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Long- and short-term efficiency in an automobile factory: An econometric case study☆

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ABSTRACT

This paper models the production technology of an automobile assembly plant as an integrated long and short-term relationship between inputs, labor and capital, and output, number of monthly assembled units. The parameters of the production function, elasticity of output to labor and capital, and the growth rate in total factor productivity (TFP), are estimated using the Error Correction Mechanism (ECR). The paper compares the TFP and the inverse of the hours per vehicle (HPV), the standard measure of productivity used in the industry, as indicators of operating efficiency of a production unit. The empirical application also highlights the potentialities of the ECM in insider and case study econometrics research, especially when the observed output and inputs of a production process deviate from the production technological frontier due to anticipated and unanticipated perturbations in the operations.

1. Introduction

This paper models and econometrically estimates the production technology of an automobile assembly plant in its first years of operation. The production technology involves two functional relationships: one, the *long-term* relationship, is the standard economic production function that gives the maximum output produced per period of time from a given combination of labour and capital services. The second functional relationship, the *short-term*, models the month-by-month changes in production, matched with changes in current and past output and input services, with planned management decisions, and with unplanned stochastic shocks. The two relationships are jointly estimated using the Error Correction Mechanism (ECM) of Engle and Granger (1987), with monthly data on output and inputs in the early years of the plant operation. The paper is an econometric case study (Jones et al., 2006) on the estimation of a production function, including the measurement of the growth rate in total factor productivity (TFP), as an indicator of improvements over time in the efficiency of the assembly operations.[1]

The automobile plant in question belongs to a multinational corporation with long experience in the industry. The results of the kind of research presented in this paper provide plant and company managers with valuable information for production planning and control. First, for budgetary purposes, management will want to know the number of hours and total cost of labour and capital services estimated for the planned capacity of the plant. Second, the initial years of operation of the plant are those when the efficiency gains from learning-by-doing and the like are expected to be higher; ignoring these initial efficiency gains may lead to over-staffing in the years of steady state operation. Third, in the short-term operations of the plant, the management team will want to distinguish the effects of changes in production due to stochastic shocks from those perturbations of the normal functioning of the production process that can be controlled through management actions. They will also want to be sure that deviations from the technological possibilities frontier of the assembly plant that inevitably result from day-to-day perturbations are transitory, and that the production process continues on a convergence path to the frontier. Our paper argues that the ECM

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[1] *Econometric case studies* (Jones et al., 2006, 2011) and *insider econometrics* (Ichniowski and Shaw, 2009) includes research papers that examine at the micro level and with up to date econometric methods, the changes in operating performance (productivity) resulting from innovations in management practices or investments in technology, for example in IT; and examines cross section data from multiple production units to explain why they differ in management practices and if such differences have any effect on their respective performance.

(*footnote continued*)

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is a valid econometric technique to aid management in the planning and control of plant operations.

The automobile industry has been acknowledged as the more innovative of the 20th century (Womack et al., 1990), with innovations in production technology, work organization, and human resources policies that have been later adopted by firms in other industries. Not surprisingly, there is a body of research on the measurement of management innovations and their effects on the productivity of plants and firms, in the automobile and in other industries. In fact, most of the management practices and innovations examined in insider and case study econometrics (team production, TQM, continuous improvement, pay for performance.) were first introduced in the automobile industry (see Hayes and Clark, 1986; Gunasekaran et al., 1994 for early work in the performance of production plants). Productivity, i.e. the ratio between output produced in a period of time and volume of production inputs, has been and continues to be a common measure of performance for researchers in economics, management, and operations, since it has well known implications for the competitiveness of firms and countries (see Syverson, 2011 for a review of productivity research).

Papers on productivity related to ours include research on the production function estimation (Lieberman et al., 1990; Lieberman and Dhawan, 2005), and the measurement of the productivity (the inverse of) of automobile assembly plants as hours per vehicle, HPV (Weyer, 2011).[2] Our work differs in that we model and estimate the economic production function of a plant producing a single car model that remains practically unchanged throughout the period of study. We use monthly observations of inputs and output data, and measure output in physical units. Prior papers on production functions estimation use annual company data from firms that produce several differentiated car models, and output is measured in monetary units. Ichniowski and Shaw (2009) in their methodological paper alert us to the aggregation bias that may result when using firm level data to examine the performance of process and plant operations, as well as the limitations of using monetary units of output in efficiency measurement, when output prices reflect the market power of firms. Moreover, we take advantage of our monthly data to model the production process as two interrelated input–output relationships, one a long-run relationship and the other short-term. Gabaix (2011) shows the errors in estimating parameters of functional relationships using macroeconomic aggregates that hide the heterogeneity and variability of input–output relationships at the firm level. The time series econometric estimation used in our paper gives the estimated parameters of the long-term relationship, controlling for the dynamics in output and input relationships resulting from short-term shocks and perturbations, thus minimizing aggregation bias of the kind pointed out by Gabaix.

The measure of operating efficiency used in this paper is the TFP parameter of the economic production function, which differs from the (inverse) partial-labour productivity measure of HPV, used by industry analysts and managers. Steward (1983) and Ghobadian and Husband (1990) pointed out time ago the relevance of multi-factor productivity measures in operations management. The operating efficiency of a production unit measures the capabilities of transforming inputs into outputs. Productivity, on the other hand, is simply a ratio between output and input quantities. Greater labour productivity (lower HPV) will not necessarily be an indicator of superior operating efficiency if, for example, the unit with greater productivity produces with a more capital-intensive technology than the less productive one. If the production process of a plant is modelled with the economic production function, the measure of operating efficiency is the TFP term of the production function; variations in labour productivity are indicative of variations in TFP if the capital-to-labour ratio remains unchanged, and the technology shows constant returns to scale.

