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ON THE DETERMINANTS OF TOTAL FACTOR PRODUCTIVITY GROWTH: EVIDENCE FROM SPANISH MANUFACTURING FIRMS

FABIO CASTIGLIONESI
Tilburg University

CARMINE ORNAGHI
University of Southampton

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 are simultaneously estimated. Our main finding is that the average total factor productivity (TFP) growth is fully explained by embodied technical progress (i.e., either new capital goods or human capital). Our results contradict the existence of a positive contribution of economywide neutral technological progress in determining average TFP growth. They also leave little room for large, unpriced effects external to the firm, both at the aggregate and at the 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

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. Of our data set, whose structure is briefly illustrated in this section and then detailed in Section 3, we ask two main questions: (i) Are changes in 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

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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, proportions of skilled employees, types of capital investment undertaken, and innovation in production processes. Moreover, a unique feature of this data set is that it provides growth rates of firm-specific prices for outputs and intermediary inputs, thus allowing 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 et al. (1992) and Bernard et al. (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, aggregate 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 the heterogeneity of firms explicitly. They permit a detailed examination of how individual characteristics drive cross-sectional productivity differentials, and how the latter affect average productivity growth. Empirical studies at micro level allow analysis of the determinants of productivity changes, leaving the effects of reallocation aside.

Furthermore, by digging deep into micro data, it is possible to learn something about productivity growth that data at the industry level cannot possibly disclose. First, only with firm-level data can we estimate a model that 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 its importance at industry, or economywide, 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 TFP growth are simultaneously estimated and compared. For this purpose, we consider the following possible explanations: disembodied and physical capital–embodied technological progress, human capital accumulation, learning by doing (LBD), and external effects at the industry and economywide levels.

Our estimation builds up progressively from a simple regression that reveals a large and unexplained residual, which represents the (unweighted) average TFP growth across firms. First, we analyze the contributions of traditional disembodied variables as sources of average TFP growth. We consider firm-specific 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&Dspillovers with the industry R&D expenditure. We also consider the median ratio of skilled employees (i.e., with a bachelor's or higher degree) at the industry level, instead of the median wage. Our results show the importance of disembodied variables in affecting average TFP growth.

Then we take into account the relevance of embodied variables as an engine of 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 deal with 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 to affecting average TFP growth. We find that embodied variables alone can fully explain average TFP growth. This result seems to suggest that previous studies might have greatly overestimated the actual relevance of spillover effects on TFP growth. Last, but not least, in all specifications, constant returns to scale cannot be rejected.

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 since 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 the classical definition of LBD: internal to the firm, short-lived, and due to the adoption of new processes. However, the measures do not affect the much more sizable explanatory power of embodied physical and human capital.

To sum up, our paper delivers three main results. First, average TFP growth is fully explained by embodied technical progress; that is, economywide neutral (or disembodied) technical change plays virtually no role. Indeed, the positive contribution of human capital and R&D spillovers to average 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 (LBD): when measured as cumulative output, LBD is nonsignificant, but when measured as output or time from the last innovation, it contributes to the firm's productivity. Third, we find compelling evidence of constant returns to scale across all the estimated specifications.

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 concludes. A more detailed description of how the variables are computed is provided in the Appendix.

2. RELATED LITERATURE

There is a vast empirical literature on productivity growth. Based on growth accounting measures, Abramovitz (1956) carried out one of the first attempts to determine 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 in 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 TFP growth to its original determinants.

More recently, Greenwood et al. (1997) estimate how much of U.S. postwar 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 economywide neutral technical progress. In contrast, using firm-level data and measures of the quality of human capital, we find that economywide neutral technical progress plays almost no role in our dataset. Our results are consistent with those of Henderson and Russell (2005). Studying the composition of labor productivity growth in 52 countries, they find that technological change is decidedly nonneutral 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 economywide LBD. However, they find that firm-specific LBD has a significant effect on firm output. We define our estimating equation in growth rates instead. 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 TFP growth is of the same order of magnitude as 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 by 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.

3. DATA AND ANALYSIS OF TOTAL FACTOR PRODUCTIVITY 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% 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% 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 because they cease to answer the questionnaire (attrition). 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 all yearly observations are dropped 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 a more precise computation of productivity changes. Further information on the ESEE can be found in González et al. (2005) and Ornaghi (2006).

