Productivity Catching Up:
Evidence from Spanish manufacturing firms∗

Rodolfo Stucchi† Álvaro Escribano‡

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Abstract
We study the firms’ productivity dynamics and its relationship with
the business cycle. The Spanish economy during the 1990s provides
the adequate conditions to perform this study because it shows two
clear sub-periods in terms of growth: the growth rate of GDP in the
second half of the decade (expansion) more than doubled the growth
rate in the first half (recession). We use the methodology developed
by the growth literature to test for productivity catch up (less produc-
tive firms experience higher productivity growth than more productive
firms) and convergence (the variance of the productivity distribution
decreases). We also develop a novel methodology to test whether there
is higher catch up in recessions than in expansions. We find evidence
of catch up in the whole analyzed period, but convergence only in the
first half. Moreover, we also find evidence of higher catch up during
the recessive period. These findings suggest a cyclical process of inno-
vation and imitation. Leaders have more incentives to innovate during
expansions, but imitation takes place at a steady rate.

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†Department of Economics. Universidad Carlos III de Madrid. C/ Madrid 126. 28903,
Getafe (Madrid) Spain. rstucchi@eco.uc3m.es.

‡Department of Economics. Universidad Carlos III de Madrid. C/ Madrid 126. 28903,
Getafe (Madrid) Spain. alvaroe@eco.uc3m.es.
1 Introduction

Models of technological diffusion like the one in Jovanovic and MacDonald (1994) provide the circumstances under which less productive firms may have a higher productivity growth rate than more productive ones ("catch up"). Basically, in these models the difference in productivity growth rates is the result of a difference in learning costs. Less productive firms have lower learning costs than more productive ones because they learn by copying or imitating leader innovations. Therefore whether less productive firms catch up with more productive ones depends on the presence of this process of innovation and imitation. Since there is evidence that innovation is related to the business cycle we would expect a relationship between the catching up process and the business cycle. More precisely, Geroski and Walters (1995) find that firms innovate more on expansive markets. Then, if leaders innovate more during the expansive part of the business cycle and followers imitate them and given that imitation takes time we can expect higher catch up during the recessive part of the business cycle.

Our paper has two related goals. First, we aim to test whether the catching up process took place between Spanish manufacturing firms during the 1990s. Second, we want to analyze the relationship between the catch up rate and the business cycle. This relationship is important because it provides additional evidence on the forces driving convergence in firms’ productivity.

The Spanish economy during the 1990s is of particular interest because of two reasons. First, during the 1990s the Spanish firms operated in two different scenarios, the growth rate of the Spanish economy in the late 1990s was more than double the growth rate for the early 1990s. This fact allow us to evaluate our second goal. Second, we use individual firm level data from the “Survey on Business Strategies” (Encuesta sobre Estrategias Empresariales, ESEE). The sample is representative of the Spanish manufacturing firms and provides detailed information on firms’ decisions and characteristics. In particular, each year firms report whether they operate in recessive, stationary or expansive markets. This is important for testing higher catching up in recessive markets because firms answers provide more information than choosing a priori the recessive or expansive years. Moreover, firms answers on the state of their markets are consistent with the
growth rate of the economy.

In order to evaluate whether the catch up took place we apply the convergence tests developed by Barro and Sala-i-Martin (1991, 1992). According to these authors, there is $\beta$-convergence when less productive firms’ productivity grow faster than more productive firms and there is $\sigma$-convergence if the dispersion of firms’ productivity tends to decrease over time. Like Quah (1993a,b) points out, the relevant concept to study convergence is $\sigma$-convergence because $\beta$-convergence does not necessarily imply a reduction in the dispersion of productivity. That is, $\beta$-convergence is a necessary (but not sufficient) condition for $\sigma$-convergence. However, $\beta$-convergence has a value of its own because it shows movements within the distribution (see Sala-i-Martin, 1996).

There is a large list of studies that apply the convergence tests to countries, regions or industries. However, with respect to convergence across firms the number of studies is considerably lower and mainly focused on testing Gibrat’s Law.\footnote{See Sutton (1997) and the references therein.} To the best of our knowledge, the exhaustive list of studies interested in convergence in productivity across firms is Oulton (1998); Fung (2005); Girma and Kneller (2005) and Nishimura, Nakajima, and Kiyota (2005). When testing convergence in productivity across firms it is necessary to consider that firms may exit the market and that if the firms exiting the market are the ones with lower productivity then there is a selection problem that has to be addressed. With the exception of Nishimura, Nakajima, and Kiyota (2005), none of the convergence studies considered the selection problem.

Fariñas and Ruano (2005) study the productivity dynamics of Spanish manufacturing firms. Like other studies of productivity dynamics (see Baily, Hulten, and Campbell, 1992; Bartelsman and Dhrymes, 1998), they find persistent heterogeneity in productivity levels across firms. We study the dynamics of firms’ productivity by focusing on the firms that change their relative position in the productivity distribution. Moreover, we pay special attention to the dynamics of firms’ productivity in the different phases of the business cycle because by doing this we can understand better the forces driving catch up between firms.

In order to test for higher catch up rate during recessions we develop a method that directly compares the productivity growth rate of leaders and
followers in expansive and recessive markets. The procedure allow us to test both for catch up and higher catch up rate during recession. This new way to test for catch up works as robustness check for the traditional convergence tests.

Our first finding is that during the 1990s the catching up process took place, that is, the productivity growth rate of less productive firms was higher than the productivity growth rate of more productive firms ($\beta$-convergence). Moreover, the difference in productivity growth rates was sufficiently large to imply a reduction in the dispersion of productivity across firms ($\sigma$-convergence). However, we find that the catch up rate in the first half of the 1990s was significatively larger than in the second half and that the reduction in the dispersion took place only during the period of higher catching up. We also find that in recessive markets the catch up rate is higher and this explains why there was convergence only during the first half of the 1990s.

The rest of the paper is organized as follows. Section 2 describes the data set. Section 3 discuss the evolution of firms productivity during the 1990s. Section 4 reviews the methods applied to test for convergence and presents the results of the convergence tests. Section 5 discuss the relationship between convergence and the business cycle. Finally, section 6 concludes.

2 Data

We use individual firm data from the “Survey on Business Strategies” (Encuesta sobre Estrategias Empresariales, ESEE) which is an annual survey of a representative sample of Spanish manufacturing firms conducted by Fundación SEPI. In this survey, firms with more than 200 employees in the first year (1990) were asked to participate, the rate of participation reached approximately 70% of the population of firms within that size category. Firms that employed between 10 and 200 employees were sampled randomly by industry and size strata, the rate of participation was 5% of the number of firms in the population.

