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ABSTRACT

Changes in the Functional Structure of Firms and the Demand for Skill*

We describe and analyse the changes in the occupational structure of French manufacturing firms between 1984 and 1995. Firms employ a much greater proportion of engineers and researchers working on the design and marketing of new products and a much lower proportion of high-skilled experts working in administration-related activities. Firms have also reduced the share of production-related activities at both the levels of high-skilled and low-skilled workers. We develop a very simple labour demand model that shows the role played by technological change. By reducing the costs of activities that are the easiest to program in advance (notably for product fabrication), new information technologies make it possible to allocate more human and material resources to the activities that are the most difficult to program in advance, notably for the conception and marketing of new products. We show that this is the main channel through which new information technologies increase the demand for skill.

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1. Introduction

In most Western countries, firms employ a greater proportion of skilled workers compared to 20 or 30 years ago, even though the relative cost of skilled labor has not decreased. A consensus explanation has gradually emerged: goods and services are produced by technologies that require greater skills than in the past. Technological progress, it is argued, is intrinsically biased towards skilled labor[1].

Many studies have tried to test this assumption by analyzing the impact of new technologies on the demand for skills. The results of these evaluations are mixed: the diffusion of new technologies is accompanied by a substitution of high-skilled for low-skilled labor. This movement, however, only explains a relatively small part of the shift in demand for skilled workers[2]. Contemporary technological advancement seems to imply something of greater complexity than the simple substitution of computers for low-skilled labor, without, however, knowing exactly what is involved.

The underlying nature of technical progress is far from being fully identified,

[1] See for instance, Katz and Murphy (1992), Berman Bound and Griliches (1994), Autor, Katz et Krueger, (1998), Berman, Bound and Machin, (1998). See also the survey by Chennels and Van Reenen (1999).

[2] See Dunne, Haltiwanger and Troske (1996), Machin and Van Reenen (1998) or Goux and Maurin (2000) for firm-level or industry-level evidence. See also DiNardo et al. (1996), DiNardo and Pishke (1997), Entorf and Kramarz (1997), Troske (1997), Doms, Dunne and Troske (1997) for studies based on individual-level data.

and thus a number of questions remain unanswered. Why and how does technological change affect the demand for skills? What are the specific technologies and/or the specific forms of technological change that actually cause skill upgrading? And what are the specific skills that benefit the most from technological innovations?

In this paper, we try to address these issues and go beyond the existing evidence on skill-biased technological change (SBTC). We have concentrated on an often neglected aspect: contemporary technological progress fundamentally modifies the nature of the activities assigned to workers within firms. By reducing the relative costs of activities that are the easiest to program in advance and to automate (notably for product fabrication), new technologies make it possible to allocate more human and material resources to non-routine activities, notably for the conception and marketing of new products. The activities that are the most difficult to translate into formal language and program in advance require on average a higher proportion of skilled labor than the other activities : this is one of the main reasons why technological advancement appears, in the end, to be biased towards high-skilled labor.

1.1. New Technologies and New Organizations

A few recent studies have tried to further understand contemporary technological advancement and better identify the reasons for its impact on the demand for labor (Caroli and Van Reenen, 1999, Bresnahan et al., 1999a and 1999b). According to these studies, new technologies (NT) modify, above all, the way in which decisions are made in a firm. The new technologies give way to the emergence of a more decentralized organization where responsibilities are more widely distributed. To be fully operational, this new form of decentralized organization requires a greater number of skilled workers than before. Within this analytical framework, the SBTC can be interpreted as the consequence of the re-organization of the workplace, made possible by the diffusion of new technologies[3].

In this paper, we develop and test a different, yet complementary, interpretation. Our working hypothesis is not that the diffusion of new technologies modifies decision-making processes within firms, but that it modifies the nature of the activities that are assigned to workers.

In a firm, not all the workers are allocated to manufacturing and production activities. Some workers are there to insure the legal and administrative man-

[3]Such a complementarity between technology and work organization is also emphasized by David (1986) to explain the slow diffusion of electricity in US manufacturing until the 1920s.

agement of the firm. Others are needed to insure the transportation, distribution and delivery of the goods produced. Finally, some workers are responsible for making market studies and working on the conception and development of future products.

Generally speaking, these elementary activities differ in complexity and average skill level needed to do them. These activities, however, also differ in the degree to which they can be formalized and programmed in advance. The most programmable activities are, on average, simpler to perform than the less-programmable ones, but the two dimensions simple-to-perform versus easy-to-program are nonetheless conceptually and empirically very different from each other[4].

This paper tests the assumption that skill-biased technological change corresponds, above all, to the decline in the most programmable activities in favor of those that are the least programmable, whether designing new products that are better adapted to the market or promoting and distributing those new products

[4] To repair a machine is not necessarily a complex activity, but -by construction- it is very difficult to program this activity in advance. Conversely, the production process of chemicals can be very complex, but relatively easy to formalize and program. In the sociological literature, the degree to which a given activity can be formalized has long been acknowledged as a major determinant of firm organizations. In his case study of a French monopolistic firm, Crozier (1963) reckons that some activities - like machine repair- cannot be formalized, nor programmed in advance, even in a highly bureaucratic organization. In his demonstration that no organization can stand complete formalism, Perrow (1970) makes a distinction between activities that cannot be routinized (research, sales) and those that can be programmed (like production) .

where there is the greatest demand. In other words, our general conjecture is that the dominant effects of new technologies are not that they favor the substitution of complex activities (exercised by high-skilled workers) for simple ones (exercised by low-skilled workers), but that they significantly modify the nature of the activities that workers must perform.

1.2. A Test for the Causal Effects of New Technologies

To test our hypothesis, we have used a unique French administrative database with longitudinal information at the firm level on the distribution of both high-skilled and low-skilled jobs across five categories of elementary activities: Conception/Development, Logistics/Transportation, Administration, Production and Sales/Marketing.

Generally speaking, the statistical and econometric analysis is consistent with our working hypothesis. From a simple, descriptive viewpoint, our dataset reveals that firms have greatly modified the distribution of workers across the different activities over the last few years, concurrent with the emergence of new technologies. Firms have reduced the share of jobs linked to production-related activities, at both the levels of high-skilled and low-skilled workers. On the other hand, they have reinforced jobs linked to the conception and marketing of products.

Firms employ a much greater proportion of upper-level professionals working on the design and development of new products and a much lower proportion of high-skilled experts working on organizing and supervising the production processes. Statistically, more than half of the increase in skill level can be explained by the increase in the share of conception/development and sales/marketing activities, where the need for high-skilled workers is the highest[5].

Going a step further, we have developed and tested a labor demand model, which confirms the role played by the diffusion of new technologies. Within the group of skilled workers, the diffusion of computers and computer-aided technologies increase significantly the relative productivity of conception/development and sales/marketing activities.

In sum, the introduction of new technologies results in an increase in the demand for high-skilled workers and our paper reveals how that occurs. New technologies substitute for workers whose activities can be readily formalized and programmed. New technologies reduce the demand for production workers in manufacturing, but new information technologies (like computer-aided design) also

[5] Given that conception and sales/marketing activities correspond to cognitive non-manual tasks, these findings are consistent with Autor, Levy and Murnane (2001). Conceptualizing jobs in terms of routine versus non-routine and cognitive versus manual, they find that computerization is associated with a rise in the relative industry demand for non-routine cognitive tasks.

reduce the demand for engineers doing routine design work.

