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César Alonso-Borrego (*)

UNIVERSIDAD CARLOS III DE MADRID

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Abstract

The aim of this paper is to analyze the evolution of productivity and how firm behavior and institutional conditions affects productivity. For that purpose, we use a longitudinal sample of Spanish manufacturing and services companies between 1983 and 2006, as well as OECD indicators on product market regulations. The productivity measurement is based on the control function approach, to overcome the endogeneity bias. Both for manufacturing and services firms, we have found that the share of temporary employment tends to reduce productivity, the effect being stronger for services firms, which make a more intensive use of this employment type. Our results also show that increases in competition lead to productivity improvements. Besides, those manufacturing firms who keep undertaking in-house production of services tend to be more productive. The lack of competition in the services sector may be preventing firms to increase specialization while outsourcing non-manufacturing activities.

Keywords: TFP, Competition, Employment composition, Endogeneity.

JEL classification: L10, L11, L22, L23, C23.

1 Introduction

There is an increasing concern about measurement of productivity and the study of the factors underlying productivity growth. Bartelsman and Doms (2000) underline the importance of microdata studies to address this issue. Among the factors under study, we can mention the effect of skill mix, technology adoption (Brynjolfsson and Hitt, 1996; Jorgenson and Stiroh, 1999), foreign capital (Javorcik, 2004) and competition conditions on productivity. Nevertheless, even though the services sector exhibits the largest and increasing share in OECD countries, most of empirical analysis has focused on manufacturing industries. Among the exceptions, we should mention Mairesse and Kremp (1993) and Girma and Kneller (2005), who showed the leading role of the services sector in IT (Information Technology) investment in recent years.

The aim of this paper is to analyze the evolution of total factor productivity (TFP) and how it is affected by firm behavior and institutional conditions. For that purpose, we use a longitudinal sample of Spanish manufacturing and services companies between 1983 and 2006, with information about production, intermediate inputs, physical capital, employment and other complementary information. We also exploit OECD complementary information providing indicators on product market regulations, which measure the degree to which policies inhibit or promote competition.

Regarding firm behavior, among other things, we account for employment composition –in particular, the share of temporary employment–, as well as the different business activities undertaken within the firm. Our concern with the services sector, in addition to manufacturing, is justified by the increasing share of the services industries in the last decades in developed countries, together with a sharp drop in the primary sector, and a smaller but persistent decrease in the share of manufacturing industries. This latter fact is partly explained by the tendency of manufacturing to outsource many services activities that had been undertaken by them in the past. Among the activities undertaken by the firm, we observe a significant fraction of manufacturing firms that report services activities among them, even though a majority of them report only manufacturing activities. We will analyze how this differential behavior affects productivity.

Regarding the effect of economic regulations, the situation is very different for manufacturing and services industries. Manufacturing firms have been faced to increasing international competition. However, competition faced by services firms is more local, and the non-tradable nature of many services goods allows local firms to deter competition through other sources of market power and through formal or informal collusive arrangements between local firms (Oulton, 1998). In fact, whereas most regulations in manufacturing industries have been lifted in Spain during the last two decades, there remains a long way for deregulating the services sector. According with the OECD indices of market regulation, and despite the advances towards deregulation, Spain remains ranked as the fourth OECD country with the high levels of regulation (Maravall, 2007). However, the effects of anti-competition regulation in the services sector exceed the firms within this sector. Since output of services industries provides intermediate inputs to other economic sectors, the effect of restrictive product market regulation in services may substantially affect other non-services industries. Namely, it may affect non-service firms in several extents: their propensity to contract out services, their organization of work and production, the resource allocation between firms, and their potential productivity improvements (Conway and Nicoletti, 2006).

The approach to measure TFP at the firm level is based on estimating a technology of production using an output measure and information on the amount of all the observable inputs, and computing TFP as the residual from estimation. The major problem in technology estimation is the endogeneity bias due to unobserved firm-specific productivity shocks correlated with the observed inputs (see Griliches and Mairesse, 1995). For such a reason, OLS estimation renders inconsistent estimates of the technological parameters. The two alternative approaches to treat the endogeneity problem are the fixed effects approach and the control function approach. The key assumption behind the fixed effects approach is that unobserved firm-specific productivity shocks are invariant over time, and therefore any fixed effects transformation, such as first-differences, allows to recover the parameter estimates by means of GMM estimation while removing the unobserved input term. The main caveat of this approach is the potential weakness of the instruments, which can jeopardize parameter identification. The control function approach, proposed by Olley and Pakes (1996), tackles the endogeneity problem in a more general way. Essentially, the firm-specific productivity shocks, which are assumed to follow a Markov process, can be recovered by means of a variable which keeps a monotonic relationship with the firm-specific shock, such as capital investment or intermediate inputs.

After computing TFP per firm and per year, the longitudinal variation can be exploited to enquire how firm behavior, measured through workforce composition, organizational structure, and capital and technological decisions, affects productivity differences (see Heshmati, 2003). When controlling for input endogeneity, we achieve estimates of technological parameters that reduce the downward bias of the capital coefficient for most manufacturing and services sector. The descriptive analysis of productivity based on our measures points out that the sign and the degree of correlation between changes in productivity and output growth differs very much across industries. The distribution of TFP reveals a substantial firm persistence in the relative TFP ranking both for manufacturing and services firms, although the latter ones exhibit a larger mobility.

The main results regarding productivity determinants, which are analyzed separately for manufacturing and services firms, can be summarized as follows. In the case of manufacturing firms, we find a strongly negative effect of anti-competitive regulations in the services sector. At the same time, manufacturing firms that keep in-house production of services tend to exhibit higher productivity. These two estimates suggest that lack of competition in local services may hamper the productivity gains associated with increasing specialization and outsourcing of complementary non-manufacturing activities. We find that the share of temporary employment and the market share, as an inverse measure of market competition, has a negative effect on productivity, both for manufacturing and services firms. However, such effects are significantly larger for services firms, which make a more intensive use of temporary employment, and operate in less deregulated markets.

The rest of the paper is organized as follows. In Section 2, we explain our strategy to estimate production technology. In Section 3, we produce our productivity measures and undertake a descriptive analysis, The determinants of productivity are assessed in Section 4, and Section 5 summarizes the main results and concludes.

2 The measurement of productivity

To characterize technology, we posit a double logarithmic specification on grosss output and inputs, which is supported by a Cobb-Douglas technology,

$$y_{it} = \beta_0 + \beta_L l_{it} + \beta_M m_{it} + \beta_K k_{it} + v_{it},$$

where, for each firm i in year t, y_{it} denotes the log of gross real output, and l_{it}, m_{it}, denote the logarithms of the variable inputs, labor and intermediate inputs, k_{it} is the log of fixed capital stock, and v_{it} is an unobserved term containing any unobserved factors affecting production. Estimation of the technology of production is affected by the endogeneity bias due to the correlation between production inputs and unobserved productivity shocks (cf. Griliches and Mairesse, 1995). Formally, this problem can be written, in terms of the unobserved term, as

$$v_{it} = \omega_{it} + u_{it}.$$

The random variable ω_{it} represents firm-specific further factors, unobserved to the econometrician, which affect productivity, such as managerial ability, firm specific human capital, efficiency in the use of technology and inputs, which are known to the firm when deciding the amounts of capital, labor and intermediate inputs. The random variable u_{it} is an idiosyncratic term, which includes measurement error in output or shocks affecting output that are unknown when the firm decided the amount of inputs. The random variable ω_{it} is usually referred as unobserved productivity, productivity shock, or total factor productivity (TFP), and it is expected to be related with input decisions. On the other hand, u_{it} is the usual 'noise' term, assumed to be independent of inputs and of the productivity shock.

