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EMPLOYMENT OCCUPATIONAL STRUCTURE, TECHNOLOGICAL CAPITAL AND REORGANIZATION OF PRODUCTION

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Abstract

This paper analyzes the role of skill-biased technological progress on the recent changes in the occupation al structure of Spanish manufacturing employment. Our dataset consists of a panel of Spanish manufacturing firms during the period 1986-1991. We confirm a puzzle that has been found in other OECD countries: investment in capital inputs is clearly procyclical, but destruction of unskilled jobs and creation of skilled jobs have been concentrated during the recession. However, we also find that the number of firms who invest by first time in technological capital has been clearly countercyclical. Based on this evidence, we estimate a dynamic model where firms take discrete decisions about what labor and capital inputs to use, and continuous decisions on the amount of each selected input. After controlling for individual heterogeneity and self-selection we find that these two decisions have different effects on occupational structure. In particular, we find that for new innovative firms the introduction of technological capital has significant and sizeable effects on the occupational structure of employment.

Key Words
Labor demand, Occupational structure, Reorganization effects, Dynamic panel data models.
JEL Classification: C33,J21,J44,L23.

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1 Introduction

During the eighties, blue collar permanent employment has lived a significant reduction in Spanish manufacturing in favor of an increase in skilled permanent employment. This fact matches the empirical evidence observed in this period for other developed countries. Recent empirical studies using either industry-level or plant-level data from several OECD countries show that jobs reallocations between firms or between industries hardly explain most of the observed changes in occupational structure. Their estimated effects of fixed capital and technological capital on the skill distribution support the existence of skill-biased technological progress (see Bernan, Bound and Griliches (1994), Machin (1993), Dunne, Haltiwanger and Troske (1996) and Machin, Ryan and van Reenen (1996) among others). However, another common result is that capital and technological capital can only explain a small proportion of the secular and cyclical variation in the proportion of blue collar workers, which remains characterized by unobservable factors. This result raises the question of what these unobservables represent.

In this paper we present empirical evidence about three potential factors that might contribute to interpret the nature of these unobservables. First, changes in occupational structure might be strongly related to the reorganization of the production process associated to the introduction of new capital inputs, rather than to the increase in the stocks of existing capital inputs. Second, estimates of the long run elasticities of labor inputs with respect to capital inputs based on static models may be downward biased, because such models ignore the quasi-fixed nature of labor inputs and the dynamics of labor demand decisions. Finally, there may be dynamic feedback effects between occupational structure and technological capital, in the sense that firms who have implemented changes in occupational structure in the past might find less costly to introduce additional technological capital (i.e., dynamic complementarities between occupational structure and technological capital)

We present a dynamic model for the demand of five labor inputs (managers, professionals, commercials, clerical workers and production workers) and three capital inputs (fixed capital, R&D and purchased technological capital). In this model firms decide what particular inputs to use and in what amount. Our model considers that the decision on introducing a new input into the production process may generally have different implications than the decision on rising the stock of an existing input. The introduction of a new input into the production process may require certain restructuring of the production process which may also imply a reorganization of the workforce. For instance, the acquisition of new capital embodying new techniques can generate skill-obsolescence of the existing workforce, requiring new workers whose skills are adapted to the new technology (see Aghion and Howitt, 1994). Furthermore, in order to investigate whether some changes in occupational structure might be implemented in advance to technological innovations, we allow for feedback effects between the decisions on occupational structure and investment in capital stocks.

The model is estimated using a panel of Spanish manufacturing firms between 1986 and 1991. This dataset contains firm-level annual information on the number of workers by five occupations (managers, professionals, commercials, clerical workers and blue collar workers) on fixed capital as well as R&D investment and purchases of technological capital externally generated to the firm. While other datasets just report aggregate data on white collar employees, our dataset breaks down white collars into four occupations. This allows us to distinguish the behavior in the demands for different white collar occupations.

Section 2 presents preliminary evidence about the trend in the occupational structure of Spanish manufacturing employment. Our results concerning reallocation of workers between firms with different skill labor intensities confirm those from previous studies that found a negligible effect on the changes in occupational structure. We observe significant differences in the paths of different white collar occupations; particularly, professionals and commercials show large increases in their participation in total employment. This evidence contrasts with the significant drop in the participation of blue collars in total employment. In fact, we observe that the processes of creation of professional and commercial jobs and destruction of blue collar jobs are clearly countercyclical, and therefore the most important changes in occupational structure have been concentrated during the recession. We also examine the trends in capital and technological capital investment at the end of section 2. We find that while investments in R&D and technological capital have been strongly procyclical, the number of firms that introduce new capital inputs (i.e., R&D or technological capital) evolves countercyclically. This result is consistent with models that postulate the optimality of the reorganization of production during recessions [see Cooper and Haltiwanger (1993) and Caballero and Hammour (1994) among others]. Our empirical concern, that we address in sections 3 and 4, is the role of the introduction of new capital inputs on the changes in the occupational structure.

In section 3 we present the model and the estimation strategy. We postulate log-linear Markov decision rules for labor inputs and capital inputs, which can be derived from an intertemporal model of inputs demands under time-separable and marginally increasing reorganization and adjustment costs. Since we separate the continuous decision on rising the stock of existing inputs from the discrete decision on introducing a non-existing input into the production process, optimal decision rules for the introduction of a new production input are also postulated. We control for unobserved individual heterogeneity and for potential self-selection due to the fact that firms endogenously decide what combination of inputs to use.

The estimation results presented in section 4 can be summarized as follows. First, we find significant differences in the demand elasticities for different labor inputs with respect to fixed capital, the largest ones being for professional and commercial employees. Second, the marginal effect of R&D and technological capital on different labor inputs is non significant. However, the reorganization of production associated to the adoption of technological capital has induced significantly large changes in occupational structure, particularly a fall in the proportion of blue collar jobs and a rise in the proportion of commercial jobs. We thus find sizeable elasticities, in the short and in the long run, of white collar occupations with respect to fixed capital and with respect to the introduction of technological capital into the production process. Finally, even though we find positive and significant feedback effects from occupational structure to investments in capital inputs, these effects are small in the short run and negligible in the long run.

Although we use noisy proxies for the decision about reorganization of production (i.e., dummy variables for the introduction of R&D capital and technological capital generated out of the firm), we find strong and significant effects of these variables on occupational structure. From this result we conclude that, at the individual firm level, changes in occupational structure have been mainly implemented in accordance with qualitative changes in the organization of production. The availability of datasets containing more detailed and disaggregate information about the introduction of new capital inputs and some other variables capturing the reorganization of the production process will allow to implement a more direct test of the hypothesis that reorganization of production is the leading explanatory factor for the changes in occupational structure.

2 Trends in the Occupational Structure of Spanish Manufacturing Employment

The main dataset consists of a balanced panel of 1,080 manufacturing firms collected from the database of *Central de Balances del Banco de España*[1] (CBBE hereinafter) who remained in the sample every year between 1986 and 1991. The criteria for selection of the sample and construction of the variables used in the empirical analysis (market value of

[1]Bank of Spain's Central Balance Sheet Office

the stocks of fixed capital, R&D capital and technological capital, and wages for different types of workers) are described in the Data Appendix.

Table 1 presents the time path of the proportions in permanent employment of different occupations using our sample of 1080 firms from the CBBE. The last row of this table reports the annual percentual growth in real output. The primary fact consists on the large increase in the proportion of white collars, particularly in the proportion of professional and commercial workers. In addition, we observe upward trends in the proportions of white collar occupations; the largest changes occurred in 1990-1991, just at the beginning of a recession.[2] In the rest of this section we present preliminary evidence about several factors that may have contributed to these changes.

2.1 Between Firms and Within Firms Variations in Occupational Structure

A potential explanation for the reduction in blue collar employment is the increasing competition in international trade from emerging economies where unskilled labor is cheaper. This competition may have decreased the participation in total output, and consequently in total employment, of industries that are intensive in production labor. In order to measure the contribution of this effect we have decomposed the total changes in each labor input share into three terms. The first term measures the change in the input share due to reallocation of employment between firms. The second term measures the change in the input share due to changes in the occupational structure within individual firms. Finally, the third component captures the covariance between the previous two terms, that is, the change in the input share as a result of firms changing both their occupational structure and their participation in total aggregate employment. Equation (1) presents this decomposition.

