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On the Determinants of TFP Growth: Evidence from Spanish Manufacturing Firms

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On the Determinants of TFP Growth: Evidence from Spanish Manufacturing Firms*

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Abstract

This paper explores the main determinants of productivity growth. The analysis is performed using Spanish firm-level data. We define a framework where the relative magnitudes of alternative, but not exclusive, sources of technical change is simultaneously estimated. Our main finding is that almost all the advances in technology need to be embodied either in new capital goods or in human capital. Our results contradict the existence of a positive contribution of neutral technological progress in determining the aggregate TFP growth. They also leave little room for large, unpriced effects external to the firm, both at the aggregate and industry level. We find evidence of firm-specific learning by doing, short-lived and due to adoption of new processes.

Keywords: TFP Growth, Technical Change, Human Capital, Learning by Doing.

JEL Classification: L60, O30, O33.

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1 Introduction

This paper takes a fresh empirical look at the main determinants of total factor productivity (TFP) growth, using a particularly rich set of Spanish firm-level data. To our dataset, whose structure is briefly illustrated below and then detailed in Section 3, we ask two main questions: i) Are changes in aggregate TFP attributable to 'embodied' or 'disembodied' technological change? ii) Is there evidence of large, unpriced spillovers across firms and industries?

We make use of an unbalanced micro-panel dataset of Spanish manufacturing firms observed with annual frequency during the period 1990-2006. This dataset proves to be particularly suitable for disentangling the impact of specific individual sources of productivity growth, as it includes detailed observations on firms' outputs, inputs, proportion of skilled employees, type of capital investment undertaken and innovation in production process. Moreover, a unique feature of this dataset is that it provides firm-specific prices for outputs and intermediary inputs, thus allowing for the construction of a more reliable measure of firms' productivity change.

Several empirical studies have found widespread heterogeneity among firms within an industry (see, among others, Baily, Hulten and Campbell, 1992, and Bernard, Eaton, Jensen and Kortum, 2003). This evidence challenges the restrictive assumptions underlying the use of a measure of aggregate productivity based on the representative firm paradigm. Indeed, aggregate productivity may measure factors other than true technological changes. In particular, average productivity growth can be the outcome of reallocation of inputs from less to more efficient firms within an industry and from less to more efficient industries within the economy.[1] In other words, if resources get reallocated from bad to good firms, an empirical analysis based on the representative firm paradigm would show no change in total inputs but a rise in output, and we would conclude that there was a rise in aggregate TFP growth.

Firm-level studies recognize explicitly the heterogeneity of firms. They permit a detailed examination of how individual characteristics drive cross-sectional productivity dif-

[1] Basu and Fernald (1995) find higher productivity at higher levels of aggregation and they suggest that this effect is due to reallocation of resources from less productive to more productive firms.

ferentials, and how the latter combine into aggregate productivity growth. Empirical studies at micro level allow to analyze the determinants of aggregate productivity changes leaving the effects of reallocation aside.

Furthermore, by digging deep into micro data, it is possible to learn something about aggregate TFP growth that data at the industry level cannot possibly disclose. First, only with firm-level data can we estimate a model which discriminates between economies that are external to the firm but internal to the industry. In particular, our approach allows us to assess the relevance of each variable at firm level (without spillovers to other firms in the sector) as opposed to the importance at industry, or economy-wide, level. Second, by exploiting the information contained in micro data, it is possible to construct detailed variables that can better capture all the different sources of productivity growth. For instance, our survey allows us to infer when a firm investment involves a change of technology and production process and when it is just 'more of the same' (i.e. capital deepening).

Our approach is empirical in nature and is based on the estimation of a number of differently specified reduced-form equations. Our regressions are motivated and inspired by various dynamic models of technological progress and innovative activity. We consider a general framework where the relative magnitudes of alternative, but not necessarily exclusive, sources of productivity growth are simultaneously estimated and compared. To this purpose, we consider the following possible explanations: disembodied and physical-capital-embodied technological progress, human capital accumulation, learning-by-doing, and external effects at the industry and aggregate level.

Our estimation builds up progressively from a simple regression, which reveals a large and unexplained residual. First, we analyze the contributions of traditional disembodied variables as sources of aggregate TFP growth. We consider firm-specific learning-by-doing (LBD), and unpriced externalities, such as human capital and R&D spillovers. To assess the effect of firm-specific LBD, we follow the common practice of using the cumulative output per employee (see Bahk and Gort, 1993, among others). Moreover, following the relevant literature, we capture human capital spillovers with the industry median wage and R&D spillovers with the industry R&D expenditure. We also consider the ratio of skilled employees (i.e., with bachelor or higher degree) over the total number of workers at the industry level instead of the median wage. Our results show the importance of disembodied variables in affecting aggregate TFP growth.

Then we take into account the relevance of embodied variables as an engine of aggregate TFP growth. We measure the impact of new capital goods by means of two variables: the average vintage of the physical capital, and an index of new technology usage. We account for differences in human capital using two variables: firm wages and the percentage of R&D employees at the firm level. To avoid endogeneity issues, we also estimate a specification with the ratio of skilled workers at the firm level instead of firm wages. Once the measures of embodied technological progress are considered, the variables that capture firm-specific LBD, human capital externalities and R&D spillovers do not show any relevance in affecting aggregate TFP growth. We find that embodied variables alone can fully explain aggregate TFP growth. This result seems to suggest that previous studies might have largely overestimated the actual relevance of spillover effects on aggregate TFP growth. Last, but not least, we find compelling evidence of constant returns to scale across all the estimated specifications: either constant returns to scale cannot be rejected or, when rejected, quantitatively they are very close to constant.

Finally, in order to better assess firm-specific LBD, we consider two alternative measures that, in our view, are closer in spirit to the theoretical idea behind LBD: cumulative output since the introduction of a process innovation and time after the introduction of a process innovation. These two variables should capture the idea that a change in production must trigger a new learning cycle. When considered together with the embodied variables, these alternative measures of firm-specific LBD retain some explanatory power. This is coherent with classical definition of LBD: internal to the firm, short-lived and due to the adoption of new processes. However, they do not affect the much more sizeable explanatory power of embodied physical and human capital.

To sum up, our paper delivers three main results. First, advances in technology need to be embodied in new capital goods or in human capital. That is, aggregate TFP growth is fully explained by embodied technical progress. Economy-wide neutral (or disembodied) technical change such as spillovers play virtually no role. Indeed, the positive contribution of human capital and R&D spillovers on aggregate TFP growth vanishes when estimated in a model that also includes the variables capturing the quality of human and physical capital. Second, we find mixed evidence of firm-specific learning-by-doing: when measured as cumulative output, LBD is insignificant, but when measured as output or time from the last innovation it contributes to firm's productivity. Third, in many specifications, constant returns to scale cannot be rejected and, when rejected, quantitatively returns to scale are very close to constant.

The paper is organized as follows. In Section 2, we review the empirical literature underlying the motivations of the paper. In Section 3, we illustrate the dataset, the main features of the TFP growth measure to be investigated, and we specify the empirical model adopted. In Section 4, we explain how the variables have been constructed. In Section 5, we discuss the estimation results. Section 6 is the conclusion. A more detailed description of how the variables are computed is provided in the Appendix.

2 Related Literature

There is a vast empirical literature dealing with productivity growth. Based on growth accounting measures, Abramovitz (1956) carried out one of the first attempts in determining the sources of productivity growth. His results indicated that the main sources of U.S. productivity growth were still unidentified. This finding led to Abramovitz's (1956, p. 11) famous comment: "Since we know little about the cause of productivity increase, the indicated importance of this element may be taken to be some sort of measure of our ignorance about the causes of economic growth".

At roughly the same time, Solow (1957) provided an analytical framework for interpreting the existence of an exogenous residual, and also used it to measure a very large, and unexplained total productivity factor. It was clear that *squeezing down* the residual was the crucial issue to deal with. Jorgenson and Griliches (1967) argued that in a growth-accounting framework where technological progress was embodied into the measurable inputs, the residual could be eliminated altogether. That is, as an empirical matter, output growth might be attributed entirely to input growth, once changes in the quality of those inputs were taken into account. However, after being criticized by Denison (1969), they retreated from their position (Jorgenson and Griliches, 1972). Adopting a conceptually different approach (i.e., making use of microeconomic data and econometric techniques), we are able to squeeze the residual down to zero by attributing aggregate TFP growth to its original determinants.

More recently, Greenwood, Hercowitz and Krusell (1997) estimate how much of the U.S. post-war technology progress is due to the embodied part and how much is due to the neutral part. They calibrate a vintage capital model, finding that investment specific technological progress accounts for 60% of the growth in output. However, they attribute the unexplained 40% of aggregate TFP growth to neutral technical progress. In contrast, by using firm-level data and measures of the quality of human capital, we find that neutral technical progress plays almost no role in our dataset. Our results are consistent with those by Henderson and Russell (2005). Studying the composition of labor productivity growth in 52 countries, they find that technological change is decidedly non neutral and that it is mainly driven by physical and human capital accumulation.