The endogeneity problem arises from the fact that ω_{it} is known to the firm when deciding the amounts of inputs, so that ω_{it} is a state variable in the firm's decision problem, which affects input choices. As a consequence, input choices will be correlated with total factor productivity, and therefore OLS estimation will yield inconsistent estimates of the technological parameters. I will discuss the approaches that have been proposed in the empirical literature to overcome this endogeneity problem due to the simultaneity between unobserved productivity shocks and input choices. A complete discussion of this issue can be followed in Ackerberg, Benkard, Perry and Pakes (2007) and Aguirregabiria (2009), among others.

There are two traditional solutions: Instrumental variables and fixed effects. The instrumental variables approach has relied on the use of appropriate external instruments for the production inputs. As usual, such instruments must fulfill two conditions: being uncorrelated with the unobservables, what includes the productivity shock, yet correlated with the production inputs. The natural candidates are, then, the prices of inputs, assuming that we can observe them at the firm level. The first condition is very likely to hold if firms operate in perfectly competitive markets for inputs. For the second condition to hold, we need, in line with input choices by firms, to find enough cross-sectional variation in input prices. This requirement is hard to hold if firms use homogeneous inputs and buy them in competitive markets. On the contrary, it is more likely to observe variation in input prices across firms if inputs are firm-specific, but then the exogeneity of such variation (i.e., no correlation with firm's productivity) is dubious. Besides, input prices are very often non reported by firms, and they are mostly observed with some level of aggregation.

The second one is the fixed effects approach, for which panel data is required. Actually, fixed effect estimators where primarily introduced to deal with the estimation of production functions (Mundlak, 1961; Hoch, 1962). The key assumption behind the fixed effects approach is that unobserved firm-specific productivity shocks are invariant over time, so that the unobserved term can be written as

$$v_{it} = \omega_i + u_{it},$$

so the firm-specific productivity shock might be removed by means of a within-firm or a first-differences transformation (also denoted as fixed-effects transformation). Assuming that the idiosyncratic term u_{it} is serially uncorrelated, and uncorrelated with current and future input choices, technological parameters can be consistently estimated applying OLS to the fixed-effects transformation of the model. It must be noticed that lack of correlation of u_{it} with current and future input choices requires strict exogeneity of the production inputs, so that shocks affecting output after input choices have been done do not affect future input choices either. The failure of the required assumptions is behind the usual result that the fixed-effects estimates obtained for the technological parameters are usually very small. An additional problem is that the downward bias induced by measurement error in the explanatory variables can be amplified by the fixed-effects transformation (see Griliches and Hausman, 1986).

The requirement of the classical fixed effects approach that the explanatory variables –in our context, production inputs– must be strictly exogenous is very unrealistic. However, such requirement can be substituted by the weaker assumption that input choices are predetermined with respect to the idiosyncratic term u_{it}. In other words, u_{it} is uncorrelated with current and past input choices (so that productivity 'surprises' can only affect future input choices). Such assumption generates moment conditions by which lagged levels of the production inputs are uncorrelated with the fixed effect transformation of the idiosyncratic term. In other words, lagged inputs can be used as instruments for the production function in first differences. (see Arellano and Bond, 1991). In addition to the predeterminedness of inputs and the lack of serial correlation in the idiosyncratic term, the validity of lagged inputs as instruments relies heavily on the serial correlation of production inputs. The main caveat of this approach is the potential weakness of the instruments, which can jeopardize parameter identification. Typically, lagged levels of the production inputs are used as instruments for the production function in first-differences. In practice, instruments are poorly correlated with endogenous regressors when the serial correlation of the regressors in first differences is weak. Besides, as it happened with the classical fixed effects approach, the fixed effects transformation is subject to the problem of measurement error in inputs. As a consequence, estimates are typically imprecise and subject to large finite-sample biases.

To deal with this 'weak instruments' problem, Arellano and Bover (1995) and Blundell and Bond (1998) have proposed adding further conditions to the standard GMM estimator (Arellano and Bond, 1991) that can improve parameter identification. Assuming that input and output changes are uncorrelated with the unobserved firm-specific productivity shock ω_i, we can exploit additional moment conditions by which twice lagged first differences of inputs are valid instruments for the production function in levels. Blundell and Bond (2000) provide evidence based on Monte Carlo experiments and on production function estimates for UK data, by which the estimator exploiting these further conditions, denoted as system-GMM largely improves the estimation precision with regard to the standard GMM estimator.

In any case, the fixed effect approach, even in their most promising proposals, is flawed by the strong assumption that the firm-specific productivity shock ω_i is constant over time. As Ackerberg et al. (2007) posed, this assumption is more questionable the longer the time length for which panel data are available. In fact, the estimation of production functions is often linked to periods of data containing major changes affecting firms, such as deregulation, changes in trade policies, etc. Such changes are expected to have differential effects on the productivities of different firms, and therefore assuming ω_i is time-invariant is very unrealistic.

Olley and Pakes (1996) proposed a different approach to undertake the endogeneity problem in the estimation of technology of production. Olley and Pakes do not require the firm-specific productivity shock ω_{it}, to be time-invariant: they assume ω_{it} to follow a first order Markov process, without requiring any parametric assumption. Since they use series expansions, they actually consider a nonlinear AR(1),

$$\omega_{it} = \rho_1 \; \omega_{i,t-1} + \rho_2 \; \omega_{i,t-1}^2 + ... + \varepsilon_{it}.$$

In essence, the Olley-Pakes method is a control function approach (Heckman and Robb, 1985). Instead of instrumenting the endogenous regressors, they include external variables to approximate the productivity shock, which is the endogenous part of the error term. We require such variables to keep a monotonic relationship with the productivity shock, so an increase in such variable unambiguously indicates a positive productivity shock.

Olley and Pakes consider fixed capital as a quasi-fixed input, and take the usual assumption that capital is accumulated by firms through a deterministic dynamic investment process,

$$k_{it} = (1 - \delta) \, k_{i,t-1} + i_{i,t-1}$$

where i_{it} denotes the investment expenditure at period t. It is assumed that there is time-to-build, so that it takes time to install the new capital that the firm acquired at $t-1$, not being productive until period t. Investment demand can be defined by means of an unknown function

$$i_{it} = i\left(k_{it}, \omega_{it}\right).$$

Since investment depends on fixed capital stock and firm unobserved productivity, we can invert the "investment function", and therefore, express the unobserved productivity as a non parametric function of investment and capital. The only limitation when using investment as proxy is that estimation must be restricted to the subsample of observations with positive investment in order to fulfill the monotonicity condition.[1] Since the form of the "investment function" is unknown, the technological coefficient of capital cannot be identified when we introduce the approximation to the productivity shock in terms of investment and capital. Hence, in a first stage we can only identify the technological coefficients for labor and intermediate inputs. Inverting the optimal decision rule for investment, we can get:

$$\omega_{it} = h_t(k_{it}, i_{it})$$

and therefore we can write the production function equation as follows:

$$\begin{aligned} y_{it} &= \beta_0 + \beta_L l_{it} + \beta_M m_{it} + \beta_K k_{it} + h_t(k_{it}, i_{it}) + v_{it}, \\ y_{it} &= \beta_L l_{it} + \beta_M m_{it} + \phi_t(k_{it}, i_{it}) + v_{it}. \end{aligned}$$

where $\phi_t(k_{it}, i_{it}) = \beta_0 + \beta_K k_{it} + h_t(k_{it}, i_{it})$. This is the equation that is estimated in the first stage, using a non parametric estimation of $\phi_t(k_{it}, i_{it})$ or, similarly, a second or third order polynomial approximation in k_{it} and i_{it}.