[2] In order to test for the robustness of this evidence to possible outliers and influential values affecting the weighted time averages we also looked at the time medians of the occupational shares. They also show sizeable increases in the shares of white collar occupations.

$$\Delta P_t^j = \sum_{i=1}^{N} \Delta s_{it} P_{i,t-1}^j + \sum_{i=1}^{N} s_{i,t-1} \Delta P_{it}^j + \sum_{i=1}^{N} \Delta s_{it} \Delta P_{it}^j \tag{1}$$

where t and i are the time and firm indices respectively, and j denotes the type of occupation; $P_t^j = L_t^j / L_t$ and $P_{it}^j = L_{it}^j / L_{it}$ are the proportions of labor input j in aggregate permanent employment and in firm i, respectively; $s_{it} = L_{it}/L_t$ denotes the weight of firm i in total aggregate employment at period t; finally, Δ denotes the time difference operator.

This decomposition is reported for each permanent labor input and by year in Table 2. The main result from this table is that within-firms variations in labor inputs proportions constitute the leading source of changes in the occupational structure. This is particularly the case for professional and commercial workers, whose growth represent the largest contribution to the increase in white collar employment. Moreover, even though there is a significant contribution of between-firms reallocation of employment to the rise in the proportions of managerial and clerical employment, its total contribution to the changes in occupational structure is small. This evidence is similar to that found by Bernan *et al.* (1994) for the US and by Machin *et al.* (1996) for other OECD countries. Consequently, the main changes have occurred at the individual firm level. We devote the rest of the paper to disentangle what factors have mostly contributed to the changes in the occupational structure of individual firms.

2.2 Creation and Destruction of Jobs for Different Occupations

Our next step is to analyze what differences in job destruction and job creation across occupations are behind the observed changes in occupational structure. We present in Table 3 the job creation and job destruction rates for total employment and for each occupation, using the statistics defined by Davis, Haltinwanger and Schuh (1996).[3] For

[3]For each input and for a given year, the job creation rate is computed as a size-weighted average of the growth rates in that labor input, for those firms with positive growth rates. The job destruction rate

total employment, the pattern of job creation and job destruction rates and their magnitudes are similar to those obtained by Dolado and Gómez (1995) for Spain and by Davis, Haltinwanger and Schuh (1996) for the US. Job destruction is countercyclical and more volatile than job creation. The creation process is rather smooth, as shown by the small reduction in the job creation rate during the years of recession, 1990-1991. These facts are consistent with the existence of increasing marginal hiring costs and labor market rigidities, which would imply that the optimal firms' policy is to smooth the creation process at the expense of sharpening the destruction process, as stressed in Caballero and Hammour (1996).

The most interesting results in this table concern the job creation and destruction rates by occupations. We find that the countercyclical pattern in job destruction and the smoothness in job creation are exacerbated in the case of blue collars. Furthermore, job creation rates of managers, professionals and commercials reach their peak at 1990, a year in which a recession started. In fact, job creation of professional workers presents a countercyclical pattern.

This evidence provides support for those theories that emphasize the cleansing effects of recessions [see Cooper and Haltiwanger (1993) and Caballero and Hammour (1994)]. In a context of continuous technical progress, these theories predict that restructuring will be intensified during recessions, for the opportunity cost of displaced production workers is lower than during expansion times. Therefore, an important proportion of firms might find optimal to reorganize their production process in order to adapt to technological innovations during downturns. Adoption of a new technology will imply installation of new capital that will also require the reorganization of the workforce. This reorganization will generally consist on expansion and contraction of employment of different occupations. The very fact that the most important changes in the skill

averages the absolute values of the growth rates for those firms with negative growth rates.

composition take place when recession starts (see Table 1), and the fact that the highest destruction rate for unskilled workers and the highest creation rates for skilled workers occur in 1990 (see Table 3), are consistent with these theoretical implications. In this context, our empirical question will be whether there exist some variables whose changes during 1990-91 might capture changes in the organization of production (e.g., capital and technological capital investments).

Table 3 provides an informative picture about the contribution of job creation and job destruction to the changes in the absolute magnitudes of the different occupations. However, since the initial proportions of occupations were very different, Table 3 does not indicate the quantitative contributions of the rates of growth of the different labor inputs to the changes in occupational structure. To do this, we perform the following decomposition of ΔP_t^j,

$$\Delta P_t^j = \sum_{k=1}^{5} \Delta P_t^{jk} \tag{2}$$

where ΔP_t^{jk} is the change in the proportion of labor input j if the only input changing its stock at period t were input k. For $\Delta L_t^j / L_{t-1}$ close to zero it follows that

$$\Delta P_t^{jj} = (1 - P_{t-1}^j)\frac{\Delta L_t^j}{L_{t-1}} \qquad ; \qquad \Delta P_t^{jk} = -P_{t-1}^j \frac{\Delta L_t^k}{L_{t-1}} \quad for\ k \neq j \tag{3}$$

In Table 4 we present this decomposition for the change in the proportion of blue collar employment only, though the results are very similar for other occupations. There we find that the growth of professionals and commercials, and the drop in blue collars, explain almost 100 percent of the fall in the proportion of blue collar jobs. Thus, tables 3 and 4 together suggest that changes in occupational structure are mainly due to the large job creation rates of professionals and commercials, and to the huge destruction of blue collars jobs, particularly in 1990-91.

2.3 Trends in Capital and Technological Capital Investments

Table 5 presents the time path of firms' net investments in three capital inputs: fixed capital stock, R&D capital, and technological capital externally generated to the firm. We also include the time path of real output and total employment. Whereas investment in fixed capital does not exhibit any clear cyclical behavior, the paths of investments in R&D and technological capital show a strongly procyclical pattern. This finding mismatches the evidence found for changes in occupational structure. Given that a large number of firms do not incorporate R&D and technological capital stocks in their production process (about 90 percent of our sample in 1986), we also report in Table 5 the number of firms introducing R&D or technological capital into the production process in each year (that we will call 'new innovative firms'). Despite this cyclical responsiveness of innovating capital stocks, we see that the number of new innovative firms reaches its maximum in 1990. This result is consistent with the reorganization of production during recessions, and suggests that the variables indicating the introduction of innovations into the production process can capture part of the qualitative decisions about reorganization of the production process. Given that the number of new innovative firms in our dataset is non negligible (in the sample period there are 162 and 71 firms introducing by first time R&D capital and technological capital, respectively), it may be possible to identify the effects of introducing new inputs in the production process.

In principle, since the temporal dimension of our panel covers less than one complete business cycle, our previous results referred to aggregate information are not very conclusive. However, given the large cross-sectional variability in firms' idiosyncratic shocks, our estimates in section 4 display large and significant effects of business cycle on the different inputs demands. We will see that the sign of these effects are exactly the ones described above.

3 An Empirical Model of Production Reorganization and Occupational Structure

Consider a firm i that produces an homogeneous good combining capital inputs and labor inputs according to a particular technology represented by

$$Y_{it} = f(X_{it}, I_{it}; \epsilon_{it}) \tag{4}$$

where Y_{it} is real output; X_{it} denotes the vector of stocks of the different capital and labor inputs, $(X_{it}^1, ..., X_{it}^J)'$; I_{it} denotes the vector $(I_{it}^1, ..., I_{it}^J)'$, where I_{it}^j is the indicator function for the event "input j is used by firm i at period t"; and ϵ_{it} represents unobservables from the point of view of the econometrician that can include aggregate shocks, industry-specific shocks, idiosyncratic shocks as well as time-invariant firm-specific characteristics affecting technology.

Although the productivities of the different inputs, and the degree of complementarity or substitutability between them, depend on the stocks of such inputs, they may also depend on what inputs are effectively used by the firm and therefore I_{it} appears in the production function in addition to X_{it}. We are implicitly assuming that bringing in a non-existing input implies a deeper reorganization of the production process than adjusting the stock of an already existing input.[4] Consequently, there may be discontinuities when a new input is introduced in the production process.