The paper is organized in the following way: first, we describe our data. In Section III, we provide some simple statistical evidence showing that technical change increases the demand for non-routine, non-manual activities within the different skill groups. In Section IV, we develop a model that makes it possible to identify the relationship between the diffusion of computers (and computer-aided technologies) and the relative productivity of the different types of skills and activities.

2. Data

We have used data from several different French data sources (see the data appendix). The first one is the Enquête Structure des Emplois (ESE). This administrative database gives the occupational structure of all French work establishments with more than twenty workers. Our second source is the Bénéfices Industriels et Commerciaux (BIC), which is an annual fiscal report that provides information on the economic activity of all French firms that employ more than twenty workers, or whose total sales exceed 3 million French francs (some US$500,000). Information on the wage structure comes from the French Labor Force Surveys, and the information on the diffusion of new technologies comes mostly from the Enquête sur la Technique et l'Organisation du Travail auprès des Travailleurs Occupés (TOTTO), the 1987 supplement to the Labor Force Survey. We have also used a survey on organizational changes conducted by the French Ministry of Industry.

2.1. Data on Firms' Occupational Structure and Economic Activity

We have used the 1984-1995 ESE files aggregated at the firm level to measure firms occupational structure[6]. The ESE gives the detailed industry (four-digit classification) and identification number (SIREN) of each firm. It also provides the detailed distribution of workers across elementary activities and skill levels. More specifically, workers' positions are coded according to the Nomenclature des Professions et Catégories Socioprofessionnelles (PCS), which is the official French socioeconomic classification (four digits, 355 different positions). This classification is used as a reference in French collective agreements[7]. The first digit corresponds to the four main skill levels that are distinguished in French collec-

[6] For each establishment, the first 9 digits of its identification number (SIRET number) is the identification number of the firm to which it belongs. Thus, it is possible to gather establishments that belong to the same firm.

[7] The PCS classification is not a standard occupational classification. Two persons with the same occupation can be coded differently depending on their employment status (wage earner versus non-wage earner), their sector (public versus private) and within each sector depending on their relative position within the skill hierarchy (which is, in general, defined in terms of education, seniority and relative wages). Occupation specific distinctions only occur within groups of workers (i.e., categories socioprofessionnelle) that are homogeneous from an employment status, sector and skill-level viewpoint.

tive agreements[8] : (a) cadres (i.e. mostly upper-level managers, engineers and professionals), (b) professions intermédiaires (i.e. lower-level managers and professionals, supervisors, technicians), (c) ouvriers et employés qualifiés (i.e. skilled manual and non-manual workers) and (d) ouvriers et employés non qualifiés (i.e. low-skilled manual and non-manual workers). Our definition of high-skilled workers combines (a) and (b). It includes managers, professionals, engineers, technicians and supervisors. Our definition of low-skilled workers combines (c) and (d).

The second and third digits of the PCS classification correspond to either the type of industry or the type of activity of the worker. The fourth digit is occupation specific. In this paper, we have broken down workers' positions into the five main classification activities: Administration, Sales/Marketing, Production, Logistics/Transportation and Conception/Development. Administrative jobs are those related to law, accounting, business management and other general administrative work. Sales/Marketing includes sales staff, engineers and professionals involved in product marketing and advertising. Production workers range from unskilled blue-collar workers to production engineers. The Logistics/Transportation

[8] The collective agreements specify the typical relative wage and educational level for each position. The first digit makes it possible to identify sets of jobs that have about the same position in the hierarchy of wages and educational level.

category includes cleaners, repairmen, drivers and those who supervise and organize those activities. Finally, the Conception/Development activity includes all workers who design new products and conduct studies for the development and marketing of new products[9].

The dataset we have used in this paper corresponds to the matching of the ESE and the BIC surveys. Each year, we know for each firm: the number of workers in each of the nine (activity x skill level) cells[10], the industry, and the value added. We have focused on the manufacturing industries and on firms that were not sampled, dropped and then re-sampled between 1984 and 1995. This makes an unbalanced panel that contains about 10,000 firms each year. Taken together, these firms employ on average 1,500,000 workers each year. Table 1 describes the average distribution of these workers across activities and skills over the 1984-95 period.

[9] Hollanders and Ter Weel (1999) use industry-level data to analyze the impact of R&D diffusion on the distribution of workers across three basic job categories : blue collar workers, scientists/engineers and other white collar workers. Our analytical framework is different : the distribution of workers across activities is different from the distribution across scientists, blue collar and white collar workers. For instance, we have scientists and engineers within all the different activities. Within our framework, to analyze the increase in the share of conception jobs is different from analyzing the increase in the share of scientists and engineers.

[10] Notice that high-skilled workers can be found in each of the five main functions, while low-skilled workers can only be found in four of them: by construction, there is indeed no low-skill workers within our Conception/Development activity. All in all, we can distinguish nine (i.e. 5+4) positions according to skill level and activity.

2.2. Data on the Wage Structure

The data on the wage structure come from the French Labor Force Surveys (LFS). One interesting feature of the French statistical system is that the same occupational code (PCS) is used for collecting administrative firm-level data (such as ESE) and for the household-based surveys (such as the Labor Force surveys). The LFS conducted between 1984 and 1995 make it possible to estimate the wage structure according to skills and activities using exactly the same definitions for skills and activities as the ones used in our ESE files. Table 2 shows the mean wages and educational levels by activity. The data implies that wage differentials across skills are much greater than wage differentials across activities. This confirms that our measurements for activities and skills describe two distinct dimensions of the occupational structure. The activities describe the very different types of work that employee do, even though within each skill level, the wages and educational levels do not vary across activities.

2.3. Data on new technologies

The French Labor Force Survey is a rotating panel. Every year, a third of the sample exits. In addition to the questions included in the LFS, the exiting respondents are given a special supplement. In 1987, the supplement was on new technologies. About 9,000 workers were interviewed. For each respondent, we know whether he/she (a) uses a personal computer (PC), (b) uses a numerical-command (NC) machine [11]. These data make it possible to estimate the diffusion rates of PC and manufacturing technologies.

In addition, we have estimated for each industry the share of firms that have introduced computer-aided production management as well as computer-aided inventory management and computer-aided design between 1989 and 1992. To construct these three variables, we have used a survey on organizational changes conducted in 1993 by the French Ministry of Industry. These variables provide measurements for the extent to which some basic activities are programmable in advance. Table 3 shows that the rates of diffusion for the different technologies vary significantly across industries. The use of computers is three times greater in the energy production sector than in the food product sectors. NC machines are much more frequently used in the automobile sector than in the food product sectors.

[11] This kind of production technique is typically found in the chemicals industry as well as in certain food processing industries such as for milk or fruit juice.

3. The Impact of Technological Change on the Demand for Skilled labor: Some Basic Evidence

In this section, we provide some simple statistical tests to find out the impact of technological change on the labor-demand composition. To anticipate the findings, our tests suggest that technological change favors (a) the substitution of high-skilled for low-skilled labor within the different activities, (b) the substitution of jobs linked to the conception/development and sales/marketing of new products for those linked to production-related activities. We also find that the employment shifts towards conception/development and sales/marketing activities have a stronger impact on the aggregate demand for high-skilled labor than the employment reallocations towards high-skilled jobs within activities : shift (b) is larger than shift (a).