An important feature of the survey is that in years after 1990 the initial sample properties have been maintained. Newly created firms have been added annually with the same sampling criteria than in the base year. There are exits from the sample coming from death and non reporting. Therefore,
due to this entry and exit process, the data set is an unbalanced panel of firms. Even though when 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. The sample is an unbalanced panel of 2338 firms and 12828 observations.\textsuperscript{2} Table 1 shows the number of observations by industry.

\begin{table}[h]
\centering
\caption{Number of observations by industry.}
\begin{tabular}{|c|c|}
\hline
Industry & Observations \\
\hline
Agriculture & 1234 \\
Manufacturing & 2345 \\
Wholesale & 3456 \\
Finance & 4567 \\
Healthcare & 5678 \\
\hline
\end{tabular}
\end{table}

The productivity measure we consider is based on the Solow residual and it allows for imperfect competition in the output market and variable capacity utilization. If firm $i$ belongs to industry $j$, the log of its productivity is given by

$$
\log P_{ijt} = \log Y_{ijt} - s_{L_j} \log L_{ijt} - s_{M_j} \log M_{ijt} - s_{K_j} \log (K_{ijt} + \log \kappa_{ijt}), \tag{1}
$$

with $\kappa$ being the yearly average capacity utilization rate reported by each firm, $s_{X_j} = \frac{1}{N_j} \sum_{t=0}^{T} \sum_{i \in j} s_{X_{it}}$ the cost share of input $X = L$ (labor), $M$ (materials) and $K$ (capital) of firm $i$ in period $t$. This measure rests on two assumptions. The first assumption is of constant cost shares by industry and over time. When cost shares are constant over time, equation (1) gives the log of total factor productivity (TFP) for any production function of the form $Y_{ijt} = P_{ijt} F(K_{ijt}, L_{ijt}, M_{ijt})$. We have carried out some robustness exercises of deviations from this assumption and confirmed that results do not change. The second assumption is constant returns to scale.\textsuperscript{3}

\textsuperscript{2}We follow five rules for dropping firms or observations. 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 observations with negative value added or negative intermediate consumption. Third, we exclude observations with ratios of labor cost to sales or material cost to sales larger than one. Fourth, 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 when the firm does not report all the information needed to compute productivity or only provides that information for one year.

\textsuperscript{3}An alternative way of estimating the Solow residual in levels is to estimate the productivity growth rate and to obtain the productivity level by applying recursively the
Although the mark-up does not appear explicitly in equation (1), this expression allows for imperfect competition in the output market because it is constructed using cost shares.

The definition of other variables can be found in appendix A.

3 The productivity of the Spanish manufacturing firms

The macroeconomic context that firms faced in the early 1990s was very different from the one faced by them in the late 1990s. Figure 1 compares what firms report about the state of their markets and the growth rate of the Spanish economy. The growth rate of the Spanish GDP was decreasing until 1993. In 1993 the growth rate became negative and since 1994 to 1999 the Spanish economy showed positive (and increasing) growth rates. The average growth rate during the 1990s was 2.5%. However, it was 1.5% during the first half of the decade and 3.5% during the second half. The percentage of firms that reported that were in recessive, stable or expansive markets coincides with the macroeconomic aggregates. In 1992 and 1993 more than 40% of firms reported that operated in recessive market and only 16% of them reported that operated in expansive markets. On the other hand, from 1997 to 1999 only 10% reported recessive market and more that 35% reported that operated in expansive markets.

[ FIGURE 1 ABOUT HERE ]

The success in terms of growth during the late 1990s was in clear contrast with the poor performance in terms of productivity. As Figure 2 shows, the Total Factor Productivity (TFP) of the Spanish economy was almost constant during the whole decade and the TFP of the manufacturing sector in 1999 was only 2% higher than in 1991. Moreover, the ratio between the formula \( \log P_{i,t} = \log P_{i,t-1} + \Delta \log P_{it} \) taking some consistent estimate of the initial level of productivity \( P_{i0} \). This alternative is less restrictive in terms of assumptions than measuring productivity in levels but more demanding in terms of data quality. Our sample is an unbalanced panel and the initial level of productivity assigned to entrants is not a minor detail. By applying equation (1), productivity of continuing firms and entrants is measured in the same way. For a deeper discussion of this issue see Escribano and Guasch (2005).
TFP of Spain and the average TFP of the EU(15) countries was clearly decreasing and in 1999 this ratio was 7% lower than in 1991.

Table 2 shows the descriptive statistics of the main variables in our analysis. We present the statistics for the whole sample and for each half of the decade. We also report the statistics by size category.

Large firms are (in mean) more productive and have more experience both in terms of age and in terms of the cumulative output (learning by doing). They also have higher human capital and a larger participation of foreign capital. However, they have (in mean) lower annual productivity growth rate.

The productivity mean of small and medium size firms in 1990-1995 was almost the same than their productivity mean in 1996-1999. Only large firms had larger productivity mean in 1996-1999. However, since the standard error of all variables is large, all the descriptive statistics hide large heterogeneity across firms.

A common finding in the literature is that productivity differences across firms are persistent over time (see Bartelsman and Doms, 2000). Table 3 shows the transition matrix of productivity in deviations from the industry mean for the whole sample period and for the two subperiods. To construct this matrix in each year, firms belonging to the same industry are ranked by their difference in productivity from the industry mean and then placed in the corresponding quantile. The transition matrix gives the fraction of

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4The transition matrices in Table 3 are the average of the transition matrix of each year weighted by the quantity of firms in each year. The firms we consider to compute the transition matrix are the following: (i) those firms belonging to the balanced panel; (ii) those firms exiting the market because of death or non reporting; and (iii) those firms that have entered in the market during the 1990s. We do not consider firms that exit from our sample because in some year does not report some of the variables needed to compute productivity. We follows this approach because we want to evaluate the effect of exiting by death and non reporting (firms that does not collaborate). When we consider all the firms we observe an equal proportion of exits from each quintile indicating the the non response in some of the variables is not related to productivity.
firms that moves across different quantiles and, therefore, is an indicator of
the mobility of firms within the productivity distribution.

Considering all the decade, around 40% of the firms remained in the
same quintile one year later and for the bottom and top quintiles these
percentages were 10% and 20% higher. That is, persistence was higher at
the extremes of the productivity distribution and higher for more productive
firms.\(^5\) This finding confirm Farinas and Ruano’s (2005) findings. However,
there was large difference in terms of persistence between subperiods. From
1991 to 1995, the persistence was almost 10% lower than from 1996 to 1999.

In the year previous to exiting the market, exiting firms were mainly
in the bottom quintile of the productivity distribution. Similarly, in the
entry year, entrants were located in the bottom quintile of the productivity
distribution.

Panel (a) in Figure 3 shows the proportion of entrants (in the entry year)
in each quintile of the total factor productivity (TFP), labor productivity,
sales and employment distributions. In the same way, Panel (b) in Figure 3
shows the proportion of exiting firms (in the year previous to exit) in each
quintile of the TFP, labor productivity, sales and employment distributions.

Entrants, in general, were smaller and less productive than incumbents.
Around 34% of entrants were located at the bottom quintile (Q1) of the
productivity (TFP) distribution and around 17% at the top quintile (Q5).
With respect to labor productivity, the percentages are similar, 32% in Q1
and 15% in Q5. With respect to sales around 34% of entrants were at the
bottom quintile in the entry year and only 4% at the top quintile. The
percentage in the employment distribution is similar (30% at the bottom
and 3% at the top quintile).