In this context, an obvious question is why not all the firms in the same industry and producing the same good are using the same type of inputs, that is, why there is no synchronization in the introduction of new inputs by similar firms. Under discontinuities in the production function at zero levels of some inputs, different levels of the stocks

[4]The adoption of a new type of technological capital, even in a small amount, may entail important changes in the tasks of the different workers. For example, if the tasks of professional workers are tightly related to the new capital, their productivity increase might outweight the productivity fall of the remaining workers. Some clerical workers might be allocated to tasks in assistance of professionals and, therefore, the productivity of other non professional workers might decrease.

of existing inputs may imply different decisions about the introduction of a new input.[5] Notice that the existence of lump-sum costs associated to the introduction of a new input will suffice to stagger such decision, yet the existence of lump-sum costs is not a necessary condition.

We observe in our sample a significant group of firms that systematically keep some particular inputs out of the production process. These inputs tend to be professional and commercial workers, and also R&D and technological capital. However, an important number of firms have been adopting these inputs at different years during the sample period. Although the persistence in the exclusion of specific inputs can be mostly due to industry-specific and firm-specific technological differences, the existence of firms adopting new inputs points out that several firms have been incorporating technical progress at different years. In the estimation of the model we will control for individual heterogeneity and address whether there is empirical support for the second argument.

At each period t, firm i decides the demand of each input in order to maximize its expected discounted stream of current and future profits, taking as given technology, stocks of inputs at period $t-1$, current input prices, and adjustment costs associated to the introduction of new inputs and to changes in the stocks of existing inputs. We assume that the firm has perfect knowledge about current prices and technological shocks, yet future shocks and inputs prices are uncertain to the firm. We also assume that adjustment costs are time-separable. Finally, both aggregate and idiosyncratic shocks are assumed to follow strictly exogenous and stationary first order Markov stochastic processes.

In this context, this model corresponds to a Markov decision model where the optimal decisions at each period are functions of the stocks of inputs at $t-1$, the vector of indicators at $t-1$, current relative input prices and exogenous shocks. In general, the

[5]Firms with a relatively large stock of blue collar workers and a small stock of professionals may not find optimal to introduce a new capital input because the productivity increase of professionals may not outweight the productivity fall of blue collars and the cost of introducing the new input.

optimal decision rules can be represented as

$$X_{it}^{j} = X^{j}(X_{i,t-1}, I_{i,t-1}, W_{it}, \epsilon_{it}) \qquad if \quad I_{it}^{j} = 1 \tag{5}$$

$$I_{it}^{j} = I^{j}(X_{i,t-1}, I_{i,t-1}, W_{it}, \epsilon_{it}) \tag{6}$$

where W_{it} is the vector of relative prices of inputs. Defining x_{it}, w_{it} as the natural logarithms of X_{it} and W_{it} respectively, we can write log-linear approximations to the optimal decision rules about the stocks of inputs given by (5) as

$$x_{it}^{j} = x_{i,t-1}'\alpha^{j} + I_{i,t-1}'\beta^{j} + w_{it}'\gamma^{j} + \epsilon_{it}^{j} \qquad if \quad I_{it}^{j} = 1 \qquad (j = 1, ..., J) \tag{7}$$

Notice that the lagged values of both the stocks of inputs and the indicator of inputs usage may affect the demands of inputs through two channels. First, considering technology, there may exist contemporaneous complementarities that will imply that lagged values of those variables will affect inputs demands even if adjustment costs are separable between inputs. Second, as a result of nonseparabilities between adjustment costs of different inputs (either convex or lump-sum adjustment costs), there may appear dynamic complementarities. In this paper, however, we will not attempt to disentangle these two effects, for we are mainly interested in the total marginal effect.

It must be stressed that the variables $I_{i,t-1}^{k}$ indicating the introduction of a new input may partly capture the reorganization effects in the absence of variables which genuinely represent reorganization of the production process. Even though these indicators are noisy measures of reorganization decisions, they can provide relevant information. Let the parameter of interest be $\Gamma = E(y|R = 1) - E(y|R = 0)$, where $R = 1$ indicates a reorganization of production. Since we just observe I (the indicator for the introduction of a new input) instead of R, we can only estimate $\gamma = E(y|I = 1) - E(y|I = 0)$. It can be shown that $\gamma/\Gamma = q_1 - q_0$, where $q_j = pr(R = 1|I = j)$. Therefore, if the probability of reorganization rises when the firm is introducing new inputs into the production process (i.e., $q_1 > q_0$), the sign of our estimated effect will be correct although its absolute magnitude will underestimate the effect of reorganization.

Notice that we will not pursue an structural approach to the estimation of this model nor derive the explicit solution of the model. As we are mainly concern on the leading factors which explain the observed changes in occupational structure, our approach based on the log-linear approximations in (7) is appropriate. Hence, we will not concentrate on the alternative mechanisms through which these effects have taken place (i.e., complementarity in the production function, non separability in adjustment costs). Nevertheless, our specification encompasses static specifications and certain dynamic specifications with convex adjustment costs.

We characterize the unobservables $\{\epsilon_{it}^j\}$ as:

$$\epsilon_{it}^j = \eta_i^j + \delta_{(i)}^j\, t + A_t^j + u_{it}^j \tag{8}$$

where, for each firm i and each input j, η_i^j captures unobservable firm-specific time invariant effects; $\delta_{(i)}^j$ is the parameter associated to the industry trend in the demand of input j; A_t^j is the aggregate shock in the demand of input j at period t; and u_{it}^j is an idiosyncratic shock. There are two main econometric problems associated to the estimation of the equations set in (7): individual heterogeneity and self selection. The unobserved heterogeneity problem arises because the variables associated to the stocks of inputs (i.e., $x_{i,t-1}$, $I_{i,t-1}$), which are predetermined endogenous variables, are in general correlated with the time invariant firm-specific effect. Absence of control for this effect would induce spurious correlation effects between the demands of different inputs.[6] The fact that at certain periods some firms keep certain inputs out of the production process introduces a

[6]For instance, some firms may be using more professsional workers and more technological capital than the average because of unobserved firm-specific technological characteristics. If we ignore these effects, we may wrongly conclude that rises in technological capital have increased the demand for professionals.

self selection problem. Assume, for the sake of presentation, that the discrete decision on inputs usage is affected by the same observables and unobservables than the continuous decision about the optimal stock of the input. The statistical model representing both two decisions would thus be a standard Tobit model (see Amemiya, 1985). In such a case it is well known that, abstracting from the individual heterogeneity problem, the OLS estimator of the parameters in equation (5) will be biased towards zero. The rest of this section describes our econometric approach to deal with these problems.

For the equation for input j, we select the subsample of observations for which equation (5) holds at two consecutive periods, t and $t-1$, and take first differences. We obtain:

$$\Delta x_{it}^{j} = \Delta x_{i,t-1}'\alpha^{j} + \Delta I_{i,t-1}'\beta^{j} + \Delta w_{it}'\gamma^{j} + \delta_{(i)}^{j} + \Delta A_{t}^{j} + \Delta u_{it}^{j} \qquad if \quad I_{it}^{j} I_{i,t-1}^{j} = 1 \tag{9}$$

where both $\delta_{(i)}^{j}$ and ΔA_{t}^{j} are parameters to estimate. If $\{u_{it}^{j}\}$ is *iid* over time, Δu_{it}^{j} will be uncorrelated with $x_{i,t-2}$, $I_{i,t-2}$ and previous lags of these variables. In general, for $\{u_{it}^{j}\}$ following a MA(q) process $x_{i,t-2-q}$, $I_{i,t-2-q}$ and previous lags will be valid instruments. Let Z_{it} be a vector of instruments such that $E[\Delta u_{it}^{j}|Z_{it}] = 0$. Given our sample selection, the unobservable variable is $\{\zeta_{it}^{j}\} = \{\Delta u_{it}^{j}|I_{it}^{j}I_{i,t-1}^{j} = 1\}$, and in general $E[\zeta_{it}^{j}|Z_{it}] = E[\Delta u_{it}^{j}|Z_{it}, I_{it}^{j}I_{i,t-1}^{j} = 1] \neq 0$. We can write the conditional choice probability or *propensity score* as $p_{it}^{j} = pr(I_{it}^{j}I_{i,t-1}^{j} = 1|Z_{it}) = pr(Z_{it}\pi_{t}^{j} + \nu_{it}^{j} > 0)$, where π_{t}^{j} is a parameter vector and ν_{it}^{j} is an error term. If the ν_{it}^{j} are independently distributed with respect to Z_{it} (see Stoker, 1991), then the conditional expectation $E[\Delta u_{it}^{j}|Z_{it}, I_{it}^{j}I_{i,t-1}^{j} = 1]$ can be obtained as a function of the *propensity score*:

$$E[\Delta u_{it}^{j}|Z_{it}, I_{it}^{j}I_{i,t-1}^{j} = 1] = G(p_{it}^{j}) \tag{10}$$