Generally speaking, these preliminary results are consistent with our general hypothesis that technological change increases the demand for non-programmable cognitive activities and that this is the main channel through which it increases the demand for skilled workers. In the next section, we will provide a more general test for this hypothesis and try to identify the role of new information technologies.

3.1. Within-Industry Skill Upgrading: Measurement and Interpretation

The usual method for evaluating the impact of technological change on the demand for skilled labor is by measuring the share of skill upgrading that can be explained by within-industry employment reallocation. To understand the rationale behind this method, let us consider an economy composed of $i = 1, .., S$ industries (or firms), each using both high-skilled and low-skilled workers in quantities L_{Hit} and L_{Lit} at date t. Let us assume that the production function for industry i is given by $\frac{1}{A_{it}} F_i(\frac{L_{Hit}}{a_{Hit}}, \frac{L_{Lit}}{a_{Lit}})$, where F_i is a first-degree homogenous function and A_{it} is the Hicks-neutral technological progress component. The key parameters in this analysis are a_{Hit} and a_{Lit}. They represent the technological progress dimensions that impact in different ways the high-skilled and low-skilled labor input. Employers are assumed to minimize their cost $(w_{Ht}L_{Hit} + w_{Lt}L_{Lit})$ subject to $(A_{it}y_{it} \leq F_i(\frac{L_{Hit}}{a_{Hit}}, \frac{L_{Lit}}{a_{Lit}}))$, where w_{Ht} (w_{Lt}) represents the wage paid to high-skilled (low-skilled) workers

Within this framework, the standard theory of the firm implies that the relative demand for skilled input $(\frac{L_{Hit}}{a_{Hit}}/\frac{L_{Lit}}{a_{Lit}})$ necessarily decreases with its relative cost $(a_{Hit}w_{Ht}/a_{Lit}w_{Lt})$[12]. In the absence of significant variations in the relative wage

[12] According to the Shepard's lemma, the demand for labor k at date t in industry i can be

(i.e., holding w_{Ht}/w_{Lt} constant), this theoretical relationship between relative prices and quantities implies that variations in the relative demand for skilled workers within industry i (i.e., $\Delta(L_{Hit}/L_{Lit}) \neq 0$) necessarily signal skill-biased technological changes within that industry (i.e. $\Delta(a_{Hit}/a_{Lit}) \neq 0$). Put differently, when relative wages are stable (as shown by table 4), significant within-industry skill upgrading provides a very simple test for the existence of biased technological change[13].

We have used our dataset to measure the contribution of within-industry employment reallocation to the aggregate skill-upgrading in France (see the first three rows of Table 4). The results are in line with the SBTC hypothesis: the contribution of within-industry employment reallocation[14] is positive and large, while the contribution of between-industry reallocation is almost negligible. All in all, given that the relative wages remain stable between 1984 and 1995, tech-

written $L_{kit} = a_{kt}A_{it}y_{it}c_{ik}(a_{Ht}w_{Ht}, a_{Lt}w_{Ht})$, where the unit cost function c_{ik} is homogenous of degree zero and decreases with $a_{kt}w_{kt}$. Thus $\frac{L_{Hi}}{a_{Hit}}$ $(\frac{L_{Lit}}{a_{Lit}})$ can be written as a decreasing (an increasing) function of $a_{Hit}w_{Ht}/a_{Lit}w_{Lt}$.

[13]This result is fairly general: we have made no specific assumptions about the production functions F_i (in particular, about the elasticity of substitution between the different inputs). This is no doubt why this decomposition method is so attractive and so frequently used. Notice, however, that a significant contribution of within-industry reallocation signals biases in the technological changes (i.e. $\Delta(a_{Hit}/a_{Lit}) \neq 0$), but neither the sign nor the magnitude of the within-industry contribution convey any information about the direction or the magnitude of the biases.

[14]Formally, this contribution corresponds to $\sum_i \frac{L_{it}}{L_t}\Delta(\frac{L_{Hit}}{L_{it}})$.

nological change seems to be one plausible cause for the skill upgrading that took place within the French manufacturing industry during that period.

3.2. Labor Demand Movements Within Activities and Within Skill Groups

The preceding analysis implicitly assumes that high-skilled (low-skilled) labor is homogenous and that technological change has the same impact on all high-skilled (low-skilled) jobs. It neglects the fact that there are several different categories of high- and low-skilled jobs within each firm. Firms do not amount to one sole activity. In addition to their manufacturing activities, they must prospect the new markets and define new products. They must also transport their products to the distribution centers, sell them and manage after-sales service. In every firm, different kinds of activities, and thus different forms of high- and low-skilled labor, necessarily coexist. These facts lead us to ask the following questions: To what extent is technological change favorable to all types of labor? To what extent is it more beneficial to some types of labor than to others? The purpose of this section is to extend our analytical framework in order to provide simple answers to these questions.

We still assume there are two skill levels, but now we assume that they are distributed across two different elementary activities[15] P and Q. Thus, we have $(2 \times 2 = 4)$ labor inputs. The production in industry i can now be written as (we momentarily drop subscript i):

$$(1) \quad y_t = F\left(\varphi_P\left(\frac{L_{PHt}}{a_{PHt}}, \frac{L_{PLt}}{a_{PLt}}\right), \varphi_Q\left(\frac{L_{QHt}}{a_{QHt}}, \frac{L_{QLt}}{a_{QLt}}\right)\right)$$

where F is the production function, $L_t = (L_{PHt}, L_{PLt}, L_{QHt}, L_{QLt})$ the vector of labor inputs. The a_{Pkt} (a_{Qkt}) parameter denotes the component of technical progress that affects skill k $(k = H, L)$ and activity P (Q). For now, to keep the framework as simple as possible, we assume that the φ_P and φ_Q can be proxied by constant elasticity of substitution (CES) functions. Within this framework, the high-skilled/low-skilled labor ratio can be expressed a very simple (log) linear function of relative wages and asymmetries linked to technological change[16]. After first-differentiation, we obtain (for each elementary activity $A = P$ or Q):

$$(2) \quad \Delta \ln \frac{L_{AHt}}{L_{ALt}} = (1 - \sigma_A)\Delta \ln \left(\frac{a_{AHt}}{a_{ALt}}\right) - \sigma_A \Delta \ln \left(\frac{w_{AHt}}{w_{ALt}}\right),$$

where σ_A is the elasticity of substitution of high-skilled for low-skilled labor within activity A, while $\frac{w_{AHt}}{w_{ALt}}$ represents the relative wage of skilled labor within

[15] This analytical framework can be easily generalized to N different elementary activities, see Maurin and Thesmar (2001). In the empirical application, we actually distinguish five elementary activities.

[16] By construction, we have $\frac{\partial y_t}{\partial L_{Akt}} = \frac{\partial F}{\partial \varphi_A} \frac{\partial \varphi_A}{\partial L_{Akt}}$ for each A and k. Within this framework, the marginal rate of subsitution can be written $\frac{\partial y_t}{\partial L_{AHt}} / \frac{\partial y_t}{\partial L_{ALt}} = \frac{\partial \varphi_A}{\partial L_{AHt}} / \frac{\partial \varphi_A}{\partial L_{ALt}} = (a_{AHt}/a_{ALt})^{(\sigma_A - 1)/\sigma_A} (L_{AHt}/L_{ALt})^{-1/\sigma_A}$. Equality (2) corresponds to the equality between this marginal rate of substitution and the relative cost w_{AHt}/w_{ALt}.

