.537***
	(0.089)	(0.092)	(0.089)	(0.088)	(0.089)
Log(W)	0.139	0.040	0.142	0.149	0.172
	(0.106)	(0.111)	(0.106)	(0.106)	(0.106)
Log(K)	0.018	0.009	0.023	0.013	0.009
	(0.049)	(0.050)	(0.049)	(0.049)	(0.049)
V	0.000	-0.002	-0.001	0.001	0.028***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.011)
AGE_F	0.060***		0.041**	0.063***	0.054***
	(0.011)		(0.017)	(0.011)	(0.011)
$\log(\Sigma Y)_F$		0.179*			
		(0.093)			
Trend		0.041*			
		(0.024)			
AGE_F^2			0.000		
			(0.000)		
AGE_S				0.071***	
				(0.019)	
AGE_S^2				-0.001***	
				(0.000)	
AGE_F*V					-0.001***
					(0.000)
Obs.	4499	4497	4499	4499	4499
Firms	1319	1318	1319	1319	1319
F-test (β_j=0)	30.99***	43.82***	28.40***	27.15***	29.05***
F-test (μ_i=0)	3.48***	3.03***	3.48***	3.47***	3.49***
R^2	0.09	0.08	0.09	0.09	0.09

Notes :
(1) ***, **, and * signify one, five, and ten per cent significance levels, respectively.
(2) All regressions include time dummies.
(3) Standard errors in parentheses.

Variables used:
L is the number of employees
W is the real wage rate
V is vintage capital
AGE_F is the age of the firm
AGE_S is the average age by sector
$\text{Log}(\Sigma Y)_F$ is firm's cumulated production

Table 5: FE estimates – young firms

	(1)	(2)	(3)	(4)	(5)
log(L)	0.021	-0.077	0.022	0.021	0.016
	(0.095)	(0.099)	(0.095)	(0.095)	(0.096)
Log(W)	-0.139	-0.241**	-0.138	-0.139	-0.144
	(0.113)	(0.115)	(0.113)	(0.113)	(0.113)
Log(K)	0.227***	0.200***	0.229***	0.227***	0.224***
	(0.049)	(0.049)	(0.049)	(0.049)	(0.050)
V	0.002	0.002	0.002	0.002	-0.003
	(0.010)	(0.010)	(0.010)	(0.010)	(0.016)
AGE_F	0.085***		0.074**	0.085***	0.092***
	(0.017)		(0.032)	(0.017)	(0.023)
$\log(\Sigma Y)_F$		0.354***			
		(0.084)			
Trend		0.005			
		(0.026)			
AGE_F^2			0.001		
			(0.002)		
AGE_S				0.004	
				(0.039)	
AGE_S^2				-0.000	
				(0.001)	
AGE_F*V					0.001
					(0.002)
Obs.	2943	2943	2943	2943	2943
Firms	1056	1056	1056	1056	1056
F-test (β_j=0)	16.16***	28.25***	14.70***	13.46***	14.71***
F-test (μ_i=0)	2.48***	2.73***	2.72***	2.75***	2.73***
R^2	0.08	0.08	0.08	0.08	0.08

Notes :
(1) ***, **, and * signify one, five, and ten per cent significance levels, respectively.
(2) All regressions include time dummies.
(3) Standard errors in parentheses.

Variables used:
L is the number of employees
W is the real wage rate
V is vintage capital
AGE_F is the age of the firm
AGE_S is the average age by sector
$\text{Log}(\Sigma Y)_F$ is firm's cumulated production

5. Appendix Data used

Our data source for our empirical analysis is the “Encuesta Sobre Estrategias Empresariales” from the Ministerio de Industria y Energia (MINER, Madrid) and the Fundación Empresa Pública (Madrid). The data is not exhaustive and covers only around 22% of total Spanish employment in manufacturing industry. However, the ESEE includes almost all manufacturing companies with more than 200 employees, and is a representative sample of manufacturing firms with less than 200 employees. The unit of observation is at the firm-level, including firms with more than 10 employees. We have gained access to an annual panel of approximately 2100 Spanish manufacturing firms for the period 1990 to 1998. The ESEE provides a number of variables at the firm level that are of interest to the present study, namely the number of employees and their remuneration, sales, capital stock, intermediate product used for production, age, and the average age of capital stock, separately for machinery and buildings.

The vintage capital variable was thus constructed by using the weighted average of those two components of the capital stock. All nominal variables were deflated using sectoral price indices, where each firm’s economic activity was classified (by the data) into one of 18 sectors of the nomenclature CNAE74, which is an altered version of the European Nace 70 codes.