Therefore, for the subsample of observations with $I_{it}^{j}I_{i,t-1}^{j} = 1$ the following moment conditions hold:[7]

[7]Of course, for those inputs which are always used by all the firms, $p_{it}^{j} = 1$, all i, t, and thus the

$$E(Z_{it}[\Delta x^j_{it} - \Delta x'_{i,t-1}\alpha^j - \Delta I'_{i,t-1}\beta^j - \Delta w'_{it}\gamma^j - \delta^j_{ID(i)} - \Delta A^j_t - G(p^j_{it})]) = 0 \qquad (11)$$

We follow a two stage approach. In a first stage we obtain estimates of the propensity scores p^j_{it}. In a second stage we estimate the parameters in equation (7) using the GMM estimator proposed by Arellano and Bond (1991), based on the moment conditions in (11), and substituting $G(p^j_{it})$ by a polynomial in the estimated propensity scores. In order to test the validity of the sets of instruments Z_{it} we use the Hansen-Sargan test of overidentifying restrictions and the test of second-order serial correlation in Δu^j_{it}.

4 Estimating the Model

We first estimate probit models for the propensity scores for those inputs which are not used by certain firms, that is, professional and commercial workers, and R&D and technological capital. In order to allow for conditional heteroskedasticity over time, we estimate probit equations for each input year by year. The goodness-of-fit of these models, according to the percentage of correct predictions on the event $I^j_{it}I^j_{i,t-1} = 1$, ranges from 82.66% for R&D capital to 98.45% for professionals.[8] We then include second-order polynomials in the inverse of the Mill's ratio in the corresponding decision rules equations for professionals, commercials, R&D capital and technological capital. The coefficients of these polynomials were interacted with time dummies in order to allow for generalized heteroskedasticity.[9]

selected sample is trivially the whole sample.

[8]A prediction on $I^j_{it}I^j_{i,t-1} = 1$ (resp. $I^j_{it}I^j_{i,t-1} = 0$) is said to be correct if the predicted probability is higher (resp. lower) than 0.5.

[9]The inverse of the Mill's ratio is defined as $\phi(-Z_{it}\pi^j)/\Phi(-Z_{it}\pi^j)$, where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the distribution and the density function of the standard normal variable [see Amemiya (1985)].

We also tried alternative functional forms in the propensity scores -the estimated probability and the value of the normal density evaluated on the estimated index- and set the degree of the polynomial up to order three. However, neither these alternative functionals nor higher order polynomials make significant differences in the parameter estimates of the decision rules.

We present the estimation results of the log-linear approximations to the optimal decision rules for labor inputs and capital inputs in Tables 6 and 7 respectively. For each of the labor demand equations the dependent variable is the logarithm of the stock of the corresponding permanent labor input. For the capital equations, the dependent variables are the logarithms of the stocks of fixed capital, R&D capital, and technological capital, respectively. We consider these last two variables as separate variables to distinguish between innovative capital based on search for innovations implemented by the firm and that based on successful innovations purchased by the firm but externally generated to the firm.

The set of explanatory variables can be classified in four groups: (1) logarithm of beginning-of-period stocks of capital inputs; (2) logarithm of beginning-of-period stocks of labor inputs; (3) indicators on inputs usage at the former period; (4) relative prices of labor inputs, and proxies for idiosyncratic and industry shocks. Regarding relative prices, we include the logarithm of the relative wage of white collar employees with respect to blue collar ones and the logarithm of the firm's price of output. Time dummies are included to control for aggregate shocks equally affecting all firms. The price of physical capital is excluded from estimation, for being collinear with time dummies. For these reasons, and given the lack of specific prices for R&D and technological capital, we expect the price of output to capture the joint effects from the omission of capital prices and disaggregated wages by occupation, as well as the way in which production-related variables has been deflated. In order to capture industry-specific trends characterizing changes in occupational structure, we include industry dummies and an index of capacity utilization at the 2 digit industry-level. Finally, we also include the logarithms of current firm's output to control for changes in demand conditions affecting individual firms.

In all the equations we maintain the same instruments set, which contains all the strictly exogenous variables (industry-specific variables) and the values of all the predetermined variables dated $t-2$ and earlier. In the equations for professionals and commercials, and R&D and technological capitals, we also include the selectivity correction terms in the instruments set, since they ought to be valid instruments if the former instruments are valid.

In each of the labor demand equations in Table 6, the Sargan-Hansen test cannot reject the overidentifying restrictions for significance levels larger than 30%, although this significance level falls to 13% in the case of commercials. Similar results are also obtained for the equations of R&D capital and technological capital in Table 7, although for fixed capital we find evidence against the overidentifying restrictions. The Arellano-Bond test of second-order autocorrelation also presents strong evidence in favor of the validity of our instruments, except for the equation of technological capital.[10] The evidence against model specification for fixed capital and technological capital can be due to the existence of more complex dynamics which have not been captured by the model. Such dynamics could be attributed both to irreversibilities or lump-sum adjustment costs for capital investment, and to differences in the efficiency of different capital vintages that would introduce autocorrelated measurement errors in our capital variables.

In all the estimated equations, the lagged endogenous variable shows a positive and very significant effect. Since we are controlling for individual heterogeneity, this evidence points out the importance of adjustment costs in inputs demand decisions. The set of industry dummies appear clearly significant except for clericals, supporting evidence in favor of industry-specific trends in inputs demands. Furthermore, in the equations were sample selection is accounted for, the selectivity correction terms were clearly significant, providing strong evidence in favor of endogenous self-selection for professionals and R&D and technological capitals.

[10]Our results on the specification tests contrasts sharply with the ones obtained when beginning-of-period stocks of inputs were not included in the model (non reported in the paper), assuming out adjustment costs. In that case both the overidentifying restrictions and the null hypothesis of no second order autocorrelation are clearly rejected.

The effect of lagged capital stock is fairly large and significant in the demand for professionals and commercials, but negative (although non significant) for blue collars. Considering firms with positive stocks of R&D capital and technological capital, increases in lagged stocks of these variables on the demands for managers, professionals and commercials have small and non significant effects. Therefore, since the proportions of these three occupations have experienced important rises, we can conclude that increases in R&D and technological capital do not help to explain changes in occupational structure of employment. This result is also consistent with the strong procyclical behavior of technological capital investment and the countercyclical path in the creation of professional and commercial jobs and in the destruction of blue collar jobs.

Considering the effects of introducing new capital inputs, the introduction of R&D capital has no significant effects on the demand of any labor input. However, that is not the case for the introduction of technological capital. Firms who have decided to adopt this input had reduced blue collars by 26%, and increased commercials by 36%. This result highlights that the introduction of technological capital is a much more relevant indicator of production reorganization than the introduction of R&D capital. The reason seems to be straightforward: whereas R&D capital is based on firms' expenditures on search for innovations (so that reorganization of production after the introduction of R&D will occur only if innovations are successfully generated), technological capital is based on firms' purchases of successful innovations, what makes reorganization of production more likely.

Regarding the effects of introducing new labor inputs in the production process, we should underline two results. First, the demands of professional and commercial employees the first year in which these inputs are used are 71% and 30% larger, respectively, than these demands after this initial period. This result reflects the existence of lump-sum adjustment costs or other discontinuities associated to the introduction of a new labor input. In addition, we see that firms adopting professionals as a new input have reduced clericals in 17%, while those bringing commercials into the production process have reduced blue collars in 11%.

Both the magnitude and significance of the effects associated to the introduction of new inputs are very robust to changes in the sets of instruments and explanatory variables. We consider that these results provide strong evidence in favor of the non-neutrality with respect to occupational structure of some types of reorganization in production. In particular, the reorganization in the production schedule after the introduction of technological capital have exerted an important reduction in the demand of blue collars and a rise in the demand of commercials.