[1] This can result in an efficiency loss, depending on the proportion of observations which must be left out for estimation. This fact led Levinsohn and Petrin (2003) to propose intermediate inputs instead of investment as a proxy, for which the monotonicity condition is more likely to be held for the whole sample.

In the first stage we have then identified the technological parameters of labour and intermediate inputs, but not the capital parameter. For the sake of exposition, assume that ω_{it} follows a linear AR(1) process,

$$\omega_{it} = \rho\omega_{i,t-1} + \varepsilon_{it}$$

To see how to identify the capital coefficient in the second stage, we first define $\tilde{y}_{it} \equiv y_{it} - \beta_L l_{it} - \beta_M m_{it}$. Taking into account that $\omega_{i,t-1} = h_{t-1}(k_{i,t-1}, i_{i,t-1})$, it is clear that $E(\tilde{y}_{it} \mid k_{it}, \omega_{i,t-1}) = E(\tilde{y}_{it} \mid k_{it}, k_{i,t-1}, i_{i,t-1})$, and we can write:

$$\begin{aligned} E(\tilde{y}_{it} \mid k_{it}, k_{i,t-1}, i_{i,t-1}) &= \beta_0 + \beta_K\ k_{it} + \rho\ h_{t-1}(k_{i,t-1}, i_{i,t-1}) \\ &= \beta_0 + \beta_K\ k_{it} + \rho\ \left[\phi_{t-1}(k_{i,t-1}, i_{i,t-1}) - \beta_0 - \beta_K\ k_{i,t-1}\right] \end{aligned}$$

so that,

$$\tilde{y}_{it} = \beta_0^* + \beta_K\ k_{it} + \rho\ \left[\phi_{t-1}(x_{i,t-1}) - \beta_K\ k_{i,t-1}\right] + \varepsilon_{it} + v_{it}$$

This is the equation that we estimate in the second stage, using the predicted values for $\tilde{y}_{it}$ and $\phi_{t-1}(k_{i,t-1}, i_{i,t-1})$ obtained in the first stage, so β_K and ρ can be properly estimated in the second stage. Since we substitute $\tilde{y}_{it}$ and $\phi_{t-1}(k_{i,t-1}, i_{i,t-1})$ by predictions based on the estimates of the technological coefficients of labor and intermediate inputs, and by a non parametric estimation of $\phi_{t-1}(.)$, the standard errors of the estimated coefficients of β_K and ρ must be corrected. Alternatively, appropriate standard errors can be computed by bootstrap methods.

3 Productivity estimates

3.1 The Data

The main data source is the Balance Sheets of the Bank of Spain (CB hereinafter), which contains firm-level annual information on the balance sheets and other complementary information on economic variables, such as employment by contract duration (fixed-term or indefinite), output, intermediate inputs, physical capital and the total wage bill. The sample consists on an unbalanced panel of firms in manufacturing and non-financial services industries, with a public share below 50 percent, from 1983 to 2006. To obtain the final sample, we have eliminated those for which some of the following variables were negative or took implausible values: book value of capital stock, sales, gross output, total labor costs, permanent employment, and temporary employment. Due to the fact that response is completely voluntary, largest firms are over-represented in the sample. The details are presented in Appendix 1.

The data set also provides information about each firm activity, in accordance with the 2-digit NACE classification. The industry code and its share in total firm output, up to four different industry affiliations, is reported. The sample distribution of firms by its main industry is provided in Table A1. In a few number of cases, we have grouped those related industries for which the number of firms available in the sample was too small to provide precise estimates of the technological coefficients.

3.2 Production function estimates

To allow for differences across industries, we estimate a production function for each industry separately. We have used three alternative procedures: OLS, system-GMM (non reported here) and Olley-Pakes, using fixed capital investment as a proxy for firm-specific productivity shock ω_{it}. For our Olley-Pakes estimates, we have approximated the aforementioned function $\phi_t(k_{it}, i_{it}) = \beta_0 + \beta_K k_{it} + h_t(k_{it}, i_{it})$ by means of a third-order polynomial in k_{it} and i_{it}, where the slopes have been assumed to be constant across time, but we have allowed for differences in the constant term across time by means of binary year dummies. Furthermore, we have assumed a linear AR(1) structure for the firm-specific productivity shock.

In Table 1 we report the OLS estimation results of the technological parameters for each industry, whereas the Olley-Pakes estimates are reported in Table 2. In general, we observe that the Olley-Pakes estimates of technological coefficients for labor and intermediate inputs are generally lower than the corresponding OLS estimates, and the opposite occurs for the estimates of the technological coefficient of the capital stock. The same pattern appears when we consider the system-GMM estimator of the technological parameters (non reported here), though the moment conditions which exploits are rejected in the case of several industries.

The evidence reported is coherent with the successful bias correction provided by the control function approach. The magnitude of the estimated technological coefficients and the qualitative results are in accordance with the ones obtained by Javorcik (2004). Nevertheless, the magnitude of the capital coefficients in Table 2 seems to be too low in an important number of industries. In addition, the estimates of ρ, the coefficient of the AR(1) process characterizing the total productivity shock, is, in the case of many sectors, too close to unity. Our estimate for the capital coefficient is in line with a recent work by Van Beveren (2010).

Interestingly, the estimates of the technological parameters for service industries are not much different from those for manufacturing industries. This evidence resembles Mairesse and Kremp (1993), which is one of the few contributions regarding production function estimates for non-financial services industries.

3.3 Descriptive analysis of productivity

Once that we have estimated the technological parameters at the industry level, our measure of TFP is obtained from the residual of the estimation of the technologies of production. In other words, we then recover our estimate of total factor productivity (TFP) by plugging in the estimated technological parameters in the production function,

$$\widehat{\omega}_{it} \equiv \widehat{\ln TFP}_{it} = y_{it} - \widehat{\beta}_L l_{it} + \widehat{\beta}_M m_{it} + \widehat{\beta}_K k_{it},$$

where we have substituted the estimated technological parameters for the industry to which firm i belongs.

In Table 3A and 3B, we have calculated for each industry the annual rates of change of aggregate output growth and aggregate TFP in 5-year periods, using each firm's share in output as weights. In general, we find that output growth exhibits much larger magnitudes, in absolute value, than TFP growth, particularly since 1990. The simple correlation coefficients between output and productivity are negative both at the aggregate level and for most of the 2-digit industries in manufacturing and services.

