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

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We analyze recent changes in the occupational structure of French manufacturing firms. Firms employ a greater proportion of engineers working on the design and marketing of new products and a lower proportion of high-skill experts working in administration-related activities. Firms have also reduced the share of production-related activities at both the levels of high-skill and low-skill workers. We develop a labor demand model that shows the role played by technological change. New technologies make it possible to allocate more human resources to the activities that are the most difficult to program in advance.

I. Introduction

In most Western countries, firms employ a greater proportion of skilled workers today as compared to 20–30 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 toward skilled labor.[1]

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[1] See, e.g., Katz and Murphy (1992), Berman, Bound, and Griliches (1994), Autor, Katz, and Krueger (1998), and Berman, Bound, and Machin (1998). See also the survey by Chennells and Van Reenen (2002).

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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-skill labor for low-skill 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-skill labor, without, however, knowing exactly what is involved.

The underlying nature of technical progress is far from being fully identified, 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 article, 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 nonroutine 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 toward high-skill labor.

A. 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 (Bresnahan, Brynjolfsson, and Hitt 1999, 2002; Caroli and Van Reenen 2001). 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,

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

the SBTC can be interpreted as the consequence of the reorganization of the workplace that is made possible by the diffusion of new technologies.[3]

In this article, 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, rather, 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 ensure the legal and administrative management of the firm. Others are needed to ensure 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 the 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 article 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 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-skill workers) for simple ones (exercised by low-skill workers) but that they significantly modify the nature of the activities that workers must perform.

[3] Such a complementarity between technology and work organization is also emphasized by David (1990) to explain the slow diffusion of electricity in U.S. manufacturing until the 1920s.

[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 (e.g., research and sales) and those that can be programmed (e.g., production).

B. 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-skill and low-skill jobs across five categories of elementary activities. These are conception/development, logistics/transportation, administration, production, and sales/marketing.

Generally speaking, our statistical and econometric analysis is consistent with our working hypothesis. From a simple, descriptive viewpoint, our data set 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-skill and low-skill 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-skill 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-skill workers is the highest.[5]

Going a step further, we have developed and tested a labor demand model that 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-skill workers, and this article 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 reduce the demand for engineers doing routine design work.

The organization of this article is as follows. In Section II, we describe our data. In Section III, we provide some simple statistical evidence showing that technical change increases the demand for nonroutine, nonmanual activities within the different skill groups. In Section IV, we develop a model that makes it possible to identify the relationship between the

[5] Given that conception and sales/marketing activities correspond to cognitive nonmanual tasks, these findings are consistent with Autor, Levy, and Murnane (2003). Conceptualizing jobs in terms of routine vs. nonroutine and cognitive vs. manual, they find that computerization is associated with a rise in the relative industry demand for nonroutine cognitive tasks.

diffusion of computers (and computer-aided technologies) and the relative productivity of the different types of skills and activities.

II. Data

We have used data from several different French data sources (see app. A). The first source is the *Enquête structure des emplois* (ESE). This administrative database gives the occupational structure of all French work establishments with more than 20 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 20 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 cccupés* (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.

A. Data on Firms' Occupational Structure and Economic Activity

We have used the 1984–95 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 collective agreements:[8] (*a*) *cadres* (i.e., mostly upper-level managers, engineers, and professionals); (*b*) *pro-*

[6] For each establishment, the first nine 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 vs. non–wage earner), their sector (public vs. 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., *catégories socioprofessionnelle*) that are homogeneous from an employment status, sector, and skill-level viewpoint.