We present now an explorative analysis of the features of the productivity growth computed as the Solow residual according to equation (3) in Section 3.1. Figure 1

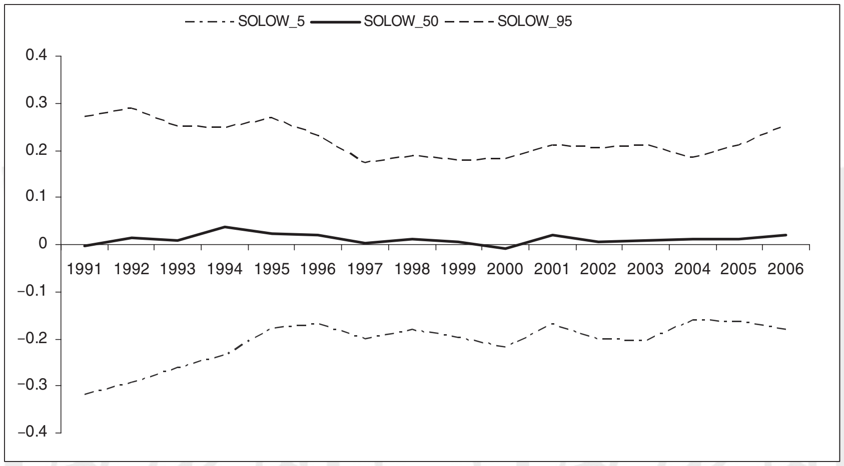

FIGURE 1. Growth of Solow residual across years. The growth of the Solow residual is computed according to equation (3). Numbers 5, 50, and 95 refer, respectively, to percentile 5, median, and percentile 95 of the distribution.

plots the 5th, 50th and 95th percentiles of the productivity growth distribution of Spanish manufacturing firms during the period 1990–2006.

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 doubt 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 et al. (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% of these low productivity firms are still in the first quintile and 39% of them disappear. Only 2% 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% of these new companies are in the first quintile in 2002.

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 that are in the bottom (or top) quintile in 1992 tend to be

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	

Notes: Productivity is defined as the Solow residual (in levels). Firms in quintile 1 have the lowest productivity levels in their industries, whereas those in quintile 5 have the highest productivity in their industries. "Death" refers to the firms alive in 1992 that closed down (or changed industry) before 2002. "New entry" refers to the quintile positions in 2002 of the firms established after 1992.

TABLE 2. Education and innovation for least/most productive firms

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

Notes: Firms in quintile 1 have the lowest productivity levels in their industries, whereas those in quintile 5 have the highest productivity in their industries. 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.

there 10 years later. Results are similar if we use ranks weighted by size or labor productivity.

Table 2 analyzes the average education and innovation over the period 1992–2002 for firms with the lowest/highest productivity levels in the 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% 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% of educated workers and an innovation rate of 0.14 (i.e., an innovation every seven years).

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

Notes: 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 a value of 1 if a firm introduces a process innovation in any year. Averages are computed over all available observations for each firm.

Table 3 reports the quintiles of average productivity growth of each firm in the data set. Because the data set 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.

Tables 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

$$Q_{it} = A_t \cdot e^{(\eta_i + z_{it})} \cdot \mathrm{LBD}_{it} \cdot (\mathrm{HC}_{it} \cdot L_{it})^{\beta^L_{it}} (\mathrm{EMB}_{it} \cdot K_{it})^{\beta^K_{it}} \cdot M_{it}^{\beta^M_{it}}, \qquad (\mathbf{1})$$

where Q represents the output, M the materials, and L and K the conventional measures of labor and physical capital, whereas 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 disembodied technical change, which captures economywide 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 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 linear equation

$$\Delta q_{it} = \Delta a_t + \Delta \mathrm{lbd}_{it} + \beta_{it}^L \Delta l_{it} + \beta_{it}^L \Delta \mathrm{hc}_{it} + \beta_{it}^K \Delta k_{it} + \beta_{it}^C \Delta \mathrm{emb}_{it} + \beta_{it}^M \Delta m_{it} + \Delta z_{it}, \qquad \textbf{(2)}$$

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

$$\Delta q_{it} = \beta_{it}^L \Delta l_{it} + \beta_{it}^K \Delta k_{it} + \beta_{it}^M \Delta m_{it} + \Delta \mathrm{TFP}_{it}, \qquad \textbf{(2A)}$$

where

$$\Delta \mathrm{TFP}_{it} \equiv \Delta a_t + \Delta \mathrm{lbd}_{it} + \beta_{it}^L \Delta \mathrm{hc}_{it} + \beta_{it}^K \Delta \mathrm{emb}_{it} + \Delta z_{it}, \qquad \textbf{(2B)}$$

TFP growth is defined in equation (2A) as the output growth that is not explained by standard input growth. Although 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 economywide disembodied technical change, Δa_t,is one component of TFP growth. Specifically, the term Δa_tcaptures 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} captures not only firm-level neutral technological change but also 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 economywide productivity growth will be overestimated, because Δa_twill capture any firm-specific effect that is left unexplained.