Our paper is also related to research on insider and case-study econometrics. For example, Ichniowski et al. (1997) study the effect of the application of certain human resource practices on the productivity of steel finishing plants; Lazear (2000) investigate the impact on productivity of the introduction of performance-related pay; Hamilton et al. (2003) study team work and productivity, and Jones et al. (2010) produce a time series econometric study on the effects on worker productivity of a wide range of changes in compensation. Our paper is novel in that it models the production process in two interrelated functional relationships, one that captures the production technology embedded in the plant, and the other that accounts for the day-to-day operating conditions that cause deviations from the technological frontier. As part of this short-term relationship, we include interventions at different moments in time, such as a change in the number of production shifts, the schedule of vacation times, and a labor strike that – although these are not properly the managerial innovations examined by insider and case-study econometrics – from an econometric point of view, they are treated as if they were. Thus, ECM econometrics could also be a useful econometric tool in studies that deal with managerial innovations.

In this paper, we estimate the long- and short-run relationships with a one-step ECM (Stock, 1987) applied to time series data generated by the assembly plant. The estimation mechanism corrects for spurious correlations that may appear when the economic variables in levels follow a common time trend (as often happens with inputs and outputs of a production process). It also corrects for omitted variable biases that can occur when the estimation of the long-term relationship (economic production function) ignores the correlation between inputs and outputs caused by short-term perturbations in the production process. The estimation will indicate whether the production process converges to the long-term relationship or not. If convergence is not rejected, then the estimation provides consistent and efficient estimates of the parameters of the production function (output-to-input elasticity and the growth rate in TFP). At the same time, from the short-term estimation, we obtain the deviations from the long-term output growth rate caused by the perturbations of the production process.

The remainder of the paper is organised as follows: Section 2 offers a description of the automobile assembly plant and the data collected for the research study. In Section 3, we formulate the theoretical and econometric models of the production technology. Section 4 presents the results of our econometric estimation of the parameters that summarize the production technology. In Section 5, we compare the results of our research with other published papers on the automobile industry. Section 6 presents our conclusions and summarizes our main findings.

2. Description of the assembly plant operations, data collection, and data values

The construction of the automobile assembly plant began in 1978 and was completed in 1982. This was the first plant the multinational parent company installed in Spain, and today it continues in full operation. At that time, many of the world's leading automobile manufacturers had assembly facilities in Spain (Fiat-Seat and Fasa-Renault since the 1950s, Citroen, Chrysler, and

[2] Other related papers not specific to the automobile industry are Brynjolfsson and Hitt (2003), Liu and Wang (2008), Lee and Johnson (2011), Autant-Bernard et al. (2011), Kerstens and Managi (2012), Wacker et al. (2006).

Audi since the 1960s, Ford since the early 1970s); after the installation of our plant near Zaragoza, Volkswagen opened an assembly plant near Pamplona (Navarra). The factory in Zaragoza was designed to assemble a small compact utility automobile.

Production began with a single shift, and with many workers who had little or no experience in building automobiles—in fact, they had very little experience in manufacturing tasks in general. The parent company hired 5133 workers (almost 1% of the population within a radius of 20 km) although, in anticipation of future personnel needs, 7000 individuals benefited from initial training programs. The very limited experience in the automobile industry of the workers hired from the local communities necessitated fleshing out the work force with assembly-line workers and technicians from other assembly plants of the parent company, largely from other parts of Europe. The foreign employees were gradually replaced as more skilled labour became available locally. From the outset, a significant part of the plant's output was earmarked for export to final markets demanding quality and reliability.

By the middle of 1984, two years after operations had begun, the production process was entering the phase of steady output. The plant employed a total of 8906 workers; most of the skilled workers and technicians from other plants had returned to their home plant, and the employees from the local community continued to receive intensive training programs. In 1984, the plant built 259,991 cars, very close to the number that was initially planned. In these early years of operation, the plant reported operating losses, due to the large fixed costs, and to the fact that the number of assembled cars was much lower than the plant's full capacity.

The data series used in our study begins in the second semester of 1984, when the high volatility in production observed in the first months of operation had been substantially reduced, and the labour force was stabilized with employees who would continue to assemble cars in subsequent years. The data set includes monthly values of units assembled, the number of employees, the stock of capital invested in the assets of the plant, and a record of the main operating decisions taken by management in negotiation with the trade unions. The whole data set extends for 91 months, ending by December 1992 (seven-and-a-half year period), just before the time when the plant was preparing for assembling a new car model. During the period of study there were no major changes in the design of the car model assembled, neither there were substantial changes in the plant layout and basic machinery, and the plant was under the direction of the same management team. Therefore it is realistic to assume that the underlying production technology remained homogeneous along the whole period of estimation.

2.1. Measurement of the variables

The data for this study was obtained from the company files in the years 1994 to 1997, while one of the authors was an intern at the plant. Since the time elapsed from the months when the original data was generated was still relatively short, there were many in the plant who could respond to questions of clarification, as needed. The support from the staff of the plant in the data collection assured the quality of the data available for the study, and also that no important event that could distort the input–output relationships was omitted.

The plant output was recorded in the files as units of "standard cars" assembled during each of the 91 months included in the data set. The output measure was in physical units, which has clear advantages over output measured in monetary units (for example, value added in the production process) when estimating the production function. The production function is theoretically defined in physical units of output produced per unit of time, while the monetary value of the output produced includes quantity produced and price. Removing the price effects to obtain proxy values of the physical units produced is not a simple matter, since company prices often are not observable by the researcher. Although the car model assembled in the plant was practically the same during the 91-month period, if there were any change that justified so the number of cars assembled per time period was adjusted by a standardization factor in order to assure comparability among units of cars assembled each month of the study period. We are then quite confident that the output was measured in number of standard cars assembled each month, for the whole time period.

The inputs of the production function include labour and capital services. The labour services are measures by the number of full-time equivalent employees working in the plant during each month (assuming 8 h working per day). During the recorded years, the employee training programs were much less intensive and comprehensive than they had been in the first two years of production; employee turnover was practically nil, mainly because the salary and working conditions the plant offered to its employees were much better than other employment alternatives in the area. Differences in the quantity of services from the labour input from one month to another could then be attributed to differences in the quantity of the input, not the quality.

Capital input services were estimated from the balance sheet reporting the fixed assets from previous investments in the plant, net of depreciation allowances and net of assets retired from operation. The nominal or current prices at which the assets were valued in the balance sheet were transformed into monetary units at constant prices of the year 1983, using for this purpose the price index for capital goods elaborated by the Spanish Statistical Office (INE). The price index of capital goods will change over time, according to changes in the production costs of the asset, and also according to possible changes in quality (incorporated technical progress). Thus, the stock of capital assets at replacement cost, used as a measure of capital input services in the production process, is expected to be close to the capital services of homogeneous quality.