Microeconometric empirical analysis has also explored the sources of productivity, although without discerning the importance of embodied and disembodied sources of growth. Bahk and Gort (1993) estimate a model in levels based on U.S. plant-level data. They mainly focus on the effect of LBD on firm output, neglecting the existence of economic-wide LBD. However, they find that firm-specific LBD has a significant effect on firm output. We define, instead, our estimating equation in growth rates. As long as we are interested in explaining the sources of economic growth, we believe that our approach is more appropriate.[2] We also consider a broader array of variables measuring the magnitude of embodied technological progress and human capital. Our point estimate for the effect of firm-specific LBD (measured by total cumulative output per employee) on aggregate TFP growth is of the same order of magnitude to the one reported in Bahk and Gort (1993). However, when proxies for embodied technological progress and human capital are added, this effect disappears. Similarly, Moretti (2004) finds a positive externality in education analyzing a sample of U.S. manufacturing firms. However, he does not consider a complete set of variables to capture embodied physical capital and human capital as an explanation of firm productivity growth.

[2] A model specified in first differences has the further advantage of eliminating firm-specific effects that are persistent over time (Griliches and Mairesse, 1995).

3 Data and Analysis of TFP Growth

The data used in this study are retrieved from the Encuesta Sobre Estrategias Empresariales (ESEE), an unbalanced panel of Spanish manufacturing firms observed for the period 1990-2006. The survey has been sponsored by the Ministry of Industry and it is published by the Fundacion Empresa Publica. In the first year of the survey, 5 percent of all manufacturing firms with between 10 and 200 employees were randomly selected by industry and size strata. At the same time, all firms with more than 200 workers were asked to participate, and 70 percent of these firms decided to respond to the questionnaire.

Firms can disappear from the sample either because they stop their activity (exit due to shutdown) or they cease to answer the questionnaire (attrition). In order to preserve representativeness, a sample of newly created firms was added to the survey every year. Detailed information about the evolution of the sample can be found at www.funep.es/esee/esee_evolucion_t.htm.

Our sample includes firms with at least three consecutive observations, after dropping all yearly observations for which some of the variables required to perform the estimation are not available. The ESEE provides detailed data on firms' output, inputs, innovation, research activities and quality of workers. An interesting feature of this survey is that it includes observations on price changes for output and intermediary inputs, thus allowing for a more precise computation of productivity changes. Further information on the ESEE can be found in González, Jaumandreu and Pazo (2005) and Ornaghi (2006).

We present now an explorative analysis on the features of the productivity growth computed as the Solow residual according to equation (3) below. Picture 1 plots the 5, 50 and 95 percentiles of the productivity growth distribution of Spanish manufacturing firms during the period 1990-2006.

INSERT PICTURE 1 ABOUT HERE

Although the difference between high productivity firms (percentile 95) and low productivity firms (percentile 5) tends to decrease across the years, we find a high dispersion of productivity growth across the period. The persistent dispersion of productivity growth over time already casts some doubts on the plausibility of theoretical models where technological progress is freely available (Solow, 1956). If this were the case, the dispersion of productivity growth should be minimal. Such dispersion, instead, can be justified in a context where firms adopt a wide range of technologies, internalize their costs/benefits, and are managed by entrepreneurs with different skills.[3]

Following Baily, Hulten and Campbell (1992), Table 1 represents a transition matrix among productivity classes. This matrix is constructed by classifying the manufacturing firms by quintiles according to their level of productivity in 1992, and in 2002, at the industry level. The number in each cell shows where the firms are in 2002, given their starting quintile in 1992. For instance, consider the firms that are in the first quintile in 1992. In 2002, 42 percent of these low productivity firms are still in the first quintile and 39 percent of them disappear. Only 2 percent of them are able to move up to the fifth quintile. For the firms established after 1992, we report their quintile in 2002. For example, 27 percent of these new companies are in the first quintile in 2002.

INSERT TABLE 1 ABOUT HERE

The figures in Table 1 suggest that there is not only great dispersion in productivity growth, but also persistence in this dispersion at the micro level across the years. That is, firms which are in the bottom (or top) quintile in 1992 tend to be there ten years later. Results are similar if we use ranks weighted by size or labor productivity.

Table 2 analyses the average education and innovation over the period 1992-2002 for firms with the lowest/highest productivity levels in year 1992. We find that firms that move from the lowest quintile in 1992 to the highest quintile in 2002 have a share of skilled workers of 10 percent and an innovation rate of 0.41 (i.e., almost an innovation every two years). In contrast, firms that are in the lowest quintile both in 1992 and in 2002 have only an average of 3 percent of educated workers and an innovation rate of 0.14 (i.e., an innovation every seven years).

[3]Note that, by the same token, this also casts a doubt on models of technological progress based on aggregate spillovers. If external effects are free and industry- or system-wide, why would individual firms be affected so differently by them?

INSERT TABLE 2 ABOUT HERE

Table 3 reports the quintiles of the average productivity growth of each firm in the dataset. Since the dataset is unbalanced, firm averages are computed over different periods. Firms with the highest average productivity growth are characterized by the highest level and growth of education, and by the highest innovation ratio. In contrast, firms with the lowest productivity growth display remarkably lower values of education (both in levels and growth) and innovation.

INSERT TABLE 3 ABOUT HERE

Table 2 and 3 show that there is a high correlation between productivity growth and the human capital and innovation efforts at the firm level. This evidence anticipates qualitatively the result of the econometric model.

3.1 The Empirical Model

We assume that the production function of firm i can be written at any point in time t as:

$$Q_{it} = A_t \cdot e^{(\eta_i + z_{it})} \cdot LBD_{it} \cdot (HC_{it} \cdot L_{it})^{\beta_{it}^L} (EMB_{it} \cdot K_{it})^{\beta_{it}^K} \cdot M_{it}^{\beta_{it}^M} \tag{1}$$

where Q represents the output, M the materials, L and K the conventional measures of labor and physical capital, while HC and EMB represent the level of efficiency of labor (i.e. human capital) and physical capital (i.e., index of technology embodied in the firm's equipment), respectively. The term LBD represents firm-specific learning by doing. The term A is the aggregate disembodied technical change that captures economic-wide improvements in the way firms can transform inputs into output. The term η_i refers to unobserved firm-specific factors of production, such as entrepreneurial ability, that determine persistent differences in productivity levels over time (i.e., firm fixed effects). Finally, the term z_{it} refers to a firm-specific, mean-zero residual productivity growth (for instance, it could measure firm-specific effects of spillovers aggregating to zero).

Taking logarithms and first differences, we obtain the following linear equation

$$\Delta q_{it} = \Delta a_t + \Delta lbd_{it} + \beta_{it}^{L}\Delta l_{it} + \beta_{it}^{L}\Delta hc_{it} + \beta_{it}^{K}\Delta k_{it} + \beta_{it}^{C}\Delta emb_{it} + \beta_{it}^{M}\Delta m_{it} + \Delta z_{it}, \quad (2)$$

where lower case letters are logarithms of their upper case counterparts while Δ stands for differences between year t and $t-1$.[4] First differencing implies that firm-fixed effect η_i are eliminated from the specification. Equation (2) can be rewritten as:

$$\Delta q_{it} = \beta_{it}^{L}\Delta l_{it} + \beta_{it}^{K}\Delta k_{it} + \beta_{it}^{M}\Delta m_{it} + \Delta TFP_{it}, \quad (2A)$$

where

$$\Delta TFP_{it} \equiv \Delta a_t + \Delta lbd_{it} + \beta_{it}^{L}\Delta hc_{it} + \beta_{it}^{K}\Delta emb_{it} + \Delta z_{it}. \quad (2B)$$

TFP growth is defined in equation (2A) as the output growth that is not explained by standard inputs growth. While TFP growth and disembodied technical change are used as synonymous in most of the growth literature, equation (2B) shows that, in our empirical framework, the aggregate disembodied technical change, Δa_t, is one component of TFP growth. Specifically, Δa_t captures aggregate changes in TFP that are not associated with growth in firm-specific LBD, and in quality embodied in labor and physical capital. In the empirical regression, the term Δz_{it} will also capture any noise deriving from measurement errors and functional form discrepancies. Note that, in the absence of proper measures for the quality of labor and capital, the importance of disembodied productivity growth will be overestimated since Δa_t will capture any firm-specific effect that is left unexplained.

In the next section, we will explain at length all the variables which are constructed to capture the different components of ΔTFP. However, it is important to notice the following. First, the aggregate component of disembodied technological progress Δa_t is captured with a complete set of time dummies. By using the Suits method we can constrain the sum of the coefficients of these dummies to be equal to zero, so that the constant term represents the average growth of the aggregate TFP across the sample period ($\Delta\bar{a}$).[5] Secondly, assume that the variables x_1 and x_2 are used to capture firms'

[4] This notation will hold throughout the paper.

[5] Assume that the econometrician uses a set of time dummies. The identifying restriction usually employed is to force one of these time dummies to be zero. Suits (1984) shows that the time dummies

human capital, that is $\Delta hc_{it} = \alpha_1 \Delta x_{1,it} + \alpha_2 \Delta x_{2,it}$. By substituting this expression in equation (2B) we find that the coefficient of x_1, $\beta_{it}^L \cdot \alpha_1$, does not necessarily correspond to that of labor, β_{it}^L. The asymptotic equivalence between the two would hold only if $\alpha_1 = 1$. This shows that the estimated coefficients for all the variables capturing the quality of labor and physical capital do not need to be equal to those of conventional labor and physical capital.