[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.

fessions intermédiaires (i.e., lower-level managers and professionals, supervisors, and technicians); (*c*) *ouvriers et employés qualifiés* (i.e., skilled manual and nonmanual workers); and (*d*) *ouvriers et employés non qualifiés* (i.e., low-skill manual and nonmanual workers). Our definition of high-skill workers combines *a* and *b*. It includes managers, professionals, engineers, technicians, and supervisors. Our definition of low-skill 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 article, 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 workers include 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 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 data set we have used in this article corresponds to the matching of the ESE and the BIC surveys. Each year, we know for each firm the following: the number of workers in each of the nine (activity × skill level) cells,[10] the industry, and the value added. We have focused on the manufacturing industries and have excluded firms that were sampled, dropped, and then resampled between 1984 and 1995. This makes a panel that contains about 10,000 firms each year. Taken together, these firms employ on average of 1,500,000 workers each year. Table 1 describes the average distribution of these workers across activities and skills over the period 1984–95.

[9] Hollanders and Ter Weel (2002) 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 workers, 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-skill workers can be found in each of the five main functions, while low-skill workers can only be found in four of them: by construction, there are 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.

Table 1
The Distribution of Workers across Activities and Skills

Activity	Share in Total Employment	Share in Low-Skill Employment	Share in High-Skill Employment	Share of High-Skill Workers
Administration	14.2	11.8	20.0	41.2
Sales/marketing	4.7	.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.—Enquête structure des emplois (1984–95, unbalanced panel). Field: manufacturing industries.

B. 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 LFS). 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 imply 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 employees do, even though within each skill level the wages and educational levels do not vary across activities.

C. Data on New Technologies

The LFS 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 or she uses (*a*) a personal computer (PC) or (*b*) 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

[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.

Table 2
Hourly Wage and Educational Attainment in Each Activity Skill Group

	High-Skill Jobs		Low-Skill Jobs	
Activity	Skill 1	Skill 2	Skill 3	Skill 4
Administration:				
High school dropout (%)	29.2	47.5	68.8	83.2
	(.8)	(.7)	(.4)	(1.1)
Hourly wage	52.9	32.8	23.9	21.8
	(.5)	(.2)	(.1)	(.3)
Sales/marketing:				
High school dropout (%)	29.8	52.9	60.0	85.1
	(.8)	(.7)	(24.4)	(.7)
Hourly wage	48.9	32.1	23.3	16.7
	(.4)	(.3)	(4.2)	(.2)
Production:				
High school dropout (%)	24.7	72.6	94.2	94.2
	(.8)	(.4)	(.1)	(.1)
Hourly wage	50.5	33.8	21.2	18.1
	(.4)	(.1)	(.1)	(.0)
Logistics/transportation:				
High school dropout (%)	33.2	64.5	95.7	95.6
	(2.7)	(.7)	(.3)	(.2)
Hourly wage	49.8	31.3	21.8	19.3
	(1.1)	(.2)	(.2)	(.1)
Conception/development:				
High school dropout (%)	11.0	42.0		
	(.4)	(.7)		
Hourly wage	51.6	31.4		
	(.4)	(.2)		

Sources.—French Labor Force Surveys (1984–95). Field: manufacturing industries.
Note.—Hourly wages are expressed in 1982 French francs. Skill 1 = upper-level professionals, managers, engineers; skill 2 = lower-level managers and professionals, supervisors, and technicians; skill 3 = skilled manual and nonmanual workers; skill 4 = unskilled manual and nonmanual workers. Standard deviations are in parentheses.

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. Numerical command machines are much more frequently used in the automobile sector than in the food product sectors.

III. The Impact of Technological Change on the Demand for Skilled Labor

In this section, we provide some simple statistical tests to find out the impact of technological change on the composition of labor demand. To anticipate the findings, our tests suggest that technological change favors (*a*) the substitution of high-skill for low-skill labor within the different activities and (*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 toward con-