Looking at aggregate manufacturing and services, we find that productivity is countercyclical, this pattern being much stronger for manufacturing. This evidence is in line with the aggregate analysis done by Núñez and Pérez (2000), who find negative correlations between output and productivity, very specially in the case of manufacturing. Besides, the countercyclical pattern is atenuated after 1990. There are, though, remarkable differences across industries and over time. Textile and Clothing industries exhibit the strongest countercyclical pattern, and with a sharp fall in productivity since 2000. On the other hand, the Chemical industry exhibits a procyclical pattern, which is nevertheless atenuated in the most recent years. Among the manufacturing industries that experience a productivity increase, we must emphasize Chemical, Non metallic materials, and Machinery industries. In the case of services, most industries have experienced a productivity slowdown since 2000. The exceptions are Construction and Real estate.

We have examined the mobility across the productivity distribution of our sample of firms. For this purpose, following Foster, Haltiwanger and Krizan (2006), we have ranked firms into quintiles of the TFP distribution, and compute the transition matrices in a ten-year period. It must be noted that in our data set we cannot separately identify firm exits due to liquidation from firm exits due to non participating in the survey in a given year, and firm entries due to a firm birth from firm entries due to inclusion in survey of a existing firm. The transition matrices from 1985 to 1995 and from 1995 to 2005 for manufacturing and services are reported in Tables 4A and 4B, respectively. In any case, the major patterns resemble those found in Foster, Haltiwanger and Krizan (2006) for the US retail sector.

We observe that entry is the most likely origin, and takes place uniformly for every quintile in the TFP distribution, and exit is the most likely outcome. This pattern is stronger in the case of services firms; particularly, exit has a higher relative importance. However, as mentioned earlier, and unlike Foster et al. (2001) for the US, and Gómez-García, Puente and Gómez (2007) for Spain, we cannot attribute entry and exit to creation and liquidation of firms.

If we concentrate on continuing firms, we find, even after ten years, a substantial persistence in relative TFP ranking. Manufacturing firms in the top quintile have a probability of staying there above 25%, whereas the probability of moving to the two lowest quintiles is below 9%. About a third of manufacturing firms in the lowest quintile stay in it after ten years, and the probability that firms in the lowest quintile will move to the two highest quintiles is below 7%. We observe a similar but stronger pattern for the most productive services firms: those in the top quintile have a 30% probability of staying in the top quintile, and a probability below 7% of moving to the two lowest quintiles. The pattern for continuing services firms with the lowest productivity is qualitatively similar to the corresponding manufacturing firms, but the relative mobility to other quintiles is larger. In general, we find significant frequencies of movements across quintiles, both for manufacturing and services firms. Our results resemble the qualitative findings in Gómez-García et al. (2007). However, we find a lower persistence, both in manufacturing and services. These differences arise from two facts: Gómez-García et al. (2007) used a more representative sample of Spanish companies, and consider a shorter time period when analyzing transitions..

We can conclude that there exist large TFP differences across firms, and movements across the TFP distribution are quite frequent. In the next section, we will go into the role of firm behavior and regulatory aspects on total factor productivity.

4 The determinants of productivity

We now concentrate on the impact firm behavior and market regulations on productivity. The most important restrictions to competition are circumscribed to non-manufacturing industries, which, because of the characteristics of their products, are much less faced to international competition. But the effect of product market regulations in these non-manufacturing industries are not confined to these industries themselves (Conway and Nicoletti, 2006), because all firms in the remaining industries use the output of non-manufacturing industries as intermediate inputs. Indeed, about 80% of the output of the business services sector was used as an intermediate input in the production processes of non-manufacturing industries in the countries for which harmonized input-output data exist. As Conway and Nicoletti (2006) illustrate, under more restrictive regulations in the non-manufacturing sector that supply, among others, manufacturing firms, the price of the supplied intermediate goods will tend to be higher, and their quality will tend to be lower. In turn, this will affect the own development of all industries that use non-manufacturing intermediate goods, in many extents: costs of firm entry, resource allocation between firms, potential productivity improvements, and work and production organization. For this purpose, we use complementary industry-level data on impact indicators of regulation in the services sector industries. Local firms within these industries are suppliers of intermediate inputs of firms in other industries. The OECD indicators of regulation impact (RI), constructed by Conway and Nicoletti (2006) are industry-specific indicators that measure the effects of regulation and competition conditions in non-manufacturing sectors on each industry. The impact indicators weight the effect of restrictive regulations in services sectors with the importance of services sectors as suppliers of intermediate inputs to the industry. The indicators cover information in four main areas: state control, barriers to entry, involvement in business operations, and market structure. The information summarised by the indicators is "objective", as opposed to survey information based on subjective assessments of markets participants, and consists of rules, regulations, and market conditions. The resulting indicators of non-manufacturing regulation comprise energy, transport and communication, retail distribution, and professional services. In order to measure the effective impact of regulation on competition, data on actual market and industry structure is used so as to proxy for the impact of policy enforcement. The indicators are calculated using a bottom-up approach in which the regulatory data are quantified using an appropriate scoring algorithm and then aggregated into summary indicators by sector of activity in each of the four areas or across them. Further details can be found in Conway and Nicoletti (2006).

Regarding firm organization of work and production, we take into account two different aspects: qualitative information related with the outsourcing of services by manufacturing firms, and the composition of the firm workforce. The lack of well-developed non-manufacturing industries may affect the incentives of manufacturing firm to specialize in manufacturing activities, thus gradually outsourcing an increasing proportion of non-manufacturing tasks that had been fully undertaken by the same manufacturing firms in the past. In fact, there is evidence that the deregulation of non-manufacturing industries towards higher competition has increasingly led manufacturing firms (Fixler and Siegel, 1999) to contract out services so as to benefit from smoothening production cycles, specialisation and labor cost savings (Abraham and Taylor, 1996; Siegel and Griliches, 1992). The propensity of the firm to outsource will depend on the price of the external service product, relative to the opportunity cost of in-house production (Heshmati, 2003).

In our data set, we observe the four main activities in which the firm is involved, as well as the share in total sales of each activity. For each manufacturing firm, we can observe whether it is undertaking the in-house production of services activities, which will depend on firm organization and on the degree of deregulation of the services industries that supply services to manufacturing firms. The decision of the firm to undertake or outsource services will depend on the difference between the price of the external service and the opportunity cost of in-house production. And the opportunity cost of in-house production will be very much affected by the price and quality of the external service products. For manufacturing firms, we define the binary variable InHouse, indicating whether the manufacturing firm keeps undertaking services activities or not. Indeed, for our sample of manufacturing firms, the correlation coefficient between our indicator of regulation impact (RI) and the qualitative variable InHouse is positive and significant, but its magnitude is small (0.036), and does not change when we account for firm-specific unobserved heterogeneity (amounting to 0.038).

Work organization is another important aspect that may affect productivity. To control for differences in work organization across firms and over time, we consider the composition of employment. In particular, we exploit the distinction between temporary employees (those with fixed-term contracts) and permanent employees (those with indefinite-duration or permanent contracts), which is particularly relevant for Spain. Currently, temporary employees currently amount to 30% of the total workforce, with a larger share in non-manufacturing. The removal on the restrictions to use temporary contracts in 1984 led to a widespread use of them. Although there have been several partial reforms since 1997, mostly aimed at limiting the widespread use of temporary contracts and favoring the use of permanent contracts, they have proved fairly ineffective, to the extent that the proportion of temporary workers have remained stable around 30% for the total economy (with a slightly lower incidence in manufacturing). The regulatory framework has shaped a strongly dual labor market by which 30% of the working people, those with temporary contracts, bear most of employment rotation, to the extent that all the flexibility of the labor market is provided by them. Aguirregabiria and Alonso-Borrego (2009) find that the introduction of temporary contracts led to an increase in the employment level, but at the expense of a lower productivity per worker. The current regulations of the Spanish labor market seems to fail in providing incentives for firm-specific human capital investment.