In the next section, we will explain at length all the variables that are constructed to capture the different components of ΔTFP. However, it is important to notice the following. First, the 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 unweighted average growth of the TFP across the sample period ($\Delta \bar{a}$).[5] Second, assume that the variables x_1 and x_2 are used to capture firms' human capital; that is, $\Delta \mathrm{hc}_{it} = \alpha_1 \Delta x_{1,it} + \alpha_2 \Delta x_{2,it}$. By substituting this expression into 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:

$$\mathrm{SR}_{it} \equiv \Delta q_{it} - s_{it}^L \Delta l_{it} - s_{it}^M \Delta m_{it} - \left(1 - s_{it}^L - s_{it}^M\right) \Delta k_{it}, \qquad \textbf{(3)}$$

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 nonconstant 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

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

We assume that labor and materials are variable factors that fully adjust to their equilibrium value in every period, whereas 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):

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

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

where μ_{it} is the firm's markup.

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.

Substituting conditions (5A) and (5B) into equation (4) gives

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

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

$$\text{SR}_{it} = (\mu_{it} - 1)\left[s_{it}^L(\Delta l_{it} - \Delta k_{it}) + s_{it}^M(\Delta m_{it} - \Delta k_{it})\right] + (\lambda_{it} - 1)\Delta k_{it} + \Delta \text{TFP}_{it}. \tag{7}$$

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.[6] We then control for the effects of under- or overutilization of firms' installed capacity, adding to equation (7) the rate of change in capacity utilization (Δut_{it}),

$$\mathrm{SR}_{it} = (\mu_{it} - 1)\mathrm{share}_{it} + (\lambda_{it} - 1)\Delta k_{it} + \theta \cdot \Delta ut_{it} + \Delta\mathrm{TFP}_{it}, \qquad \textbf{(8)}$$

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

The last equation shows that the Solow residual can be decomposed into the true productivity growth term, $\Delta\mathrm{TFP}_{it}$, a markup component, a scale factor, and the degree of capacity utilization. Finally, assuming that the markup and scale coefficients are approximately constant,[7] we obtain the specification to be estimated:

$$\mathrm{SR}_{it} = (\mu - 1)\mathrm{share}_{it} + (\lambda - 1)\Delta k_{it} + \theta \cdot \Delta ut_{it} + \Delta\mathrm{TFP}_{it}. \qquad \textbf{(9)}$$

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.

Because our data set reports growth rates of 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 changes in (output and input) prices at firm level were not observed, it would be necessary to deflate the growth of revenues (and the cost of materials) using industry deflators. Let us define firm i revenues growth as $\Delta P_i Q_i \approx \log(P_{it}Q_{it}) - \log(P_{it-1}Q_{it-1}) = \log(P_{it}/P_{it-1}) - \log(Q_{it}/Q_{it-1}) \approx \Delta P_i + \Delta Q_i$. Let us also assume that only the average change in the industry price of output ΔP_I is available to the econometrician. Then, instead of the true output change ΔQ_i, the construction of the SR would be affected by measurement errors, as it would be based on change in deflated output $(\Delta P_i + \Delta Q_i - \Delta P_I)$. Similar measurement errors would be introduced for intermediary inputs.

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 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 ΔVINT 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.[8] Although 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, because 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), which can possibly measure other, unpriced effects of human capital. Whereas the formervariable enters our empirical specification in growth rates (Δw), the latter is simply the difference between two consecutive years (ΔR&D_l).

The use of firm wages might lead to endogeneity problems because productivity increases might cause an increase of wages through rent sharing. This possibility is actually confirmed in our empirical estimates: when present levels or growth of wages are added to the set of instruments, the Hansen Test of overidentifying restrictions rejects the validity of the instruments used. We consider therefore Δwas an endogenous variable. The set of instruments we use in our estimates includes past values of labor, materials, and investments, and also changes in the quality of labor measured by the change in 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 the impact on productivity of changes in wages because of experience and skills. 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's or higher degree to 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,

$$\mathrm{CQ\_}L_{it} = \left(\sum\nolimits_{j=0}^{t-1} Q_{ij}\right) \Big/ L_{it}.$$

As we deal with growth rates, the latter variable is computed as the logarithmic difference between two subsequent time periods ($\Delta \mathrm{cq\_}l_{it}$). 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 by 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).