In the empirical literature, TFP growth is usually measured by the Solow residual (SR), computed as the difference between output growth and a weighted average of inputs' growth rates:

$$SR_{it} \equiv \Delta q_{it} - s_{it}^L \Delta l_{it} - s_{it}^M \Delta m_{it} - (1 - s_{it}^L - s_{it}^M)\Delta k_{it}, \tag{3}$$

where s_{it}^L and s_{it}^M are the cost shares of labor and materials over total revenues, respectively. Using the Tornquist approximation, these shares are actually computed as averages over adjacent years, e.g. $s_{it}^L \equiv \frac{1}{2}\left(\frac{W_{it}*L_{it}}{P_{it}*Q_{it}} + \frac{W_{it-1}*L_{it-1}}{P_{it-1}*Q_{it-1}}\right)$.

The SR in equation (3) does not correspond to the true TFP growth in the presence of non-constant returns to scale and market power (Hall, 1990; Klette, 1999). Therefore, we need to take into consideration these possible biases when explaining the determinants of the TFP growth. In the case of constant returns to scale, we have $\beta_{it}^L + \beta_{it}^M + \beta_{it}^K = 1$. We do not impose this restriction *a priori*. We use instead the general relationship $\beta_{it}^L + \beta_{it}^M + \beta_{it}^K = \lambda_{it}$, where λ_{it} is the scale factor for firm i. Accordingly, equation (2A) can be written as:

$$\Delta q_{it} = \beta_{it}^L(\Delta l_{it} - \Delta k_{it}) + \beta_{it}^M(\Delta m_{it} - \Delta k_{it}) + \lambda_{it}\Delta k_{it} + \Delta TFP_{it}. \tag{4}$$

We assume that labor and materials are variable factors which fully adjust to their equilibrium value in every period while capital is a quasi-fixed factor characterized by some rigidities in the short run. If we further assume that firms enjoy a certain degree of market power in the output market but are price takers in the inputs market, short-run profit maximization would give the following conditions (see the Appendix):

$$\beta_{it}^L = \frac{\partial \ln Q_{it}}{\partial \ln L_{it}} = \frac{\partial q_{it}}{\partial l_{it}} = \mu_{it} s_{it}^L, \tag{5A}$$

can be interpreted more easily by imposing the alternative restriction that the sum of their coefficients is zero. The intercept would in fact show the yearly average across the whole period, while the time dummies would show deviations from this average.

$$\beta_{it}^{M} = \frac{\partial \ln Q_{it}}{\partial \ln M_{it}} = \frac{\partial q_{it}}{\partial m_{it}} = \mu_{it} s_{it}^{M}, \tag{5B}$$

where μ_{it} is the firm's mark-up.

Equilibrium conditions (5A) and (5B) show that the unknown coefficients of the variable inputs, β_{it}^{L} and β_{it}^{M} can be replaced with firm-specific share parameters, s_{it}^{L} and s_{it}^{M}, computed using accounting data. This approach emphasizes the economic structure of the production decision taken by firms, thus minimizing the use of statistical assumptions about the coefficient of the production function.[6]

Substituting conditions (5A) and (5B) in equation (4) gives:

$$\Delta q_{it} = \mu_{it}[s_{it}^{L}(\Delta l_{it} - \Delta k_{it}) + s_{it}^{M}(\Delta m_{it} - \Delta k_{it})] + \lambda_{it}\Delta k_{it} + \Delta TFP_{it}, \tag{6}$$

and using the specification of the Solow residual stated in equation (3), we obtain:

$$SR_{it} = (\mu_{it} - 1)[s_{it}^{L}(\Delta l_{it} - \Delta k_{it}) + s_{it}^{M}(\Delta m_{it} - \Delta k_{it})] + (\lambda_{it} - 1)\Delta k_{it} + \Delta TFP_{it}. \tag{7}$$

Hulten (1986) has drawn attention to the bias affecting the estimates of equation (7) when the degree of capacity utilization is not properly taken into account.[7] We then control for the effects of under or over utilization of firms' installed capacity, adding to equation (7) the rate of change in capacity utilization (Δut_{it}):

$$SR_{it} = (\mu_{it} - 1)share_{it} + (\lambda_{it} - 1)\Delta k_{it} + \theta \cdot \Delta ut_{it} + \Delta TFP_{it}, \tag{8}$$

where $share_{it} \equiv [s_{it}^{L}(\Delta l_{it} - \Delta k_{it}) + s_{it}^{M}(\Delta m_{it} - \Delta k_{it})]$.

The last equation shows that the Solow residual can be decomposed into the true productivity growth term, ΔTFP_{it}, a mark-up component, a scale factor, and the degree of capacity utilization. Finally, assuming that the markup and scale coefficients are

[6] It is important to notice that if firms anticipate the effects of LBD, then the firm's optimization problem would be more complex: in particular, a profit-maximizing firm might be willing to incur losses early on, in order to increase its knowledge and make productivity gains later in time. This suggests that the first-order conditions (5A) and (5B) have to be considered only approximate in the case where firms are aware of LBD effects. In the Appendix we provide a formal treatment of the dynamic problem when LBD is anticipated by the firm, and how this changes the FOC of the relevant problem.

[7] In particular, Hulten (1986, p. 38) shows that the 'false' residual (that in our specification corresponds to the Solow residual) is "equal to the true residual plus the rate of change of capital utilization".

approximately constant,[8] we obtain the specification to be estimated:

$$SR_{it} = (\mu - 1)share_{it} + (\lambda - 1)\Delta k_{it} + \theta \cdot \Delta ut_{it} + \Delta TFP_{it} \tag{9}$$

4 Variables

This section highlights the contents of the relevant variables used in this study. More detailed explanations of how the variables are computed, together with their descriptive statistics, can be found in the Appendix. Our dependent variable is the Solow residual (SR), defined according to equation (3) as the difference between the output growth rate and the input-share weighted average of the input growth rates.

Since our dataset reports firm-specific prices for intermediary inputs and outputs, we can compute a precise measure of the SR. Using the ESEE, Ornaghi (2006) finds that more reliable estimates of production function parameters are obtained when firm-level prices are observed. If firm-level prices were not observed, it would be necessary to deflate revenues and cost of materials using industry deflators. Let us define firm i revenues as P_iQ_i and the cost of materials as G_iM_i (where G_i is the unit cost of input M_i). Let us also assume that only the average industry price of output P_I and price of materials G_I are available to the econometrician. Then, instead of the true output Q_i and materials M_i, the construction of the SR would be affected by measurement errors as it would be based on deflated output (P_iQ_i/P_I) and deflated materials (G_iM_i/G_I).

We use two variables to assess the impact of shifts in quality embodied in capital (EMB) on productivity growth: the average vintage of capital and an index of new technology usage. Embodied technological progress relies on the basic idea that each successive vintage of investment is more productive than the last (Solow, 1960). Empirically

[8] We can consider the markup and the scale coefficients μ and λ as average parameters. Differences between firms or across time will be captured by the error term ε_{it}. The assumption of constant markup and returns to scale might seem restrictive. However, allowing these two variables to vary across sectors by interacting the variables $share$ and Δk with industry dummies, we find that the point estimates of the coefficients of these interaction terms are not statistically significant. Baily, Hulten and Campbell (1992) also find constant return to scale in the Longitudinal Research Database of the Census Bureau.

we can measure the importance of the vintage theory by computing the weighted average age of the capital stock ($VINT$) with ascending values for more recent vintages and then using the variable $\Delta VINT$ to assess the importance of changes in average vintage on productivity shift. The detailed construction of this variable is reported in the Appendix.

Technology usage ($TECH$) is a zero-one dummy variable indicating whether firm i has adopted at least one new advanced technology among computer-automated design, robotics and numerically controlled machines in period t.[9] While capital investments can include information-processing technologies or transport equipment, the variable $TECH$ refers specifically to process technologies that increase the level of automatization of a factory. However, some caution is needed about what exactly is being identified, since $TECH$ may capture technical changes in process technologies that may be associated with simultaneous changes, e.g. to organization or management, that also have consequences for productivity.

Following Becker (1964), we assume that returns to human capital are captured by the employees and consequently reflected in their wages. Accordingly, we use firm wages (W) as a measure of labor quality. At the same time we add a second variable, the share of R&D employees in the total workforce ($R\&D\_l$), that can possibly measure other, unpriced effects of human capital. While the former variable enters our empirical specification in growth rates (Δw), the latter is simply the difference between two consecutive years ($\Delta R\&D\_l$).

We are aware that using firm wages might lead to endogeneity problems due to the fact that productivity increases might cause an increase of wages through rent-sharing. This possibility is actually confirmed in our empirical estimations: when present levels or growth of wages are added to the set of instruments, the Sargan Test of overidentifying restrictions rejected the validity of the instruments used. We consider therefore Δw as an endogenous variable. The set of instruments we use in our estimations includes past values of labor and capital, and also changes in the quality of labor (i.e., the percentage of skilled workers and R&D employees). This approach is similar to that used in previous empirical studies and it shares with them the limitation that it might not fully identify

[9] Doms, Dunne and Roberts (1995) use a similar variable to study the role of technology use in the survival and growth of manufacturing plants.

the impact of changes in wages due to experience and skills on productivity. As a check of robustness, we also estimate a specification where the variable firm wages is replaced by a more direct measure of human capital: the ratio of the number of employees with a bachelor or higher degree over the total number of workers (EDU).