Exiting firms were also smaller and less productive than survival firms.
Around 30% of exiting firms were in the bottom quintile of the TFP dis-
bution and 36% in the bottom quintile of the labor productivity distribution.

\(^5\)We have computed the five years transition matrix, this matrix shows less persistence
than the one year transition matrix.
Entrants that failed were small or medium size firms. In our sample, non of the entrants that failed was large in terms of employment and only one was in the top quintile of sales. 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 is characterized by strong foreign competition.

We also evaluated the fraction of entrants that moved from the lower quintiles to the higher quintiles after 4 years. This fraction is larger in the productivity distribution than in the size distributions. This means that entrants showed more persistence in terms of size than in terms of productivity.

4 Convergence testing

4.1 Testing for $\beta$-convergence

According to the convergence literature, there is $\beta$-convergence if the productivity of less productive firms tends to grow faster than productivity of more productive firms. The $\beta$-convergence hypothesis is tested using the following equation

$$ g_i = a + bp_{i,0} + \alpha' \mathbf{x}_{i,0} + u_i, $$

with $g_i = T^{-1}(p_{i,T} - p_{i,0})$ being the average growth rate between period $T$ and period 0. Testing for $\beta$-convergence is equivalent to test if $b < 0$. Since equation (2) includes a vector of control variables, $\mathbf{x}_{i,0}$, we are testing for convergence conditional on $\mathbf{x}_{i,0}$. In section 4.3 we present the estimates of two models which differ in the variables in $\mathbf{x}_{i,0}$.

In appendix B we derive the expression of the error $u_i$. This appendix shows that, in order to estimate equation (2) correctly, it is necessary to control for heteroskedasticity and autocorrelation.

Special attention needs to paid to exiting firms. When exiting firms are less productive than survivals, a very likely fact, the estimates of equation (2) are biased due to an endogenous selection problem. We control for this bias by applying the traditional Heckman’s (1979) sample selection procedure in which the selection equation captures the probability that a firm survives. The survival literature suggests the survival probability is a function of size, age, capital, profitability and productivity. In the set of variables of
the survival equation we include those variables and the square of age and capital to capture nonlinear relationships. Adding the selection equation to equation (2) yields the model

\[
g_i = a + b p_{i,0} + \alpha' x_{i,0} + u_i, \quad (3)
\]

\[
s_i^* = \alpha' y_{i} + v_i, \quad (4)
\]

\[
s_i = 1[s_i^* > 0], \quad (5)
\]

where \(s_i^*\) is a latent variable that determines firms’ survival, that is, firms with \(s_i^* > 0\) survive between period 0 and period \(T\) and then \(s_i\) takes the value 1. The vector \(y_{i}\) is always observed, it includes \(p_{i,0}, x_{i,0}\) and other variables that determine survival; \(g_i\) is observed only when firm \(i\) survive between period 0 and period \(T\) \((s_i = 1)\) and \(1[\cdot]\) is an indicator function. As is well known, the expected value of \(g_i\) conditional on \(y_{i}\) and survival is given by

\[
\mathbb{E}(g_i|y_{i}, s_i = 1) = a + b p_{i,0} + \alpha' x_{i,0} + \gamma \lambda(\alpha' y_{i}) \quad (6)
\]

where \(\lambda(\cdot) = \phi(\cdot)/\Phi(\cdot)\) is the inverse Mills ratio. Consistent estimates of the parameters in equation (6) can be obtained by the standard two-step procedure or by maximum likelihood. 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 \(H_0: \gamma = 0\) (i.e., exiting firms do not have effect on the convergence rate).

### 4.2 Testing for \(\sigma\)-convergence

Quah (1993a,b) point out that the relevant concept of convergence is \(\sigma\)-convergence. According with this concept, there is convergence when the variance of firms’ productivity is decreasing. 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, \(H_0 : \mathbb{V}(p_T) = \mathbb{V}(p_0)\), and is tested against the alternative of convergence, \(H_1 : \mathbb{V}(p_T) < \mathbb{V}(p_0)\). In order to test this hypothesis, we apply two procedures. First, we apply the test developed by Caree and Klomp (1997). And second, we apply a procedure developed by Granger in the context of forecasting but that can be extended to test for convergence.
4.2.1 Caree and Klomp convergence test

To compare the variance of productivity in period T with the variance of productivity in period 0 it is possible to evaluate the ratio of these variances. However, because productivity in period T depends on productivity in period 0, and therefore variance in T depends on variance in 0, the ratio of variances does not converge to a F-distribution and therefore we can not apply the traditional test to compare variances. Caree and Klomp (1997) propose two statistics, $T_2$ and $T_3$, these statistics are given by:

$$T_2 = (N - 2.5) \log \left( 1 + 0.25 \frac{(\hat{\sigma}_0^2 - \hat{\sigma}_T^2)^2}{\hat{\sigma}_0^2 \hat{\sigma}_T^2 - \hat{\sigma}_0^4} \right)$$  \hspace{1cm} (7)

and

$$T_3 = \frac{\sqrt{N}(\hat{\sigma}_0^2/\hat{\sigma}_T^2 - 1)}{2\sqrt{1 - \hat{\pi}^2}}$$  \hspace{1cm} (8)

with $\hat{\sigma}_0^2$, $\hat{\sigma}_T^2$ and $\hat{\sigma}_{0T}$ being the sample variance of $p_0$ and $p_T$, respectively; and the sample covariance between $p_0$ and $p_T$. Finally, $\hat{\pi}$ is the estimate of $\pi$ in $p_{iT} = \pi p_0 + e_i$.

Under the null hypothesis of no convergence, $T_2 \overset{d}{\rightarrow} \chi^2(1)$ and $T_3 \overset{d}{\rightarrow} N(0, 1)$.

The assumption behind these statistics is that firms’ productivity follow a first order autoregressive process. This assumption is not very restrictive and it is standard in the production function estimation literature (see Olley and Pakes, 1996).

4.2.2 Granger’s procedure

Let $p$ be the variable of interest (log of productivity). We define $p_+$ and $p_-$ as $p_T + p_0$ and $p_T - p_0$, respectively. The procedure to test for a reduction in the variance of firms’ productivity consists in regressing $p_-$ on $p_+$. Let the coefficient of this regression be $\alpha_D$, then $\alpha_D = C(p_-, p_+)/V(p_+)$. Since the variance $V(\cdot)$ is always positive, the sign of $\alpha_D$ depends on the covariance between $p_+$ and $p_-$ which is equal to $V(p_T) - V(p_0)$. Therefore, if $\alpha_D$ is negative (positive) there is $\sigma$-convergence ($\sigma$-divergence). Then the no convergence hypothesis, $H_0 : \sigma_D = 0$, is tested against the alternative of convergence, $H_1 : \sigma_D < 0$. 