A. Once the relative wage $\frac{w_{AHt}}{w_{ALt}}$ is stable (i.e., $\Delta \ln \left(\frac{w_{AHt}}{w_{ALt}}\right) = 0$), the variations in high-skilled/low-skilled labor ratio provide us with a direct measurement of the impact of technological change on the relative demand for skilled labor within activity A.

Let us now assume that F can also be proxied by a CES function and that both F, φ_P and φ_Q have the same elasticity of substitution[17] σ. Under these two supplementary assumptions, we obtain for each skill level $k \in \{H, L\}$,

$$(3) \quad \Delta \ln\left(\frac{L_{Pkt}}{L_{Qkt}}\right) = (1-\sigma)\Delta \ln \left(\frac{a_{Pkt}}{a_{Qkt}}\right) - \sigma \Delta \ln \left(\frac{w_{Pkt}}{w_{Qkt}}\right).$$

Once the relative wage $\frac{w_{Pkt}}{w_{Qkt}}$ is stable within a given skill group $k \in \{H, L\}$, the substitution rate of activity P for activity Q represents a direct measurement for the impact of technological change on the relative demand for activity P within this skill group.

All in all, to test for the impact of technological change on the relative demand for skills, we only have to compare the dynamics of the relative wage and the substitution rate of high- for low-skilled labor within each activity. Symmetrically, to test for the impact of technological change on the relative demand for activity P, we only have to compare the dynamics of the between-activities wage differentials and the substitution rate of activity P for the other types of activities within each

[17] This assumption is relaxed in the last section.

skill group.

Tables 5 and 6 provide the basic ingredients for these comparisons. Table 5 shows the average substitution rate of high-skilled for low-skilled labor within the different elementary activities (production/manufacturing, administration, sales/marketing, logistics/transportation, and conception/development), while Table 6 shows the average substitution rate of each basic activity for the other activity within the different skill groups. We obtain three basic results :

(1) First, we find a movement towards more highly skilled labor within the different activities (table 5). At the same time, the within-activity wage differentials remain very stable across time[18]. These results suggest that technological change is intrinsically favorable to high-skilled work. Technological change does not affect each activity uniformly, however. The impact is particularly strong within the logistics/transportation activities and negligible within administration-related ones.

(2) Second, within the highly skilled labor group, we find a move towards non-routine cognitive activities. More specifically, we observe significant substitutions of conception/development and sales/marketing activities for production

[18] This result is consistent with Goux and Maurin (2002) who find that relative labor costs remain highly stable in France over the last decade.

and administration activities (table 6, section a). At the same time, we do not observe any significant variations in the relative wages of conception/development workers or in the relative wages of administration high-skilled workers. These results suggest that technological change is intrinsically favorable to the substitution of conception/development and sales/marketing activities for administration and production activities within the group of high-skilled workers.

(3) Third, within the less skilled group, there is a move towards more administrative and sales/marketing activities (table 6, section b). At the same time, the relative wages of workers in administration or production-related activities do not vary significantly across time. Technological change seems intrinsically favorable to non-manual activities within the group of low-skilled workers.

Our findings confirm that technological change does not uniformly affect all types of activities and skills. New technologies favor, above all, high-skilled jobs related to non-routine, cognitive activities and low-skilled jobs related to non-manual activities.

To evaluate the overall impact of activity-biased technical change on aggregate skill upgrading, we have decomposed the within-industry skill upgrading (Δ_{within}) into a between-activity component (Δ_{WB}) and within-activity components (Δ_{WWA} for $A = P, Q$):

$$(4) \quad \Delta_{within} = \underbrace{\sum_{i,A=P,Q} \frac{L_{it}}{L_t}.\frac{L_{AHit}}{L_{Ait}}.\Delta\left(\frac{L_{Ait}}{L_{it}}\right)}_{\Delta_{WB}} + \underbrace{\sum_{A=P,Q}\sum_{i} \frac{L_{it}}{L_t}.\frac{L_{Ait}}{L_{it}}.\Delta\left(\frac{L_{AHit}}{L_{Ait}}\right)}_{\Delta_{WWA}}$$

Table 4 provides the results of this decomposition. Interestingly, the between-activity component (Δ_{WB}) is more important than the within-activity components. Employment reallocation from production and administrative activities towards sales/marketing and conception/development activities accounts for an increase of 2.8 points in the share of skilled workers, while within-activity employment reallocation from low- to high-skilled jobs only accounts for an increase of 2.3 points. The majority of the increase in skill level can be explained not because technological progress intrinsically favors high-skilled jobs, but because it favors certain forms of activities that require the most highly-skilled workers.

4. The Impact of the Diffusion of New Technologies

The preceding analysis suggests that technological advancement has several distinct effects on the demand for labor. It leads to the substitution of high-skilled for low-skilled workers within the firms' different elementary activities. At the same time, for the highly skilled group, it favors the development of conception/development and sales/marketing activities to the detriment of administration and production-related activities. For the less skilled workers, it increases the relative importance of non-manual activities.

In sum, technological progress involves more complex restructuring than the simple substitution of new technologies for low-skilled labor within firms.

As convincing and simple as this may seem, the method developed in section 3 does not make it possible to identify the underlying source of the changes in labor demand. Therefore, many questions remain unanswered. Why does technological progress lead to the replacement of administration and production specialists by conception or sales and marketing experts? What kind of new technologies drives these shifts?

In order to shed light on these issues, we have performed supplementary regressions using direct information on technological change. As described by equation (2), if the relative cost of skilled labor remains unchanged (as shown by table 5), then a labor-demand movement towards skilled jobs necessarily arises from new technologies. We test this assumption by regressing (for each activity) the variations of the high-skilled/low-skilled labor ratio on variables measuring the diffusion of new technologies[19] (see Table 7). Interestingly, we find a positive correlation between the diffusion of personal computers and computer-aided management tech-

[19] We have also introduced time dummies to control for the potential impact of the annual variations in the relative cost of high-skilled labor .

nologies and the increase in the share of high-skilled workers within administration, logistic/transportation and sales/marketing activities. These findings provide direct evidence that new information technologies substitute for low-skilled workers within most elementary activities.

In table 8, we analyze the impact of new information technologies on the labor-demand movements towards the most immaterial and least programmable activities. More specifically, we focus on two specific labor-demand movements, (a) the movement from (Production+Administration+Logistic/Transportation) activities towards (Conception/Development+Sales/Marketing) activities, within the group of high-skilled jobs and (b) the movement from (Production+Logistic/Transportation) activities towards (Administration+Sales/Marketing) activities within the group of low-skilled jobs. The first movement captures the increasing importance of cognitive non-routine activities within the group of high-skilled jobs. The second movement measures the increasing importance of non-manual actvitivies within the group of low-skilled jobs. As shown by equation (3), if the relative wages between activities are unchanged (as shown by table 6), then such labor-demand shifts arise necessarily from technological changes.