In addition, we must control for other sources that may affect productivity, so as to ensure that the potential determinants of productivity are properly isolated. We consider qualitative information on the participation of foreign capital and the public sector in the social capital of the firm. For this purpose, we define the variables Foreign and Public, which are binary variables indicating whether there is at least a 10% share of foreign capital and of the public sector, respectively. We have also qualitative information about whether the firm is quoted in the stock market (Quoted), and whether the firm belongs to a company group (Group). Regarding firm activity, we introduce the ratio of exports (sales abroad) to total firm sales, Exports/Sales, and the qualitative variable Multi, which indicates whether the firm operates in two or more two-digit industries.

Finally, following Nickell (1996), we use the firm market share, MShare, defined as the lagged ratio of firms sales to total sales in the main industry in which the firm operates. We consider the lagged market share in order to avoid reverse causality, by which firms with high TFP growth may achieve higher market shares. As argued by Nickell (1996) and Sutton (1996), although this measure of market share is not expected to provide a reliable competition measure at the cross-section level because of differences among industries, it can provide a proper measure of competition pressure over time.

It must be noted that, given the lack of a theoretical model to justify the set of explanatory variables, our estimates are capturing partial correlations, which cannot be given a causal interpretation. The evidence provided can help to understand what variables are susceptible to affect productivity, but further research is needed to support a causal interpretation of the estimated effects.

In Tables 5A and 5B, we report the estimates of different productivity specifications for manufacturing and services, respectively. In each specification, the model, which establishes the logarithm of TFP as a function of the aforementioned covariates, is transformed in first differences in order to control for firm-specific time-invariant effects. In addition, we have included time dummies in all estimations. All the columns include the regulation indicators (RI) variable as regressor. The inclusion of additional variables, which has variation by industry and over time, does not change either the magnitude or the significance level of this variable, being significant at the 5 percent level. We thus find that productivity of manufacturing firms is hampered by stricter regulation in non-manufacturing sectors. Interestingly, and in relation with this fact, we find that those manufacturing firms which have kept a certain in-house production of services needed to undertake their main activity tend to be more productive that those which have contracted out all relevant services. The coefficient of in-house production of services is positive and statistically different than zero at the 2 percent level. Its estimated value is robust to the inclusion of additional variables, which do not alter the magnitude and significance level.

With regard to the employment composition effects, we find that productivity tends to decrease with the share of temporary employment. The coefficient of this variable is negative, and it is estimated with high precision. This result is consistent with the findings in Dolado and Stucchi (2008) and Aguirregabiria and Alonso-Borrego (2009), and the fact that the firm incentives to invest in firm-specific human capital are lower the higher the share of temporary employment. In addition, the exports to sales ratio has a positive and significant effect, suggesting that a higher exposure to international competition tends to make firms more productive.

Another interesting aspect related with market competition is concerned with the market share variable, which may be interpreted as an inverse measure of the competition conditions in the industry in which the firm operates. The estimated coefficient suggests that a fall in market share would tend to increase productivity, this effect being highly significant. This result resembles the findings by Nickell (1996) and Disney et al (2003). The remaining variables that have been considered were clearly insignificant.

We reproduce the same sort of estimates for the services industries in Table 5B, except for the regulation indicator variable. We find that the regulation indicator (RI), which measure the knock-on effects of other services in each industry, is small and clearly non significant. Also, export activity does not have a significant effect. It must be noted that in the case of non-manufacturing industries, the industry own output contributes in a large extent to the corresponding regulation indicator, so it essentially measures the own industry indicator of anti-competitive regulation.

The variables that exhibit a significant effect on productivity are the share of temporary employment and the market share, both with the expected signs. Interestingly, the magnitudes of the corresponding coefficients are much higher in absolute value for services than for manufacturing firms. We thus observe that the negative effect of temporary employment on productivity is much more important for services firms, which, in addition, tend to use a higher proportion of temporary workers.

5 Conclusions

In this paper, we have analyzed the features of total factor productivity (TFP) using longitudinal data on Spanish firms in manufacturing and non-financial services. In line with the most recent literature, we have addressed the measurement of TFP taking into account the endogeneity of inputs through a control function approach in the estimation of tecnological parameters. Our preferred estimates, which are obtained separately by two-digit industry, seem to correct the endogeneity biases as expected, so that we get a higher capital coefficient. Nevertheless, it apparently keeps being too low for several industries. The descriptive analysis of our firm-level productivity measures shows that the aggregate productivity figures on manufacturing and services, which exhibit a high positive correlation with output growth, mask strong differences among industries. Besides, we also find strong persistence along the ranking of the TFP distribution, even considering a long ten-year period, but with a significant mobility across the quintile of the TFP distribution. Besides, the mobility between quintiles appears to be much frequent in services than in manufacturing firms.

We have exploited our longitudinal measures of TFP to analyze the effects of market regulation, competition conditions, and firm behavior regarding work organization. In the case of manufacturing firms, we have also accounted for the in-house production of services activities, exploiting the information on whether the manufacturing firm is still undertaking services activities.

One important result, in the case of manufacturing firms, is that the regulation indicators of the impact in manufacturing industries of restrictions to competition on non-services industries is strongly negative, and robust to the specification choice. In relation to this, we have considered the qualitative information on whether the manufacturing firm undertakes in-house production of services, which otherwise had been outsourced to external services firms. Manufacturing firms undertaking in-house service production tend to enjoy a better productivity performance. This result suggest that the under-development in the services sector towards more competition may be preventing firms to increase their levels of specialization while outsourcing non-manufacturing activities.

Both for manufacturing and services firms, we have found that the share of temporary employment tends to reduce productivity. Behind this result, it lies the lower incentives of firms to invest in firm-specific human, the higher the proportion of fixed-term employment. The duality of Spanish labor market, by which most employment creation is done through temporary contracts, seems to hamper firms productivity. The negative effect of temporary employment is much higher in the case of services firms, which also resort to a larger extent to temporary employment.

Our measure of lagged market share, as an inverse measure of competition conditions has, as expected, a negative effect on productivity. The result suggests that increases in industry competition boost firms to improve their performance. Interestingly, the effects of our competition measure appear to be much more important for services firms. This result is not surprising. Many national regulations to prevent competition in manufacturing firms have been removed in the years that followed the joining of EEC by in 1986, and the remaining ones are quite ineffective in protecting national firms, given the nature of manufactured goods. On the contrary, the level of regulation in the Spanish services sector is still very high, and the non-tradable nature of the produced goods makes restrictions to international competition very effective.