The relative wage rate between white collar and blue collar workers has the expected sign for all occupations except for clericals and blue collars, although the estimated coefficient is only significant in the case of professionals. Finally, the demand of professionals and commercials is countercyclical: a percentual increase in real sales implies a short-term reduction of 6 and 10 percent respectively. We observe a procyclical pattern in the demand for managers and blue collars, with short run elasticities of 7 and 14 percent respectively. The demand for clericals, however, does not appear to be responsive to fluctuations in the economic activity.

In Table 7 we find interesting effects of employment occupational structure on capital investment decisions. The change in beginning-of-period blue collars has negative effects on R&D capital and technological capital, although these effects are non significant. More interestingly, we find significant and sizeable effects of professionals and commercials on R&D capital and technological capital, and positive and significant effects of managers on fixed capital and R&D capital. These positive effects give evidence of feedback effects between labor inputs and capital inputs, suggesting that the observed tendency in occupational structure (in favor of an increase in white collar occupations) may have anticipated growths in fixed capital and technological capital. These feedback effects, though significant, are not very large. Finally, the positive coefficients on real output for R&D and technological capital point out the procyclical behavior of investment in these two capital inputs, with estimated short run elasticities about 14 and 12 percent respectively.

In order to analyze the contribution of these dynamic interactions between occupational structure and capital investments to the observed changes in occupational structure, we report in Table 8 the long run elasticities for each white collar occupation. In the first column we report the long run elasticities ignoring employment dynamics in inputs demands. In the last two columns we report the long run elasticities accounting for dynamics, although we ignore feedback effects between occupational structure and capital stocks in the second column. These computations are based on the estimated equations reported in Tables 6 and 7, and on estimated equations for total employment and temporary employment (non reported in this paper). The remarkable differences between the first two columns emphasize the importance of dynamics for estimating long-run elasticities. However, the small differences between the last two columns point out the irrelevance of the feedback effects in the long run. It is worth to note the high values of the long run elasticities of white collar inputs with respect to the introduction of technological capital. This confirms the importance of this kind of reorganization of the production process over changes in occupational structure both in the short and in the long run.

5 Conclusions

This study is concerned with the significant change of occupational structure in manufacturing, consisting on a shift towards skilled labor, occurred in Spain and other OECD countries during the eighties. Our data consist of a balanced panel of 1080 manufacturing firms along the period 1986-1991 containing information on five different labor inputs, fixed capital stock and R&D and technological capital. The fact that we have disaggregated information on white collar employees by four occupations makes possible to consider different firm's behavior in the demands for different white collar occupations. We explore two alternative explanations to the results from Dunne, Haltiwanger and Troske (1996) and others, which found that although capital and technological capital have significant effects on the skill composition of the workforce they leave most of the secular and cyclical variation unexplained. These potential explanations are the existence of dynamic feedback effects between occupational structure and capital stocks, and the nonhomotheticities in the technology associated to the adoption by some firms of non-existing inputs, like upgraded-skill labor and technological capital.

Our results can be summarized as follows. First, we find that the main changes in occupational structure took place during the recession, which favors the theory about the optimality of restructuring during downturns. Second, our results exhibit significant differences between the effects on occupational structure of the continuous decision of increasing the stock of technological capital and the discrete decision of introducing technological capital by first time. In particular, we observe that the introduction of new technological capital into the production process contributes to explain sizeable changes in occupational structure. In contrast, the introduction of R&D capital has no significant effect, that we attribute to the fact that, contrary to technological capital, R&D capital does not measure unambiguous introduction of successful innovations.[11] This evidence, and the fact that changes in occupational structure are countercyclical, confirms the previous descriptive evidence on the optimality of restructuring during recessions. Finally, estimates from the decision rules for capital inputs show significant yet small effects of variables related to occupational structure, and therefore the capital-labor feedback effects are negligible in the long run.

[11]This explanation could be tested if data on successful innovations internally generated by the firm were available, for we would expect to find a significant coefficient for this variable.

Data Appendix

A Construction of the data set

The main data set has been taken from the database of the *Central de Balances del Banco de España* (CBBE). This database contains annual information on the balance sheets and other complementary information on economic variables for a large number of Spanish companies whose main activity was manufacturing between 1982 and 1993. This dataset was started in 1982 collecting data on firms 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. The firms included in this data base represent almost 40% of the total Value Added in Spanish manufacturing. For the purpose of the paper, we have only used observations for those years where disaggregated information on permanent employees by occupations is reported: managerial, professional, clerical, commercial and production workers. This disaggregated information has been reported by the CBBE from 1986 and until 1991.

The sample consists on a balanced panel of 1,080 non-energy manufacturing firms, with a public share lower than 50 percent and with positive employment and labor costs, reported to the Bank of Spain's Central Balance Sheet Office from 1986 to 1991. To obtain this final sample, we applied sequentially the following filters:

- Filters needed to construct the market value of the stock of fixed capital:

1. Book value of the stock of fixed capital, total accumulated depreciation and annual depreciation of the stock of fixed capital must be positive.

2. The average life of fixed capital must lie between percentiles 1st and 99th, and the average age of the fixed capital must be lower than the 80% of its average life.

3. The absolute growth in the book value of the stock of fixed capital cannot be greater than 300%.

- Filters related with the performance of the firm:

1. Sales, gross output and total labor costs must be positive.

2. Accounting equity must be positive.

3. The firm cannot change from one industry to another.

4. Both permanent non production employment and permanent production employment must be positive.

Table A1 presents the distribution of firms in this balanced panel by size (measured as the time average of firm's employees) and by 2-digits industry. The total number of employees at these firms is around 180,000, that represents approximately 8% of total Spanish manufacturing employment during this period.

We have also used a complementary dataset to obtain wages for blue collar and white collar jobs. The CBBE dataset reports the firm's average wage rate for total employees, though the wage rate for each labor input is not reported. Information on average wages for white collar and blue collar employees is reported by the *Encuesta de Salarios* (ES).

This survey provides 3 digit industry-level information about wage rates in an annual basis, irrespective of the contract duration. We also took information on average wages for temporary and permanent employees at the 2-digit industry level from the survey *Distribución de Salarios* (DS).

Table A1
Distribution of firms by 2-digit industry and by size
Balanced panel 1986-1991 (1080 firms)

		Small	*Med1*	*Med 2*	*Large*	*Total*
Iron, steel and metal (22)	Abs. freq.	1	4	3	2	10
	% by ind.	10.00	40.00	30.00	20.00	100.00
	% by size	0.66	1.07	1.03	0.76	0.93
Bldg. materials glass, ceramics (24)	Abs. freq.	12	38	21	17	88
	% by ind.	13.64	43.18	23.86	19.32	100.00
	% by size	7.89	10.16	7.22	6.46	8.15
Chemicals (25)	Abs. freq.	15	42	39	54	150
	% by ind.	10.00	28.00	26.00	36.00	100.00
	% by size	9.87	11.23	13.40	20.53	13.89
Non-ferrous metal (31)	Abs. freq.	15	55	22	16	108
	% by ind.	13.89	50.93	20.37	14.81	100.00
	% by size	9.87	14.71	7.56	6.08	10.00
Basic machinery (32)	Abs. freq.	13	27	22	13	75
	% by ind.	17.33	36.00	29.33	17.33	100.00
	% by size	8.55	7.22	7.56	4.94	6.94
Office machinery (33)	Abs. freq.	0	0	0	1	1
	% by ind.	0.00	0.00	0.00	100.00	100.00
	% by size	0.00	0.00	0.00	0.00	0.09
Electric materials (34)	Abs. freq.	3	14	15	23	55
	% by ind.	5.45	25.45	27.27	41.82	100.00
	% by size	1.97	3.74	5.15	8.75	5.09
Electronic (35)	Abs. freq.	1	2	7	6	16
	% by ind.	6.25	12.50	43.75	37.50	100.00
	% by size	0.66	0.53	2.41	2.28	1.48
Motor vehicles (36)	Abs. freq.	2	12	12	14	40
	% by ind.	5.00	30.00	30.00	35.00	100.00
	% by size	1.32	3.21	4.12	5.32	3.70
Ship building (37)	Abs. freq.	0	3	1	2	6
	% by ind.	0.00	50.00	16.67	33.33	100.00
	% by size	0.00	0.80	0.34	0.76	0.56
Other motor vehicles (38)	Abs. freq.	0	1	4	3	8
	% by ind.	0.00	12.50	50.00	37.50	100.00
	% by size	0.00	0.27	1.37	1.14	0.74
Precision instruments (39)	Abs. freq.	1	1	0	2	4
	% by ind.	25.00	25.00	0.00	50.00	100.00
	% by size	0.66	0.66	0.00	0.76	0.37