The variable $\Delta\text{cq\_l}_{it}$ 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 LBD 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, $\text{CQ\_}L\text{\_}I$. Also, in this case, we consider the logarithmic difference between two periods ($\Delta\text{cq\_}l\text{\_}i_{it}$). 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 they can use the new technology effectively. The second variable is the time (computed as number of years) since the introduction of a process innovation, $\text{time\_}i$.

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 ($\Delta\text{med\_}w_{jt}$) 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 median ratio of workers with a bachelor's degree at the industry level ($\Delta\text{ind\_EDU}_{jt}$). 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 by the growth of R&D expenditure at the industry level ($\Delta\text{ind\_R\&D}_{jt}$).

The richness of information provided by these firm-level data 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 upward, 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 the 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 input 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 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 U.S. data, such as Basu and Fernald (1995) or Burnside et al. (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 empirical specification, we report results based both on consistent one-step estimators [as suggested by Arellano and Bond (1991)] and on two-step estimators with small sample correction [as proposed by Windmeijer (2005)]. We also report the Hansen 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 used to estimate a production function in first differences: low and nonsignificant 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 particularly problematic when applied to persistent data. We believe that our analysis presents some advantages over 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 materials, 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 data set that allows us to construct different variables to capture embodied technological progress. For instance, human capital is captured by the growth rate of wages (Δw), the change in the proportion of workers with a bachelor's or higher degree (ΔEDU) and the growth of R&D employees (ΔR&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.[9] 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, growth rates of firm-level prices allow us to obtain more precise measure of the dependent variable SR.[10]

The coefficients of time dummies (θ) and industry dummies (ϕ) are estimated using the Suits method, so that they are constrained to add up to zero; that is, $\sum_{t=1991}^{2006} \theta_t = 0$ and $\sum_{j=1}^{14} \phi_{\text{ind}\_j} = 0$.[11] Accordingly, the constant included in each regression represents the (unweighted) average growth of TFP across firms and over time. The value of the constant plays a crucial role because it can be considered as the part of productivity growth that is left unexplained, and that is generally considered as economywide neutral technological change.

First of all, we estimate the average growth of 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 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 TFP. Table 4 reports the results.

Column (1) shows that the yearly average TFP growth across the Spanish manufacturing firms in our sample is 2.1%. 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. A similar result is obtained in all the other specifications. Although we find a negative value of markups when we estimate the model without embodied variables, results in Columns (3) and (5) show that the coefficient of share is not statistically different from zero when such variables are included, suggesting that Spanish manufacturing firms do not enjoy a large degree of market power.[12] The last control variable, Δut, is positive and statistically significant in almost all the specifications, 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 (0.102) in the one-step regression and 0.122 in the two-step regression) is of the same order of magnitude as the one reported in their article (0.079). The estimated coefficients

TABLE 4. LBD, externality, and embodied growth

	Dependent Variable: Growth of Solow Residual				
Independent Variables	1	2 One-Step	2 Two-Step	3 One-Step	3 Two-Step
Average TFP growth ($\Delta\bar{a}$):					
Constant	0.021***	0.0009	−0.0027	−0.006	−0.0082
	(0.0012)	(0.0056)	(0.0057)	(0.00347)	(0.0067)
LBD:					
Δcq_l_{it}		0.102***	0.122***	0.024	0.058
		(0.034)	(0.034)	(0.038)	(0.038)
Externality:					
Δmed_w_{jt}		0.258**	0.227**	0.130	0.123
		(0.113)	(0.105)	(0.108)	(0.102)
Δind_R&D$_{jt}$		0.020**	0.018**	0.010	0.005
		(0.008)	(0.008)	(0.008)	(0.008)
Embodied:					
TECH$_{it}$				0.125***	0.098***
				(0.036)	(0.032)
ΔVINT$_{it}$				0.016***	0.014***
				(0.003)	(0.003)
Δw_{it}				0.242***	0.229***
				(0.085)	(0.05)
ΔR&D_l_{it}				0.298*	0.289*
				(0.169)	(0.159)
Control:					
share$_{it}$	−0.198**	−0.196***	−0.175***	−0.083	−0.060
	(0.078)	(0.058)	(0.058)	(0.051)	(0.050)
Δk_{it}	0.021	−0.023	0.019	−0.022	−0.032
	(0.161)	(0.152)	(0.151)	(0.139)	(0.138)
Δut_{it}	0.293**	0.242	0.260*	0.193	0.216
	(0.142)	(0.154)	(0.158)	(0.143)	(0.147)
Industry dummies[a]:					
Chemicals	0.011***	0.011***	0.011***	0.008***	0.007**
Electronics	0.007**	0.011***	0.010***	0.009***	0.007**
Cars & Motors	0.011***	0.011***	0.011***	0.010***	0.008**
Time dummies	Incl.	Incl.	Incl.	Incl.	Incl.
Sample period	1990–2006	1990–2006	1990–2006	1990–2006	1990–2006
Observations	15,886	15,886	15,886	15,886	15,886
M1	−12.39	−12.38	−12.33	−11.14	−12.11
[p-values]	[<.01]	[<.01]	[<.01]	[<.01]	[<.01]

TABLE 4. Continued.