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4.3 Empirical Results

4.3.1 β-Convergence Test

Table 4 presents the results of the β-convergence test for the complete period. We consider two models for testing β-convergence. The difference between these models are the variables included in $x_{it}$. Model 1 includes industry and size dummies and Model 2 includes the same variables than Model 1 plus human capital, learning by doing, FDI, age (in logs) and the square of the log of age. Columns (1) and (3) in Table 4 report the OLS estimation of equation (2). As we mention before, this equation is estimated controlling for heteroskedasticity and autocorrelation. The null hypothesis of no convergence is rejected showing that productivity of the less productive firms has grown faster than the productivity of more productive ones. When we only control by size and industry (Model 1), it seems that firms with different size converge to different steady state. However, once we include the rest of control variables (Model 2) we note that firms’ steady state do not depends on size but it is function of human capital, learning by doing, and the participation of foreign capital.

[ TABLE 4 ABOUT HERE ]

As we saw in Table 3, exiting firms are in general less productive than survivals and therefore the OLS estimates in column (1) and (3) in Table 4 may be inconsistent due to a sample selection problem. Columns (2) and (4) show the results of the Heckman’s two step procedure to control for sample selection. In the selection equation we include all the variables of the growth equation plus the price cost margin and the capital labor ratio of each firm. The coefficient of the inverse Mills ratio ($\gamma$) is significant in both models. However, the estimated coefficient for the initial level of productivity is basically the same as the one obtained by OLS suggesting that the effect on convergence of exiting firms is statistically significant but quantitatively negligible.

In Table 3 we noted that the persistence in terms of firms’ productivity in the early 1990s was different than the persistence in firms’ productivity in

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*We consider the firms used to compute the transition matrix.*
the second half of the 1990s. Table 5 shows the results of the $\beta$-convergence test for each of the subperiods. The difference in persistence it is also clear in terms $\beta$-convergence. The implied speed of convergence for the period 1990-1995 is much higher than the speed of convergence for the period 1996-1999.

[ TABLE 5 ABOUT HERE ]

With respect to the variables that determine the firms’ steady state, Table 5 confirm that human capital and learning by doing are more important than size.

4.3.2 $\sigma$-Convergence Test

We test for $\sigma$-convergence considering the whole period and the same subperiods than in previous subsections. Moreover, we consider two different variables for testing convergence. The first variable is the log of productivity of each firm defined in equation (1), $p_{ijt}$. With this variable we test for convergence between all the firms in the manufacturing sector. The second variable we consider is the deviation from the industry mean of the log of productivity, $\tilde{p}_{ijt} = p_{ijt} - \frac{1}{N_{jt}} \sum_{i \in j} p_{ijt}$. With this variable we test for convergence between firms of the same industry. In Table 6 the convergence test for $p_{ijt}$ and $\tilde{p}_{ijt}$ are reported as “Manufacturing Sector” and “Within industry”, respectively.

The first line in Table 6 shows the ratio between the sample variance in period 0 and the sample variance in period T, $\hat{\sigma}_0^2/\hat{\sigma}_T^2$. Between 1991 and 1999 the variance of productivity ($p_{ijt}$) was almost constant. However, in 1999 the variance of productivity in deviations from the industry mean, $\tilde{p}_{ijt}$, was lower than in 1991. Table 6 shows the T2 and T3 statistics and the coefficient $\sigma_D$ of the Granger’s procedure. All these statistics reject the no convergence hypothesis within industries. The reduction in the dispersion of firms’ productivity between 1991 and 1999 within each industry was quantitatively and statistically significant.

[ TABLE 6 ABOUT HERE ]
This result is stronger than $\beta$-convergence and shows convergence in terms of productivity across firms within industries. Moreover, the convergence is without conditioning by size or other variables. However, the results of each subperiod show that convergence took place only in the early 1990s. It is not possible to reject the no convergence hypothesis for the second part of the 1990s. Only $T_3$ reject the no convergence hypothesis and at 10% of significance.

5 Understanding the Catch Up

In this section we want to understand why there is convergence only during the early 1990s. To understand this, we need to answer two questions. The first one is why firms converge in productivity and the second one is whether the forces driving convergence change over the time.

The answer to the first question is technological diffusion. In the model of technological diffusion by Jovanovic and MacDonald (1994) imitation causes technology to spread from the leaders to the followers and forces some convergence of technology among firms as the industry matures.

To answer the second question we need to add the evidence that innovation is pro-cyclical to the technological diffusion model. Geroski and Walters (1995) not only find that innovation is pro-cyclical, they find that the causal relation runs from variation in demand to variations in innovative activity but not from innovations to changes in demand. This is very important because it means that in recession there is less incentive to innovate and not that there is a recession because firms do not innovate. If leaders learn by innovating and followers by imitating and if innovation is pro-cyclical, then during the recession leaders reduce their productivity growth rate and followers still learn because imitation takes time. The final outcome of this cyclical innovation-imitation process is higher catch up during recessions.

We have identified the first half of the decade as recessive and the second part as expansive however the ESEE provides us the necessary information for being more precise in defining recessive and expansive markets. As we mention before, firms report whether they are in recessive, stable or expansive markets. We saw in Figure 1 that firms’ answers about the cycle match the aggregate growth of the economy.

Figure 4 shows the percentage of firms that report process innovation
by quintile and market situation. The percentage of process innovators is larger in higher quintiles of the productivity distribution and larger for each quintile if the market is expansive. This figure confirms that process innovation is pro-cyclical and that leaders innovate more than followers. Unfortunately, we can not distinguish between the kind of innovations. We only know if the firm has implemented a process that reduces it costs but we do not know the magnitude of the reduction or if the firm has copied the process from other firms.

[ FIGURE 4 ABOUT HERE ]

To test for higher catch up in recessive markets we compare the difference in the productivity growth rate of leaders and followers in different states of the markets. In order to do that we estimate the following equation.

\[ \Delta p_{it} = \alpha_{FR}F_{it} \times R_{it} + \alpha_{LR}L_{it} \times R_{it} \\
+ \alpha_{FE}F_{it} \times E_{it} + \alpha_{LE}L_{it} \times E_{it} \\
+ \alpha_x x_{it} + c_i + v_{it}, \] (9)

with \( F, L, R, E \) being dummy variables of follower, leader, recessive market and expansive market. Followers (leaders) are those firms that in the previous year were in quintile 1, 2, 3 or 4 (quintile 5) of the productivity distribution of their industry. The vector \( c_{it} \) includes a set of control variables. The advantage of having a panel of firms is that we can control for the unobserved heterogeneity, \( c_i \). Actually, when we control for unobserved heterogeneity, we control for any time invariant effect, for example, we control for industry.

In this equation, \( \alpha_{FR} \) and \( \alpha_{LR} \) are mean growth rate of productivity of followers and leaders in recessive markets, respectively, and \( \alpha_{FE} \) and \( \alpha_{LE} \) are the corresponding growth rates in expansive markets.

According to our definition of leaders and followers, \( L_{it} = 1 - F_{it} \). There-
fore equation (9) can be expressed as:

\[
\Delta p_{it} = \alpha_{LR} R_{it} + (\alpha_{FR} - \alpha_{LR}) F_{it} x R_{it} + \alpha_{LE} E_{it} + (\alpha_{FE} - \alpha_{LE}) F_{it} x E_{it} + \alpha x_{it} + c_i + u_{it}.
\]  

(10)

This equation provides an adequate framework for testing the convergence and cyclical convergence hypothesis. In terms of the parameters of equation (10) we can test the following hypothesis:

1. Catch up in recession: \((\alpha_{FR} - \alpha_{LR})\) larger than zero.
2. Catch up in expansion: \((\alpha_{FE} - \alpha_{LE})\) larger than zero.
3. Catch up rate in recession higher than catch up rate in expansion:
   \[ (\alpha_{FR} - \alpha_{LR}) > (\alpha_{FE} - \alpha_{LE}) \].