According to table 8, there is a link between the diffusion of personal computers (and NC machines) and the rise in the share of development/marketing activities within the group of high-skilled jobs. New information technologies and new production technologies seem to complement not only high-skilled jobs, but also activities involving non-programmable problem and interactive activities within the group of high-skilled jobs. In contrast, none of the technologies analyzed in this paper can be directly associated with an increase in the share of non-manual activities within the group of low-skilled jobs.

In sum, our data provide some direct evidence that the diffusion of new technologies has actually shifted the demand for labor not only towards the most complex and highly-skilled activities, but also towards the least programmable ones, regardless of their complexity. They also suggest that the connection between new technologies and the changes in the nature of activities assigned to low-skilled workers cannot be identified under the assumption of constant elasticity of substitution used to obtain equations 2 and 3.

4.1. Extensions

As a matter of fact, the previous diagnoses are only valid under rather restrictive assumptions on the elasticities of substitution between the different labor inputs[20]. In this last subsection, we develop a model that does not impose restrictions on

[20] To be more specific, they assume that the elasticities of subsitution between skill groups and between tasks are the same.

the degree of substitution between the different activities and skills.

Keeping the notations from the preceding sections, let us assume that the production at date t is given by $\frac{1}{A_t}F\left(\frac{L_{PHt}}{a_{PHt}}, \frac{L_{PLt}}{a_{PLt}}, \frac{L_{QHt}}{a_{QHjt}}, \frac{L_{QLt}}{a_{QLt}}\right)$ where F is an α-degree homogenous production function. Employers are assumed to minimize their costs ($W_t = w_{Ht}L_{PHt} + w_{Ht}L_{QHt} + w_{Lt}L_{PLt} + w_{Lt}L_{QLt}$) subject to $A_t y_t \leq F(\frac{L_{PHt}}{a_{PHt}}, \frac{L_{PLt}}{a_{PLt}}, \frac{L_{QHt}}{a_{QHt}}, \frac{L_{QLt}}{a_{QLt}})$.

Within this framework, determining the asymmetries of technological progress is simply a question of determining the extent to which the different a_{Akt} parameters (with $A = P, Q$ and $k = H, L$) follow different trends over time. For the sake of simplicity, let us assume that the ($\gamma_{Ak} = \frac{da_{Akt}}{a_{Akt}} - \frac{da_{PLt}}{a_{PLt}}$) differentials are constant within the different industries and across time. For an elementary activity A, ($\gamma_{AH} < \gamma_{AL}$) means that the technological progress is skill-biased and raises the relative productivity of skilled workers within A. Within a given skill group k, ($\gamma_{Ak} < \gamma_{Pk}$) means that there exists an activity-biased technological change which raises the productivity of A-type activities compared to P-type activity within k.

With these notations, let us consider a firm j and Δ_{jt} the impact of technological change on j's costs (i.e., $\Delta_{jt} = (w_{Ht}\Delta L_{PHjt} + w_{Ht}\Delta L_{QHjt} + w_{Lt}\Delta L_{PLjt} + w_{Lt}\Delta L_{QLjt})/\ W_{jt}$). The basic theory of the firm provides us with a fairly simple linear relationship between Δ_{jt} , the output growth rate $\frac{\Delta y_{jt}}{y_{jt}}$ and the γ_{Ak} parameters. More specifically, we have (see appendix A):

$$(5) \quad \Delta_{jt} = \frac{1}{\alpha}.\frac{\Delta y_{jt}}{y_{jt}} - \sum_{(A,k)\neq(P,L)} \gamma_{Ak} M_{Akjt} + v_i + u_{jt}$$

where M_{Akjt} represents the share of activity A-skill k labor in the wage bill[21] while i is j's industry, v_i an industry fixed effect which captures the Hicks neutral component of techological change and u_{jt} a zero-mean random variable which represents measurement errors.

Equation (5) simply shows that skill-biased technological change (i.e., $\gamma_{AH} < \gamma_{AL}$) reduces the total costs all the faster when skilled-labor accounts for a large proportion of the wage bill. Similarly, once it is biased towards non-programmable activities, technological change reduces total costs all the faster when these activities represent an important proportion of the firms' activities. Within this framework, we only have to regress Δ_{jt} on the different share of labor inputs in the wage bill (controlling for the output growth rate and industry dummies) to evaluate the asymmetries of technological progress[22]. Generally speaking, the

[21] The share of low-skilled production workers in the wage bill (i.e., M_{PLjt}) is taken as reference.

[22] From an econometric viewpoint, the main problem with equation (5) is that the shares of labor inputs in the wage bill are likely to be measured with errors at the firm level. Such measurement errors in the explanatory variables can generate significant endogeneity biases in standard OLS estimates. To address this issue, the estimations will be carried out by the generalized method of moments. This estimation technique allows for the endogeneity of the regressors and the heteroskedasticity of the residuals. The instrumental variables correspond

most negative regression coefficients correspond to the highest γ_{Ak} and make it possible to identify the labor inputs which productivity benefits the most from new information technologies.

Table 9 shows the results of these regressions[23]. The highest estimated γ_{Ak} (i.e. the most negative regression coefficients) correspond to conception/development-related jobs and to sales/marketing and administration-related high-skilled jobs. The main effect of technological change is to increase the relative productivity of these three categories of high-skilled workers[24]. The lowest estimated γ_{Ak} (i.e. the most positive regression coefficients) corresponds to Sales/Marketing low-skilled jobs and to production-related high-skilled jobs. Technological change contributes to a decrease in the relative productivity of the engineers and technicians in charge of the production process and of the routine clerks that contribute

to the lagged value (for two and three periods) of the forcing variables. We provide Sargan statistics to test for the orthogonality between the disturbance and the regressors.

[23] Table 9 also shows that (a) the estimated $1/\alpha$ is positive and significantly greater than 1, which is consistent with the usual hypothesis on decreasing return-to-scale, (b) the Sargan statistics indicate no significant correlation between our instruments and the error terms. We have also checked that the inclusion of dummy variables indicating the years of entry and exit from the panel as supplementary forcing variables did not affect our estimations (see Table 9, model 2). This result indicates that the attrition process is not a significant source for biases (Verbeeck and Nijman, 1996).

[24] The basic interest of these models is to show the role of technical changes without imposing restriction on the elasticities of substitution. The estimated productivity impacts cannot be interpreted as direct explanations for the observed changes in the occupational structure, however. The employment effects of these productivity impacts actually depend on elasticities of substitution.

to sales/marketing activities. In general, technological advancement leads to an increase in the productivity of high-skilled jobs linked to the most immaterial activities to the detriment of the high-skilled jobs most directly involved in the manufacturing and transportation processes. It should also be emphasized that technological change increases the relative productivity of high-skilled workers within the administration-related and sales/marketing activities. New technologies could be the key to explaining skill upgrading within these two categories of activities.

We have performed supplementary regressions (not reported) assuming that the impact of new information technologies on labor-demand composition varies across sectors according to the diffusion of new technologies. If T_i denotes the share of workers that use technology T in sector i at the beginning of the period, these models assume that $\gamma_{Aki} = \gamma_{Ak} + \alpha_{Ak} T_i$ where α_{Ak} can be interpreted as the impact of technology T on workers' productivity within the group of jobs that corresponds to activity A and skill k. These regressions confirm that the increase in the relative productivity of conception/development and sales/marketing activities is significantly stronger in industries where the introduction of computer-aided production and inventory management is the easiest. They also reveal some correlation between the diffusion of computers and the relative productivity of conception/development (non-manual) activities within the high-skilled (low-skilled) group. The regression coefficients α_{Ak} are poorly estimated, however.