	Dependent Variable: Growth of Solow Residual				
Independent Variables	1	2 One-Step	2 Two-Step	3 One-Step	3 Two-Step
M2	−0.97	−0.70	−0.64	−1.20	−1.05
[p-values]	[.33]	[.48]	[.52]	[.23]	[.29]
Hansen test (df)	93 (85)	128 (141)	128 (141)	139 (139)	139 (139)
[p-values]	[.25]	[.76]	[.76]	[.48]	[.48]

Notes: Heteroskedasticity robust S.E. in parentheses. One-step refers to results based on consistent one-step estimators, as suggested by Arellano and Bond (1991). Two-step refers to the corresponding two-step estimates using Windmeijer (2005) small sample correction. Instrumental variables: labor, materials, and investments lagged levels at $t-2$ and $t-3$ 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 specifications 2 and 3; change in the ratio of R&D employees (ΔR&D_l), innovation dummies (INNO), and vintage (ΔVINT) are used in specification 3.
[a]Only coefficients that are significant at 10% or more are reported.
***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

of Δind_R&D$_{jt}$ and Δmed_w_{jt} suggest that the productivity of firms in industries with greater increases in R&D expenditure and in human capital rises more than the productivity of firms in other 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 TFP growth.

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 2.1% of TFP growth. The coefficients of the four variables that capture changes in human capital or improvements in physical capital are found to be significant, whereas the coefficients of firm-level LBD, human capital spillovers, and knowledge spillovers are not statistically significant.

The coefficient of the vintage variable (ΔVINT) in the one-step regression, for example, suggests that a one-year decrease in average vintage leads to 1.6% growth in firm-specific 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 U.S. economy [see Greenwood et al. (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) establishe also the existence of a positive correlation between TFP growth and human capital. The estimated coefficient of $\Delta w$is 0.24with the one-step estimator and 0.23 with the two-step estimator. These values are in line with the income share of labor and they are similar to the coefficients reported in other studies [see, for instance, Hellerstein and Neumark (2004)].[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 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 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 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 plants (and therefore, plants that 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 $\Delta\mathrm{cq\_}l$ loses all its explicative power in the full specification.

However, 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.[14] This means that our statistical model is successful in explaining the average growth of TFP, $\Delta\bar{a}$, but the determinants of firm-specific TFP growth, Δz_{it}, remain largely unexplained. Indeed, as already pointed out, the error term Δz_{it} not only captures measurement errors, but also could capture firm-level neutral technological change.

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. We thus define an alternative model that use the share of employees with a bachelor's degree (ΔEDU) to measure the quality of labor at firm level and, similarly, the median share of skilled workers at industry level (Δind_EDU) to capture human capital spillovers. Second, the variable cumulative output per employee is likely to be correlated with the dependent variable by construction. Accordingly, we use the variables of cumulative output since last innovation ($\Delta\mathrm{cq\_}l\_i$) and time since last innovation(time_i) as an alternative proxy for firm-specific LBD. Table 5 reports the results.

The specifications in Table 5 confirm the previous findings: (i) the average TFP growth is squeezed to zero when variables capturing embodied technological progress are included; (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 spillover is not significant once we control for the quality of capital and labor of the