Table 1 shows a sample of the data set of inputs and output available for the estimation of the production function. For each semester of the years covered by the study, from September 1984 to March 1992, the table shows the monthly average for the six-month values of the respective variable. The data shows

Table 1
Six-month averages of the monthly quantities of *Labour* (equivalent number of full-time workers), *Capital* (stock of fixed assets at the end of the previous month in constant euros) and *Output* (number of standard cars assembled) for the automobile assembly plant.
Source: Data collected from the company files.

Year	First/second semester	Labour	Capital	Output
1984	2nd Half	8367	107,788	21,878
1985	1st Half	8295	126,818	23,856
1985	2nd Half	8238	129,009	22,313
1986	1st Half	8160	130,400	26,898
1986	2nd Half	8065	130,845	24,373
1987	1st Half	8112	131,156	23,859
1987	2nd Half	8259	131,922	25,742
1988	1st Half	8999	132,800	32,264
1988	2nd Half	9125	133,698	27,938
1989	1st Half	9106	134,286	34,444
1989	2nd Half	9242	135,933	28,685
1990	1st Half	9357	135,742	34,893
1990	2nd Half	9424	125,820	28,895
1991	1st Half	9357	128,272	34,891
1991	2nd Half	9300	132,360	30,852
1992	1st Half	9257	142,494	34,272

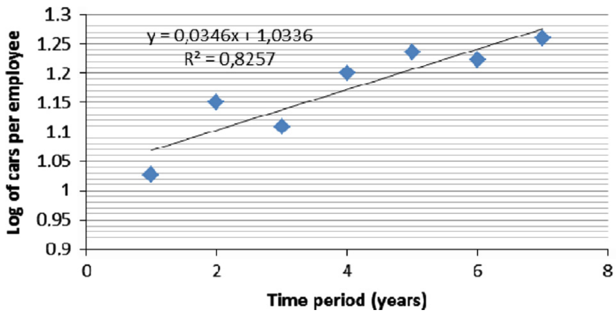

Fig. 1. Growth rate in number of cars per employee (year data).

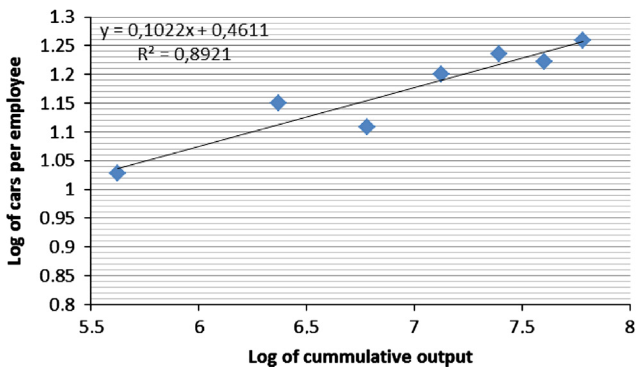

Fig. 2. Relationship between cumulative output and labour productivity (year data, both variables in logs).

volatility within the same semester, not shown in the table, but also from one semester to the next. As we will see, part of this volatility has to do with management decisions such as changes in the number of production shifts, and other reasons beyond our control. The plant was planned for an assembly capacity, with three shifts, of over 400,000 cars per year. This is more than double the plant capacity of the standard plant of US manufacturers and closer to the standard capacity of Japanese manufacturers (Lieberman et al., 1990).

Labour productivity is an important variable for managers and automobile industry analysts (Weyer, 2011). According to the data collected for this study, the apparent labour productivity, number of cars per employee and year, increases over time: in 1984 the plant assembled on average 31 cars per employee; in 1990 the average number of cars per employee rose to 41 cars, approximately 40 HPV, a 33% increase. Fig. 1 shows the representation of time trend in number of cars per employee (in year values, to remove seasonal effects). The estimated coefficient of the time variable, which is the year average estimate of labour productivity growth, is almost 3.5%. Fig. 2 complements this information, but now the relationship is between the log of cumulative output and the log of labour productivity.[3] The estimated coefficient of the log of cumulative output (x variable) is 0.10. This value implies that as cumulative production doubles, labour productivity increases by 7.2%. The fit of the econometric model to the data is similar in both figures. The productivity of capital experiences a jump from the first semester of 1989, coinciding with a period of lower capital per employee compared to the ratio in the first three years of observation.

For comparative purposes, data from other Spanish automobile assembly plants in the same years indicates that the Spanish company Seat produced 11 cars per employee in 1980, while all plants installed in Spain showed an apparent labour productivity on average between 25 and 30 cars per employee (Pradas Poveda, 2000). The plant productivity in our study was above the industry average in apparent labour productivity, among other reasons because it was built with up to date production technology and organization. The comparison of productivity with that in assembly plants of other manufactures does not account for differences in technology and organization.

The second set of data collected for estimating the production technology includes the observed perturbations in the normal functioning of the plant that are expected to (transitorily) affect the relationship between inputs and outputs. Such perturbations include: the change from two 12-h shifts in the operation of the plant, to three shifts of 8 h each; the months in the year when the majority of the workers of the plant take vacation time, in many cases coinciding with time periods when maintenance programs were scheduled; the days the plant stopped production because workers went on strike.

The change from two to three shifts is expected to have an ambiguous effect on operating efficiency. On the one hand, shorter shifts are expected to have a positive effect on the operating efficiency of the plant because workers can work more intensively during an 8-h working period than during 12 h. On the other hand, running three shifts requires two periods of turnaround on the production line, while with two shifts there is only one turnaround—presumably, each time the workers in the line were replaced by the workers of the entering shift, some production time was lost.

Consulting the company files reveals that, at certain months every year, the plant reduced its assembly operations to perform maintenance and other fine-tuning activities. These activities were scheduled to coincide with the vacation periods established by labour laws and collective bargaining. During our period of analysis, the months and years when the plant reduced operations for these purposes include: April 86, August 87, August 88, March 90, December 90, March 91 and August 91.The number of days the plant stopped operations and/or substantially reduced assembly activity varied from one month to the next, so in our empirical analysis we allow for differences in the estimated effects of these events on the production process, and on the output of the plant.