Table 3
The Diffusion of New Technologies across Industries

	Percent of Workers Using:		Percent of Firms Having Introduced:		
	Personal Computer	Numerical Command Machine Tool	Computer-Aided Design	Computer-Aided Production Management	Computer-Aided Inventory Management
Food products	7.9	1.1	N.A.	N.A.	N.A.
	(.6)	(.2)			
Energy	22.8	1.5	43.8	43.8	18.8
	(1.4)	(.4)	(12.4)	(12.4)	(9.8)
Intermediate goods	11.8	7.2	4.0	59.7	62.5
	(.5)	(.4)	(1.9)	(1.9)	(1.8)
Equipment goods	22.4	6.0	54.7	60.4	66.8
	(.6)	(.4)	(2.2)	(2.2)	(2.1)
Automobile	13.6	8.4	54.0	63.0	72.0
	(1.0)	(.8)	(5.0)	(4.8)	(4.5)
Consumption goods	8.5	3.3	36.7	57.5	57.7
	(.4)	(.3)	(2.1)	(2.1)	(2.1)

Sources.—French Labor Force Survey, 1987, supplement on technology (cols. 1 and 2); 1993 Survey on Organizational Changes (cols. 3, 4, and 5). Field: manufacturing industries.

Note.—Column 1 shows the rates of personal computers' users in 1987; col. 2, the rates of workers using numerically commanded machines in 1987; col. 3, the share of firms that have introduced new computer-aided design between 1987 and 1990; col. 4, the share of firms that have introduced computer-aided production management between 1989 and 1992; and col. 5, the share of firms that have introduced computer-aided inventory management between 1989 and 1992. Standard deviations are in parentheses.

ception/development and sales/marketing activities have a stronger impact on the aggregate demand for high-skill labor than the employment reallocations toward high-skill jobs within activities; the shift described in *b* is larger than the shift described in *a*.

Generally speaking, these preliminary results are consistent with our general hypothesis that technological change increases the demand for nonprogrammable 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 attempt to identify the role of new information technologies.

A. Within-industry Skill Upgrading: Measurement and Interpretation

The usual method for evaluating the impact of technological change on the demand for skilled labor is 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 $i = 1, \dots, S$ industries (or firms), each using both high-skill and low-skill workers in quantities L_{Hit} and L_{Lit} at date t. Let us assume that the production function for industry i is given by $(1/A_{it})F_i((L_{Hit})/(a_{Hit}), (L_{Lit})/(a_{Lit}))$, where F_i is a first-degree homogeneous function and A_{it} is the Hicks neutral technological progress component. The key parameters in

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

	1984–89	1990–95	1984–95
Variation in the share high-skilled jobs	2.8	2.4	5.1
Between-industry	.2	.0	.0
Within-industry	2.6	2.4	5.1
Decomposition of the within-industry skill upgrading:			
Between-activity:	1.7	1.0	2.8
Administration	.1	.0	.0
Sales/marketing	.7	.3	1.1
Production	−.3	−.2	−.5
Logistics/transportation	.0	.0	.0
Conception/development	1.1	1.0	2.2
Within-activity:	.9	1.3	2.3
Administration	.3	.3	.6
Sales/marketing	.0	.1	.1
Production	.5	.7	1.1
Logistics/transportation	.1	.2	.4
Conceptualization/development*			

Source.—Enquête structure des emplois (1984–95, unbalanced panel). Field: manufacturing industries.
Note.—The top three rows of the table provide the decomposition of skill upgrading into its within-industry and between-industry components (see n. 13). Rows 4–12 provide the decomposition of the within-industry component into its between-activity and within-activity components (see eq. [4]). Industries are defined by the French two-digit-classification (i.e., 55 manufacturing sectors). Figures may not add up to the indicated total due to rounding.
* There are no figures in this row because there are no low-skilled persons in this specific activity.

this analysis are a_{Hit} and a_{Lit}. They represent the technological progress dimensions that affect in different ways the high-skill and low-skill labor input. Employers are assumed to minimize their cost $w_{Ht}L_{Hit} + w_{Lt}L_{Lit}$ subject to $[A_{it}y_{it} \leq F_i((L_{Hit})/(a_{Hit}), (L_{Lit}/(a_{Lit}))]$, where $w_{Ht}(w_{Lt})$ represents the wage paid to high-skill (low-skill) workers.