To measure firm-specific LBD, we follow Bahk and Gort (1993) and use the cumulative output, from the birth of the firm to $t-1$, per unit of labor input. That is:

$$CQ\_L_{it} = (\sum\nolimits_{j=0}^{t-1} Q_{ij})/L_{it}.$$

As we deal with growth rates, the latter variable is computed as logarithmic difference between two subsequent time periods (Δcq_l_{it}). We study the effect of firm-specific LBD for firms of all ages (that is, including firms whose birth occurred before the beginning of the sample period). On empirical grounds, the main implication of this left-censoring problem is that we need to set the initial cumulative output at an arbitrary value. Initial values of the cumulative output are computed multiplying the average value of the firm's output reported in the survey by a coefficient that depends on the year of birth of the firm (see the Appendix for more details).

However, the variable Δcq_l_{it} is likely to be highly correlated with the past productivity growth of the labor force of the firm. To the extent that past TFP accounts for the largest share of past labor productivity, a significant total cumulative output per employee may just be due to a high degree of persistence in TFP. This observation casts some doubt on the actual reliability of this variable as a true measure of the pure learning-by-doing effect. More than a proxy for the learning process internal to the firm, it seems to be a different measure of past TFP growth.

We then define two alternative variables to measure firm-specific LBD. The first one is computed as the cumulative output per employee since the introduction of a process innovation, CQ_L_I. Also in this case we consider the logarithmic difference between two periods ($\Delta cq\_l\_i_{it}$). The underlying assumption is that a new learning process starts after the introduction of a new technology. A positive and significant coefficient for this variable would indicate that firms need a certain period of time before using the new technology effectively. The second variable is the time (computed as number of years) since the introduction of a process innovation, $time\_i$.

Finally, we consider measures of unpriced spillovers in human capital and R&D expenditure. Human capital externalities arise when the presence of educated and more qualified workers increases the productivity of other workers. Accordingly, in order to measure the importance of human capital externalities in productivity changes, we compute the logarithmic difference of median wage (Δmed_w_{jt}) for industry j and year t. Also in this case, to avoid the endogeneity problems that might be caused by the simultaneity between wages and productivity, we consider an alternative measure of human capital externalities: The change in the ratio of workers with a bachelor degree at the industry level (Δind_EDU_{jt}). Regarding R&D spillovers, we follow Griliches (1979) and the literature that followed, by including an external pool of R&D knowledge in the production function framework. In accordance with this literature, we measure this unpriced externality with the growth of R&D expenditure at the industry level ($\Delta ind\_R\&D_{jt}$).

The richness of information provided by the firm-level data above cannot be offered by industry-level data. First of all, some data cannot be obtained by simply aggregating firm-level statistics. For instance, differently from output and standard inputs, there is nothing that can measure the aggregate capacity utilization. The correct procedure would require accounting for capacity utilization at plant level and then aggregating upwards, a rather difficult task that is likely to produce large measurement errors. Moreover, even in the presence of a careful aggregation procedure, there are still some variables that could not be computed at aggregate level, such as cumulative output since the last innovation.

At the same time, it is also difficult to simulate industry data by aggregating our firm-level observations. The first problem is that we cannot observe the output that is not sold to final consumers but used as intermediary inputs by other firms. Basu and Fernald (1995) use value-added because, although it does not in general have an interpretation as a measure of production, it accounts for the fact that "aggregate quantity of output used as intermediate input equals the aggregate quantity of intermediate inputs used by all firms". Second, the econometric analysis we perform in our paper requires the use of a large number of observations. Given that we are working with 14 industries over a period of 17 years, it would be impossible to use panel data techniques with 238 observations. It must be noticed that influential studies based on US data, such as Basu and Fernald (1995) or Burnside, Eichenbaum and Rebelo (1995), use a large number of industries and years (for instance, Basu and Fernald used more than 800 observations).

5 Results

Our model is specified in terms of rates of change in the variables (log first-differences). This implies that persistent differences in unobservable firm-level characteristics are eliminated from the specification. Variable inputs such as labor and materials are possibly correlated with the error term in equation (9) because of their simultaneous determination with output. To solve this problem, we take advantage of the panel data structure of our sample and use lagged levels of the endogenous variables as instruments for the equations in differences.

Our specifications are estimated with the Generalized Method of Moments (GMM) as in Arellano and Bond (1991). For each set of estimates, we report the Sargan test of the overidentifying restrictions, and tests for serial correlation. If equations in levels are assumed to have uncorrelated zero mean error terms, disturbances of specifications in first-differences are expected to present both negative first order autocorrelation and absence of second order serial correlation. This pattern is confirmed in all the regressions by the M1 and M2 statistics, respectively.

However, GMM techniques do not usually produce satisfactory results when estimating a production function in first differences: low and insignificant capital coefficients and unreasonably low estimates of returns to scale are often obtained. One of the main problems is that the GMM method relies on using lagged levels of capital, labor and materials (or other variables) as instruments for the specification in first-differences. This approach seems to be particularly problematic when applied to persistent data. We believe that our analysis presents some advantages with respect to other studies in the literature (Blundell and Bond, 2000, among them).

First of all, our approach does not require estimating the coefficients of labor, capital and material, the series that are rather persistent over time. Using the equilibrium conditions explained in Section 3.1, we impute these coefficients using the income share of labor and material. Second, we have a rich dataset that allows us to construct different variables to capture embodied technological progress. For instance, human capital is captured by growth rate of wages (Δw), the change in the proportion of workers with a bachelor or higher degree (ΔEDU) and the growth of R&D employees ($\Delta r\&d\_l$). Moreover, we use $TECH$ in the specification to capture capital embodied in advanced technologies, and the innovation dummy $INNO$ in the set of instruments. This means that the set of instruments includes not only past values of endogenous variables but also alternative measures of embodied technological progress.[10] Finally, as discussed in Section 4, Ornaghi (2006) finds that more reliable estimates of production function parameters are obtained when firm-level prices are observed. In the present context, firm-level prices allow us to obtain more precise measure of the dependent variable SR.

The coefficients of time dummies (θ's) and industry dummies (ϕ's) are estimated using the Suits method, so that they are constrained to add up to zero, i.e. $\sum_{t=1991}^{2006} \theta_t = 0$ and $\sum_{j=1}^{14} \phi_{ind\_j} = 0$.[11] Accordingly, the constant included in each regression represents the average growth of aggregate TFP across firms and over time. The value of the constant plays a crucial role since it can be considered the part of aggregate productivity growth that is left unexplained, and that is generally considered as economy-wide neutral technological change.

First of all, we estimate the average growth of aggregate TFP controlling for market power, returns to scale and capacity utilization. The analysis then proceeds in two steps. First, we estimate a specification that includes only firm-specific LBD and disembodied sources of aggregate TFP growth in the form of human capital externalities and R&D spillovers. Second, we add firm-specific measures of quality of labor and capital. In this way, we can evaluate whether productivity differences among firms are driven either by disembodied factors or by adjustments in the quality of labor and capital. Finally, our empirical framework allows us to assess whether the embodied and disembodied variables can squeeze down the constant term, thus explaining the average growth of aggregate TFP. Table 4 reports the results.

[10] Note that this approach is useful to solve problems of measurement errors, as long as the errors of the regressor and the instrument (e.g. $TECH$ and $INNO$) are not correlated (see Wooldridge, 2002, sect. 5.3).

[11] These constraints are actually implemented imposing $\theta_{1991} = -\left(\sum_{t=1992}^{2006} \theta_t\right)$ and $\phi_{ind\_1} = -\left(\sum_{j=2}^{14} \phi_{ind\_j}\right)$.

INSERT TABLE 4 ABOUT HERE

Column 1 shows that the yearly average growth in aggregate TFP across the Spanish manufacturing firms in our sample is 2%. The coefficient of Δk in Column 1 is not statistically different from zero: we cannot then reject the null hypothesis of constant returns to scale for our basic specification. However, small deviations from the constant return to scale hypothesis are detected when we add the variables capturing quality of capital (see Table 4, Column 3, and Table 5, Column 5), or when we use firm-specific LBD (see Table 5, Column 4). These results show that our regressions do not present the low estimate of returns to scale usually found using estimators in differences (see Griliches and Mairesse, 1995). This result can be due to the fact that: i) our approach makes use of equilibrium conditions to construct the Solow Residual, minimizing the use of statistical assumptions about the coefficients of the production function, and/or ii) we use highly quality data, in particular firm-level prices for output and intermediary inputs, that reduce the impact of measurement errors (see Ornaghi, 2006).

The low point estimates for the *share* coefficient in all the specifications in Table 4 (and in the following table) suggest that Spanish manufacturing firms do not enjoy a large degree of market power.[12] Among the control variables, Δut is the only one to be positive and statistically significant in all the specifications, thus confirming the importance of controlling for capacity utilization when analyzing productivity changes at the firm level. We postpone a detailed discussion of the coefficients of the time dummies and industry dummies to the end of this Section.