Finally, disagreements between management the unions (on working conditions and salaries) led to a strike that lasted three months, from April to June 1987.

3. Theoretical and econometric models

This section presents the theoretical and econometric models proposed to describe the production technology embedded in the new assembly plant. The general assumption underlying our proposed models is that the inputs and the outputs of the plant for every period of time, a month in our case, maintain a short-term and a long-term relationship. The only underlying restriction linking the two models is that the short-term relationship belongs to the domain of the long-term technological possibilities determined by the production function. This means that, if all short-term perturbations were removed under the new situation, the plant would always operate at one point of the long-term relationship.

The long-term relationship provides a theoretical benchmark for the maximum level of production for the state of knowledge at a given moment of time, and for given input quantities used in production. However, in practice, regular production does not take place under the smooth conditions proposed by the production

[3] Levitt et al. (2011) examine “learning by doing” in a production plant in a setting similar to that of this paper, although they do not estimate the parameters of the production function. See also Adler and Clark (1991) and Argote and Epple (1990).

function, but rather within fluctuations in inputs and outputs resulting from stochastic shocks and constraints, from decisions imposed by labour regulations, and from managerial decisions, agreed or not with the employees, about the number of production shifts, vacation periods, hiring practices, and so on.

The inputs and output variables that enter the production function may show a time trend that must be accounted for in the estimation of the technology parameters, to ensure that the estimated econometric model gives the true parameters of an underlying technology and not just a spurious association among variables that move in the same direction over time. More specifically, in order for the econometric formulation of the production function to make economic sense, the associated variables must be integrated in the first order. Moreover, in addition to a common time trend, the input and output variables that enter the production function may share stochastic shocks, and simultaneous movements by temporary changes in the production process caused by certain management interventions—for example, the decision to change from two to three production shifts. If these shocks and perturbations are not explicitly modelled as part of the econometric formulation of the production function, then the estimated coefficients of the long-term technology may be biased due to the effects of omitted variables.

The short-term relationship between changes in output and changes in inputs, together with any stochastic or management-related perturbation is "functionally free". With this hypothesis in mind, the function to be estimated is formulated as a pure empirical relationship with no explicit economic theory supporting the econometric representation. The "true" underlying economic relationship between the dependent and the explanatory variables will be selected by pure statistical criteria, of statistical significance and goodness of fit. Although the estimated parameters of the short-term production process cannot be related to the parameters of the long-term production function (since the two functional relationships model two different processes), some of the estimated parameters of the function-free model can be informative for the management of the firm—for example, the output loss during a strike, and therefore the consistent estimation methodology is also a goal in the short-term model estimation.

Since the long-term and the short-term formulations of the underlying production technology of the plant model two different processes, they could be estimated separately, assuring that the variables and error terms satisfy the statistical properties required to obtain efficient and consistent estimation of the parameters. If there is any restriction on the short-term functional relationship between inputs and output imposed by the long-term production function, it could be added as part of the short-term model once the long-term has been estimated. The original ECM for time series econometrics proposed by Engle and Granger (1987) operated as a two-step estimation process where the residuals from the long-term relationship were included as additional explanatory variables of the short-term relationship, to ensure that, even though the two processes are different, the latter does not fall out of the time path set by the former.

Stock (1987) transformed the original two-step ECM into a one-step estimation in which the parameters of the long-term economically meaningful functional relationship among the variables, and the parameters of the function-free short-term econometric formulation of the process are estimated simultaneously. The estimation of the car assembly plant technology we perform in this paper will use the one-step method. The method has the advantage in that the estimation of the long-term production function controls for variables that are part of the short-term model, that would be omitted in the first phase estimation of the two-step method. If these omitted variables (for example, those that capture management decisions) were correlated with the input quantities, then the estimation of the technology parameters would be biased. We now describe the actual functional forms proposed for econometric estimation.

3.1. The long-term production function

The steady state production function that models the production technology embedded in the assembly plant is formulated as a Cobb–Douglas type of economic production function, of the form

$$Q_t = A_0 e^{\theta t} K_t^{\alpha} L_t^{\beta} e^{\varepsilon_t} \tag{1}$$

where, Q_t is the output capacity of the plant in period t (one month in our particular application). Production capacity varies with the units of capital services in month t, K_t, and with the units of labour services supplied by the employees, also in month t, L_t. The parameters α and β are positive and less than one to satisfy the standard properties of the economic production function (i.e. positive marginal input productivity, but decreasing with the level of input used). A_0 is a parameter of the production function that measures the total factor productivity (TFP) of the underlying technology in month $t=0$, when we begin the modelling exercise. Eq. (1) allows for a constant growth rate in the TFP over time equal to θ per month. The variable ε_t accounts for possible omitted variables assumed to be independent of the other variables on the right-hand side of (1). The parameters that summarize the production technology are the initial TFP, A_0, the TFP constant productivity growth rate, θ, and the capital and labour elasticity parameters α and β, respectively. From the values of these parameters, it is possible to know if the production function has constant ($\alpha+\beta=1$), decreasing ($\alpha+\beta<1$) or increasing ($\alpha+\beta>1$) returns to scale.

The parameters of the production function provide management with valuable information for estimating the production capacity, and for the control of operations. In this respect, the term $\theta(t_2-t_1)$ gives the increase in plant capacity beyond that resulting from changes in the input quantities from time period t_1 to time period t_2. This change in capacity in the form of TFP growth will be especially important in new plants, due, for example, to learning by experience results. The elasticity parameters α and β give the labour and capital input cost shares, respectively, if the inputs and resulting output combination is chosen in a cost-minimizing way, for given input prices. Thus, comparing the actual with the estimated input cost allows plant managers to determine if the plant has operated with a cost-minimizing input mix, or not. Of course, for these assessments to have any value for managers, the estimated parameters must be unbiased estimates of the true technology parameters.