Within this framework, the standard theory of the firm implies that the relative demand for skilled input $[(L_{Hit})/(a_{Hit})]/[(L_{Lit})/(a_{Lit})]$ 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 (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

[12] According to Shepard's lemma, the demand for labor k at date t in industry i can be written as $L_{kit} = a_{kt}A_{it}y_{it} \cdot c_{ik}(a_{Hit}w_{Ht}, a_{Lit}w_{Lt})$, where the unit cost function c_{ik} is homogeneous of degree zero and decreases with $a_{Hit}w_{Ht}$. Thus $(L_{Hit}/a_{Hit}) \cdot (L_{Lit}/a_{Lit})$ can be written as a decreasing (an increasing) function of $a_{Hit}w_{Ht}/a_{Lit}w_{Lt}$.

skill upgrading provides a very simple test for the existence of biased technological change.[13]

We have used our data set 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 is positive and large,[14] while the contribution of between-industry reallocation is almost negligible. All in all, given that the relative wages remain stable between 1984 and 1995, technological change seems to be one plausible cause for the skill upgrading that took place within the French manufacturing industry during that period.

B. Labor Demand Movements within Activities and within Skill Groups

The preceding analysis implicitly assumes that high-skill (low-skill) labor is homogeneous and that technological change has the same impact on all high-skill (low-skill) jobs. It neglects the fact that there are several different categories of high-skill and low-skill 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-skill and low-skill 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 that there are two skill levels, but now we assume that they are distributed across two different elementary activities P and Q.[15]

[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 $\sum_i (L_{it}/L_t) \cdot \Delta(L_{Hit}/L_{it})$.

[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.

Thus, we have (2 × 2 = 4) labor inputs. The production in industry i can now be written as (we momentarily drop subscript i):

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

where F is the production function and $\boldsymbol{L}_t = (L_{PHt}, L_{PLt}, L_{QHt}, L_{QLt})$ is 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-skill/low-skill labor ratio can be expressed as 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),

$$\Delta \ln\left(\frac{L_{\mathrm{AH}t}}{L_{\mathrm{AL}t}}\right) = (1 - \sigma_A)\Delta \ln\left(\frac{a_{\mathrm{AH}t}}{a_{\mathrm{AL}t}}\right), - \sigma_A \Delta \ln\left(\frac{w_{\mathrm{AH}t}}{w_{\mathrm{AL}t}}\right), \tag{2}$$

where σ_A is the elasticity of substitution of high-skill labor for low-skill labor within activity A, while $w_{\mathrm{AH}t}/w_{\mathrm{AL}t}$ represents the relative wage of skilled labor within A. Once the relative wage ($w_{\mathrm{AH}t}/w_{\mathrm{AL}t}$) is stable (i.e., $\Delta \ln(w_{\mathrm{AH}t}/w_{\mathrm{AL}t})$), the variations in high-skill/low-skill 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, σ.[17] Under these two supplementary assumptions, we obtain for each skill level $k \in (H, L)$,

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

Once the relative wage 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-skill labor for low-skill labor within

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

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

Table 5
Trends in the Relative Costs and the Relative Quantities of High-Skill Workers within Four Elementary Activities (Average Annual Percent Increase, 1984–95)

	Administration	Sales/ Marketing	Production	Logistics/ Transportation
Percent increase in high-skill/low-skill labor ratio	−.3	1.8	1.9	2.6
	(.1)	(.1)	(.1)	(.1)
Percent increase in high-skill/low-skill wage ratio	−.1	1.8	.2	.2
	(1.4)	(2.8)	(.6)	(1.1)

Sources.—Enquête structure des emplois (1984–95, unbalanced panel); French Labor Force Surveys (1984–95). Field: manufacturing industry.
Note.—For each firm, let $L_{PHt}(L_{PLt})$ be the number of high-skill (low-skill) 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 ($\times$ 100) of $\ln(L_{PHt}/L_{PLt})$ across firms and years. For each industry (two-digit code), let $W_{PHt}(W_{PLt})$ be the hourly wages of high-skill (low-skill) 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.