Specification in Column 2 includes firm-specific LBD and other unpriced externalities, namely human capital spillovers and R&D spillovers. Although our empirical model differs from the one used by Bahk and Gort (1993), our estimate for the coefficient of the cumulated output per employee (0.084) is of the same order of magnitude as the one reported in their article (0.079). The estimated coefficients of $\Delta ind\_R\&D_{jt}$ and Δmed_w_{jt} suggest that the productivity of firms in industries with higher increase in R&D expenditure and in human capital rises more than the productivity of firms in other

[12] Siotis (2003) has found that markups charged by Spanish firms have been considerably reduced in the nineties, after Spain entered the EU.

industries. Spillovers can then explain differences in productivity among industries. The constant term is now very small and not statistically different from zero: disembodied factors in the form of firm-level LBD and industry spillovers can account for (almost) all the average growth of aggregate TFP.

Column 3 reports the results when variables measuring the quality embodied in labor and physical capital are added to the empirical specification. The constant term is negative but not statistically different from zero: variables included in the specification can squeeze down the original 2% growth of aggregate TFP. The coefficients of the four variables that capture changes in human capital or improvements in physical capital are found to be significant while the coefficients of firm-level LBD, human capital spillovers and knowledge spillovers are not statistically significant.

The coefficient of the vintage variable ($\Delta VINT$) suggests that 1-year decrease in average vintage leads to a 1.6% growth in TFP. Assuming a capital share of 30%, this estimate implies an annual rate of growth in capital-embodied productivity of 5.3% per year during the sample period. This result is in line with the existing literature on relative-price-based measures of embodied technical change for the US economy (see Greenwood, Hercowitz and Krusell, 1997; Cummins and Violante, 2002). Similarly, the coefficient of $TECH$ suggests that firms adopting new advanced technology experience a significantly higher growth of productivity around the year of the adoption.

Results in Column 3 establishes also the existence of a positive correlation between aggregate TFP growth and human capital. The estimated coefficient of Δw is 0.29. This value is in line with the income share of labor and it is similar to the coefficients reported in other studies. For instance, Hellerstein and Neumark (2004), using a variable that is also constructed using data on US wages, estimate a coefficient for the quality of labor of 0.40.[13] An increase in the share of R&D employees is also found to have a positive impact on firms' productivity growth.

Even if Column 3 shows that the effect of human capital externalities on aggregate TFP growth disappears when the embodied variables are also considered, we cannot dismiss the existence of human capital externalities. Indeed, it might be the case that

[13] Doms, Dunne and Troske (1997) also find that firms adopting new technologies and, consequently, increasing their productivity performance, have skilled workforces prior to the adoption.

individuals augment their human capital through 'exchanges of ideas' with more skilled neighbors. However, our results clearly point out that any additional skill acquired (which is by definition embodied) *does not* come for free to the firms employing them.

Results in Column 3 are in contradiction with the findings of Bahk and Gort (1993), where firm-specific LBD is significant, despite controlling for the quality of capital and labor. We believe that this is because the sample they use is confined to newly established firms (and therefore, firms which use new machinery and equipment). Moreover, as discussed in Section 4, the cumulative output per employee is likely to be highly correlated with the average productivity of work. This can explain why the variable Δcq_l loses all its explicative power in the full specification.

The model estimated in Column 3 is not able to fully account for the firm-specific TFP growth. We consider the square of the correlation between the observed values and predicted values of the dependent variable as a measure of goodness-of-fit. We find that the correlation between observed SR and predicted SR is 0.33, which can be interpreted as a pseudo-R^2 of 0.11. This means that our statistical model is successful in explaining the average growth of aggregate TFP $\Delta\bar{a}$ but the determinants of firm-specific TFP growth Δz_{it} remain largely unexplained.[14]

The empirical models estimated in Table 4 can raise two concerns already discussed in Section 4. First, the variable wage might lead to endogeneity problems. Second, the variable cumulative output per employee is likely to be correlated with the dependent variable by construction. We then define an alternative model that use the share of employees with a bachelor degree (ΔEDU) to measure the quality of labor at firm level and, similarly, the share of skilled workers at industry level (Δind_EDU) to capture human capital spillovers. At the same time, we use the variables cumulative output since last innovation (Δcq_l_i) and time since last innovation ($time\_i$) as an alternative proxy for firm-specific LBD. Table 5 reports the results

INSERT TABLE 5 ABOUT HERE

[14] To the best of our knowledge, the paper by Paquet and Robidoux (2001) is the only empirical study on productivity that reports the R^2. The authors seek to explain the SR by an array of various macro variables. The specification is estimated by OLS using quarterly data from 1970 to 1993 for Canada. They report an R^2 that varies from 0.02 to 0.10.

The specifications in Table 5 confirm the previous findings: i) the average aggregate TFP growth is squeezed to zero; ii) changes in human capital and improvements in the technology of machinery and equipment have a positive and significant effect on firms' productivity growth; and iii) the estimated coefficient of human capital spillovers is not significant once we control for the quality of capital and labor of the firms.[15] However, Column 5 shows that the variables measuring firm-specific LBD retain significance in the complete specification. Note that the negative coefficient of the variable $time\_i$ must be interpreted in the same way as the positive coefficient of the variable Δcq_l_i. In fact, while Δcq_l_i decreases as time passes, the variable $time\_i$ by construction grows with time.[16] In both cases, the coefficients suggest that there is a decrease in learning: high when a new innovation is introduced, lower and lower in the following years. The extent of the firm's learning process is short-lived, and due to adoption of new processes.

It is important to note that Table B1 in the Appendix shows a high degree of dispersion in the Solow residual. It might be the case then that some outliers with very large annual changes in the SR affect our estimates. We check the robustness of our results when observations for the top and bottom one percent of the SR distribution are dropped and we find point estimates very close to those reported in the tables above.

Finally, we analyze the results on time and industry dummies. In tables 4 and 5 we do not report the values of the coefficients of the time dummies while we report only the values of the significant industry dummies. We find that there are three year dummies that show a significantly higher growth: 1994, 1995 and 1996. This is consistent with Picture 1, where these three years show a higher median TFP growth than other years. The coefficient of these three dummies are statistically significant even in specification 3 in Table 4 where we control for the quality of physical and human capital. These results may have two explanations. First, there are some high-frequency changes of aggregate TFP

[15] The large point estimate of Δind_EDU could be due to the fact that ΔEDU and $\Delta R\&D\_l$ may underestimate the relevance of human capital (for example, the share of skilled workers does not capture human capital accumulated on the job or the quality of education received).

[16] The average firm faces decreasing learning effects over time because higher growth in cumulative output per employee is experienced in the first year after the introduction of the innovation (t+1) and then the growth becomes lower in the following years. See the Appendix for an example and further details.

that our approach cannot explain. In other words, it seems that we can explain aggregate TFP growth in the medium to long-run, but the sources of short-run fluctuations in aggregate TFP remain more obscure. This implies that TFP shocks play a role at high frequencies, in addition to investment specific shocks.

Second, it is possible that our specification, despite controlling for capacity utilization and number of hours of work, does not account for other changes in factor usage (such as varying labor effort) that in the short-run may affect the correct computation of productivity changes. On this point, Basu and Fernald (1995) note that "changes in measured productivity may be caused by systematic, unmeasured changes in capacity utilization and labor effort".

We find that there are three industries which grow faster than the average manufacturing sector: chemicals, electronics and motor vehicles. Compared to an average growth of aggregate TFP of 2 percent, these three industries are found to have an higher aggregate TFP growth between 0.3 and 0.9 percent. Even when we account for the quality of the physical and human capital, the point estimates of these dummies are unchanged. While this result might weaken the findings of this paper, it is important to note that these industries are characterized by large investment in R&D, a feature that is not fully captured by our specification.[17]

In order to account for the innovativeness of these three industries, we make two changes to the previous specifications. First, we consider the dummy variable $INNO$ instead of the dummy variable $TECH$ since the former variable is more likely to pick up the effects of process innovation that are not solely confined to the use of new technologies. Second, we include R&D expenditure in the set of instrumental variables. Table 6 reports the results.

INSERT TABLE 6 ABOUT HERE

The insignificant value of the constant term in Column 7 shows that this alternative specification can explain the average growth of aggregate TFP in these three industries.

[17] The average R&D intensity (i.e. R&D expenditure over sales) of the firms in these three industries is 1.5 percent, while the average for the firms in the rest of the sample is only 0.4 percent.

Overall, estimates are similar to those reported in Tables 4 and 5. It is interesting to note that the coefficients of $\Delta R\&D\_l$ and Δcq_l_i are now larger: this suggests a more prominent role of human capital and learning-by-doing in these industries.

6 Conclusion

In this paper we investigate the contribution of various sources of technical change that have been identified in the literature in order to explain aggregate TFP growth. Among the strengths of the paper is the use of a microeconomic approach to analyze the macro debate on embodied versus disembodied sources of growth. The use of micro data is more appropriate to study the source of technological progress since these are mainly the results of decisions and activities undertaken by firms. Measures of aggregate productivity based on the representative firm paradigm can pick up factors other than true technological progress (such as reallocation effects across firms). However, if the empirical analysis is done at the firm level the constant of the panel regression would not be contaminated by reallocation effects across firms. This indicates that the estimated constant in the micro-level regressions is a better measure of aggregate TFP.

It is worth pointing out two limits, among the many, of our approach. First, while we can account for the sources of firms aggregate TFP growth, we cannot explain much of the dispersion of firms-specific TFP growth. As productivity measures also include unwanted components, due to measurement errors and model misspecification, firm-level studies can mainly aim at explaining the systematic part of firms TFP growth.