TABLE 5. LBD, externality, and embodied growth

	Dependent Variable: Growth of Solow Residual			
Independent Variables	4 One-Step	4 Two-Step	5 One-Step	5 Two-Step
Average TFP growth ($\Delta\bar{a}$):				
Constant	0.0154***	0.0167***	−0.0019	−0.0007
	(0.024)	(0.0021)	(0.0032)	(0.0030)
LBD:				
Δcq_l_i_{it}	0.028***	0.028***	0.025***	0.026***
	(0.005)	(0.005)	(0.005)	(0.005)
Time_i_{it}	−0.001***	−0.001***	−0.001**	−0.001**
	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)
Externality:				
Δind_EDU_{jt}	1.432***	1.170***	0.530	0.550
	(0.403)	(0.365)	(0.408)	(0.379)
Embodied:				
TECH_{it}			0.129***	0.103***
			(0.030)	(0.031)
$\Delta\mathrm{VINT}_{it}$			0.017***	0.014***
			(0.003)	(0.003)
$\Delta\mathrm{EDU}_{it}$			0.824***	0.628**
			(0.282)	(0.266)
ΔR&D_l_{it}			0.266*	0.357**
			(0.151)	(0.153)
Control:				
share_{it}	−0.313***	−0.301***	−0.070	−0.070
	(0.064)	(0.063)	(0.048)	(0.046)
Δk_{it}	0.021	0.054	0.104	0.110
	(0.165)	(0.164)	(0.115)	(0.113)
Δut_{it}	0.386**	0.405**	0.308**	0.306**
	(0.170)	(0.173)	(0.121)	(0.120)
Industry dummies:[a]				
Chemicals		0.008*		
Electronics	0.012***	0.012***	0.008**	0.008**
Cars & Motors	0.014***	0.014***	0.012***	0.012***
Time dummies	Incl.	Incl.	Incl.	Incl.
Sample period	1990–2006	1990–2006	1990–2006	1990–2006
Observations	15,886	15,886	15,886	15,886
M1	−11.85	−12.00	−12.00	−12.89
p-values	[<.01]	[<.01]	[<.01]	[<.01]

TABLE 5. Continued.

Independent Variables	Dependent Variable: Growth of Solow Residual			
	4 One-Step	4 Two-Step	5 One-Step	5 Two-Step
M2	−1.12	−1.09	−0.30	−0.16
p-values	[.26]	[.27]	[.74]	[.87]
Hansen test (*df*)	142 (143)	142 (143)	176 (170)	176 (170)
p-values	[.49]	[.49]	[.35]	[.35]

Notes: Heteroskedasticity robust S.E. in parentheses. One-step refers to results based on consistent one-step estimators, as suggested by Arellano and Bond (1991). Two-step refers to the corresponding two-step estimates using Windmeijer (2005) small sample correction. Instrumental variables: labor, materials, and investments lagged levels at $t-2$ and $t-3$; lagged levels of industry median wage (med_w) and industry R&D expenditure (ind_R&D) at $t-2$ and $t-3$ in both specifications; lagged levels of R&D employees at $t-2$ and $t-3$ in specification 5. LBD since last innovation (Δcq_l_i) and time since last innovation (time_i) in both specifications. Change in the ratio of R&D employees (ΔR&D_l), innovation dummies (INNO), and vintage (ΔVINT) are used in specification 5.
^{a}Only coefficients that are significant at 10% or more are reported.
***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

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, whereas 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.[17]

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, only the values of the significant industry dummies. We find that there are three year dummies that show significantly higher growth: 1994, 1995, and 1996. This is consistent with Figure 1, where these three years show higher median productivity growth than other years. The coefficients 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 TFP that our approach cannot explain. In other words, it seems that we can explain average TFP growth in the medium to long run, but the sources of short-run fluctuations in TFP growth 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 three industries grow faster than the average manufacturing sector: chemicals, electronics, and motor vehicles. Compared to an average growth of TFP of 2.1%, these three industries are found to have a TFP growth between 0.7 and 1.1% higher. Even when we account for the quality of the physical and human capital, the point estimates of these dummies are unchanged. Although this result might weaken the findings of this paper, it is important to note that these industries are characterized by high investment in R&D, a feature that is not fully captured by our specification.[18]

In order to account for the innovativeness of these three industries, we slightly modify our empirical specification to include the dummy variable INNO instead of the dummy variable TECH, because the former variable is more likely to pick up the effects of process innovation, which are not solely confined to the use of new technologies. Table 6 reports the results.

The nonsignificant value of the constant term in Column (7) shows that this alternative specification can explain the average growth of TFP in these three industries. Overall, estimates are similar to those reported in Tables 4 and 5. It is interesting to note that the coefficients of $\Delta\mathrm{R\&D\_}l$ and $\Delta\mathrm{cq\_}l\mathrm{\_}i$ are now larger: this suggests a more prominent role of human capital and LBD 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 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, because 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.