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 skill group.

Tables 5 and 6 provide the basic ingredients for these comparisons. Table 5 shows the average substitution rate of high-skill for low-skill labor within the different elementary activities (except for conception/development, because there are no low-skilled persons in this specific activity), 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.

First, we find a movement toward 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-skill work. Technological change does not affect each activity uniformly, however. The impact is particularly strong within the logistics/transportation activities, and it is negligible within administration-related ones.

Second, within the high-skill labor group, we find a move toward nonroutine cognitive activities. More specifically, we observe significant substitutions of conception/development and sales/marketing activities for production and administration activities (see table 6). At the same time, we do not observe any significant variations in the relative wages of

[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.

Table 6
Trends in the Relative Costs and the Relative Quantities of Elementary Activities within High-Skill and Low-Skill Groups (Average Annual Variations × 100, 1984–95)

	Administration	Sales/ Marketing	Production	Logistics/ Transportation	Conception/ Development
High-skill group:					
$\Delta \ln(L_{PHt}/L_{QHt})$	−2.0	.6	−.5	−.4	1.6
	(.1)	(.1)	(.1)	(.1)	(.1)
$\Delta \ln(W_{PHt}/W_{QHt})$	−.2	.1	.6	.0	−.7
	(1.6)	(1.2)	(.8)	(1.1)	(1.1)
Low-skill group:					
$\Delta \ln(L_{PLt}/L_{QLt})$	1.2	.5	−1.0	.1	
	(.1)	(.1)	(.1)	(.1)	
$\Delta \ln(W_{PLt}/W_{QLt})$	−.3	−1.8	.3	−.2	
	(.7)	(2.8)	(.5)	(.8)	

Sources.—Enquête structure des emplois (1984–95, unbalanced panel); French Labor Force Surveys (1984–95). Field: manufacturing industry.
Note.—For each firm and each activity P (among the five listed as column headings), let L_{PHt} (L_{PLt}) be the number of high-skill (low-skill) jobs in activity P and let L_{QHt} (L_{QLt}) be the number of high-skill (low-skill) jobs in all other activities. For each activity, the table gives the average annual increase (× 100) of $\ln(L_{PHt}/L_{QHt})$ and $\ln(L_{PLt}/L_{QLt})$ across firms and years. For each sector (two-digit code), let $W_{PHt}(W_{PLt})$ be the hourly wages of high-skill (low-skill) 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.

conception/development workers or in the relative wages of administration high-skill 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-skill workers.

Third, within the less skilled group, there is a move toward more administrative and sales/marketing activities (see table 6). 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 nonmanual activities within the group of low-skill workers.

Our findings confirm that technological change does not uniformly affect all types of activities and skills. New technologies favor, above all, high-skill jobs related to nonroutine cognitive activities and low-skill jobs related to nonmanual 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}, first right-hand-side expression) and within-activity components (Δ_{WWA}, second right-hand-side expression) for $A = P, Q$):

$$\Delta_{\text{within}} = \sum_{i, A=P,Q} \frac{L_{it}}{L} \cdot \frac{L_{AHit}}{L_{Ait}} \cdot \Delta\left(\frac{L_{Ait}}{L_{it}}\right) + \sum_{A=P,Q} \frac{L_{it}}{L} \cdot \frac{L_{Ait}}{L_{it}} \cdot \Delta\left(\frac{L_{AHit}}{L_{Ait}}\right). \quad (4)$$

Table 4 provides the results of this decomposition. It is interesting that the between-activity component (Δ_{WB}) is more important than the within-activity components. Employment reallocation from production and administrative activities toward 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-skill jobs to high-skill 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-skill jobs but because it favors certain forms of activities that require the most highly skilled workers.