Second, this study deals with some but not all possible kinds of spillover effects. A variety of 'externality based' models of technological progress have been proposed in recent years, which use an extremely wide array of theoretically conceivable unpriced spillovers. Moreover, the finding that the spillover variables become insignificant when the measures of embodied technical progress are included does not rule out the possibility that spillovers make embodied technical change easier to achieve or to implement successfully. We focus our analysis on what we can observe and measure from the available data.[18] We recognize

[18] For instance, we try to capture R&D and human capital externalities using aggregate measures at industry level. Since we do no have measures of patent citation (Jaffe, 1986) or education level in the

that the relative importance between embodied vs. disembodied sources of growth might produce different results if better measures of externalities could be used. Nevertheless, we hope that our findings will encourage a more careful approach when assessing the relevance of unpriced externalities for productivity growth.

area where the firms operate (Moretti, 2004), we cannot perform alternative checks of robustness for the existence of R&D and human capital spillovers.

Appendix

A. Firms' Equilibrium Conditions.

Consider the firm's profit function under imperfect competition

$$P(Q_{it})Q_{it} - Cost(Q_{it}, \mathbf{w}),$$

where $\mathbf{w}$ is a vector of input prices. Maximizing with respect to any variable input, for example labor, we get the following first order condition

$$\frac{\partial P(Q_{it})}{\partial Q_{it}}\frac{\partial Q_{it}}{\partial L_{it}}Q_{it} + P(Q_{it})\frac{\partial Q_{it}}{\partial L_{it}} - \frac{\partial Cost(Q_{it}, \mathbf{w})}{\partial L_{it}} = 0.$$

This implies

$$\frac{\partial Q_{it}}{\partial L_{it}} = \frac{\frac{\partial Cost(Q_{it},\mathbf{w})}{\partial L_{it}}}{P_{it}(1+\frac{1}{\eta_{it}})},$$

where η_{it} is the elasticity of the demand curve. Defining $\frac{1}{1+\frac{1}{\eta_{it}}} \equiv \mu_{it}$, we get

$$\frac{\partial Q_{it}}{\partial L_{it}} = \mu_{it}\frac{w_{it}^L}{P_{it}},$$

where w_{it}^L is the price of labor. Multiplying by $\frac{L_{it}}{Q_{it}}$ both sides of the latter expression, we get expression (5A) in the text. Considering materials as inputs, we get expression (5B) in a similar way.

B. Firms optimization problem when firm-level LBD is anticipated.

Consider a simple example where the individual firm solves:

$$\underset{\{K_t,L_t\}}{Max}\sum_{t=0}^{\infty}\delta^t[Q_t - r_tK_t - w_tL_t]$$

subject to

$$\begin{aligned} Q_t &= A_tK_t^{\beta}L_t^{1-\beta}\left(\frac{B_t}{L_t}\right) \\ B_{t+1} &= B_t + \phi Y_t \end{aligned}$$

where LBD is measured by cumulative output per worker (B_t/L_t) as in the paper. The FOC of the firm with respect to capital K becomes:

$$\beta A_tK_t^{\beta-1}L_t^{1-\beta}\left(\frac{B_t}{L_t}\right)\left[1+\delta A_{t+1}K_{t+1}^{\beta}L_{t+1}^{1-\beta}\phi\left(\frac{1}{L_{t+1}}\right)+\delta^2A_{t+2}K_{t+2}^{\beta}L_{t+2}^{1-\beta}\phi\left(\frac{1}{L_{t+2}}\right)+...\right]=r_t$$

which shows that the firm takes into account that hiring one extra unit of capital has a dynamic effect on future production through LBD. Rearranging terms, and indicating with $s_t^K = (r_t K_t / Y_t)$ the capital cost share of output, we obtain

$$\beta = s_t^K - \beta\phi \sum_{j=1}^{\infty} \delta^j \left(\frac{Q_{t+j}}{B_{t+j}} \right).$$

The last relationship shows that the equivalence between the production function parameter β and the cost of share of capital s_t^K which is used in the paper is not fully correct when firms anticipate the effects of firm-specific LDB. In particular the coefficient on capital β is less than its share s_t^K. This bias could explain why the estimated coefficient on Δk_{it} is less than zero even in presence of constant returns to scale.

C. Variables Description.

As described in Section 3, data used in this study are published by the *Fundacion Empresa Publica.* All monetary values are adjusted for inflation using appropriate deflators, 1990 being the index year. Details on how the variables have been constructed follow.

Industry Dummies: Firms in the sample are divided in the following 14 sectors: 1) Ferrous and non ferrous metals; 2) Non-metallic minerals; 3) Chemical products; 4) Metal products; 5) Industrial and agricultural machinery; 6) Office and data processing machine; 7) Electrical and electronic goods; 8) Vehicles, cars and motors; 9) Other transport equipment; 10) Food and beverages; 11) Textiles, clothing and shoes; 12) Timber and furniture; 13) Paper and printing; 14) Rubber and plastic products.

Output (Q): Nominal output is defined as the sum of sales and the variation of inventories. We deflate the nominal amount using the firm's specific output price as reported by the firm.

labor (L): labor consists of the total hours of work. It is computed using the number of work, times the normal hours plus overtime and minus lost hours.

Materials (M): Nominal materials are given by the sum of purchases and external services minus the variation of intermediate inventories. We use firms' specific deflator based on the variation in the cost of raw materials and energy as reported by the firm.

Physical Capital (K): It is constructed capitalizing firms' investments in machinery and equipment (deflated by a specific price index for capital goods) and using sectorial rates of depreciation. The initial estimate is based on book values adjusted to take account of replacement values. The capital stock does not include buildings.

Capacity Utilization (UT): Yearly average rate of capacity utilization reported by the firms.

Solow Residual (SR): It is computed according to equation (3):

$$SR_{it} = \Delta q_{it} - s_{it}^{L}\Delta l_{it} - s_{it}^{M}\Delta m_{it} - (1 - s_{it}^{L} - s_{it}^{M})\Delta k_{it},$$

where the input measures are in log differences. Using the Tornquist approximation, the shares of labor and materials costs in total revenues are actually computed as averages over adjacent years, i.e. $s_{it}^{L} \equiv \frac{1}{2}\left(\frac{W_{it}*L_{it}}{P_{it}*Q_{it}} + \frac{W_{it-1}*L_{it-1}}{P_{it-1}*Q_{it-1}}\right)$ The exact specification for the computation of the Solow Residual is then:

$$\begin{aligned} SR_{it} &= \ln\left(\frac{Q_{it}}{Q_{it-1}}\right) - s_{it}^{L}\ln\left(\frac{L_{it}}{L_{it-1}}\right) - s_{it}^{M}\ln\left(\frac{M_{it}}{M_{it-1}}\right) - \\ &\quad -(1 - s_{it}^{L} - s_{it}^{M})\ln\left(\frac{K_{it}}{K_{it-1}}\right). \end{aligned}$$

In order to trim possible outliers in measuring TFP growth, we remove all the observations where the shares s_{it}^{L}, or s_{it}^{M}, are lower than 0.05 or greater than 0.95.

Average Vintage of Capital Stock (VINT): The variable stock of capital K stands for a vector of past investment streams. If each successive vintage of investment is more productive than the last one, we can take due account of the effect of the increased quality of capital by measuring the average vintage of the capital stock (that is, its average age). This variable represents then a sort of technology index that captures the weighted average vintage of the capital stock with ascending values for more recent vintages (see also Bahk and Gort, 1993). As we do not have the complete history of investments for firms born before entering the survey, we need to define an initial value for their vintage. We computed the initial vintage of the firms using the average ratio of physical capital over investments (C/I) across all the observations available. This ratio indicates the average number of years that it takes a firm to replace its capital stock. For example, an average ratio of physical capital to investments of 5 means that in period t a firm has completely replaced all the capital goods bought in $t-5$. Therefore, we can assume that a firm with $C/I = 5$ is using physical capital with an average age of 2.5. Then, considering also that a firm cannot have a vintage older than its year of birth, we impose the condition that the initial value of the vintage for a firm entering the survey in year τ is:

$$VINT_{i\tau} = \max\left\{year\ of\ birth - 1990; \tau - 1990 - \frac{C/I}{2}\right\}. \tag{B1}$$

Note that equation (B1) implicitly assumes that the capital goods produced in 1990 have vintage 0, those produced in 1991 have vintage 1 and so on. As we use estimation in differences, this classification does not affect results reported in Section 5.