Table A1 (cont.)
Distribution of firms by 2-digit industry and by size
Balanced panel 1986-1991 (1080 firms)

		Small	*Med1*	*Med 2*	*Large*	*Total*
Non-elaborated	Abs. freq.	22	39	26	25	112
food	% by ind.	19.64	34.82	23.21	22.32	100.00
(41)	% by size	14.47	10.43	8.93	9.51	10.37
Food, tobacco	Abs. freq.	23	22	15	20	80
and drinks	% by ind.	28.75	27.50	18.75	25.00	100.00
(42)	% by size	15.13	5.88	5.15	7.60	7.41
Basic	Abs. freq.	11	19	24	22	76
Textile	% by ind.	14.47	25.00	31.58	28.95	100.00
(43)	% by size	7.24	5.08	8.25	8.37	7.04
Leather	Abs. freq.	2	9	7	3	21
	% by ind.	9.52	42.86	33.33	14.29	100.00
(44)	% by size	1.32	2.41	2.41	1.14	1.94
Garment	Abs. freq.	4	22	20	10	56
	% by ind.	7.14	39.29	35.71	17.86	100.00
(45)	% by size	2.63	5.88	6.87	3.80	5.19
Wood and	Abs. freq.	6	18	13	6	43
furniture	% by ind.	13.95	41.86	30.23	13.95	100.00
(46)	% by size	3.95	4.81	4.47	2.28	3.98
Cellulose and	Abs. freq.	8	25	18	15	66
paper edition	% by ind.	12.12	37.88	27.27	22.73	100.00
(47)	% by size	5.26	6.68	6.19	5.70	6.11
Plastic	Abs. freq.	9	13	16	4	42
materials	% by ind.	21.43	30.95	38.10	9.52	100.00
(48)	% by size	5.92	3.48	5.50	1.52	3.89
Other	Abs. freq.	4	8	6	5	23
non-basic	% by ind.	17.39	34.78	26.09	21.74	100.00
(49)	% by size	2.63	2.14	2.06	1.90	2.13
Total	Abs. freq.	152	374	291	263	1080
	% by ind.	14.07	34.63	26.94	24.35	100.00
	% by size	100.00	100.00	100.00	100.00	100.00

Note: *Small* means firm's time average of total employment lower or equal than 25. *Med 1* means firm's time average of total employment greater than 25 and lower or equal than 75. *Med 2* means firm's time average of total employment greater than 75 and lower or equal than 200. *Large* means firm's time average of total employment greater than 200.

B Construction of variables

Employment.

Number of employees is disaggregated in permanent white collar, permanent blue collar and temporary employees. Permanent white collar employment is also disaggregated into four occupations: managerial, professional, commercial and clerical. To maintain measurement consistency, 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.

Real wages.

The measure of the firm's annual average labor costs per employee W_{it} is computed as the ratio of Total wages and salaries to Total number of employees. This measure was deflated using Retail Price Indices at the 2-digit level. (Source: National Statistics, hereinafter INE). Computation of average wages per type of worker is done using information on wages of non production and production employees at industry level from *Encuesta de Salarios* and on wages of permanent and temporary employees at industry level from *Distribución de Salarios* (Source: INE). The wage for temporary employees is computed as $W_{it}^T = W_{it}(L_{it}^T + L_{it}^P)(L_{it}^T + L_{it}^P \mu_{it}^{P,T})$, where, for period t, L_{it}^T, L_{it}^P are the average annual number of temporary employees and the number of permanent employees in the firm, respectively, and $\mu_{it}^{P,T}$ is the wage margin of permanent employees with respect to temporary employees (obtained at the industry level from *Distribución de Salarios*).

The wage of permanent employees is thus $W_{it}^P = \mu_{it}^{P,T} W_{it}^T$. The wage for permanent production or blue collar employees can be computed as $W_{it}^{Pb} = (W_{it}^P L_{it}^P)/(L_{it}^{Pb} + L_{it}^{Pw} \mu_{it}^{b,w})$, where, for period t, L_{it}^{Pb} and L_{it}^{Pw} are the number of permanent production (blue collar) employees and permanent nonproduction (white collar) employees, respectively, and $\mu_{it}^{b,w}$ is the wage margin of nonproduction employees with respect to production employees (obtained at the industry level from Encuesta de Salarios). Finally, the wage of permanent white collar employees is computed as $W_{it}^{Pw} = \mu_{it}^{b,w} W_{it}^{Pb}$.

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).

Fixed capital and investment.

We are interested in investment in depreciable fixed capital which is already productive, so Land and Capital stock in course of construction are excluded from the definition of the stock of fixed capital. Since the CBBE does not have independent estimates of investment available, gross nominal investment I_{it} must be imputed from changes in the book value of fixed capital with a correction for depreciation, that is

$$I_{it} = KNB_{it} - KNB_{i,t-1} + Dep_{it} + Rev_{it}$$

where, KNB_{it} is the book value of the net stock of fixed capital, that is,

$$KNB_{it} = KGB_{it} - ADep_{it},$$

where KGB_{it} is the book value of the gross stock of fixed capital, $ADep_{it}$ is the accumulated depreciation of the stock of fixed capital, Dep_{it} is the accounting depreciation during the year; and Rev_{it} is the net variation in the book value of fixed capital and in its accumulated depreciation due to positive and/or negative revaluations.To calculate the market value (replacement value) we use a perpetual inventory method which takes account for depreciation and inflation. To do this, an initial value for the first year that data is available for a given firm is calculated as follows:

$$q_1 K_{i1} = \frac{q_1}{q_{1-AA_i}} KGB_{it}(1 - \delta_i)^{AA_i}$$

where, q_t is the price deflator of the stock of fixed capital; KGB_{it} is the book value of the gross stock of fixed capital; δ_i is the average depreciation rate of the stock of fixed capital; and AA_i is the average age of the stock of fixed capital. The average age can be 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 in the basis of accounting information as

$$\delta_i = \frac{\sum_{t=1}^{T_i} Dep_{it}}{\sum_{t=1}^{T_i} ADep_{it}},$$

where T_i is the number of years of available data for firm i. As regards price indices, the corresponding GDP implicit deflator of investment goods is used (Source: Spanish National Institute of Statistics, INE). The recursive method to compute the replacement value of the stock of fixed capital from the second year that data is available is

$$q_{it}K_{it} = \frac{q_{it}}{q_{i,t-1}} K_{i,t-1}(1-\delta_i) + I_{it},$$

which assumes that investment occurs at the end of the year. The recursive method employed here can generate negative market values q_tK_t, or market values significantly above zero when the book value of fixed capital is zero. This fact is taken into account to eliminate firms with implausible values for the stock of fixed capital.

R&D and technological capital stocks.

The CBBE data report data on R&D investment, defined as the firm's expenditures on search for innovations, and investment in technological capital, defined as the firm's expenditures on successful innovations externally generated to the firm. We treat these two variables as separate items. Since the stocks of these R&D and technological capital are unknown, to construct the corresponding stocks we assume, following Hall and Mairesse (1995), a depreciation rate for both stocks of 15% and a presample growth in real investment of 5%. Therefore, the stocks of R&D and technological capital, for the first year in which data is available, KRD_{i1} and $Ktec_{i1}$, are calculated as

$$KRD_{it} = \frac{RD_{i1}}{0.05+0.15}, \qquad Ktec_{i1} = \frac{Rtec_{i1}}{0.05+0.15}$$

where RD_{it} and $Rtec_{it}$ are the firm's investments in R&D and technological capital at period t. From the subsequent years, we compute the stocks of R&D and technological capital using a perpetual inventory method. As prices indices, we use the Retail Price Index at the 2-digit industry level.