C. 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-skill for low-skill workers within the firms' different elementary activities. At the same time, for the high-skill 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 nonmanual activities. In sum, technological progress involves more complex restructuring than the simple substitution of new technologies for low-skill labor within firms.

As convincing and simple as this may seem, the method developed in Section III 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 drive 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 toward skilled jobs necessarily arises from new technologies. We test this assumption by regressing (for each activity) the variations of the high-skill/low-skill labor ratio on variables measuring the diffusion of new technologies (see table 7).[19] It is interesting that we find a positive correlation between the diffusion of personal computers and computer-aided management technologies and the increase in the share of high-skill workers within administration, logistic/transportation, and sales/marketing activities. These findings provide direct evidence that new information technologies substitute for low-skill workers within most elementary activities.

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

Table 7
The Impact of New Information Technologies on the Share of High-Skill Jobs within Four Elementary Activities

	Dependent Variable Is Variation in High-Skill/Low-Skill Labor Ratio within:			
	Administration	Sales/ Marketing	Production	Logistics/ Transport
Personal computer	.06*	.27*	.00	.11*
	(.01)	(.10)	(.01)	(.03)
NC machine tool	.01	.04	−.02	−.01
	(.03)	(.21)	(.02)	(.02)
Computer-aided design	.01	.01	.01	.02
	(.01)	(.07)	(.01)	(.02)
Computer-aided production management	.05*	.05	.00	.08*
	(.01)	(.07)	(.01)	(.02)
Computer-assisted inventory management	.05*	.10*	.01	.06*
	(.01)	(.06)	(.01)	(.02)
No. of observations	55,817	55,817	55,817	55,817

Sources.—Enquête structure des emplois (1984–95). Field: manufacturing industries.
Note.—For each elementary activity, this table gives the regression coefficients of the high-skill/low-skill employment ratio on the rate of personal computers' users (row 1), the rate of users of numerical command machine tool (row 2), and 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 $5 \times 4 = 20$ different regressions are available on request. Standard errors are in parentheses.
* Significant at the 5% level.

In table 8, we analyze the impact of new information technologies on the labor demand movements toward 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 toward (conception/development + sales/marketing) activities within the group of high-skill jobs and (*b*) the movement from (production + logistic/transportation) activities toward (administration + sales/marketing) activities within the group of low-skill jobs. The first movement captures the increasing importance of cognitive nonroutine activities within the group of high-skill jobs. The second movement measures the increasing importance of nonmanual activities within the group of low-skill 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-skill jobs. New information technologies and new production technologies seem to complement not only high-skill jobs but also activities involving non-programmable-problem and interactive activities within the group of high-skill jobs. In contrast, none of the technologies analyzed in this article can be directly

Table 8
The Impact of New Information Technologies on the Share of Nonprogrammable and/or Nonmanual Activities within the Different Skill Groups

	Dependent Variable Is Variations in the Cognitive Nonprogammable/Noncognitive Programmable Activity Ratio within the Group of . . .	
	High-Skill Workers	Low-Skill Workers
Personal computer	.04*	−.00
	(.02)	(.01)
NC machine tool	.09*	.00
	(.03)	(.02)
Computer-aided design	.03*	.00
	(.01)	(.01)
Computer-aided production management	.01	−.01
	(.02)	(.01)
Computer-aided inventory management	.00	−.03*
	(.01)	(.01)
No. of observations	55,817	55,817

Sources.—Enquête structure des emplois (1984–95). Field: manufacturing industries.
Note.—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), and 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-skill workers. Standard errors are in parentheses.
* Significant at the 5% level.

associated with an increase in the share of nonmanual activities within the group of low-skill jobs.

In sum, our data provide some direct evidence that the diffusion of new technologies has actually shifted the demand for labor not only toward the most complex and high-skill activities but also toward 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-skill workers cannot be identified under the assumption of constant elasticity of substitution used to obtain equations (2) and (3).

D. 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 the degree of substitution between the different activities and skills.