This paper has provided evidence about productivity, and its relation with firm behavior and regulatory conditions, with firm level data. Use of longitudinal disaggregated data at the firm or, even better, at the establishment level, is essential to understand many features of productivity growth that have consequences at the aggregate level. Nevertheless, a primary problem with our analysis is that the estimates only capture partial correlations, which do not have further interpretation due to the lack of a model that might allow us to interpret the estimated coefficients of the variables susceptible to affect productivity as causal effects. Notwithstanding, much more research is needed to get a more complete understanding of the dynamics of productivity and its determinants.

Many of the potential extensions are constrained by data availability. Specifically, we lack data on occupational or human capital composition of the firm workforce, as well as measures of innovation and IT technologies, to assess their effects on productivity. Besides, our data does not allow to identify firm exits and entries due to births and deaths of firms from the event of starting of ending firm collaboration in the survey. A further line of research that is worth to be addressed is the analysis of the dynamics of productivity. There is scarce evidence, particularly for Spain, for which we can cite Fariñas and Ruano (2004). Specifically, it would be interesting to address the determinants of the movements across the quantiles of the TFP distribution, for which a dynamic discrete choice model could be considered.

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Appendix. Data Description

The CB data set is an unbalanced panel of Spanish of manufacturing and non-financial services companies, with a public share below 50 percent, recorded in the database of the Bank of Spain's Central Balance Sheet Office. This dataset was started in 1982 collecting firm data about balance sheets, employment, and other complementary information. The firms included in the database are of large relative size (and hence oversampling larger firms). However, the tendency in subsequent years has been characterized by the addition of firms of smaller relative size.

We have dropped from the sample those firms with non-positive values for net worth, capital stock, accumulated and accounting depreciation, labor costs, employment, sales, output, or whose book value of capital stock jumped by a factor greater than 3 from one year to the next, were dropped from the sample. Table A1 presents the distribution of firms by size (measured as the time average of firm's employees) and by 2-digit industry.

VARIABLE CONSTRUCTION

Employment. Number of employees is disaggregated by contract type, in permanent employees (those with an indefinite or permanent contract) and temporary employees (those with a fixed-term or temporary contract). To maintain measurement consistency, the number of temporary employees is calculated in annual terms by multiplying the number of temporary employees along the year times the average number of weeks worked by temporary employees and divided by 52.

Output. Gross output at retail prices is calculated as total sales, plus the change in finished product inventories and other income from the production process, minus taxes derived on the production (net of subsidies).

Intermediate inputs. Intermediate inputs output at retail prices are directly reported by firms in the questionaire.

Investment. The CB does not have independent estimates of investment available. Gross nominal investment I_{it} must be imputed from changes in the book value of physical capital with a correction for depreciation, that is, $I_{it} = KNB_{it} - KNB_{i,t-1} + Dep_{it} + Rev_{it}$ where, $KNB_{it} = KGB_{it} - ADep_{it}$ is the book value of the net stock of physical (book value of the gross stock of physical capital KGB_{it} minus accumulated depreciation $ADep_{it}$); Dep_{it} is the accounting depreciation during the year; and Rev_{it} is the net variation in the book value of physical capital and in its accumulated depreciation due to positive and/or negative revaluations.

Physical capital. Physical capital is recorded at book value. However, the CBBE has constructed, for each firm, the market replacement value of capital. Essentially, this variable is constructed as $q_1 K_{i1} = (q_1/q_{1-AA_i}) \times KGB_{it}(1-\delta_i)^{AA_i}$ where q_t is the price deflator of the stock of physical capital at year t; δ_i is the average depreciation rate of the stock of physical capital; and AA_i is the average age of the stock of physical capital, which is approximated by the ratio $ADep_{i1}/Dep_{i1}$ for the first year in which data for the firm are available. Furthermore, the average depreciation rate is computed at the industry level as the ratio of accounting depreciation to average accumulated depreciation. As regards price indices, the corresponding GDP implicit deflator of investment goods is used (Source: INE). The recursive method to compute the replacement value of the stock of physical capital from the second year that data is available is $q_t K_{it} = (q_t/q_{t-1}) \times K_{i,t-1}(1-\delta_i) + I_{it}$,which assumes that investment occurs at the end of the year.

Regulation indicators. We use the OECD Indicators of Regulation Impact. These indicators measure the potential costs of anti-competitive regulation in selected non-manufacturing sectors on sectors of the economy that use the output of non-manufacturing sectors as intermediate inputs in the production process. These indicators have been calculated for 41 ISIC rev3 sectors in 21 OECD countries over the period 1975 to 2006. They are described in detail in:

Conway, P. and G. Nicoletti (2006), "Product Market Regulation in the Non-Manufacturing Sectors of OECD Countries: Measurement and Highlights", OECD Economics Department Working Paper, No 530

Table A1
Distribution of observations by industry

		Total
15	Food and drink	8696
17	Textiles	3030
18	Wearing apparel, dressing and dying of fur	1875
19	Leather and footwear	1334
20	Wood and lumber	1621
21	Pulp and paper	1454
22	Printing and publishing	2444
24	Chemicals	5373
25	Rubber and plastics	2326
26	Non-metallic mineral products	3759
27	Basic metals	1408
28	Fabricated metal products	4075
29	Machinery and equipment	4013
30+31	Manufacture of office and electrical machinery	1892
32+33	Electronic material + Precision, scientific, and optical instruments	1175
34+35	Motor vehicles + Other transport material	2346
36+ 37	Furniture and other manufacturing + Recycling	2703
45	Construction	7325
50	Sale, maintenance, and repair of motor vehicles	3519
51	Wholesale trades	17595
52	Retail trade	3408
55	Hotels and catering	2958
60+61+62	Transport (Inland + Water + Air)	2008
63	Supporting transport services, travel agencies	2014
64	Communications	255
70	Real estate	3142
72	Computer services and related activity	716
74	Professional business services and other business activities	4460

Table 1
Estimates of technological coefficients (OLS)

MANUFACTURING

Industry	$\widehat{\beta}_L$		$\widehat{\beta}_M$		$\widehat{\beta}_K$		N	N_g
15	0.14	(0.01)	0.81	(0.01)	0.06	(0.01)	8655	1023
17	0.26	(0.01)	0.73	(0.01)	0.02	(0.05)	4875	582
19	0.23	(0.03)	0.72	(0.04)	0.05	(0.01)	1043	157
20	0.20	(0.02)	0.78	(0.02)	0.03	(0.01)	1601	185
21	0.27	(0.02)	0.75	(0.02)	0.01	(0.01)	3850	467
24	0.17	(0.01)	0.81	(0.01)	0.03	(0.01)	5313	593
25	0.25	(0.03)	0.75	(0.02)	0.02	(0.01)	2275	274
26	0.23	(0.02)	0.74	(0.02)	0.07	(0.01)	3710	425
27	0.22	(0.01)	0.73	(0.01)	0.04	(0.01)	5355	683
29	0.28	(0.02)	0.72	(0.01)	0.01	(0.003)	3922	448
30	0.27	(0.02)	0.75	(0.01)	0.004	(0.01)	2978	358
34	0.28	(0.04)	0.71	(0.03)	0.02	(0.01)	2284	272
36	0.26	(0.03)	0.73	(0.03)	0.03	(0.01)	2657	314

SERVICES

Industry	$\widehat{\beta}_L$		$\widehat{\beta}_M$		$\widehat{\beta}_K$		N	N_g
45	0.28	(0.02)	0.69	(0.01)	0.03	(0.01)	7160	1063
50	0.36	(0.03)	0.58	(0.03)	0.06	(0.02)	3476	479
51	0.31	(0.01)	0.64	(0.01)	0.04	(0.01)	17100	2302
52	0.37	(0.02)	0.55	(0.02)	0.07	(0.01)	3299	481
55	0.31	(0.02)	0.62	(0.02)	0.09	(0.01)	2916	410
60	0.23	(0.04)	0.68	(0.02)	0.11	(0.03)	1974	282
63	0.32	(0.02)	0.61	(0.01)	0.15	(0.01)	1962	277
70	0.28	(0.03)	0.59	(0.02)	0.10	(0.01)	2909	530
74	0.42	(0.01)	0.59	(0.02)	0.03	(0.01)	4295	692

Standard errors in parentheses.