Equation (1) is transformed with output and input variables in logs,

$$q_t = a + \theta t + \alpha k_t + \beta l_t + \varepsilon_t \tag{2}$$

or in terms of labour productivity,

$$q_t - l_t = a + \theta t + \alpha(k_t - l_t) + (\alpha+\beta-1) l_t$$

This modified version of (2) verifies that changes in output per employee depend on TFP growth, on changes in the capital-to-labour ratio, and on the number of employees (except if returns to scale are constant), thus making clear the limitations of using labour productivity to measure operating efficiency (TFP).

3.2. The integrated long-term and short-term econometric model

The function-free short-term model of the production process is formulated as follows:

$$\Delta q_t = b + \sum_{i=1}^{12} \varphi_{i+1} \Delta q_{t-i} + \sum_{i=0}^{12} \varphi_{i+14} \Delta k_{t-i} + \sum_{i=0}^{12} \varphi_{i+27} \Delta l_{t-i} + \sum_{i=1}^{3} \xi_i DH_{it} + \sum_{i=1}^{7} \xi_{i+3} DV_{it} + \xi_{11} DT_{it} + U_t \tag{3}$$

Lower-Δ is the differences operator; Δq_t, for example, means the difference between q_t and q_{t-1}. Since q is the log of the output produced, then Δq_t is the rate of growth, positive or negative, of the output produced in month t compared with output in $t-1$. The first three sets of explanatory variables include the 12 lags of the dependent variable and the 12 lags of the growth rates in capital and labour, all weighted by the respective parameters, φ_{i+T}. The 12-month lag in the changes in output and inputs variables assumes that current rates of change in output and inputs can have effects on the rate of grow of output up to 12 months later. Whether these effects last for 12 months, or they disappear sooner, is an empirical issue that will be determined by the results of the empirical estimation; this is why we say that the short-term functional model is function-free.

The parameter b is the steady-state output growth rate if all the explanatory variables in model (3) are set equal to zero.

The explanatory variables DH, DV and DT account for the effects in the rate of change in output growth rates, resulting from the ex ante perturbations of the production process that were identified by the researcher: number of shifts, vacation periods, and strikes. As indicated, information on these variables was obtained from the company files and corroborated by consultations with the management team. The variables DH_i account for the three months the plant was on strike, $i=1,2,3$. Since the dependent variable is defined in terms of the monthly output growth rate, the dummy variable that is initially defined as taking the value of 1 in the month of the strike, and 0 otherwise, enters model (3) as a differentiated variable so it takes the value of 0 in the months prior to the strike, the value of 1 in the month when the plant is on strike, the value of -1 in the following month, and the value of 0 again for the remaining months. In the initial formulation of the model, we allow for the possibility that the effects of strikes in output growth rates are different for each of these three months.

The variable DV_i accounts for differences in the working days across months due to vacation periods. There are seven vacation periods (months) during the 91 months of observation, so sub-index i takes values from 1 to 7. The variable DV_{it} is also the difference of the original dummy variable in levels that would take the value of 1 for each of the seven months, and 0 otherwise. Therefore, DV_{it} is introduced in (3) in differences and takes the value of 0 in the months prior to the vacation period, the value of 1 in the month of vacation, the value of -1 in the month following the vacation, and the value of 0 for the remaining months. Finally, DT_t takes into account that the plant was initially operating with two shifts and changed to three shifts afterwards. Thus, following the same criteria as above, the dummy variable DT_t takes the value of 1 in the month when the plant changes from two to three production shifts, the value of -1 in the following month, and the value of 0 in the remaining months.[4] Finally, U_t is the error term, which is assumed white noise.

The parameters ξ_{i+J} will be empirically estimated. Since the dummy variable enters Eq. (3) in differences, then the estimated parameters give the change in the level of output resulting from the respective perturbation in the production process.

The link between the long-term and the short-term production process is through the constant b in Eq. (3), i.e. the constant output growth rate when all perturbations are set equal to 0. The two-step ECM assumes that parameter b is a function of the residual of Eq. (2), the difference between observed and predicted output according to the long-term production function. Eq. (2) is reformulated, substituting constant b by this residual, weighted by a coefficient to be estimated together with the other parameters of the model. The one-step ECM estimation replaces the residual by the actual difference between predicted and observed output for any value of the parameters of the production function (2).[5] Then the production function parameters are jointly estimated with the remaining parameters of model (3).

The complete formulation of the one-step econometric model for the estimation of the production technology is then written as follows:

$$\begin{aligned}\Delta q_t = {} & \varphi_0+\varphi_1(q_{t-1}-a-\theta(t-1)-\alpha k_{t-1}-\beta l_{t-1}) \\ & +\sum_{i=1}^{12}\varphi_{i+1}\Delta q_{t-i}+\sum_{i=0}^{12}\varphi_{i+14}\Delta k_{t-i}+\sum_{i=0}^{12}\varphi_{i+27}\Delta l_{t-i} \\ & +\sum_{i=1}^{3}\xi_i DH_{it}+\sum_{i=1}^{7}\xi_{i+3}DV_{it}+\xi_{11}DT_{it}+U_t \end{aligned} \tag{4}$$

where φ_0 and φ_1 are new parameters to be estimated. If φ_1 is found to be equal to 0 it would imply that the production process is fully represented by the short-term function-free model of Eq. (3), with $\varphi_0=b$, the intercept. For $\varphi_1=-1$ then Eq. (4) converges to Eq. (2) with ε_t modelled by the lagged output and input shocks, and the terms that capture the management interventions. For a value of φ_1 between -1 and 0, i.e. $-1<\varphi_1<0$, then Eq. (4) can be written as:

$$\begin{aligned} q_t = {} & \varphi_0+(1-\varphi_1)q_{t-1}+\varphi_1(-a-\theta(t-1)-ak_{t-1}-\beta l_{t-1}) \\ & +\sum_{t=0}^{12}\varphi_{i+1}\Delta q_{t-1}+\sum_{t=0}^{12}\varphi_{i+14}\Delta k_{t-1}+\sum_{t=0}^{12}\varphi_{i+27}\Delta l_{t-1} \\ & +\sum_{t=1}^{3}\xi_i DH_{it}+\sum_{t=1}^{7}\xi_{i+3}DV_{it}+\xi_{11}DT_t+U_t \end{aligned}$$

The production process is generally described as a partial adjustment process where $-1<\varphi_1<0$ is a necessary condition for the process, converging to the long-term production technology; the estimated value of φ_1 will give an estimate of the speed of convergence. From an econometric stand point, if the condition $-1<\varphi_1<0$ is satisfied, then the variables of the production function will be co-integrated as first order.