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Table 1
Shares in Permanent Employment (%) by Occupation
Source: CBBE sample of 1080 manufacturing firms, 1986-1991
Annual changes in parentheses

Occupation	**Year**						**Change**
	1986	**1987**	**1988**	**1989**	**1990**	**1991**	**1986-91**
Blue Collar	66.01	65.49	64.95	64.31	63.22	62.25	
		(-0.52)	(-0.54)	(-0.64)	(-1.09)	(-0.97)	-3.76
White Collar	33.99	34.51	35.05	35.69	36.78	37.75	
		(+0.52)	(-0.54)	(+0.64)	(+1.09)	(+0.97)	+3.76
Managers	1.97	2.01	2.05	2.10	2.18	2.20	
		(+0.04)	(+0.04)	(+0.05)	(+0.08)	(+0.02)	+0.23
Professionals	11.34	11.79	11.91	12.12	12.57	13.14	
		(+0.45)	(+0.12)	(+0.21)	(+0.45)	(+0.57)	+1.80
Commercials	7.33	7.31	7.60	7.93	8.31	8.65	
		(-0.02)	(+0.29)	(+0.33)	(+0.38)	(+0.34)	+1.32
Clericals	13.34	13.40	13.48	13.54	13.72	13.76	
		(+0.06)	(+0.08)	(+0.06)	(+0.18)	(+0.04)	+0.42
Growth in real output (%)		8.28	7.83	7.82	0.06	0.04	

Table 2
Between Firms Variation in Occupation Shares in Permanent Employment
Source: CBBE sample of 1080 manufacturing firms, 1986-1991

Occupation	**Source of change**	**Year 1987**	**1988**	**1989**	**1990**	**1991**	**Total**
White Collar	Total change	0.523	0.536	0.644	1.090	0.974	3.767
	Between firms	0.045	0.197	0.021	0.279	0.276	0.818
	Within firms	0.517	0.330	0.729	0.975	0.944	3.495
	Covariance	-0.038	0.009	-0.107	-0.165	-0.247	-0.548
Managers	Total change	0.039	0.038	0.047	0.085	0.018	0.227
	Between firms	0.031	0.037	0.005	0.034	0.046	0.153
	Within firms	0.034	0.029	0.082	0.077	0.078	0.300
	Covariance	-0.026	-0.028	-0.040	-0.026	-0.106	-0.226
Professionals	Total change	0.445	0.125	0.209	0.442	0.578	1.799
	Between firms	-0.016	0.033	-0.009	0.084	0.018	0.110
	Within firms	0.471	0.133	0.246	0.428	0.531	1.809
	Covariance	-0.010	-0.041	-0.028	-0.070	0.028	-0.121
Commercials	Total change	-0.020	0.293	0.331	0.378	0.339	1.321
	Between firms	-0.031	0.065	0.042	0.141	0.114	0.331
	Within firms	-0.026	0.146	0.280	0.242	0.298	0.940
	Covariance	0.036	0.082	0.008	-0.005	-0.074	0.047
Clericals	Total change	0.061	0.080	0.056	0.184	0.040	0.421
	Between firms	0.061	0.062	-0.017	0.021	0.098	0.225
	Within firms	0.038	0.022	0.121	0.227	0.037	0.445
	Covariance	-0.038	-0.004	-0.048	-0.064	-0.096	-0.250

Note: The decomposition of the variation in the proportion of blue collar workers has been excluded for being redundant

Table 3
Job Creation and Job Destruction (%) in Permanent Employment by Occupation
Source: CBBE sample of 1080 manufacturing firms, 1986-1990

Occupation	**Type of adjustment**	**Year** **1987**	**1988**	**1989**	**1990**	**1991**
All	Job creation	3.99	4.42	4.63	3.70	3.29
	Job destruction	2.57	2.59	2.76	4.55	5.50
Blue collar	Job creation	2.98	3.51	3.19	3.26	3.09
	Job destruction	3.57	4.02	4.53	6.38	6.39
White collar	Job creation	4.56	5.23	4.72	5.64	4.91
	Job destruction	2.82	3.39	3.24	4.05	4.05
Managers	Job creation	4.65	5.49	5.21	7.27	5.42
	Job destruction	2.51	3.31	3.27	4.70	6.34
Professionals	Job creation	6.74	5.71	5.81	9.15	8.57
	Job destruction	2.68	4.35	4.41	6.97	5.83
Commercials	Job creation	6.47	10.54	8.86	10.07	6.52
	Job destruction	6.54	6.31	4.95	6.83	4.27
Clericals	Job creation	4.26	5.75	4.57	6.54	4.77
	Job destruction	3.60	4.85	4.49	6.60	6.23
Temporary	Job creation	34.49	33.04	34.46	23.17	17.57
	Job destruction	14.55	11.83	10.62	19.18	23.71

Table 4 Contribution (%) of the rates of growth by occupation to the changes in the proportion of Blue collars						
Occupation	**Year**					
	1987	**1988**	**1989**	**1990**	**1991**	**Total**
All	-0.52	-0.54	-0.64	-1.09	-0.97	-3.76
Managers	-0.03	-0.03	-0.03	-0.04	+0.02	-0.11
Professionals	-0.31	-0.11	-0.11	-0.17	-0.23	-0.93
Commercials	+0.01	-0.20	-0.20	-0.17	-0.12	-0.68
Clericals	-0.05	-0.07	-0.01	0.00	+0.13	0.00
Blue collars	-0.13	-0.12	-0.30	-0.70	-0.76	-2.01

Table 5 Descriptive Statistics (Weighted averages) Source: CBBE sample of 1080 manufacturing firms, 1986-1991						
	Year					
	1986	**1987**	**1988**	**1989**	**1990**	**1991**
Rates of growth (%)						
Real output		8.28	7.83	7.82	0.06	0.04
Employment		1.65	1.88	1.87	-0.82	-2.21
Net investment rates (%)						
Fixed capital		1.76	2.47	2.29	2.79	2.31
R&D capital		31.37	23.00	19.96	16.50	17.56
Technological capital		20.71	17.32	16.83	15.92	11.97
Number of firms introducing new capital inputs						
R&D capital		28	15	22	51	46
Technological capital		15	15	11	23	7

Table 6
Estimates of the Dynamic Model of Occupational Structure
Dependent variables: ln(Stocks of Labor Inputs)
First-differences GMM estimation
Sub samples: $I_{t-1}^{j} I_{t}^{j} = 1$

Explanatory variables	**Managers**	**Professionals**	**Commercials**	**Clericals**	**Blue collar**
Capital stocks					
$\ln(K_{t-1})$	0.0062 (0.035)	0.0609 (0.066)	0.0316 (0.073)	0.0091 (0.055)	-0.0087 (0.053)
$\ln(KRD_{t-1})$	0.0086 (0.027)	-0.0436 (0.033)	-0.0511 (0.037)	0.0142 (0.034)	-0.0208 (0.029)
$\ln(Ktec_{t-1})$	-0.0683 (0.033)	0.0266 (0.044)	-0.1063 (0.050)	0.0510 (0.036)	0.0676 (0.034)
Labor stocks					
$\ln(L_{t-1})$	-0.0610 (0.034)	0.0160 (0.059)	0.0630 (0.065)	0.1878 (0.057)	0.0322 (0.057)
$\ln(Lman_{t-1})$	0.7273 (0.037)	0.0209 (0.052)	-0.0246 (0.057)	0.0645 (0.047)	0.1357 (0.051)
$\ln(Lpro_{t-1})$	0.0218 (0.022)	0.6181 (0.041)	0.0847 (0.035)	0.0272 (0.029)	0.0450 (0.035)
$\ln(Lcom_{t-1})$	0.0027 (0.020)	-0.0130 (0.029)	0.2028 (0.029)	0.0001 (0.026)	0.0877 (0.030)
$\ln(Lcle_{t-1})$	0.0006 (0.016)	0.0079 (0.029)	0.0266 (0.027)	0.4754 (0.031)	0.0752 (0.025)
$\ln(Lblu_{t-1})$	0.0093 (0.016)	0.0123 (0.022)	0.0628 (0.022)	-0.0077 (0.021)	0.5904 (0.029)
$\ln(Ltem_{t-1})$	-0.0014 (0.007)	-0.0206 (0.011)	0.0110 (0.010)	-0.0166 (0.010)	-0.0269 (0.010)
New inputs					
$I(KRD_{t-1} > 0)$	0.0001 (0.045)	-0.0762 (0.059)	-0.0412 (0.050)	0.0529 (0.052)	0.0330 (0.049)
$I(Ktec_{t-1} > 0)$	0.0387 (0.061)	0.0751 (0.086)	0.3624 (0.088)	-0.0730 (0.081)	-0.2607 (0.084)
$I(Lpro_{t-1} > 0)$	-0.0064 (0.030)	-0.7102 (0.093)	-0.0981 (0.049)	-0.1693 (0.048)	-0.0275 (0.052)
$I(Lcom_{t-1} > 0)$	-0.0084 (0.036)	-0.0020 (0.059)	-0.3054 (0.088)	-0.0211 (0.052)	-0.1086 (0.059)
$I(Ltem_{t-1} > 0)$	0.0036 (0.014)	0.0208 (0.024)	-0.0389 (0.028)	0.0227 (0.020)	-0.0017 (0.020)
$\ln(Y_t)$	0.0736 (0.036)	-0.0562 (0.049)	-0.1003 (0.057)	0.0564 (0.046)	0.1433 (0.051)
$\ln((Ww/Wb)_t)$	-0.0212 (0.073)	-0.2444 (0.117)	-0.0539 (0.215)	0.0472 (0.103)	-0.1145 (0.108)
$\ln(P_t)$	0.3234 (0.193)	-0.3375 (0.280)	-0.1085 (0.380)	-0.6067 (0.290)	0.2267 (0.277)
$\ln(CU_t)$	-0.0221 (0.061)	0.1580 (0.081)	0.0408 (0.077)	0.2010 (0.082)	-0.0576 (0.070)
Wald tests					
Time dummies	3.11 (0.54)	4.56 (0.34)	12.76 (0.01)	1.58 (0.81)	11.43 (0.02)
Ind. dummies	225.40 (0.00)	41.19 (0.00)	49.73 (0.00)	24.37 (0.23)	46.03 (0.00)
Prop. scores	-	27.93 (0.00)	13.55 (0.09)	-	-
m_2 (2nd auto)	-0.03 (0.97)	-1.06 (0.29)	-1.27 (0.20)	-0.12 (0.91)	-0.60 (0.55)
Sargan-Hansen	151.14 (0.55)	162.47 (0.30)	173.91 (0.13)	138.71 (0.81)	132.78 (0.89)
No. observations	4320	3687	2317	4320	4320
No. companies	1080	962	637	1080	1080