From our viewpoint, this array of results confirms that the diffusion of new technologies favors above all the activities that are the most difficult to formalize and program in advance. It is mostly because these activities require on average higher skill levels than the other activities that technological advancement appears to be biased towards skilled workers.

We have also estimated models testing whether productivity trends vary across industries with variables measuring exposure to international competition or products turnover (results not reported, see Maurin and Thesmar, 2001). These models show that there are no significant links between the degree of exposure to international trade and trends in relative productivity. Similarly, they indicate that the variations in productivity trends across activities are more or less the same whether the share of new products in total sales is high or low. The nature of competition does not seem to be as important as the ability of new technologies to perform programmable activities in determining firms' functional structure.

In sum, as far as French manufacturing industries are concerned, we have an array of findings indicating that skill-biased technological change corresponds to two basic mechanisms. The first one is the computerization of some basic low-skilled activities. The second basic mechanism is the substitution of non-programmable activities for programmable ones, regardless of the complexity level of the activities in question. In particular, the new technological environment makes it possible to increase the share of conception/marketing and sales/distribution activities, which indirectly increases the need for high-skilled workers.

5. Conclusion

Our study, based on new French data, contributes in several ways to improving our understanding of the effects of technical change on the demand for labor:

(1) New technologies increase the demand for cognitive non-programmable activities within firms, thus modifying the nature of work assigned to both highly skilled and less skilled workers. Highly skilled workers are increasingly assigned to conception/development and sales/marketing activities. Less skilled workers are increasingly assigned to non-manual administration-related activities.

(2) The increase in the share of cognitive non-programmable activities is the main channel through which new information technologies contribute to increasing the demand for highly skilled workers. These activities require more highly skilled workers than activities that can be readily formalized and programmed in advance.

(3) New technologies also increase the demand for highly skilled workers within

activities. For instance, they contribute to a significant rise in the share of highly skilled workers within production and logistics/transportation activities. But the direct substitution of new technologies for less skilled workers within activities explains a smaller proportion of the aggregate skill up-grading than labor-demand movements towards cognitive non-programmable activities.

All in all, new technologies tend to replace jobs that may be programmed in advance and favor jobs that require constant adaptation to change, notably conception/development and sales/marketing activities. By reinforcing these activities, firms are better able to respond to market changes. In this paper, we show that this is one of the main channel through which new technologies modify the demand for skills.

Understanding the effect of contemporary technological advancement on the demand for skills may contribute to developing effective training programs to help workers adapt to their firms changing needs. In our study, we show that there is a decreasing need for workers capable of carrying out projects defined in advance and an increasing need for workers capable of creating new projects and/or representing these new projects outside the firm. Further research is needed to explore whether less skilled workers can be trained to perform such activities and whether such training efforts may be a remedy for the rising job insecurity from which these workers suffer.

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Appendix : Derivation of Equation (5)

Consider a firm which minimizes $w_t'L = \sum_k w_{kt}L_k$ subject to $A_{jt}y_{jt} \leq F(\frac{L_{1jt}}{a_{1jt}}, ..., \frac{L_{Njt}}{a_{Njt}})$.

Let $(L_{1jt},...,L_{Njt})$ be the optimal vector of demand for labor. It satisfies, (a) the production constraint, $A_{jt}y_{jt} = F(\frac{L_{1jt}}{a_{1jt}}, ..., \frac{L_{Njt}}{a_{Njt}})$, and (b) the N first-order conditions, $w_{kt} = \frac{\lambda}{a_{kjt}}\frac{\partial F}{\partial l_k}, k = 1,..,N$,where λ is the Lagrange multiplier corresponding to the production constraint. Furthermore, F being homogeneous of degree α, we have,

$$\sum_k \frac{L_{kjt}}{a_{kjt}}\frac{\partial F}{\partial l_k}(\frac{L_{1jt}}{a_{1jt}}, ..., \frac{L_{Njt}}{a_{Njt}}) = \alpha F(\frac{L_{1jt}}{a_{1jt}}, ..., \frac{L_{Njt}}{a_{Njt}}).$$

The first-order condition thus implies (where $w_t'L_{jt}$ stands for $\sum_k w_{kt}L_{kjt}$),

$$\lambda = \frac{\sum_k w_{kt}L_{kjt}}{\alpha F(\frac{L_{1jt}}{a_{1jt}}, ..., \frac{L_{Njt}}{a_{Njt}})} = \frac{w_t'L_{jt}}{\alpha A_{jt}y_{jt}},$$

The first-order conditions can thus be rewritten,

$$w_{kt} = \frac{w_t'L_{jt}}{\alpha a_{kjt}A_{jt}y_{jt}}\frac{\partial F}{\partial l_k}, \forall k,$$

which is equivalent to:

$$\frac{\partial F}{\partial l_k} = \alpha \frac{a_{kjt} w_{kt}}{w'_t L_{jt}} A_{jt} y_{jt}, \forall k.$$

Now the production constraint (a) can be differentiated, which gives,

$$\sum_k \left(\frac{dL_{kjt}}{a_{kjt}} - \frac{L_{kjt}}{a_{kjt}^2} da_{kjt}\right) \frac{\partial F}{\partial l_k} = d(A_{jt} y_{jt}).$$

Using the ($\frac{\partial F}{\partial l_k} = \alpha \frac{a_{kjt} w_{kt}}{w'_t L_{jt}} A_{jt} y_{jt}$) relationships, it yields:

$$\sum_{k=1}^{N} \left(\frac{w_{kt} dL_{kjt}}{w'_t L_{jt}} - \frac{da_{kjt}}{a_{kjt}} \frac{w_{kt} L_{kjt}}{w'_t L_{jt}}\right) = \frac{1}{\alpha} \frac{dA_{jt} y_{jt}}{A_{jt} y_{jt}}$$

which can be rewritten:

$$\frac{w'_t dL_{jt}}{w'_t L_{jt}} - \sum_{k=1}^{N-1} \left(\frac{da_{kjt}}{a_{kjt}} - \frac{da_{Njt}}{a_{kjt}}\right) \frac{w_{kt} L_{kjt}}{w'_t L_{jt}} = \frac{1}{\alpha} \frac{dA_{jt} y_{jt}}{A_{jt} y_{jt}}$$

which is equation (5).

Data Appendix

Data sources	Description	Variables
Enquête sur la Structure des Emplois (ESE), 1984-1995.	Annual administrative database of the occupational structure for all French establishments with more than 20 employees. We used the 1984-1995 ESE files aggregated to the firm level.	For each year and firm, this source describes the distribution of workers across elementary tasks and skill levels.
Bénéfices industriels et commerciaux (BIC), 1984-1995.	Annual administrative database giving financial and employment data for all French firms with at least 20 employees. We used the 1984-1995 BIC files	For each year and firm, this source gives the added value.
Enquête Emploi (EE), 1984-1995.	The French Labor Force Survey conducted by the French Statistical Office. Sampling rate:1/300. About 140 000 respondents each year. We used the 1984-1995 files.	For each elementary industry, this source describes the distribution of wages across elementary tasks and skill levels.
Enquête sur les Technologies et l'organisation du travail (TOTTO), 1987	Supplement to the 1987 French Labor Force Survey. The sample consists of 20,000 workers representative of the French work force.	For each elementary industry, this survey gives the share of computers' users, the share of workers using robots and/or numerical command machines and the share of workers on automatically regulated machines.
Enquête sur le Changement Organisationnel, 1993	Survey conducted by the French ministry of industry in 1993 on a representative sample of 1,800 manufacturing firms.	For each elementary industry (within the manufacturing sector) this survey gives the share of workers that have introduced computer-aided techniques between 1989 and 1992.