Once defined the initial value for year τ, we compute the vintage variable for any subsequent year $(\tau + x)$ as follows:

$$VINT_{i,\tau+x} = \frac{VINT_{i,\tau} \cdot K_{i,\tau}(1-\delta)^x + \sum_{j=1}^{x}(\tau + j - 1990) \cdot I_{i,\tau+j}(1-\delta)^{x-j}}{K_{i,\tau}(1-\delta)^x + \sum_{j=1}^{x} I_{i,\tau+j} \cdot (1-\delta)^{x-j}}, \tag{B2}$$

where I stands for investments in physical capital, while δ is the depreciation rate (specific to each industry). For example, for a firm born in 1988, entering the survey in 1994 and whose computed average C/I is 10, the initial value of the vintage according to (B1) is $VINT_{i,1994} = \max\left\{1988 - 1990; 1994 - 1990 - \frac{10}{2}\right\} = -1$. Using equation (B2), the vintage for this firm in year 1996, for instance, is:

$$VIN_{i,1996} = \frac{VIN_{i,1994} \cdot K_{i,1994}(1-\delta)^2 + (1995 - 1990) \cdot I_{i,1995}(1-\delta) + (1996 - 1990) \cdot I_{i,1996}}{K_{i,1994}(1-\delta)^2 + I_{i,1995}(1-\delta) + I_{i,1996}}.$$

Technology Usage (TECH): Dummy variable taking value 1 when a firm reports to adopt a new advanced technology such as CAD, robotics or numerally controlled machines. Firms are asked to report whether they use any advanced technology in the year that they join the survey and, then, in 1994, 1998, 2002 and 2006. This means that we can just approximate the exact year of adoption. Therefore, we can think that this variable is measuring not only the immediate, short-run effect but also the medium-run effect of new technology adoption on productivity growth. From the econometric point of view, this is a problem of measurement error and we address it using all other variables as instruments for *TECH*, in particular the process innovation variable (*INNO*).

Process Innovation (INNO): Dummy variable taking value 1 when a firm achieves a process innovation that consists of new machines. A process innovation is assumed to have occurred when the firm answers positively to the following question: 'Please indicate if during the year t your firm introduced some significant modification of the productive process (process innovation). If the answer is yes, please indicate the way: i) introduction of new machines; ii) introduction of new machines and new methods of organization'. This variable is used as an instrument for the specifications that include capital embodied variables (i.e. $VINT$ and $TECH$).

Wage (W): Average wages are computed dividing the total cost of labor (deflated using the generic Consumer Price Index) by the number of workers. Median values of wage computed for each industry and year are used to capture human capital externalities.

R&D employees (R&D_l): Ratio of R&D employees (as reported by the firm) over total number of workers.

Education (EDU): Ratio of skilled employees (defined as employees with bachelor or higher degree) over total number of workers.

Total R&D expenditure of the industry (IND_R&D): Yearly expenditure in R&D at industry level. The variable is computed summing the R&D expenditures reported by the firms included in all the years of the survey (balanced sample). We use this variable to capture knowledge spillovers.

Cumulative Output per Employee (CQ_L): Cumulative output, from the birth of the firm to $t-1$, per unit of labor input:

$$CQ\_L_{it} = (\sum_{j=0}^{t-1} Q_{ij})/L_{it}.$$

While Bahk and Gort (1993) focus on new plants and their histories following birth, our data does not cover enough births to get a reasonable sample size. Therefore, we include firms whose birth occurred before the beginning of the sample period (1990), which means studying the effect of LBD for firms of all ages. The main implication of this left censoring problem is that we need to set the initial cumulative output at an arbitrary value. Nevertheless, given that our model is defined in growth rates, any measurement error in defining the initial value of the variable CQ_L is partially purged when taking differences between two consecutive years. Initial values of the cumulative output are computed multiplying the average value of the firm's output reported in the survey (assuming that this is a proxy for level of production in the previous years) by a coefficient that depends on the year of birth of the firm. This implies that for two firms with similar level of average production during the sample period, the difference in their cumulative output increases as the gap between the years of birth of the two firms increases. As a check of robustness, we compute alternative initial values of Δcq_l by changing the multiplicative coefficient and we find that results are very stable.

Cumulative Output per Employee since Last Innovation (CQ_L_I): Cumulative output per employee since the year of introduction of the last process innovation (see definition above):

$$CQ\_L\_I_{it} = (\sum\nolimits_{j=t-s}^{t} Q_{ij})/L_{it},$$

where s is the time elapsed since a process innovation has been introduced (i.e., $INNO_{it} = 1$). Consider the case of a firm whose output is 100 for the period 1990 to 2002 and it has introduced two process innovation in 1990 and 1997, $INNO_{i,90} = 1$ and $INNO_{i,97} = 1$. Then, the cumulative output is 100 in the year 1990, 200 the following year until it takes a value of 600 in 1996. Now, because of the introduction of a new innovation, the cumulative output in 1997 starts again from 100. If we take growth rates (log first differences), we find that Δcq_l_i always takes a positive value except in the year of a new innovation where it is negative. To avoid this problem, we set the growth rates between $t-1$ and t to 0 when $INNO_{it} = 1$, (in the previous example $\Delta cq\_l\_i_{i,97} = 0$). This example also shows that Δcq_l_i takes higher values in the year immediately after an innovation and it tends to decrease as the cumulative output increases.

Note that for the firms born before the first year of the survey, it is not possible to determine the year of the last innovation. To deal with this problem, we infer the last time the firm has introduced an innovation by looking at the frequency of innovation reported since joining the survey. For firms that introduce on average an innovation every n years, we assume that the last innovation was n years before the first innovation reported in the survey. For instance, if a firm introduces an innovation every year, we assume that it also had an innovation in the year before entering the survey, and so on. For firms that do not report any innovation, we start counting the cumulative output since the year of birth. As for the variable CQ_L, we check the robustness of the results using alternative values of the cumulative output and we find very stable point estimates.

Time since Last Innovation (time_i): This variable is a count of the number of years passed since the introduction of a process innovation. The last innovation for firms born before the first year of the survey has been computed with the same procedure used for the variable CQ_L_I.

Descriptive statistics of the variables are provided in Table B1.

PLACE TABLE B1 ABOUT HERE

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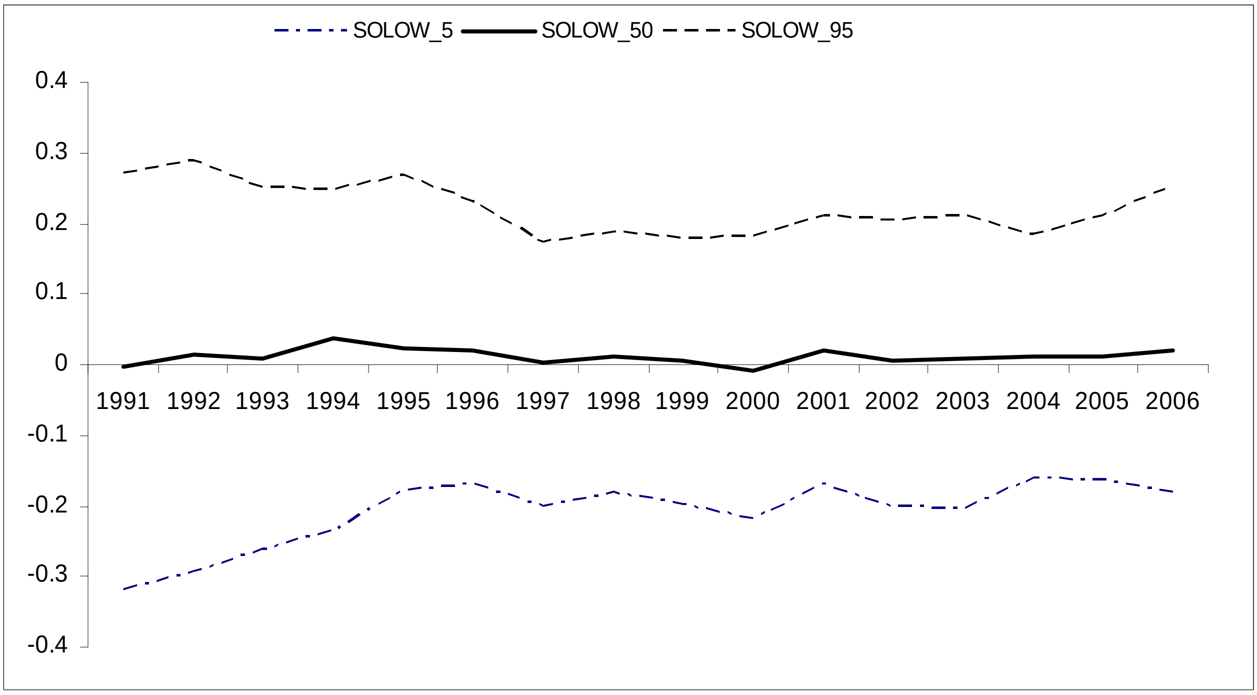
Picture 1: Growth of Solow Residual across years.



The growth of Solow Residual is computed according to equation (3). Numbers 5, 50 and 95 refers, respectively, to Percentile 5, Median and Percentile 95 of the distribution.

Table 1: Transition Matrix among Productivity Classes.

Quintile in 1992	Quintile in 2002 1	2	3	4	5	Death
1	0.42	0.12	0.04	0.01	0.02	0.39
2	0.20	0.35	0.14	0.04	0.03	0.24
3	0.07	0.17	0.29	0.22	0.07	0.19
4	0.03	0.07	0.24	0.33	0.20	0.13
5	0.00	0.01	0.05	0.20	0.58	0.16
New entry	0.27	0.26	0.20	0.14	0.13	

Productivity is defined as the Solow Residual (in levels). Firms in quintile 1 have the lowest productivity levels in their industry while those in quintile 5 have the highest productivity in their industry. “Death” refers to the firms alive in 1992 that have closed down (or changed industry) before 2002. “New entry” refers to the quintile position in 2002 of the firms established after 1992.

Table 2: Education and Innovation for Least/Most Productive Firm.