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

Keeping the notations that have been utilized in the preceding sections, let us now assume that the production at date t is given by $(1/A_t)F((L_{\mathrm{PH}t}/a_{\mathrm{PH}t}),(L_{\mathrm{PL}t}/a_{\mathrm{PL}t}),(L_{\mathrm{QH}t}/a_{\mathrm{QH}t}),(L_{\mathrm{QL}t}/a_{\mathrm{QL}t}))$, where F is an α-degree homogeneous production function. Employers are assumed to minimize their costs $W_t = w_{Ht}L_{\mathrm{PH}t} + w_{Lt}L_{\mathrm{PL}t} + w_{Ht}L_{\mathrm{QH}t} + w_{Lt}L_{\mathrm{QL}t}$ subject to $A_t y_t \leq F((L_{\mathrm{PH}t}/a_{\mathrm{PH}t}),(L_{\mathrm{PL}t}/a_{\mathrm{PL}t}),(L_{\mathrm{QH}t}/a_{\mathrm{QH}t}),(L_{\mathrm{QL}t}/a_{\mathrm{QL}t}))$.

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 $\gamma_{Ak} = (da_{Akt}/a_{Akt}) - (da_{Pkt}/a_{Pkt})$ differentials are constant within the different industries and across time. For an elementary activity A, ($\gamma_{\mathrm{AH}} < \gamma_{\mathrm{AL}}$) 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 that raises the productivity of A-type activities compared to P-type activity within k.

With these notations, let us consider a firm j and let Δ_{jt} be the impact of technological change on j's costs (i.e., $\Delta_{jt} = (w_{Ht}\Delta L_{\mathrm{PH}t} + w_{Lt}\Delta L_{\mathrm{PL}t} + w_{Ht}\Delta L_{\mathrm{QH}t} + w_{Lt}\Delta L_{\mathrm{QL}t})$). The basic theory of the firm provides us with a fairly simple linear relationship between Δ_{jt}, the output growth rate $(\Delta y_{jt}/y_{jt})$, and the γ_{Ak} parameters. More specifically, we have (see app. B):

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

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 is an industry fixed effect that captures the Hicks neutral component of technological change, and u_{jt} is a zero-mean random variable that 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 toward nonprogrammable 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

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

of technological progress.[22] Generally speaking, the 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-skill jobs. The main effect of technological change is to increase the relative productivity of these three categories of high-skill workers.[24] The lowest estimated γ_{Ak} (i.e., the most positive regression coefficients) correspond to sales/marketing low-skill jobs and to production-related high-skill 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 sales/marketing activities. In general, technological advancement leads to an increase in the productivity of high-skill jobs linked to the most immaterial activities to the detriment of the high-skill jobs most directly involved in the manufacturing and transportation processes. It should also be emphasized that technological change increases the relative productivity of high-skill 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

[22] From an econometric viewpoint, the main problem with eq. (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 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 returns to scale, and (*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 (Verbeek 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. However, the estimated productivity impacts cannot be interpreted as direct explanations for the observed changes in the occupational structure. The employment effects of these productivity impacts actually depend on elasticities of substitution.

Table 9
Technical Change and the Relative Productivities of Activities and Skills: A Generalized Method of Moments (GMM) Estimation of Equation (5)

	Model 1	Model 2
Output growth rate (dy/y)	3.59	3.36
	(.69)	(.59)
Share of the wage bill allocated to:		
Administration, high-skill	−.09*	−.13*
	(.05)	(.05)
Administration, low-skill	.04	.06
	(.06)	(.05)
Sales/marketing, high-skill	−.04	−.04
	(.03)	(.02)
Sales/marketing, low-skill	.18*	.12*
	(.07)	(.06)
Production, high-skill	.07*	.06*
	(.04)	(.03)
Production, low-skill	Reference	Reference
Logistics, high-skill	.02	.00
	(.05)	(.05)
Logistics/transportation, low-skill	.00	.00
	(.03)	(.02)
Conception/development, high-skill	−.10*	−.09*
	(.04)	(.04)
Entry and exit dummies	No	Yes
Dummies' joint significance		2.2
		(1.5)
No. of observations	55,817	55,817
Sargan (p-value)	7.1	9.2
	(.21)	(.18)