Table 1: The Distribution of Workers across Activities and Skills.

Activity	Share in total employment	Share in low-skilled employment	Share in high-skilled employment	Share of high-skilled workers
Administration	14.2	11.8	20.0	41.2
Sales/ Marketing	4.7	0.5	14.8	91.9
Production	63.8	76.6	32.8	15.1
Logistics/ Transportation	10.6	11.1	9.5	26.2
Conception/ Development	6.7	-	23.0	100.0

Source: 1984-1995 ESE, unbalanced panel. Field: Manufacturing industries. Reading: Between 1984 and 1995, administration-related jobs represent on average 14.2% of total employment, 11.8% of low-skilled jobs and 20.0% of low-skilled jobs. High-skilled jobs represent 41.2% of administration-related jobs.

Table 2: Hourly Wage and Educational Attainment in each Activity×Skill Group.

Activity	High-skilled Jobs		Low-skilled Jobs	
	Skill 1	Skill 2	Skill 3	Skill 4
Administration				
High-school dropouts (%)	29.2	47.5	68.8	83.2
	(0.8)	(0.7)	(0.4)	(1.1)
Hourly wages	52.9	32.8	23.9	21.8
	(0.5)	(0.2)	(0.1)	(0.3)
Sales/Marketing				
High-school dropouts (%)	29.8	52.9	60.0	85.1
	(0.8)	(0.7)	(24.4)	(0.7)
Hourly wages (1980 FF)	48.9	32.1	23.3	16.7
	(0.4)	(0.3)	(4.2)	(0.2)
Production				
High-school dropouts (%)	24.7	72.6	94.2	94.2
	(0.8)	(0.4)	(0.1)	(0.1)
Hourly wages	50.5	33.8	21.2	18.1
	(0.4)	(0.1)	(0.1)	(0.0)
Logistics/Transportation				
High-school dropouts (%)	33.2	64.5	95.7	95.6
	(2.7)	(0.7)	(0.3)	(0.2)
Hourly wages	49.8	31.3	21.8	19.3
	(1.1)	(0.2)	(0.2)	(0.1)
Conception/Development				
High-school dropouts (%)	11.0	42.0	-	-
	(0.4)	(0.7)		
Hourly wages	51.6	31.4	-	-
	(0.4)	(0.2)		

Source: Labor Force Surveys, 1984-1995. Field: Manufacturing industries. Note: Hourly wages are expressed in 1982 French francs. Skill 1: upper-level professionals, managers, engenieers ; skill 2= lower-level managers and professionals, supervisors, technicians; skill 3 : skilled manual and non-manual workers; skill 4: unskilled manual and non-manual workers. Reading: in administration-related activities, 29.2% of the upper-level managers and professionals (i.e., skill 1) are high-school dropouts. They earn on average 52.9 1982-French francs per hour worked.

Table 3: The Diffusion of New Technologies across Industries.

	The percent of workers using…		The percent of firms having introduced…		
	Personal Computer	NC Machine Tool	Computer Aided Design	C.A. Production Management	C.A. Inventory Management
Food Products	7.9	1.1	NA	NA	NA
	(0.6)	(0.2)			
Energy	22.8	1.5	43.8	43.8	18.8
	(1.4)	(0.4)	(12.4)	(12.4)	(9.8)
Intermediate Goods	11.8	7.2	4.0	59.7	62.5
	(0.5)	(0.4)	(1.9)	(1.9)	(1.8)
Equipment Goods	22.4	6.0	54.7	60.4	66.8
	(0.6)	(0.4)	(2.2)	(2.2)	(2.1)
Automobile	13.6	8.4	54.0	63.0	72.0
	(1.0)	(0.8)	(5.0)	(4.8)	(4.5)
Consumption Goods	8.5	3.3	36.7	57.5	57.7
	(0.4)	(0.3)	(2.1)	(2.1)	(2.1)

Field: Manufacturing Industries. Sources: LFS 1987 supplement on technology (columns 1 and 2), 1993 Survey on Organizational Changes (columns 3, 4 and 5). Reading: Column 1 provides the rates of personal computers' users in 1987, column 2 the rates of workers using numerically – commanded machines in 1987, column 3 the share of firms that have introduced new computer-aided design between 1987 and 1990, column 4 the share of firms that have introduced computer aided production management and column 5 the share of firms that have introduced C.A. inventory management. Standard deviations are in parenthesis.

Table 4: A Decomposition of Skill Upgrading in French Manufacturing Industries: The Role of Between-Activity Reallocations.

	1984-1989	1990-1995	1984-1995
Variation in the Share High-Skilled Jobs	2.8	2.4	5.1
Between-Industry	0.2	0.0	0.0
Within-Industry	2.6	2.4	5.1
Between-Activity	1.7	1.0	2.8
Administration	*0.1*	*0.0*	*0.0*
Sales/Marketing.	*0.7*	*0.3*	*1.1*
Production	*-0.3*	*-0.2*	*-0.5*
Logistics/Transport.	*0.0*	*0.0*	*0.0*
Concept./Developt.	*1.1*	*1.0*	*2.2*
Within-Activity	0.9	1.3	2.3
Administration	*0.3*	*0.3*	*0.6*
Sales/Marketing.	*0.0*	*0.1*	*0.1*
Production	*0.5*	*0.7*	*1.1*
Logistics/Transport.	*0.1*	*0.2*	*0.4*
Concept./Developt	-	-	-

Source: ESE 1984-1995 unbalanced panel. Field: Manufacturing industries. Reading: the first half of the table provides the decomposition of skill-upgrading into its within-industry and between-industry components (see footnote 14). The bottom half of the table provides the decomposition of the within-industry component into its between-activity and within-activity components (see equation 4). Industries are defined by the French 2 digits-classification (i.e., 55 manufacturing sectors). Figures may not add up due to rounding choices.

Table 5 : Trends in the Relative Costs and the Relative Quantities of High-skilled Workers within Four Elementary Activities (average annual percent increase, 1984-1995).

	Administration	Sales/Marketing	Production	Logistics/ Transport.
Percent increase in high-skilled/low-skilled labor ratio	-0.3 (0.1)	1.8 (0.1)	1.9 (0.1)	2.6 (0.1)
Percent increase in high-skilled/low-skilled wage ratio	-0.1 (1.4)	1.8 (2.8)	0.2 (0.6)	0.2 (1.1)

Source: ESE 1984-1995, unbalanced panel, LFS 1984-1995. Field: Manufacturing Industry.
Reading: For each firm, let L_{PHt} (L_{PLt}) be the number of high-skilled (low-skilled) jobs in activity P where P represents the four activities listed as column headings. For each activity, the first row gives the average annual variation (x 100) of $\ln(L_{PHt}/L_{PLt})$ across firms and years. For each industry (2 digit code), let W_{PHt} (W_{PLt}) be the hourly wages of high-skilled (low-skilled) jobs in activity P. For each activity the second row gives the average annual increase of $\ln(W_{PHt}/W_{PLt})$, across sectors and years. Standard errors are in parentheses.