Table 2
Estimates of technological coefficients (Olley-Pakes)

MANUFACTURING

Industry	$\widehat{\beta}_L$		$\widehat{\beta}_M$		$\widehat{\beta}_K$		$\widehat{\rho}$		N	N_g
15	0.12	(0.01)	0.80	(0.01)	0.08	(0.01)	0.97	(0.05)	7434	1018
17	0.19	(0.03)	0.79	(0.05)	0.02	(0.01)	0.91	(0.03)	3994	574
19	0.15	(0.02)	0.79	(0.02)	0.04	(0.01)	0.86	(0.03)	1043	157
20	0.24	(0.07)	0.71	(0.04)	0.05	(0.01)	0.94	(0.07)	1340	185
21	0.31	(0.03)	0.71	(0.03)	0.02	(0.01)	0.99	(0.12)	3237	464
24	0.20	(0.02)	0.76	(0.02)	0.05	(0.01)	0.92	(0.08)	4614	590
25	0.20	(0.03)	0.74	(0.02)	0.05	(0.01)	0.98	(0.10)	1946	272
26	0.18	(0.03)	0.72	(0.02)	0.12	(0.01)	0.94	(0.08)	3205	425
27	0.28	(0.02)	0.69	(0.02)	0.05	(0.01)	0.97	(0.04)	4496	683
29	0.31	(0.03)	0.71	(0.02)	0.01	(0.00)	0.90	(0.06)	3357	446
30	0.26	(0.03)	0.76	(0.02)	0.002	(0.01)	0.96	(0.21)	2557	357
34	0.39	(0.12)	0.65	(0.05)	−0.01	(0.01)	0.90	(0.09)	1974	272
36	0.18	(0.03)	0.74	(0.02)	0.06	(0.01)	0.99	(0.09)	2228	311

SERVICES

Industry	$\widehat{\beta}_L$		$\widehat{\beta}_M$		$\widehat{\beta}_K$		$\widehat{\rho}$		N	N_g
45	0.24	(0.02)	0.68	(0.02)	0.06	(0.01)	0.99	(0.04)	5767	1052
50	0.36	(0.04)	0.43	(0.02)	0.16	(0.01)	0.96	(0.03)	2796	475
51	0.38	(0.02)	0.53	(0.02)	0.07	(0.01)	0.94	(0.04)	13539	2276
52	0.45	(0.04)	0.37	(0.04)	0.15	(0.01)	0.92	(0.05)	2553	475
55	0.36	(0.04)	0.49	(0.07)	0.12	(0.01)	0.93	(0.07)	2444	408
60	0.19	(0.03)	0.59	(0.03)	0.20	(0.01)	0.98	(0.06)	1628	276
63	0.31	(0.06)	0.57	(0.02)	0.17	(0.01)	0.96	(0.06)	1543	274
70	0.19	(0.05)	0.48	(0.02)	0.14	(0.01)	0.98	(0.05)	2152	519
74	0.34	(0.02)	0.53	(0.03)	0.10	(0.01)	0.96	(0.03)	3368	684

Bootstrap standard errors in parentheses.

Table 3A
Growth in output and TFP for continuing firms (%): Manufacturing

Industry.		1985-1990	1990-1995	1995-2000	2000-2005
All	Output	6.2	3.1	6.1	0.4
	TFP	−1.7	0.4	0.6	0.6
15	Output	8.6	2.6	2.5	−1.7
	TFP	−2.5	0.3	1.7	1.7
17+18	Output	4.8	−1.7	−0.4	13.7
	TFP	−1.2	1.9	1.9	−6.8
19	Output	1.5	−6.6	−4.6	−3.4
	TFP	−4.3	3.6	2.4	−2.3
20	Output	5.4	1.3	10.1	4.3
	TFP	−2.4	0.7	0.5	−0.2
21+22	Output	1.8	−0.6	0.7	3.2
	TFP	−2.4	0.5	2.6	−1.9
24	Output	1.4	2.0	4.9	1.2
	TFP	−0.4	2.4	1.0	1.1
25	Output	1.6	1.7	1.3	5.3
	TFP	−2.8	0.8	3.6	−1.7
26	Output	10.0	0.6	1.5	5.3
	TFP	−1.9	1.2	3.4	−0.3
27+28	Output	2.4	−0.6	14.3	2.1
	TFP	−0.4	3.9	−4.7	0.5
29	Output	9.4	−1.3	4.0	−3.1
	TFP	−1.1	4.3	2.3	2.3
30-33	Output	14.5	6.1	6.9	3.6
	TFP	−2.2	1.8	1.9	−0.1
34+35	Output	8.5	7.2	8.6	−3.0
	TFP	−1.8	−3.3	−0.2	0.9
36+37	Output	10.6	1.9	−1.7	2.3
	TFP	−2.4	1.2	2.6	1.0

Table 3B
Growth in output and TFP for continuing firms (%): Services

Industry.		1985-1990	1990-1995	1995-2000	2000-2005
All	Output	9.7	1.4	3.5	8.0
	TFP	−1.6	−0.6	2.3	−1.3
45	Output	10.8	0.0	0.0	3.8
	TFP	−1.6	1.2	6.9	0.3
50	Output	14.8	0.0	1.9	19.9
	TFP	0.3	−0.2	7.6	−7.4
51	Output	4.4	2.2	−0.7	7.0
	TFP	−2.8	−3.0	−0.3	−0.9
52	Output	13.3	5.4	6.7	9.9
	TFP	−1.8	−2.9	1.6	−2.3
55	Output	5.5	−7.4	8.1	8.2
	TFP	−2.3	−0.7	−1.5	−4.1
60-62	Output	−4.2	16.6	6.9	14.8
	TFP	2.2	−5.8	1.1	−8.2
63	Output	15.7	−3.5	6.8	5.7
	TFP	−3.1	0.8	−4.6	−2.6
70	Output	29.2	3.9	17.9	9.2
	TFP	10.1	−10.4	0.9	4.3
74	Output	11.1	2.3	7.9	8.8
	TFP	−6.1	6.4	−0.9	−3.9