It is worth pointing out two limits, among the many of our approach. First, although we can account for the (unweighted) average TFP growth across firms, because our constant does not include any reallocation effect, we cannot explain much of the dispersion of firm-specific TFP growth. As productivity measures also include unwanted components, because of 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

TABLE 6. Chemicals, electronics, and motors

Independent Variables	Dependent Variable: Growth of Solow Residual 6	7 One-Step	7 Two-Step
TFP growth:			
Constant	0.0247***	−0.0011	−0.0099
	(0.0025)	(0.0076)	(0.0084)
LBD:			
Δcq_l_i_{it}		0.064***	0.059***
		(0.017)	(0.018)
Embodied:			
INNO_{it}		0.028***	0.027***
		(0.008)	(0.008)
$\Delta\mathrm{VINT}_{it}$		0.018***	0.015**
		(0.006)	(0.006)
ΔR&D_l_t		0.927**	0.731*
		(0.373)	(0.443)
Control:	Incl.	Incl.	Incl.
Industry dummies	Incl.	Incl.	Incl.
Time dummies	Incl.	Incl.	Incl.
Sample period	1990–2006	1990–2006	1990–2006
Observations	2,998	2,998	2,998
M1	−5.54	−5.36	−5.35
p-values	[<.01]	[<.01]	[<.01]
M2	−1.03	−0.79	−0.78
p-values	[.28]	[.43]	[.43]
Hansen test (*df*)	91 (85)	89 (85)	89 (85)
p-values	[.28]	[.35]	[.35]

Notes: Heteroskedasticity robust S.E. in parentheses. One-step refers to results based on consistent one-step estimators, as suggested by Arellano and Bond (1991). Two-step refers to the corresponding two-step estimates using Windmeijer (2005) small sample correction. Instrumental variables: labor, capital, and materials lagged levels from $t-2$ to $t-3$ in both specifications; change in the ratio of R&D employees (ΔR&D_l), innovation dummies (INNO), and vintage (ΔVINT) are used in specification 7.
***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

become nonsignificant 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.[19] We recognize that the relative importance of 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 to assessing the relevance of unpriced externalities for productivity growth.

NOTES

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.
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. Note that, by the same token, this also casts doubt on models of technological progress based on aggregate spillovers. If external effects are free and industry- or systemwide, why would individual firms be affected so differently by them?
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 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, whereas the time dummies would show deviations from this average.
6. In particular, Hulten (1986, p. 38) shows that the “false” residual (which in our specification corresponds to the Solow residual) is “equal to the true residual plus the rate of change of capital utilization.”
7. 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 z_{it}. The assumptions 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 (results available upon request). Baily et al. (1992) also find constant return to scale in the Longitudinal Research Database of the Census Bureau.
8. Doms et al. (1995) use a similar variable to study the role of technology use in the survival and growth of manufacturing plants.
9. 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) Section 5.3].
10. An alternative estimation procedure for persistent data is the so-called “System-GMM,” which requires specifying first the model in levels and then the corresponding model in growth rates. Unfortunately, it is not possible to compute the Solow residual (our dependent variable) directly in levels because we do not observe the levels of (output and input) prices but only their growth rates.
11. These constraints are actually implemented imposing $\theta_{1991} = -(\sum_{t=1992}^{2006}\theta_t)$ and $\phi_{\mathrm{ind\_1}} = -(\sum_{j=2}^{14}\phi_{\mathrm{ind\_}j})$.
12. Siotis (2003) has found that markups charged by Spanish firms were considerably reduced in the 1990s, after Spain entered the European Union.
13. Doms et al. (1997) also find that firms adopting new technologies and, consequently, increasing their productivity performance have skilled workforces prior to the adoption.
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 for Canada from 1970 to 1993. They report an R^2 that varies from .02 to .10.
15. The large point estimate of Δind_EDU could be due to the fact that ΔEDU and ΔR&D_I 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.

17. Note that Table A.1 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 1% of the SR distribution are dropped, and we find point estimates very close to those reported in the previous tables (results available upon request).

18. The average R&D intensity (i.e., R&D expenditure over sales) of the firms in these three industries is 1.5%, whereas the average for the firms in the rest of the sample is only 0.4%.

19. For instance, we try to capture R&D and human capital externalities using aggregate measures at industry level. Because we have no measures of patent citation [Jaffe (1986)] or education level in the area where the firms operate [Moretti (2004)], we cannot perform alternative checks of robustness for the existence of R&D and human capital spillovers.

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APPENDIX

A.1. FIRMS' EQUILIBRIUM CONDITIONS

Consider the firm's profit function under imperfect competition,

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

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:

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

This implies that

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

where η_{it} is the elasticity of the demand curve. Defining $\frac{1}{1+1/\eta_{it}} \equiv \mu_{it}$, 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 both sides of the latter expression by L_{it}/Q_{it}, we get expression (5A) in the text. Considering materials as inputs, we get expression (5B) in a similar way.

A.2. 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 into the following fourteen sectors: (1) ferrous and nonferrous metals; (2) nonmetallic minerals; (3) chemical products; (4) metal products; (5) industrial and agricultural machinery; (6) office and data processing machinery; (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 growth of output using the firm-specific changes in output price as reported by the firm.