Sources.—Enquête structure des emplois (1984–95). Field: manufacturing industries.
Note.—This table corresponds to the estimation of eq. (5). For each firm and each date, the dependent variable is the impact of technical change on the wage bill Δ_{it} (it can be calculated as the sum over A and k of ($M_{Ak}\Delta \ln L_{Ak}$), 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 2-years lagged values. We have also included the 3-years lagged values of the cost share of conception jobs and of the high-skill/low-skill 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. Overidentifying restrictions are tested using the Sargan statistics.
* Significant at the 5% level.

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 $\gamma_{Aki} = \gamma_{Ak} + \alpha_{Ak} \cdot T_i$, 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 (nonmanual) activities within the high-skill (low-skill) 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 toward 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-skill activities. The second basic mechanism is the substitution of nonprogrammable 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-skill workers.

IV. 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. Among its findings are the following:

1. New technologies increase the demand for nonprogrammable cognitive 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 nonmanual administration-related activities.

2. The increase in the share of cognitive nonprogrammable 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 upgrading than labor demand movements towards cognitive nonprogrammable 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 article, we show that this is one of the main channels 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.

Appendix A

Data

Table A1
Summary of Data Sources

Data Sources	Description	Variables
Enquête sur la structure des emplois (ESE), 1984–95	Annual administrative database of the occupational structure for all French establishments with more than 20 employees. We used the 1984–95 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 industriel et commerciaux (BIC), 1984–95	Annual administrative database giving financial and employment data for all French firms with at least 20 employees. We used the 1984–95 BIC files.	For each year and firm, this source gives the added value.
Enquête emploi (EE), 1984–95	The French Labor Force Survey conducted by the French Statistical Office. Sampling rate: 1/300. There are about 140,000 respondents each year. We used the 1984–95 EE 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 workforce.	For each elementary industry, this survey gives the share of computer 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.

Appendix B

Derivation of Equation (5)

Consider a firm j that minimizes $w_t'L_{jt} = \sum_k w_{kt}L_{kjt}$, subject to

$$A_{jt}y_{jt} \le F\left(\frac{L_{1jt}}{a_{1jt}}, \dots, \frac{L_{Njt}}{a_{Njt}}\right).$$

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

$$\sum_k \frac{L_{kjt}}{a_{kjt}} \cdot \frac{\partial F}{\partial l_k} = \alpha F.$$

The first-order condition thus implies that

$$\lambda = \frac{w_t'L_{jt}}{\alpha A_{jt}y_{jt}}.$$

The first-order conditions can thus be rewritten

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

which is equivalent to

$$\frac{\partial F}{\partial l_k} = \alpha \frac{a_{kjt}w_{kt}}{w_t\prime L_{jt}} A_{jt}y_{jt}.$$

Now the production constraint a can be differentiated, which gives

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

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

$$\sum_k \left(\frac{w_{kt}dL_{kjt}}{w_t'L_{jt}} - \frac{w_{kt}L_{kjt}}{w_t'L_{jt}} \cdot \frac{da_{kjt}}{a_{kjt}}\right) = \frac{1}{\alpha} \cdot \frac{d(A_{jt}y_{jt})}{A_{jt}y_{jt}},$$

which can be rewritten as

$$\frac{w_t'dL_{jt}}{w_t'L_{jt}} = \frac{1}{\alpha} \cdot \frac{d(A_{jt}y_{jt})}{A_{jt}y_{jt}} + \sum_{k \ne N} \left(\frac{da_{kjt}}{a_{kjt}} - \frac{da_{Njt}}{a_{Njt}}\right) \cdot \frac{w_{kt}L_{kjt}}{w_t'L_{jt}},$$

which is equation (5).

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