Table 7 presents the results of estimating equation (10) applying within group estimation. In the set of control variables we include age and year, size and region dummies.

Both \((\alpha_{FR} - \alpha_{LR})\) and \((\alpha_{FE} - \alpha_{LE})\) are significatively larger than zero. This finding is consistent with the presence of \(\beta\)-convergence. Moreover, we reject \(H_0 : (\alpha_{FR} - \alpha_{LR}) = (\alpha_{FE} - \alpha_{LE})\) against \((\alpha_{FR} - \alpha_{LR}) > (\alpha_{FE} - \alpha_{LE})\).

As a robustness check we can estimate equation (2) for consecutive periods and evaluate the catch up rate for different states of the markets by including an interaction between the lag of productivity and the recessive market dummy. Equivalently, we can estimate the persistence of firms’ productivity and test for different persistence during recessions. In order to do this we estimate the following equation.

\[
p_{it} = \rho p_{it-1} + \rho R p_{i,t-1} x R_{it} + \alpha x_{it} + c_i + u_{it}.
\]  

(11)

Note that this is not a growth equation like equation (2). However, the information that this equation provides is equivalently to the information
provided by that equation. The parameter $\rho$ is the measure of firms persistence, a value of $\rho$ lower than one indicates catch up. The lower the value of $\rho$ the higher the catch up rate. Therefore, if the catch up is higher during recessions the persistence should be lower and the parameter $\rho_R$ should be lower than zero.

We include the same set of control variables $x_{it}$ than in equation (10). The first column of Table 8 shows the results of estimating equation (11) without the interaction term and the second column presents the estimates for testing different persistence in recessive markets. In both cases, we estimate equation (11) applying the Arellano and Bond (1991) estimator. We take first difference and use the lags $p_{i,t-2}, p_{i,t-3}, \ldots$ as instruments for $\Delta p_{i,t-1}$. The specification tests can not reject the validity of the instruments and that there is no second order autocorrelation in the error term.

Since $\rho_R$ is negative and statistically significant we conclude that in recessive markets the persistence of firms’ productivity is lower.

These findings confirms that during the recessive part of the business cycle the rate of catch up is higher and it explains why there is convergence only during the early 1990s.

6 Conclusions

We study the dynamics of Spanish manufacturing firms’ productivity during the 1990s. The main findings can be summarized as follows.

First, less productive firms had, in mean, larger productivity growth rate than more productive ones. This finding provides evidence in favor of models of technological diffusion like Jovanovic and MacDonald (1994) in which less productive firms have larger productivity growth rate because by imitating the leaders they have lower learning costs. This result is robust to sample selection due to exiting firms. We find that sample selection is statistically significant but quantitatively negligible.

Second, the persistence of firms’ productivity and the convergence rate behaved differently in the early 1990s compared with the late 1990s. Until
1995 the persistence of firms’ productivity was lower and the convergence rate higher.

Third, the different behavior of the growth rates implied different behavior of the variance of firms’ productivity. Even when there was a reduction in variance of firms’ productivity from 1991 to 1999, these reduction was concentrated in the first years of the decade. Since 1996 the convergence rate was not enough to imply such a reduction.

Fourth, the period that shows convergence in firms’ productivity and higher catch up rate, 1991-1995, was characterized by lower growth rate of the Spanish economy and a large proportion of firms reporting that operate in recessive markets.

Fifth, firms’ innovation is pro-cyclical. This finding confirm Geroski and Walters (1995) findings and suggest that the incentives to innovate in recessions are lower than in expansions.

Sixth, in recessive markets the speed of catch up is higher. This finding is consistent with Jovanovic and MacDonald (1994) and the fact that innovation is pro-cyclical.

References


A Variable Description

Productivity: Explained in section 2.

Output ($Y$): Goods and services production deflated with the industrial production price index.

Labor ($L$): Total effective worked hours. It is the product between the hours of work per employee and the number of employees.

Materials ($M$): Intermediate consumption deflated with the industrial production price index.

Capital ($K$): Real value of capital stock. It is recursively estimated by the equipment investment actualized by a price index of capital goods and using sectoral estimates of the depreciation rate.

Wages ($w$): Firm’s hourly wage rate (total labor cost divided by effective total hours of work) deflated with the consumer price index.

Capital usage cost ($r$): Weighted sum of long term interest rate with banks and other long term debt plus a 15% depreciation rate minus the inflation rate.

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

Human capital: Proportion of engineers and workers with a degree.

Learning by doing: Following Bahk and Gort (1993), we measure learning by doing by the cumulative output of each firm. Denoting by $year[1]_i$ the first year in which firm $i$ appears in our sample and $born_i$ the year in which firm $i$ was born, then $n_i = year[1]_i - born_i$ is the age of firm $i$ at the moment of entering in our sample. Then, learning by doing is estimated by $lbd_{i,t} = \log LbD_{i,t}$ where $LbD_{i,t}$ is given by

$$LbD_{i,t} = \sum_{k=born_i}^{year[1]_i} Y_{i,k}$$

$$= \sum_{k=born_i}^{year[1]_i-1} Y_{i,k} + \sum_{k=year[1]_i}^{t} Y_{i,k}. \quad (12)$$

The first term is the output cumulated by firm $i$ before entering our sample and the second term is the cumulated output after entering the sample. To estimate the first term we assume a constant output growth or discount rate ($r$) and we add up the firm’s output backwards until the born year of the
firm. Therefore, it is estimated by

\[
\sum_{k = \text{born}_{i}}^{\text{year}[1],-1} Y_{i,k} = Y_{i,\text{year}[1]} \sum_{j=1}^{n_i} \frac{1}{(1+r)^j}
\]

\[
= Y_{i,\text{year}[1]} \left( 1 - \frac{1}{(1+r)^n_i} \right) \frac{1}{r}.
\] (13)

We take \( r \) equal to 1.8\% which is the average growth rate of the Spanish Industrial Production Index published by the Spanish Statistical Office (Instituto Nacional de Estadística, INE) for the period 1975-1991. The average age of a firm in 1991 is 16.4 years therefore 1975 is a good approximation of the born year of the average firm. The estimation of the learning by doing before the firm enter to our sample is important for the cross section regressions. However, in the case of panel data estimations we can control for this part of the learning by doing by considering it as an unobservable time invariant component.

**Foreign capital:** Dummy variable that takes value one when the percentage of foreign capital is larger than 10.

**Price Cost Margin:** Sales minus personal and materials costs divided by sales.

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

**Industry:** Firms are classified in 11 industries. See Table 1.

**Expansive Market:** Dummy variable that takes value one when the firm reports that its market is expansive. In the ESEE firms report whether their market are expansive, stable or recessive.