Quintile in 1992	Quintile in 2002				
	1	2	3	4	5
	Education				
1	0.03	0.05	0.08	0.06	0.10
5	0.04	0.02	0.09	0.12	0.14
	Innovation				
1	0.14	0.25	0.37	0.39	0.41
5	0.00	0.09	0.29	0.29	0.38

Firms in quintile 1 have the lowest productivity levels in their industry while those in quintile 5 have the highest productivity in their industry. Education is the percentage of workers with a bachelor or higher degree. Innovation is a dummy variable that takes value of 1 if a firm introduces a process innovation in any year. Figures reported are the average over the period 1992-2002.

Table 3: Education and Innovation by Productivity Growth.

Quintile	Education (levels)	Education (growth)	Innovation
1	0.072	0.0029	0.19
2	0.076	0.0026	0.25
3	0.094	0.0043	0.28
4	0.100	0.0055	0.33
5	0.131	0.0051	0.39

Firms in quintile 1 have the lowest average productivity growth. Firms in quintile 5 have the highest average productivity growth. Education is computed as the average percentage of employees with a degree (levels) and the average change in this percentage (growth). Innovation is a dummy variable that takes value of 1 if a firm introduces a process innovation in any year. Averages are computed over all available observations for each firm.

Table 4: LBD, Externality and Embodied Growth

Independent Variables	**Dependent Variable: Growth of Solow Residual**		
	1	**2**	**3**
Average TFP growth ($\Delta\overline{a}$):			
Constant	0.0201***	0.0036	-0.0052
	(0.0012)	(0.0049)	(0.0057)
LBD:			
Δcq_l_{it}		0.084***	0.024
		(0.030)	(0.032)
Externality:			
Δmed_w_{jt}		0.259**	0.125
		(0.118)	(0.118)
$\Delta ind\_R\&D_{jt}$		0.019**	0.010
		(0.008)	(0.007)
Embodied:			
$TECH_{it}$			0.081***
			(0.027)
$\Delta VINT_{it}$			0.016***
			(0.003)
Δw_{it}			0.294***
			(0.078)
$\Delta R\&D\_l_{it}$			0.354**
			(0.161)
Control:			
$share_{it}$	-0.024	-0.084*	-0.001
	(0.051)	(0.047)	(0.042)
Δk_{it}	-0.030	-0.032	-0.052*
	(0.030)	(0.032)	(0.027)
Δut_{it}	0.108***	0.155***	0.107***
	(0.026)	(0.025)	(0.023)
Industry Dummies([a]):			
Chemicals	0.008***	0.009***	0.007**
Electronics	0.005**	0.009***	0.007**
Cars & Motors	0.009***	0.009***	0.008**
Time Dummies	Incl.	Incl.	Incl.
Sample period	1990-2006	1990-2006	1990-2006
Observations	15,886	15,886	15,886
M1	-14.16	-13.85	-13.25
[p-values]	[<0.01]	[<0.01]	[<0.01]
M2	-0.84	-0.59	-0.92
[p-values]	[0.40]	[0.55]	[0.36]
Sargan Test (df)	178 (161)	194 (189)	196 (188)
[p-values]	[0.16]	[0.38]	[0.32]

Heteroskedasticity robust S.E. in parentheses. As suggested by Arellano and Bond (1991), we report results based on consistent one-step estimators. *** = significant at 1% level; ** = significant at 5% level; * = significant at 10% level. Instrumental variables: labour, capital and materials lagged levels from *t-2* to *t-5* in all the specifications; lagged levels of industry median wage (*med_w*) and industry R&D expenditure (*ind_R&D*) at *t-2* and *t-3* in specification 2 and 3*;* change in the ratio of R&D employees (*ΔR&D_l*), innovation dummies (*INNO*) and investment intensity (ratio of new investments over stock of capital) in specification 3. Exogenous variables (capacity utilization, vintage and number of R&D employees) are also included in the set of instruments. ([a]) Only coefficients that are significant at 10% or more are reported.

Table 5: LBD, Externality and Embodied Growth.

Independent Variables	**Dependent Variable: Growth of Solow Residual**	
	4	**5**
Average TFP growth ($\Delta\bar{a}$):		
Constant	0.0167***	-0.0005
	(0.0021)	(0.0029)
LBD:		
$\Delta cq\_l\_i_{it}$	0.028***	0.027***
	(0.005)	(0.005)
$Time\_i_{it}$	-0.001***	-0.001**
	(<0.001)	(<0.001)
Externality:		
Δind_EDU_{jt}	0.939***	0.415
	(0.319)	(0.326)
Embodied:		
$TECH_{it}$		0.101***
		(0.029)
$\Delta VINT_{it}$		0.018***
		(0.003)
ΔEDU_{it}		0.437**
		(0.230)
$\Delta R\&D\_l_{it}$		0.510**
		(0.214)
Control:		
$share_{it}$	-0.020	-0.001
	(0.056)	(0.041)
Δk_{it}	-0.059*	-0.048*
	(0.031)	(0.025)
Δut_{it}	0.183***	0.101***
	(0.028)	(0.024)
Industry Dummies([a]):		
Electronics	0.010***	0.007**
Cars & Motors	0.012***	0.011***
Time Dummies	Incl.	Incl.
Sample period	1990-2006	1990-2006
Observations	15,886	15,886
M1	-13.08	-13.47
p-values	[<0.01]	[<0.01]
M2	-0.99	-0.50
p-values	[0.32]	[0.62]
Sargan Test (df)	191 (176)	196 (175)
p-values	[0.20]	[0.13]

Heteroskedasticity robust S.E. in parentheses. As suggested by Arellano and Bond (1991), we report results based on consistent one-step estimators. *** = significant at 1% level; ** = significant at 5% level; * = significant at 10% level. Instrumental variables: labour, capital and materials lagged levels from *t-2* to *t-5* in both specifications; lagged levels of industry average education (*ind_EDU*) at *t-2* and *t-3* in both specifications; change in the ratio of R&D employees ($\Delta R\&D\_l$), innovation dummies (*INNO*) and investment intensity (ratio of new investments over stock of capital) in specification 5. Exogenous variables (capacity utilization, LBD, vintage and number of R&D employees) are also included in the set of instruments. ([a]) Only coefficients that are significant at 10% or more are reported (contrary to Table 4, the coefficients for the dummy Chemicals are low and not statistically different from zero).

Table 6: Chemicals, Electronics and Motors.

Independent Variables	**Dependent Variable: Growth of Solow Residual**	
	6	**7**
TFP growth:		
Constant	0.0241***	-0.0032
	(0.0022)	(0.0066)
LBD:		
$\Delta cq\_l\_i_{it}$		0.041***
		(0.015)
Embodied:		
$INNO_{it}$		0.025**
		(0.009)
$\Delta VINT_{it}$		0.014***
		(0.005)
Δw_{it}		0.180**
		(0.081)
$\Delta R\&D\_l_t$		0.652**
		(0.325)
Control:	Incl.	Incl.
Industry Dummies	Incl.	Incl.
Time Dummies	Incl.	Incl.
Sample period	1990-2006	1990-2006
Observations	3,003	3,003
M1	-5.74	-5.08
p-values	[<0.01]	[<0.01]
M2	-1.05	-1.05
p-values	[0.29]	[0.29]
Sargan Test (df)	164 (161)	222 (215)
p-values	[0.40]	[0.36]

Heteroskedasticity robust S.E. in parentheses. As suggested by Arellano and Bond (1991), we report results based on consistent one-step estimators. *** = significant at 1% level; ** = significant at 5% level; * = significant at 10% level. Exogenous variables: capacity utilization, LBD, vintage and number of R&D employees. Instrumental variables: labour, capital and materials lagged levels from *t-2* to *t-5* in both specifications; innovation dummies (*inno*), change in ratio of R&D employees ($\Delta R\&D\_l$) and past values of R&D expenditures from t-2 to t-5 in specification 7.

Table B: Descriptive Statistics

Variables		**Mean**	**Standard-deviation**	**1% Percentile**	**99% Percentile**
Output growth rate	*Δq*	0.031	0.217	-0.598	0.673
Labour growth rate	*Δl*	0.002	0.177	-0.493	0.496
Materials growth rate	*Δm*	0.021	0.294	-0.823	0.879
Physical capital growth rate	*Δk*	0.073	0.269	-0.128	1.094
Solow residual ([a])	*SR*	0.010	0.141	-0.389	0.402
Capacity utilization growth rate	*Δut*	-0.001	0.074	-0.241	0.203
Technology Usage (dummy)	*TECH*	0.062	0.242	0	1
Process Innovation (dummy)	*INNO*	0.283	0.450	0	1
Vintage change	*ΔVINT*	0.726	0.926	0	4
Wage growth rate	*Δw*	0.025	0.152	-0.427	0.471
Change in Percentage of skilled workers	*ΔEDU*	0.004	0.047	-0.121	0.162
Change in Percentage of R&D employees	*ΔR&D_l*	0.001	0.014	-0.044	0.045
Cumulated output per employee growth rate	*Δcq_l*	0.146	0.241	-0.323	0.756
Cumulative output per employee since last innovation growth rate	*Δcq_l_i*	0.203	0.276	0	1

([a]) Computed according to equation (3) in the text, that is
$SR_{it} = \Delta q_{it} - s_{it}^{L}\Delta l_{it} - s_{it}^{M}\Delta m_{it} - (1 - s_{it}^{L} - s_{it}^{M})\Delta k_{it}$