4. Results of the econometric estimation of model (4)

4.1. Statistical properties of the time series data

Prior to the estimation of (4), we examine the statistical properties of the explanatory variables, mainly output and input levels. The visual examination of the evolution of each variable over time indicates that input – and especially output – levels are affected by seasonality; this seasonality is expected since, for example, the working days differ across months and the differences are very similar across years. Although seasonality in time-series models allows for different solutions, in this case we opted to filter the original values of the inputs and output variables in logarithms.[6] The smoothed values for the variables differ from the non-smoothed values, especially in the variable for the number of cars assembled in a particular month, indicating that this is the most seasonal variable of all. The visual observation of the filtered data confirms the fall in output in April, May, and June 1987, coinciding with the months the plant endured a prolonged strike.

The next step is to examine the order of integration of each of the filtered values of the variables of the model. The visual observation of the time evolution of the variables inputs and

[4] In the empirical analysis, we test whether the perturbation in the level of output due to the change from two to three shifts lasted only one month or lasted longer.

[5] In the two-step ECM, the long-term relationship is estimated first and the error term of the estimated model is included as explanatory variable in the short-term model.

[6] The seasonal adjustment method used was the X11.

output in levels shows that the variables are increasing over time, suggesting a time trend. The Augmented Dickey Fuller (ADF) tests (Dickey and Fuller, 1981) do not reject the null hypotheses of unit roots for the variables number of cars assembled, q_t, labor, l_t, and capital, k_t, input services (p values of the asymptotic ADF statistics of 0.371, 0.835, and 0.702, respectively). As expected, the first differences of these variables, Δq_t, Δl_t, Δk_t, are integrated in order zero (p values for the asymptotic ADF statistics for the unit roots test close to zero).

Finally, we test that the proposed long-term relationship between inputs and output values, Eq. (2), is a proper production function. A necessary condition for causality from the level of inputs to the level of output is that the three variables, output, labour, and capital are co-integrated. The co-integration condition requires that the residual from the co-integrated relationship among the variables be integrated in order zero. Following the Granger theorem (Engle and Granger, 1987), our test rejects the null hypothesis that the residuals are integrated in first order of one or more with asymptotic p-value of 0.04. The Johansen (1988) test rejects the hypothesis of absence of a co-integrated relationship among the variables (p-value of 0.007), and does not reject the existence of a single co-integration value (p-value of 0.093). Granger's estimated parameters of the co-integrated relationship between output and inputs are (p values of the pseudo t-Student statistic in brackets): $\theta=0.004$ ($p<0.01$), $\alpha=0.33$ ($p<0.05$), $\beta=0.68(p<0.01)$ for TFP growth rate, and output to capital and labour statistics, respectively. The co-integrated functional relation gives an estimate of the parameters of the production function as a long-term relationship, ignoring the short-term relationships among the variables. The null hypothesis of constant returns to scale in labour and capital inputs, $\alpha+\beta=1$ is not rejected by the data ($p<0.83$).

4.2. ECM estimation and results

The estimation of Eq. (4) is performed using nonlinear estimation methods. The results are shown in Table 2. The first block at the top of the table shows the estimated parameters of the long-term production function, the input to output elasticity of capital and labour, and the trend in TFP growth, each with the respective value of the t-statistic (statistical significance). The second and third blocks of estimated parameters correspond to the parameters of the short-term model: those of the speed of convergence, and coefficients of the lagged output and input growth rates, in the first block; and those of the dummy variables on anticipated perturbations of the production process in the second block. We report only those estimated coefficients for the explanatory variables that are statistically significant ($p<0.05$); thus, from the observation of Table 2, we can identify the lag structure of output and inputs shocks that drive the production process in each year of operation.

The estimated coefficients reported for the dummy variables that model the anticipated perturbations of the production process are those selected after alternative specifications of the econometric model. In particular, we test whether the effects of changing from two to three shifts lasted for one or for several months., whether the effects of vacation times were the same in all months or differed from month to month; and whether the loss in output from the labour strike was the same, or different, in each of the three months. The selected specification, shown in Table 2, indicates that the change from two to three shifts reduced the number of cars assembled only in the month when the change took place; after that, controlling for differences in input quantities and other control variables, the level of output was not affected by the number of production shifts. The reported estimation also indicates that the effect of the labour strike on the level of output

Table 2
Results of the estimation of Eq. (4).

Model ECM		
Variable	**Estim. Coeff.**	***t*-Ratio**
Capital (α)	0.393	15.90
Labour (β)	0.607	24.54
Technical progress (θ)	0.0045	4.17
Error correction term (φ_1)	−0.175	−2.48
Δq_{t-2}	0.159	3.18
Δq_{t-9}	0.185	3.38
Δk_{t-3}	1.044	2.67
Δk_{t-8}	0.521	2.30
Δl_{t-1}	0.777	2.73
Δl_{t-5}	0.857	2.99
Δl_{t-9}	−0.757	−2.20
DT_t	−0.064	−2.00
DH_{1t}	−0.263	−5.13
DH_{2t}	−0.329	−6.77
DH_{3t}	−0.162	−4.32
DV_{1t}	0.072	2.38
DV_{2t}	0.147	4.77
DV_{3t}	−0.207	−6.61
DV_{4t}	0.080	2.64
DV_{5t}	−0.136	−4.47
DV_{6t}	−0.184	−5.99
DV_{7t}	0.266	8.36

Estimated by MNL
$R_c^2=0.845689$
Observations 91

was different in each of the three months of the strike. Finally, the estimation also rejected the null hypothesis that the effects of vacation periods in changes in output produced were the same in all seven of the vacation periods.

The R^2 of the estimation gives a value of 85%, indicating a reasonably high goodness of fit to the data. We have performed standard econometric tests of the residuals of Eq. (4) to make sure that the null hypothesis of white noise is not rejected: the test of no systematic component remaining in the error term; the Lagrange multiplier test of Breusch (1978) on the absence of autocorrelations in the residuals; the tests of homoskedasticity of residuals (Engle's, 1982 ARCH test); and the normality of residuals (Jarque-Bera, 1987 test). In no cases were the null hypotheses for absence of correlation, homoskedasticity, and normality rejected ($p>0.05$).