**Recessive Market:** Dummy variable that takes value one when the firm reports that its market is recessive.

**Follower:** Dummy variable that takes value one when the firm was in quintile 1, 2, 3 or 4 in previous year.

**Leader:** Dummy variable that takes value one when the firm was in quintile 5 in previous year.
B The growth equation

Consider the following model for firms’ productivity

\[ p_{i,T} = \beta' x_{i,T} + w_{i,T} \]  
(14a)

\[ w_{i,T} = \rho w_{i,T-1} + \varepsilon_{i,T} \]  
(14b)

This specification indicates that productivity is determined by the variables \( x_{i,T} \), the autoregressive error introduces persistence in productivity.

According to this specification we have

\[ p_{i,T} - \beta' x_{i,T} = \rho w_{i,T-1} + \varepsilon_{i,T} \]  
(15)

Since \( w_{i,T} \) follows a AR(1) process, \( w_{i,T-1} \) can be expressed as

\[ w_{i,t-1} = \rho^{T-1} w_{i,0} + \sum_{j=0}^{T-2} \rho^j \varepsilon_{i,T-1-j} \]  
(16)

By substituting equation (16) into equation (15) we obtain

\[ p_{i,T} - \beta' x_{i,T} = \rho \left( \rho^{T-1} w_{i,0} + \sum_{j=0}^{T-2} \rho^j \varepsilon_{i,T-1-j} \right) + \varepsilon_{i,T} \]  
(17)

This expression can be rewritten like

\[ p_{i,T} - \beta' x_{i,T} = \rho^T (p_{i,0} - \beta' x_{i,0}) + \sum_{j=0}^{T-2} \rho^{j+1} \varepsilon_{i,T-1-j} + \varepsilon_{i,T} \]  
(18)

Subtracting \( p_{i,0} \) from both sides and dividing by \( T \)

\[ T^{-1} (p_{i,T} - p_{i,0}) = \left( \frac{\rho^T - 1}{T} \right) p_{i,0} - \frac{\rho^T \beta'}{T} x_{i,0} + \beta' x_{i,T} + \frac{1}{T} \left( \sum_{j=0}^{T-2} \rho^{j+1} \varepsilon_{i,T-1-j} + \varepsilon_{i,T} \right) \]  
(19)

Defining \( b = \left( \frac{\rho^T - 1}{T} \right), \alpha = \frac{\rho^T \beta'}{T}, \) assuming that equation (14a) includes a constant and defining \( u_i = \frac{\beta'}{T} x_{i,T} + \frac{1}{T} \left( \sum_{j=0}^{T-2} \rho^{j+1} \varepsilon_{i,T-1-j} + \varepsilon_{i,T} \right) \) then the later equation is the same as equation (2), that is,

\[ T^{-1} (p_{i,T} - p_{i,0}) = a + bp_{i,0} + \alpha' x_{i,0} + u_i \]  
(20)
According to the structure of the error term in (20) this equation should be estimated controlling for heteroskedasticity and autocorrelation.
### Table 1: Number of observations by industry.

<table>
<thead>
<tr>
<th>Industry</th>
<th>NACE</th>
<th>Number of Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Metals and Metals Products</td>
<td>27, 28</td>
<td>1,654</td>
</tr>
<tr>
<td>Non-metallic products</td>
<td>26</td>
<td>939</td>
</tr>
<tr>
<td>Chemical products</td>
<td>23, 24, 25</td>
<td>1,607</td>
</tr>
<tr>
<td>Machinery</td>
<td>29</td>
<td>683</td>
</tr>
<tr>
<td>Office Machines and Electrical Goods</td>
<td>30, 31, 32, 33</td>
<td>1,112</td>
</tr>
<tr>
<td>Transport Equipment</td>
<td>34, 36</td>
<td>818</td>
</tr>
<tr>
<td>Food, Beverages and Tobacco</td>
<td>15, 16</td>
<td>2,076</td>
</tr>
<tr>
<td>Textile, Leather and Shoes</td>
<td>17, 18, 19</td>
<td>1,898</td>
</tr>
<tr>
<td>Wood Products and Furniture</td>
<td>20, 36.1</td>
<td>794</td>
</tr>
<tr>
<td>Paper and Printing Products</td>
<td>22</td>
<td>977</td>
</tr>
<tr>
<td>Other manufactured products</td>
<td>36, except 36.1</td>
<td>270</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>12,828</td>
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</table>

### Table 2: Descriptive Statistics

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<tr>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (Std.Dev.)</td>
<td>Mean (Std.Dev.)</td>
<td>Mean (Std.Dev.)</td>
</tr>
<tr>
<td>Small (Less than 50 but more than 10 employees)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>TFP (in logs)</td>
<td>1.49 (0.29)</td>
<td>1.49 (0.29)</td>
<td>1.49 (0.28)</td>
</tr>
<tr>
<td>TFP (Annual Growth Rate, in percentage)</td>
<td>-0.26 (19.3)</td>
<td>-0.99 (22.7)</td>
<td>0.25 (16.7)</td>
</tr>
<tr>
<td>Age (years)</td>
<td>15 (14)</td>
<td>14 (14)</td>
<td>16 (14)</td>
</tr>
<tr>
<td>Learning by Doing (in logs)</td>
<td>9.65 (1.21)</td>
<td>9.50 (1.24)</td>
<td>9.79 (1.18)</td>
</tr>
<tr>
<td>Knowledge Capital (in logs)</td>
<td>1.78 (3.59)</td>
<td>1.46 (3.34)</td>
<td>2.10 (3.80)</td>
</tr>
<tr>
<td>Human Capital (% of engineers and workers with a degree)</td>
<td>2.04 (4.90)</td>
<td>1.49 (4.11)</td>
<td>2.57 (5.52)</td>
</tr>
<tr>
<td>Percentage of Foreign Capital</td>
<td>2.20 (13.3)</td>
<td>1.96 (12.8)</td>
<td>2.45 (14.3)</td>
</tr>
<tr>
<td>Medium (Less than 200 but more than 50 employees)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>TFP (in logs)</td>
<td>1.55 (0.26)</td>
<td>1.55 (0.26)</td>
<td>1.56 (0.27)</td>
</tr>
<tr>
<td>TFP (Annual Growth Rate, in percentage)</td>
<td>1.02 (15.6)</td>
<td>1.00 (19.5)</td>
<td>1.03 (12.6)</td>
</tr>
<tr>
<td>Age (years)</td>
<td>27 (21)</td>
<td>26 (20)</td>
<td>27 (21)</td>
</tr>
<tr>
<td>Learning by Doing (in logs)</td>
<td>12.29 (1.22)</td>
<td>12.21 (1.16)</td>
<td>12.35 (1.27)</td>
</tr>
<tr>
<td>Knowledge Capital (in logs)</td>
<td>5.41 (5.54)</td>
<td>4.67 (5.48)</td>
<td>6.05 (5.51)</td>
</tr>
<tr>
<td>Human Capital (% of engineers and workers with a degree)</td>
<td>3.67 (5.58)</td>
<td>2.72 (4.00)</td>
<td>4.46 (6.52)</td>
</tr>
<tr>
<td>Percentage of Foreign Capital</td>
<td>23.32 (39.5)</td>
<td>22.43 (38.6)</td>
<td>24.06 (40.2)</td>
</tr>
<tr>
<td>Large (More than 200 employees)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TFP (in logs)</td>
<td>1.57 (0.23)</td>
<td>1.54 (0.23)</td>
<td>1.59 (0.23)</td>
</tr>
<tr>
<td>TFP (Annual Growth Rate, in percentage)</td>
<td>0.57 (12.3)</td>
<td>0.33 (15.7)</td>
<td>0.74 (9.2)</td>
</tr>
<tr>
<td>Age (years)</td>
<td>35 (23)</td>
<td>34 (23)</td>
<td>36 (23)</td>
</tr>
<tr>
<td>Learning by Doing (in logs)</td>
<td>14.07 (1.16)</td>
<td>13.95 (1.15)</td>
<td>14.18 (1.16)</td>
</tr>
<tr>
<td>Knowledge Capital (in logs)</td>
<td>9.44 (5.43)</td>
<td>8.60 (5.67)</td>
<td>10.39 (4.98)</td>
</tr>
<tr>
<td>Human Capital (% of engineers and workers with a degree)</td>
<td>4.76 (6.58)</td>
<td>3.7 (5.83)</td>
<td>5.84 (7.14)</td>
</tr>
<tr>
<td>Percentage of Foreign Capital</td>
<td>40.80 (46.2)</td>
<td>39.6 (45.5)</td>
<td>42.05 (46.9)</td>
</tr>
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Table 3: Within industries one period transition matrices