Table 4A
Transitions between TFP quantiles (%): Manufacturing

1985-1995	Q.1 (1995)	Q.2 (1995)	Q.3 (1995)	Q.4 (1995)	Q.5 (1995)	Exits	Row total
Q.1 (1985)	30.5	9.5	7.0	3.5	1.5	48.0	7.4
	13.4	*4.2*	*3.1*	*1.6*	*0.7*	*21.1*	
Q.2 (1985)	23.8	18.4	9.4	4.5	4.5	39.5	8.3
	11.7	*9.1*	*4.7*	*2.2*	*2.3*	*19.3*	
Q.3 (1985)	9.7	19.9	16.8	8.4	4.9	40.3	8.4
	4.9	*10.0*	*8.4*	*4.2*	*2.5*	*20.0*	
Q.4 (1985)	6.8	4.9	14.6	18.1	8.3	47.3	7.6
	3.1	*2.2*	*6.7*	*8.2*	*3.8*	*21.3*	
Q.5 (1985)	1.5	7.1	8.7	13.8	26.0	42.9	7.3
	0.7	*3.1*	*3.8*	*6.0*	*11.5*	*18.4*	
Entrants	18.2	19.4	20.0	21.2	21.3		61.2
	66.3	*71.3*	*73.3*	*77.8*	*79.3*		
Column total	16.8	16.6	16.6	16.6	16.4	16.9	

1995-2005	Q.1 (2005)	Q.2 (2005)	Q.3 (2005)	Q.4 (2005)	Q.5 (2005)	Exits	Row total
Q.1 (1995)	32.9	12.9	7.1	6.3	0.4	40.4	10.9
	22.0	*8.8*	*4.8*	*4.3*	*0.3*	*22.4*	
Q.2 (1995)	12.1	14.5	19.8	11.3	4.0	38.3	10.6
	7.9	*9.6*	*13.0*	*7.5*	*2.7*	*20.7*	
Q.3 (1995)	8.2	19.7	17.6	16.4	5.3	32.8	10.4
	5.2	*12.8*	*11.4*	*10.6*	*3.5*	*17.4*	
Q.4 (1995)	6.3	12.1	15.5	18.8	11.7	35.6	10.2
	3.9	*7.7*	*9.8*	*12.0*	*7.5*	*18.5*	
Q.5 (1995)	2.8	3.2	6.1	17.8	31.2	38.9	10.6
	1.8	*2.1*	*4.0*	*11.7*	*20.7*	*20.9*	
Entrants	20.4	20.0	19.3	18.3	21.9		47.3
	59.2	*59.0*	*56.9*	*54.0*	*65.3*		
Column total	16.3	16.1	16.1	16.1	15.9	19.6	

Notes to Table 4A: Q1 is the lowest TFP quintile, and Q5 is the highest. The top number in each cell row is the % of firms in Q.j that end up in end up in Q.k ten years after.
The botton number in each cell (in italics) is the % of firms in Q.k that came from Q.j ten years earlier.

Table 4B
Transitions between TFP quantiles (%): Services

1985-1995	Q.1 (1995)	Q.2 (1995)	Q.3 (1995)	Q.4 (1995)	Q.5 (1995)	Exits	Row total
Q.1 (1985)	12.2	15.9	9.8	3.7	1.2	57.3	3.5
	2.4	*3.1*	*1.9*	*0.7*	*0.2*	*22.6*	
Q.2 (1985)	9.4	14.1	14.1	15.3	5.9	41.2	3.7
	1.9	*2.8*	*2.9*	*3.1*	*1.2*	*16.8*	
Q.3 (1985)	7.3	3.7	13.4	19.5	6.1	50.0	3.5
	1.4	*0.7*	*2.6*	*3.8*	*1.2*	*19.7*	
Q.4 (1985)	2.4	3.6	6.0	16.7	15.5	56.0	3.6
	0.5	*0.7*	*1.2*	*3.3*	*3.1*	*22.6*	
Q.5 (1985)	4.0	1.3	1.3	13.3	29.3	50.7	3.2
	0.7	*0.2*	*0.2*	*2.4*	*5.3*	*18.3*	
Entrants	20.8	20.5	20.1	19.2	19.5		82.4
	93.2	*92.4*	*91.2*	*86.7*	*89.0*		
Column total	18.4	18.2	18.2	18.2	18.0	9.0	

1995-2005	Q.1 (2005)	Q.2 (2005)	Q.3 (2005)	Q.4 (2005)	Q.5 (2005)	Exits	Row total
Q.1 (1995)	23.2	11.8	6.4	3.9	1.0	53.7	6.5
	8.7	*4.5*	*2.4*	*1.5*	*0.4*	*24.4*	
Q.2 (1995)	13.8	16.6	17.1	6.9	2.8	42.9	6.9
	5.5	*6.7*	*6.9*	*2.8*	*1.1*	*20.8*	
Q.3 (1995)	3.3	13.3	17.1	20.0	7.1	39.1	6.7
	1.3	*5.2*	*6.7*	*7.8*	*2.8*	*18.3*	
Q.4 (1995)	4.1	5.9	19.9	16.3	15.8	38.0	7.1
	1.7	*2.4*	*8.2*	*6.7*	*6.6*	*18.8*	
Q.5 (1995)	3.0	4.0	4.5	13.4	36.1	39.1	6.4
	1.1	*1.5*	*1.7*	*5.0*	*13.7*	*17.7*	
Entrants	21.3	20.6	19.1	19.7	19.3		66.4
	81.7	*79.7*	*74.1*	*76.2*	*75.4*		
Column total	17.3	17.2	17.1	17.2	17.0	14.3	

See Notes to Table 4A.

Table 5A
TFP determinants: Manufacturing firms

RI	−1.3431	−1.3334	−1.3684	−1.3735	−1.6020
	(0.6849)	(0.6849)	(0.6842)	(0.6842)	(0.7109)
InHouse		0.0115		0.0132	0.0152
		(0.0047)		(0.0057)	(0.0060)
Share Temp			−0.0614	−0.0613	−0.0634
			(0.0058)	(0.0058)	(0.0063)
Export/Sales			0.0117	0.0117	0.0137
			(0.0064)	(0.0064)	(0.0068)
Foreign			−0.0005	−0.0005	−0.0019
			(0.0035)	(0.0035)	(0.0037)
Public			−0.0087	−0.0086	−0.0002
			(0.0125)	(0.0125)	(0.0143)
Quoted			−0.0172	−0.0173	−0.0167
			(0.0081)	(0.0081)	(0.0083)
Group			0.0066	0.0069	0.0038
			(0.0267)	(0.0267)	(0.0317)
Multi			0.0030	−0.0021	−0.0046
			(0.0033)	(0.0040)	(0.0042)
MShare					−0.4059
					(0.1618)

Notes to Table 5A: Variables are transformed in first differences.
All regressions include time dummies. Standard errors in parentheses.

Table 5B
TFP determinants: Services firms

RI	−0.0352	−0.0324	0.0082
	(0.1536)	(0.1533)	(0.1618)
Share Temp		−0.1020	−0.0903
		(0.0118)	(0.0130)
Export/Sales		0.0382	0.0207
		(0.0201)	(0.0220)
Foreign		−0.0061	−0.0150
		(0.0103)	(0.0114)
Public		0.0065	0.0028
		(0.0321)	(0.0343)
Quoted		0.0599	0.0382
		(0.0300)	(0.0331)
Group		0.0641	0.0574
		(0.0579)	(0.0654)
Multi		−0.0193	−0.0183
		(0.0068)	(0.0074)
MShare			−0.7068
			(0.2216)

See Notes to Table 5A.

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Unidad de Publicaciones
Alcalá, 522; 28027 Madrid
Telephone +34 91 338 6363. Fax +34 91 338 6488
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