Table 6 : Trends in the Relative Costs and the Relative Quantities of Elementary Activities within High-Skilled and Low-Skilled Groups (average annual variations x 100, 1984-1995)

	Administration	Sales/ Market.	Production	Logistics/ Transport.	Conception/ Develop t.
Section (a) : High-skilled group					
$\Delta \ln(L_{PHt}/L_{QHt})$	-2.0 (0.1)	0.6 (0.1)	-0.5 (0.1)	-0.4 (0.1)	1.6 (0.1)
$\Delta \ln(W_{PHt}/W_{QHt})$	-0.2 (1.6)	0.1 (1.2)	0.6 (0.8)	0.0 (1.1)	-0.7 (1.1)
Section (b) : Low-skilled group					
$\Delta \ln(L_{PLt}/L_{QLt})$	1.2 (0.1)	0.5 (0.1)	-1.0 (0.1)	0.1 (0.1)	-
$\Delta \ln(W_{PLt}/W_{QLt})$	-0.3 (0.7)	-1.8 (2.8)	0.3 (0.5)	-0.2 (0.8)	-

Source: ESE 1984-1995, unbalanced panel, LFS 1984-1995. Field: Manufacturing Industry. Reading: For each firm and each activity P (among the five listed as column headings), let L_{PHt} (L_{PLt}) be the number of high-skilled (low-skilled) jobs in activity P and let L_{QHt} (L_{QLt}) be the number of high-skilled (low-skilled) jobs in all other activities. For each activity, the table gives the average annual increase (x 100) of $\ln(L_{PHt}/L_{QHt})$ and $\ln(L_{PLt}/L_{QLt})$ across firms and years. For each sector (2 digit code), let W_{PHt} (W_{PLt})) be the hourly wages of high-skilled (low-skilled) jobs in activity P. For each activity the table gives the average annual increase of $\ln(W_{PHt}/W_{QHt})$, across sectors and years. Standard errors are in parentheses.

Table 7: The Impact of New Information Technologies on the Share of High-Skilled Jobs within four Elementary Activities.

	Dependent Variable: variation in the high-skilled/low-skilled labor ratio within…			
	Administration	Sales/Marketing	Production	Logistics/Transport.
Personal Computer	0.06 ** (0.01)	0.27 ** (0.10)	0.00 (0.01)	0.11 ** (0.03)
NC Machine Tool	0.01 (0.03)	0.04 (0.21)	-0.02 (0.02)	-0.01 (0.02)
Computer Aided Design	0.01 (0.01)	0.01 (0.07)	0.01 (0.01)	0.02 (0.02)
C.A. Production Management	0.05 ** (0.01)	0.05 (0.07)	0.00 (0.01)	0.08 ** (0.02)
C.A. Inventory Management	0.05 ** (0.01)	0.10 ** (0.06)	0.01 (0.01)	0.06 ** (0.02)
Nb. Obs.	55817	55817	55817	55817

Source: ESE 1984-1995. Field : Manufacturing Industries. Reading : For each elementary activity, this table gives the regression coefficients of the high-skilled/low-skilled employment ratio on the rate of personal computers' users (row 1), the rate of users of numerical command machine tool (row 2), the share of firms that have introduced computer-aided products' design (row 3), computer-aided production management (row 4) and computer-aided inventory management (row 5). The R^2 of the 5x4=20 different regressions are available on request. Standard errors in parenthesis. ** shows coefficients that are significant at 5% level.

Table 8: The Impact of New Information Technologies on the Share of Non-programmable and/or Non-manual Activities within the Different Skill Groups.

	Dependent variable: variations in the cognitive non-progammable/non-cognitive programmable activity ratio within the group of …	
	High-skilled workers	Low-skilled workers
Personal Computer	0.04**	-0.01
	(0.02)	(0.01)
NC Machine Tool	0.09**	0.01
	(0.03)	(0.02)
Computer Aided Design	0.03**	0.00
	(0.01)	(0.01)
C.A. Production Management	0.01	-0.01
	(0.02)	(0.01)
C.A. Inventory Management	0.00	-0.03**
	(0.01)	(0.01)
Nb. Obs.	55817	55817

Source: ESE 1984-1995. Field : Manufacturing Industries. Reading : The first column provides the results of the regression of the (conception/development+sales/marketing)/(production+logistic/transportation+administration) employment ratio on the rate of personal computers' users (row 1), the rates of users of numerical command machine tool (row 2), the share of firms that have introduced computer-aided products' design (row 3). computer-aided production management (row 4) and computer-aided inventory management (row 5). The second column provides the results of the regression of the (sales/marketing+ administration)/(production+logistic/transportation) employment ratio on the same six indicators of technological change, within the group of low-skilled workers. Standard errors in parentheses. ** shows coefficients that are significant at standard levels.

Table 9: Technical Change and the Relative Productivities of Activities and Skills: a GMM Estimation of Equation 5.

	Model 1	Model 2
Output growth rate (dy/y)	3.59	3.36
	(0.69)	(0.59)
Share of the wage bill allocated to …		
Administration High-skilled	-0.09**	-0.13**
	(0.05)	(0.05)
Administration Low-skilled	0.04	0.06
	(0.06)	(0.05)
Sales/Marketing High-skilled	-0.04	-0.04
	(0.03)	(0.02)
Sales/Marketing Low-skilled	0.18**	0.12**
	(0.07)	(0.06)
Production High-skilled	0.07**	0.06**
	(0.04)	(0.03)
Production Low-skilled	Reference	Reference
Logistics/Transport. High-skilled	0.02	0.00
	(0.05)	(0.05)
Logistics/Transport. Low-skilled	0.00	0.00
	(0.03)	(0.02)
Concept./Developt. High-skilled	-0.10**	-0.09**
	(0.04)	(0.04)
Entry and exit Dummies	No	Yes
Dummies' joint significance	-	2.2 (1.5)
Nb Observations	55817	55817
Sargan (P value)	7.1 (0.21)	9.2 (0.18)

Source: ESE 1984-1985. unbalanced panel. Field: Manufacturing industries.
Reading: This table corresponds to the estimation of equation 5. For each firm and each date, the dependant variable is the impact of technical change on the wage bill Δ_{jt} (it can be calculated as the sum over A and k of ($M_{Ak}\Delta lnL_{Ak}$), where M_{Ak} is the share of activity A-skill k in the wage bill). The set of regressors includes industry dummies. Standard errors are in parentheses. Estimations are carried out by the GMM. The forcing variables are instrumented by their two-years lagged values. We have also included the three-years lagged values of the cost share of conception jobs and of the high-skilled/low-skilled cost ratio in administration and logistics-related activities in the set of instruments. In order to test for endogenous attrition. Model 2 includes 14 dummies indicating the years of entry and of exit from the panel (one for each possible date of entry and one for each possible date of exit). A Fisher test for their joint significance is also provided. Over-identifying restrictions are tested using the Sargan statistics. ** shows coefficients that are significant at standard levels.