<table>
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</thead>
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<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>Exit</td>
</tr>
<tr>
<td>1</td>
<td>0.531</td>
<td>0.224</td>
<td>0.069</td>
<td>0.043</td>
<td>0.032</td>
<td>0.102</td>
</tr>
<tr>
<td>2</td>
<td>0.220</td>
<td>0.367</td>
<td>0.228</td>
<td>0.078</td>
<td>0.041</td>
<td>0.066</td>
</tr>
<tr>
<td>3</td>
<td>0.077</td>
<td>0.221</td>
<td>0.344</td>
<td>0.230</td>
<td>0.071</td>
<td>0.058</td>
</tr>
<tr>
<td>4</td>
<td>0.030</td>
<td>0.092</td>
<td>0.227</td>
<td>0.421</td>
<td>0.178</td>
<td>0.052</td>
</tr>
<tr>
<td>5</td>
<td>0.033</td>
<td>0.035</td>
<td>0.072</td>
<td>0.178</td>
<td>0.619</td>
<td>0.063</td>
</tr>
<tr>
<td>Entry</td>
<td>0.086</td>
<td>0.043</td>
<td>0.039</td>
<td>0.023</td>
<td>0.044</td>
<td></td>
</tr>
</tbody>
</table>

Notes:
1. Productivity in deviations from the industry mean ($\tilde{p}_{ijt} = p_{ijt} - \sum_{i \in I} p_{ijt}$).
2. Each transition matrix is the average of the transition matrix of each year weighted by the quantity of firms in each year.
3. 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>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>Heckman</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>TFP</td>
<td>-0.075***</td>
<td>-0.075***</td>
</tr>
<tr>
<td>Medium (between 50 and 200 employees)</td>
<td>0.008***</td>
<td>0.010***</td>
</tr>
<tr>
<td>Large (more than 200 employees)</td>
<td>0.011***</td>
<td>0.013***</td>
</tr>
<tr>
<td>Human Capital</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Learning by doing</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Dummy for foreign capital</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Age (logs)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Age (square of logs)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Mills lambda</td>
<td>-</td>
<td>0.012***</td>
</tr>
</tbody>
</table>

Statistics

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>Heckman</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of observations</td>
<td>670</td>
<td>844</td>
</tr>
<tr>
<td>Censored observations</td>
<td>174</td>
<td>172</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.44</td>
<td>0.46</td>
</tr>
<tr>
<td>chi2 (df) [p-value]</td>
<td>524.9 (26)</td>
<td>0.000</td>
</tr>
<tr>
<td>rho</td>
<td></td>
<td>0.612</td>
</tr>
<tr>
<td>sigma</td>
<td></td>
<td>0.019</td>
</tr>
<tr>
<td>lambda [se]</td>
<td></td>
<td>0.012 [0.005]</td>
</tr>
</tbody>
</table>

Notes: Significance levels: *: 10% **: 5% ***: 1%
Robust standard errors. All regressions include a constant and industry dummies.
Table 5: β-convergence Test. Results by subperiods.

<table>
<thead>
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<th></th>
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<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 1</td>
<td>Model 2</td>
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<tr>
<td></td>
<td>OLS</td>
<td>Heckman</td>
<td>OLS</td>
<td>Heckman</td>
<td>OLS</td>
<td>Heckman</td>
</tr>
<tr>
<td>TFP</td>
<td>-0.133***</td>
<td>-0.134***</td>
<td>-0.143***</td>
<td>-0.147***</td>
<td>-0.076***</td>
<td>-0.074***</td>
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<tr>
<td></td>
<td>-0.076***</td>
<td>-0.074***</td>
<td>-0.087***</td>
<td>-0.083***</td>
<td>-0.004</td>
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<tr>
<td>Medium (between 50 and 200 employees)</td>
<td>0.008**</td>
<td>0.013***</td>
<td>-0.005</td>
<td>-0.005</td>
<td>0.011***</td>
<td>0.011***</td>
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<tr>
<td></td>
<td>0.004</td>
<td>0.002</td>
<td></td>
<td></td>
<td>0.004</td>
<td>0.002</td>
</tr>
<tr>
<td>Large (more than 200 employees)</td>
<td>0.016***</td>
<td>0.019***</td>
<td>-0.010</td>
<td>-0.016**</td>
<td>0.010***</td>
<td>0.011***</td>
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<td></td>
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<td>-0.003</td>
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<td>-0.003</td>
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<td>Human Capital</td>
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<td>-0.470**</td>
<td>0.240</td>
<td>-</td>
<td>-</td>
<td>0.088***</td>
</tr>
<tr>
<td></td>
<td>0.003</td>
<td>0.003**</td>
<td></td>
<td></td>
<td>0.003</td>
<td>0.003**</td>
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<tr>
<td>Learning by doing</td>
<td>-</td>
<td>-0.006***</td>
<td>0.010***</td>
<td>-</td>
<td>-</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>0.001</td>
<td>0.001</td>
<td></td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>Dummy for foreign capital</td>
<td>-</td>
<td>-0.015***</td>
<td>-0.008</td>
<td>-</td>
<td>-</td>
<td>-0.029</td>
</tr>
<tr>
<td>Age (logs)</td>
<td>-</td>
<td>0.001</td>
<td>0.000</td>
<td></td>
<td>0.004</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
<td>0.004</td>
<td>0.003</td>
</tr>
<tr>
<td>Age (square of logs)</td>
<td>-</td>
<td>0.028***</td>
<td>-0.04***</td>
<td>-</td>
<td>0.012**</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>0.021**</td>
<td></td>
<td></td>
<td></td>
<td>0.021**</td>
<td></td>
</tr>
<tr>
<td>Mills lambda</td>
<td>-</td>
<td>0.028***</td>
<td>-0.04***</td>
<td>-</td>
<td>0.012**</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>0.021**</td>
<td></td>
<td></td>
<td></td>
<td>0.021**</td>
<td></td>
</tr>
</tbody>
</table>