The estimated values for the elasticity of output to capital and labour input services are $\alpha=0.39$and $\beta=0.61$, respectively. The two parameters are estimated imposing the condition of constant returns to scale on the long-term production function that came out of the estimated co-integrated production function reported above. The estimated value of parameter θ, which measures the average rate of growth in TFP in the time period, is positive and statistically significant with a value of 0.0045. That is to say, the total productivity of the factors increases at an average monthly rate of 0.45% (5.5% annual cumulative growth rate). This growth rate is two percentage points higher than that estimated in Fig. 1 for labour productivity; estimated TFP growth is higher than labour productivity growth because the latter was estimated ignoring the changes in capital per employee over time.

The estimated value of the parameter that measures the speed of convergence to long- term values of the production function of deviations caused by short-term shocks and perturbations of the production process, is statistically significant with a value of $\varphi_1=-0.17$. The negative and between 0 and -1 estimated value of φ_1 confirms that the condition of long-term convergence of the production process is satisfied. Additionally, from a statistical point of view, the result confirms that the output and inputs variables are co-integrated, confirming the results from the one-step estimation. The estimated value of -0.17 implies that the time to convergence to the long-term production function of deviations due to short-term shocks and perturbations lasts approximately 6 months ($1/0.17=5.9$).We are unaware of industry standards to compare and respond to the question of whether the adjustment period is considered short, long or normal. From a managerial point of view, if the speed of adjustment increases then the system is operating closer to the production frontier more periods of time.

The estimated coefficients of the lagged output and inputs growth rates indicate that current output growth can be affected by past changes in output and input growth rates that go back to 9 months earlier. All estimated significantly different from zero coefficients are positive, except the lagged change in labour input in month -9. In explaining this result, management informed us that the plant employed two kinds of employees, fixed and temporary; temporary employees provide flexibility in adjusting the labour force to changes in production needs over time, something impossible with a fully permanent workforce, given the rigid labour market regulations in Spain at that time. The same labour market legislation established that, if temporary employees were on the payroll longer than 9 months, they would automatically become permanent; to avoid this, the company rolled-over temporary employees every nine months. The estimated model indicates that the turnover of temporary employees had a negative impact on the output flow of the assembly plant. The plant management did not have clear explanations for the rest of the terms of the lagged shocks.

Finally, the estimated parameters of the variables that control for perturbations of the production process, identified ex ante by the researcher, confirm that the change from two to three shifts caused an output loss of 6.4% concentrated in the month when the change was implemented; after a month, the level of production for the given inputs was the same as when the plant operated with two shifts. The output loss caused by the strike reached its maximum of almost 33% in month 2; in month 3, the last of the strike, the relative loss in output was 16.2%, half of the loss in the previous month. The effect of vacations in the output of the plant has different signs, positive or negative, depending on the month and the year. The plant management attributed these differences to the number of days the assembly line stopped production in each month of vacation, which in turn depended on the maintenance programs implemented on each occasion. In general, the positive estimated parameters coincide with the months when the assembly line was shut down during the least number of days.

For robustness purposes, we have estimated Eq. (4) with the two-step ECM. This method consists in first estimating the co-integrated long-term relationship (Eq. (2)) and second, estimating the short-term relationship (Eq. (3)) with the residuals of the long-term relationship as explanatory variables. The results, not reported, are similar to those shown in Table 2, except for the estimated parameter of TFP, θ, whose estimated value now is 0.39%, lower than the value in the one-step estimation of Table 2. The lower estimate of TFP growth rate in the two-step estimation may be the result of ignoring the shocks and anticipated perturbations of the production process in the estimation of the long-term relationship.

5. Discussion and comparison of the empirical results

Most of the published papers on insider and case-study econometrics examine causes (why one company implements a new practice and others do not) and consequences (did operating efficiency increase with the new practice, and if so, by how much?) of implementing new management practices in work organization, human resources management, and IT investments. Our research in case-study econometrics differs from prior papers in that we model and estimate the economic production function of an automobile assembly plant and the growth rate of operating efficiency, TFP, experienced by the plant in its first years of operation. During the period of study, there were no relevant changes in the management of the plant (the plant management was the same for the whole period, although the first months of an operation are expected to be the time period with higher potential efficiency gains from learning by experience, and from the fine-tuning of the plant operations. Clearly, management would be interested in measuring and assessing these gains for capacity and input demands planning purposes. Moreover, the plant under study went from two to three operating shifts in the period and management implemented certain personnel policies (hiring part-time employees, scheduling vacation and maintenance activities). The effects of learning by experience on productivity growth, as well as the effects of number of shifts and personnel policies on output levels also fall under the interest of insider and case-study econometrics.

The econometrics methodology proposed and implemented in the paper for the estimation of the production technology of the assembly plant is the one step ECM, integrating a long-term and a short-term relationship between inputs and outputs of the production process into a single model. In the paper, the long-term relationship corresponds to the production technology of the plant represented by the economic production function. The short-term relationship takes into account that shocks and perturbations affect the smooth operations of the plant so that input and output observations may or may not belong to the technological frontier. The key question is whether that frontier exists, and if the process would converge to it in an ideal shock-free world. Our interests in the paper include obtaining consistent and efficient estimates of the parameters of the production function, and helping management to identify the potential short-term efficiency gains from controlling the anticipated (vacation periods) and the un-anticipated (hiring of temporary employees) short-term operating shocks.

Overall, our work suggests that ECM is a useful tool for insider and case- study econometrics research, especially in situations where it makes economic sense to integrate production technology, and the alteration of the regular production flow resulting from the organization and management innovations, into a single econometric model. In this respect, the researcher could investigate whether the innovations modify the production technology (the long-term relationship of inputs and output), or the innovation only affects the production flows that fall outside the production frontier. To date, insider and case-study econometric research has focused mainly on the effects of management innovation on the level of operating efficiency (labour or TFP productivity), which in the context of our analysis would be modelled as part of the short-term production process. However, if innovations are important, for example investing in IT, a structural change in the parameters of the economic production function should not be ruled out.