Note: All reported estimates are two-step. Heteroskedasticity-robust standard errors reported in parentheses. The asymptotic distributions of the Wald tests for time dummies and industry dummies are χ^2 with 4 and 20 degrees of freedom respectively. m_2 is a test of second order serial correlation, asymptotically distributed as a standard normal. The Wald tests for the propensity scores evaluate the joint significance of the coefficients of the second order polynomial in the inverse of the Mill's ratio interacted with time dummies, and are aymptotically distributed as a χ^2 with 8 degrees of freedom. The Hansen-Sargan test is a general specification test, asymptotically distributed as a χ^2 with 154 degrees of freedom. The corresponding p-values of these tests are reported in parentheses. The last two rows of the table report the number of observations and the number of companies used in estimation.

Table 7

Estimates of the Dynamic Model of Occupational Structure

Dependent variables: ln(Stocks of Capital Inputs)

First-differences GMM estimation

Sub samples: $I^j_{t-1} I^j_t = 1$

Explanatory variables	**Total Capital**	**R&D Capital**	**Techn. Capital**
Capital stocks			
$\ln(K_{t-1})$	0.7655 (0.029)	0.0810 (0.029)	-0.0823 (0.023)
$\ln(KRD_{t-1})$	0.0142 (0.016)	0.4505 (0.012)	-0.0225 (0.014)
$\ln(Ktec_{t-1})$	0.0445 (0.021)	0.0811 (0.015)	0.5646 (0.017)
Labor stocks			
$\ln(L_{t-1})$	-0.0086 (0.031)	-0.2621 (0.019)	-0.0110 (0.056)
$\ln(Lman_{t-1})$	0.0902 (0.026)	0.1240 (0.012)	-0.0029 (0.015)
$\ln(Lpro_{t-1})$	0.0099 (0.016)	0.0336 (0.009)	0.0856 (0.020)
$\ln(Lcom_{t-1})$	0.0153 (0.014)	0.0933 (0.011)	0.0389 (0.016)
$\ln(Lcle_{t-1})$	0.0017 (0.013)	-0.0383 (0.009)	0.0694 (0.014)
$\ln(Lblu_{t-1})$	0.0007 (0.012)	-0.0197 (0.011)	-0.0147 (0.028)
$\ln(Ltem_{t-1})$	0.0047 (0.005)	-0.0055 (0.003)	-0.0036 (0.005)
New inputs			
$I(KRD_{t-1} > 0)$	-0.0605 (0.028)	-	0.0321 (0.017)
$I(Ktec_{t-1} > 0)$	-0.0284 (0.038)	0.0382 (0.014)	-
$I(Lpro_{t-1} > 0)$	-0.0357 (0.027)	-0.0347 (0.016)	-
$I(Lcom_{t-1} > 0)$	-0.0254 (0.030)	-0.2166 (0.038)	-0.0559 (0.043)
$I(Ltem_{t-1} > 0)$	-0.0045 (0.011)	-0.0354 (0.008)	0.0401 (0.013)
$\ln(Y_t)$	0.0367 (0.024)	0.1434 (0.009)	0.1164 (0.017)
$\ln((Ww/Wb)_t)$	0.0910 (0.074)	0.3997 (0.062)	0.0887 (0.111)
$\ln(P_t)$	-1.1476 (0.122)	-0.3073 (0.136)	-0.7538 (0.342)
$\ln(CU_t)$	0.0773 (0.036)	0.0500 (0.024)	-0.0210 (0.030)
Wald tests			
Time dummies	33.68 (0.00)	59.04 (0.00)	11.84 (0.02)
Ind. dummies	93.45 (0.00)	1613.48 (0.00)	151.68 (0.00)
Prop. scores	-	58.94 (0.00)	115.94 (0.00)
m_2 (2nd auto)	-0.20 (0.84)	-0.89 (0.37)	-1.99 (0.05)
Sargan-Hansen	190.43 (0.02)	153.05 (0.33)	92.00 (0.99)
No. observations	4320	646	466
No. companies	1080	214	143

Note: See Note to Table 7.

Table 8
Long Run Elasticities for White Collar Labor Inputs
based on the model estimates

	W/o dynamics	With dynamics	
		W/o feedback	With feedback
Elasticities for $Lman/Lblu$			
K	0.0149	0.0076	-0.0013
KRD	0.0294	0.1476	0.1614
$Ktec$	-0.1359	-0.2792	-0.2970
$I(KRD > 0)$	-0.0328	-0.0768	-0.0741
$I(Ktec > 0)$	0.2994	0.5930	0.5951
Y	-0.0697	-0.0980	-0.0761
Ww/Wb	0.0933	0.2461	0.2647
P	0.0967	0.5005	0.6840
Elasticities for $Lpro/Lblu$			
K	0.0696	0.1346	0.1376
KRD	-0.0228	-0.0244	-0.0231
$Ktec$	-0.0410	-0.0031	-0.0140
$I(KRD > 0)$	-0.1091	-0.2541	-0.2560
$I(Ktec > 0)$	0.3358	0.6559	0.6645
Y	-0.1995	-0.5207	-0.5065
Ww/Wb	-0.1299	-0.2445	-0.2570
P	-0.5643	-1.4222	-1.3753
Elasticities for $Lcom/Lblu$			
K	0.0403	0.0393	0.0355
KRD	-0.0303	0.0391	0.0460
$Ktec$	-0.1739	-0.1557	-0.1655
$I(KRD > 0)$	-0.0742	-0.1328	-0.1312
$I(Ktec > 0)$	0.6231	0.8864	0.8862
Y	-0.2436	-0.4654	-0.4510
Ww/Wb	0.0606	0.1894	0.1963
P	-0.3353	-0.8837	-0.7888
Elasticities for $Lcle/Lblu$			
K	0.0178	0.0139	0.0168
KRD	0.0350	0.1120	0.1115
$Ktec$	-0.0166	-0.0020	-0.0108
$I(KRD > 0)$	0.0199	0.0225	0.0180
$I(Ktec > 0)$	0.1877	0.3831	0.4010
Y	-0.0869	-0.2557	-0.2545
Ww/Wb	0.1617	0.4105	0.4005
P	-0.8334	-1.6807	-1.6574