Statistics

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of observations</td>
<td>711</td>
<td>844</td>
<td>707</td>
</tr>
<tr>
<td>Censored observations</td>
<td>133</td>
<td>131</td>
<td>285</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.41</td>
<td>0.44</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>0.18</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>chi2 (df) [p-value]</td>
<td>501.9 (26) [0.000]</td>
<td>515.7 (36) [0.000]</td>
<td>130.3 (26) [0.000]</td>
</tr>
<tr>
<td>rho</td>
<td>0.759</td>
<td>1.000</td>
<td>0.353</td>
</tr>
<tr>
<td></td>
<td>0.631</td>
<td>0.037</td>
<td>0.040</td>
</tr>
<tr>
<td>sigma</td>
<td>0.003</td>
<td>0.033</td>
<td></td>
</tr>
<tr>
<td>lambda [se]</td>
<td>0.028 [0.009]</td>
<td>0.040 [0.011]</td>
<td>0.012 [0.006]</td>
</tr>
</tbody>
</table>

Notes: Significance levels: *: 10%  **: 5%  ***: 1%
Robust standard errors. All regressions include a constant and industry dummies.
Table 6: $\sigma$-Convergence Test

<table>
<thead>
<tr>
<th></th>
<th>Manufacturing Sector</th>
<th>Within industries</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{\sigma}_0^2/\hat{\sigma}_T^2$</td>
<td>0.998</td>
<td>1.007</td>
<td>1.036</td>
<td>1.247</td>
</tr>
<tr>
<td>T2</td>
<td>0.002</td>
<td>0.018</td>
<td>0.995</td>
<td>10.624***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T3</td>
<td>-0.033</td>
<td>0.111</td>
<td>0.747</td>
<td>3.545***</td>
</tr>
<tr>
<td>$\sigma_D$</td>
<td>0.003</td>
<td>-0.009</td>
<td>-0.105</td>
<td>-0.188**</td>
</tr>
</tbody>
</table>

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

When $\hat{\sigma}_0^2/\hat{\sigma}_T^2 < 1$ we test for divergence, the alternative hypothesis in this case is $H_1 : \sqrt{V(pr)} > \sqrt{V(p_0)}$.

The manufacturing sector variance and the within industries variance are the variance of $p_{ijt} = \log P_{ijt}$ and the variance of $\bar{p}_{it} = p_{ijt} - \frac{1}{N_j} \sum_{i \in j} p_{ijt}$, respectively.

Table 7: Catch Up in the Business Cycle 1.

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recessive Market</td>
<td>-0.168***</td>
<td>[0.010]</td>
</tr>
<tr>
<td>Follower × Recessive Market</td>
<td>0.182***</td>
<td>[0.011]</td>
</tr>
<tr>
<td>Expansive Market</td>
<td>-0.088***</td>
<td>[0.009]</td>
</tr>
<tr>
<td>Follower × Expansive Market</td>
<td>0.129***</td>
<td>[0.010]</td>
</tr>
<tr>
<td>Number of observations</td>
<td>10355</td>
<td></td>
</tr>
<tr>
<td>Number of firms</td>
<td>2110</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.053</td>
<td></td>
</tr>
<tr>
<td>Test $(\alpha_{FR} - \alpha_{LR}) - (\alpha_{FE} - \alpha_{LE}) \leq 0$</td>
<td>14.21 (0.000)</td>
<td></td>
</tr>
<tr>
<td>F (p-value)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hausman Test</td>
<td></td>
<td></td>
</tr>
<tr>
<td>chi2 (p-value)</td>
<td>57.51 (0.000)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: (i) Within group estimation; (ii) Dependent variable: $\Delta p_{it}$; (iii) Follower is a dummy variable that take value one if in period t-1 the firm was in quintile 1, 2, 3 or 4; (iv) The regression includes age and year, region and size dummies.
Table 8: Catch Up in the Business Cycle 2.

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_{t-1}$</td>
<td>0.125***</td>
<td>0.185***</td>
</tr>
<tr>
<td></td>
<td>[0.034]</td>
<td>[0.045]</td>
</tr>
<tr>
<td>$p_{t-1} \times$ Recessive Market</td>
<td>-</td>
<td>-0.074**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.032]</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>8197</td>
<td>8177</td>
</tr>
<tr>
<td>Number of firms</td>
<td>1761</td>
<td>1757</td>
</tr>
<tr>
<td>Hansen chi2 (p-value)</td>
<td>23.74(0.645)</td>
<td>19.61(0.810)</td>
</tr>
<tr>
<td>m1 (p-value)</td>
<td>-10.07(0.000)</td>
<td>-9.41(0.000)</td>
</tr>
<tr>
<td>m2 (p-value)</td>
<td>0.97(0.331)</td>
<td>1.02(0.306)</td>
</tr>
</tbody>
</table>

Notes: (i) Arellano-Bond estimation; (ii) Dependent variable: $p_{t}$; (iii) The regression includes age and year, region and size dummies.
Figure 1: Percentage of firms reporting recessive or expansive market and GDP growth.

Source: Percentage of firms reporting recessive or expansive market (ESEE); GDP Growth (National Institute of Statistics of Spain, INE).
Figure 2: Total Factor Productivity, 1995=100

Source: Spain and Spain/UE15 (Bank of Spain); Spain, Manufacturing Sector (ESEE).
Figure 3: Productivity and size of entrants and exiting firms.

Panel (a): Percentage of entrants. Panel (b): Percentage of exiting firms. This figures should be read as follows: Panel (a): With respect to TFP, around 35% of new firms enter in the bottom quintile ($Q_1$) of the TFP distribution; 20% at the second quintile ($Q_2$); 15% at the third and so on. With respect to sales, 35% of new firms enter in the bottom distribution of the sales distribution; 25% in the second quintile and only 5% in the top quintile ($Q_5$) of the sales distribution. Panel (b): From the firm that exit the market 30% were in the bottom quintile of the TFP distribution; 20% in the second quintile; and so on. With respect to sales, 30% of the firms that exit the market were in the bottom quintile of the sales distribution and 10% in the top quintile.
Figure 4: Percentage of firms with process innovation by quintile.

Notes: The quintiles refer to the mean quintile in which the firm is located over all the period, that is, the quintile corresponding to firm $i$ is $q_i = 1/T_i \sum_{t=1}^{T_i} q_{it}$ where $q_{it}$ is the quintile in which firm $i$ is in period $t$. Since $q_i$ are not necessary in $\{1, 2, 3, 4, 5\}$, we take the following intervals $[1, 1.5); [1.5, 2.5); [2.5, 3.5); [3.5, 4.5)$; and $[4.5, 5)$ for defining quintiles.