Labor (L): Labor consists of the total hours of work. It is computed using the number of workers, 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 firm-specific deflators based on the variation in the cost of raw materials and energy as reported by the firm.

Physical Capital (K): Physical capital is constructed by capitalizing firms' investments in machinery and equipment (deflated by a specific price index for capital goods) and using sectoral 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*):* Solow residual is computed according to equation (3),

$$\mathrm{SR}_{it} = \Delta q_{it} - s_{it}^{L}\Delta l_{it} - s_{it}^{M}\Delta m_{it} - \left(1 - s_{it}^{L} - s_{it}^{M}\right)\Delta k_{it},$$

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.,

$$s_{it}^{L} \equiv \frac{1}{2}\left(\frac{W_{it}\times L_{it}}{P_{it}\times Q_{it}} + \frac{W_{it-1}\times L_{it-1}}{P_{it-1}\times Q_{it-1}}\right).$$

The exact specification for the computation of the Solow residual is then

$$\mathrm{SR}_{it} = \ln\left(\frac{Q_{it}}{Q_{it-1}}\right) - s_{it}^{L}\ln\left(\frac{L_{it}}{L_{it-1}}\right) - s_{it}^{M}\ln\left(\frac{M_{it}}{M_{it-1}}\right) - \left(1 - s_{it}^{L} - s_{it}^{M}\right)\ln\left(\frac{K_{it}}{K_{it-1}}\right).$$

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 ta 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 $\tau$is

$$\mathrm{VINT}_{i\tau} = \max\left\{\text{year of birth} - 1990;\ \tau - 1990 - \frac{C/I}{2}\right\}. \qquad (\mathbf{A.1})$$

Note that equation (A.1) 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 the results reported in Section 5.

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

$$\mathrm{VINT}_{i,\tau+x} = \frac{\mathrm{VINT}_{i,\tau}\cdot K_{i,\tau}(1-\delta)^{x} + \sum_{j=1}^{x}(\tau + j - 1990)\cdot I_{i,\tau+j}(1-\delta)^{x-j}}{K_{i,\tau}(1-\delta)^{x} + \sum_{j=1}^{x} I_{i,\tau+j}\cdot(1-\delta)^{x-j}}, \qquad (\mathbf{A.2})$$

where I stands for investments in physical capital, whereas 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 (A.1) is $\mathrm{VINT}_{i,1994} = \max\{1988 - 1990; 1994 - 1990 - \frac{10}{2}\} = -1$. Using equation (A.2), the vintage for this firm in year 1996, for instance, is

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

*Technology Usage (*TECH*):* A dummy variable taking a value of 1 when a firm reports adopting 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*):* A dummy variable taking a value of 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 the following question: positively: "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) to total number of workers.

*Education (*EDU*):* Ratio of skilled employees (defined as employees with a bachelor's or higher degree) to total number of workers.

Total R&D *expenditure of the industry (*IND_R&D*):* Yearly expenditure on R&D at industry level. The variable is computed by 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:

$$\mathrm{CQ\_}L_{it} = \left(\sum\nolimits_{j=0}^{t-1} Q_{ij}\right) \Big/ L_{it}.$$

Whereas 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 differences are taken between two consecutive years. Initial values of the cumulative output are computed by 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 levels 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 $\Delta\mathrm{cq\_}l$ 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 preceding definition):

$$\mathrm{CQ\_}L\_I_{it} = \left(\sum\nolimits_{j=t-s}^{t} Q_{ij}\right) \Big/ L_{it},$$

where s is the time elapsed since a process innovation has been introduced (i.e., $\mathrm{INNO}_{it} = 1$). Consider the case of a firm whose output is 100 for the period 1990 to 2002 and that has introduced two process innovations in 1990 and 1997, $\mathrm{INNO}_{i,90} = 1$ and $\mathrm{INNO}_{i,97} = 1$. 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 $\Delta\mathrm{cq\_}l\_i$ 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 $\mathrm{INNO}_{it} = 1$ (in the previous example $\Delta\mathrm{cq\_}l\_i_{i,97} = 0$). This example also shows that $\Delta\mathrm{cq\_}l\_i$ takes higher values in the year immediately after an innovation and 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 an innovation every n years on average, 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 from 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 A.1.

TABLE A.1. Descriptive statistics

Variables		Mean	Standard deviation	1st percentile	99th 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, $\mathrm{SR}_{it} = \Delta q_{it} - s^L_{it}\Delta l_{it} - s^M_{it}\Delta m_{it} - (1 - s^L_{it} - s^M_{it})\Delta k_{it}$.