Another theme in the existing literature can be found in those papers that model the production function of automobile manufacturers. Lieberman et al. (1990) summarize much of this work on the production function and productivity estimations for the industry before 1990. The paper also provides estimates of the main parameters of the production technology for manufacturers of US and Japan with firm-level data from 1950 to 1987. Lieberman and Dhawan (2005) provide updated estimates of the parameters of the production function for the same national car-makers, again using firm-level data for the period 1965–1997. Table 3 shows the estimated shares of labor costs over Value Added, and the estimated output to labor input elasticity for US and Japanese

Table 3
Comparative labour costs shares and output to labour elasticity.

	Labour costs/value added	Output to labour elasticity (%)
US:1950–1987 (Lieberman et al., 1990)	71%	31
Japan: 1950–1987 (Lieberman et al., 1990)	58%	58
Case study: 1984–1992	***68%***	***61***
US and Japan: 1965–1997 (Lieberman and Dhawan, 2005)	n.r.	74

Table 4
Comparative estimates of annual average TFP growth rates for automobile manufacturers.
Source: Company estimates from Lieberman et al. (1990). US and Japan from Lieberman and Dhawan (2005).

	Period	% Annual growth (TFP)
GM	1950–1987	2.0
Ford	1950–1987	2.1
Chrysler	1950–1987	2.7
Toyota	1950–1987	6.0
Nissan	1950–1987	5.2
Mazda	1950–1987	5.7
Case study	***1984–1992***	***5.5***
US and Japan	1965–1997	2.5

car-makers and for the assembly plant of our study. Table 4 compares estimated values of average annual TFP growth for individual manufacturers and for the plant in our study.

From Table 3, we first observe that the labor cost share over value added of the plant of our study is closer to that of US automobile manufacturers, and larger than that of the Japanese. This could be expected, since the plant belongs to a US manufacturer. Additionally, the higher capital cost share over value added of Japanese manufacturers, reported by Lieberman et al. (1990), reflects a greater capital intensity of the production process of Japanese firms, compared to those in the US. The output to labor elasticity shown in Table 3 has been estimated assuming constant returns to scale, so the complementary value to one is the estimated output to capital elasticity. Notice that the estimated output to labor elasticity of Japanese firms is the same as the estimated labor cost share of value added, while for the US manufacturers, the estimated elasticity is much lower than the labor cost share. For our plant, the labor cost share and the output to labor elasticity are relatively close. The difference between labor cost share and estimated elasticity suggests that US car manufacturers may not select the input mix way that minimizes costs, or that they have market power such that the value added (equal to the sum of labor costs and profits) includes economic profits.

The more recent estimate of the elasticity of output to labor input, reported in the last row of Table 3 is obtained with pooled firm-level data of manufacturers of US and Japan. The estimated production function in Lieberman and Dhawan (2005) shows increasing returns to scale, so the sum of the elasticity of output to labor and to capital inputs adds to a number greater than one, 1.09. The estimated elasticity of output to capital is equal to 36% $(1.09-0.73=0.36)$. The cost shares of labor and capital are not reported.

Finally, the estimated average annual growth rates in TFP shown in Table 4 indicate that productivity growth is higher in Japanese than in US car manufacturers—double, in fact. The Spanish plant of the US car manufacturer shows a growth rate in TFP similar to that of Japanese firms and therefore higher than that of US manufacturers. This result may be explained by the fact that the plant of our study is relatively young and efficiency gains from learning by doing may still be large. However, it also true that the plant has proven to be highly competitive during the time it has been in operation.[7]

6. Conclusion

The operating efficiency of production processes is a priority for any firm in a competitive market. Productivity, a ratio between output produced in a given period of time and quantity of inputs used in production during the same time period, is a usual measure of operating efficiency. The automobile market is highly competitive, so car manufacturers express permanent concerns for productivity gains over time. The hours per vehicle, HPV, is one of the most common measures of performance used by these manufacturers in benchmarking exercises for competitiveness evaluation purposes (Weyer, 2011, The Harbour Report [T]). The HPV is calculated at the plant and car-model level, as the number of working hours of all the plant employees in a given time interval, a month for example, divided by the number of cars produced in the same time period. The inverse of the HPV, cars produced per unit of labour time, is a measure of labour productivity. Carmakers want to reduce (increase) HPV (labour productivity) as a way of improving efficiency and reducing operating costs.

HPV has the advantage that the calculation is relatively simple, since it involves two variables that are available to any plant manager and are also easy to communicate to consultants or analysts doing the benchmarking exercise. However, there are significant limitations to the validity of these exercises to draw conclusions on comparative operating efficiency if the plants compared differ in technological and operational conditions, especially if there are differences in capital intensity and in the degree of scale economies of their respective production technologies. Efficiency measures, such as the TFP used in this paper, involve the relationship between output per period and an aggregated measure of capital and labour input services, thus overcoming the distortions in labour productivity as indicator of operating efficiency when capital intensity differs across production units.

It is understandable that benchmarking exercises based on TFP measures of operating efficiency will be more complicated, because discrepancies in the aggregation formulae for labour and capital are likely to appear. However, this paper claims that for internal control and self-evaluation of operating efficiency levels and evolution over time, TFP and TFP growth are more reliable measures of the level and of the gains in operating efficiency over time than labour productivity or its inverse, HPV. Moreover, as we show in this paper, the estimation of time trends in operating efficiency can be obtained as one of the parameters of the model that includes the long-term relationships postulated by the production function, together with short-term input-output relationships that capture the everyday dynamics of production. This further helps to separate shocks and operating perturbations, more or less under managerial control, from true efficiency gains from, for example, learning by doing, or from new management techniques. The time series econometrics used for the one step estimation of the full model is the ECM. We believe that the application of the ECM to the modelling of an automobile assembly plant in its initial years of operation presented in this paper, gives promising results for the use of this technique in future research in insider and case-study econometrics.

[7] Villanueva Ruiz and Huerta Arribas (1997) and Galve Górriz and Ortega (2000) provide additional evidence of the continuous improvement and productivity gains in this plant in the years following the time period of our study.

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