Collection
Études théoriques

no ET0403
Different strokes for differents folks :
examining the effects of
computerization
on Canadian workers

by
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February 2004

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ABSTRACT

Computerization (the diffusion of a combination of hardware and software) has accelerated in the last 30 years due to advances in electronic technologies, the advent of the microprocessor and the tremendous development of the software industry. The process of codification has intensified and routine tasks have tended to disappear, changing the architecture of jobs and, therefore, the structure of employment. A number of occupations have become increasingly associated with the computer, and these jobs require highly skilled workers. Using a production function framework, we found that computerization is not labour-saving but is instead labour-using. Despite this general trend, important inter-industrial differences prevail in the association of skills patterns with the computer. By transforming the structure of jobs, the computer has changed the skills requirements: the knowledge, management and data category of workers is closely associated with the use of computers while for good workers the relationship is a substitutive one due to expert systems software. The computer because of the highly tacit nature of the tasks does not affect the service category of workers. Though the uniqueness of the computer revolution should not be exaggerated, the computer has certainly acted as a catalyst given its pervasiveness and its capacity to merge with other technologies.

Marie Lavoie and Pierre Therrien

INTRODUCTION

The employment effects of technology, in general, and of computers, in particular, have been a topic of controversy. Observers have often assumed, albeit largely by default, that technological change is the main cause of increasing wage inequality and the shift from unskilled to skilled in the labour force. For those who share this pessimistic vision, the end result is structural unemployment, where displaced workers have considerable problems becoming reemployed since they may not have the skills needed to work in a context in which technology is key.

This hostile view of technological change is however counterbalanced by another, more positive school of thought which claims essentially that technological change is a necessary condition for economic growth and, therefore, better standards of living and better income distribution (Freeman : 2002). Among other things, it improves life expectancy through the development of new medical tools improving the diagnosis and treatment of diseases, it provides for the production of cheaper commodities and it can reduce the human input needed for routine and boring jobs. In any event, technological change has both negative and positive aspects.

In this paper, we focus on the effect of computerization on the employment structure by looking at degrees of complementarity and substitution of the computer for different groups of workers. The reason we limit our research to the computer, while there are also many other technologies, is that we assume computer equipment (hardware and software) is largely responsible for the huge transformation in employment patterns. This is due to the vast scope of its diffusion, the related reduction in costs, as well as the pervasiveness of its applications. However, its impact is often taken for granted and only the job-reducing aspect across industries and occupations is emphasized. The purpose of this paper is to go beyond this accepted wisdom and explain inter-industrial and inter-occupational differences in the employment structure.

Depending on the production process of an industrial sector and the nature of the occupation, the computer can induce strong employment-enhancing effects as well as significant employment destroying ones. Our main assumption is that computerization complements some categories of skills and replaces others, depending on the nature of the tasks − tacit vs. codified and core vs. complementary. Of course, it would be simplistic to relate an increase in the demand for knowledge workers exclusively to skill-biased computerization. Technological change cannot be limited to computer technologies and computers may have a minimal effect compared with the development of other equipment advanced manufacturing technologies that radically transforms the production processes of industries. Moreover, the computer technology/skill complementarity may also be supplemented by supply-side factors, organizational change, increasing intensity of international trade in certain industrial sectors and the speed of structural adjustment. Given the explosive rate of computing technological change, its impact is, however, worth assessing.

1.   CONCEPTUAL FRAMEWORK

The social consequences of unemployment and displacement of employment are so great that we need to have a better understanding of the related role of technological change. We cannot stop technological change but we can certainly attempt to adapt more quickly and efficiently to it by being able to better project its impact on future occupations and provide decision-makers with an appropriate picture on which to base adequate policy implementation.

Over time there have been pessimistic and optimistic views of the employment effects of technological change. In fact, what we have seen is a spiral trend of job creation and destruction. In the period covered in this study (1971-1996), the labour market showed substantial change, with structural unemployment becoming increasingly severe from one recession to another. At the same time, the skill profile changed too, with high-skilled workers assuming a dominant position. This was also the period during which computerization recorded the most rapid growth, as technology advanced by leaps and bounds

We still do not really understand the dynamic of the underlying forces which have been affecting the employment structure. We do know, however, that the different kinds of knowledge embodied in different categories of workers in various industries respond differently to the impact of diverse technologies. In short, the codification capacity of the computer combined with the differentiated nature of knowledge – codified and tacit – seems therefore to be part of the explanation. Moreover, whether a computer is used for core or for complementary activities also seems to matter in terms of its employment effects.

The effect of computerization on employment composition is especially interesting given the computer's widespread industrial diffusion, its rapid change in quality over the last three decades and its adoption by a range of workers with quite different sets of skills. However, it is very important to recognize that computing is quite often a complementary activity for a multitude of occupations and industries and, therefore, does not constitute a core activity, thus leaving significant room for other technologies in explaining employment transformation.

Our study follows the 'skill-biased' tradition of using a production function formulation where technological change (computerization) is described in terms of its biases, which are typically defined as labour-saving, capital-saving and neutral.

This paper assesses how the importance of investment in computers relative to other machinery and equipment (computer investment/machinery and equipment investment) affects the employment structure. The key question in our research is whether the declining demand for goods workers (low-skilled) and the relative increase in other categories of occupations (knowledge, data

and management) can be explained by the accelerated diffusion of computers[1]. This leads us to specify four sets of assumptions related to these potential effects.

(i)   The first possible explanation is that there is a skill-biased technical change, that is, that the increasing use of computers (or change in production techniques) is biased in favour of some categories of workers (labour-using bias or complementarity). By changing skill requirements in an industry, computerization increases the optimal ratio of some categories of occupations to other categories per unit of output. This change could be related to increasing complexity in certain work which is too tacit to be codified and which requires other skills[2] ;

(ii)   The second possible explanation is that computerization reduces the quantity of a particular category of workers per unit of output given that the core tasks of the workers are codifiable. Automating routine aspects of certain tasks means that fewer workers in a given occupation will be required (substitution bias or labour-saving bias) ;

(iii)   The third explanation posits a neutral effect, i.e. that the computer plays no role given the highly tacit nature of the tasks performed in an occupation ;

(iv)   The fourth explanation would be that by transforming the task content of an occupation, it is likely that computerization will not require a change in the number of workers but instead will transform the task content of an occupation either by upgrading or de-skilling work[3].

With a unit of analysis at the sectoral level such as that used in the present study, it is impossible to determine the magnitude of this last effect and this is why only the first three assumptions will be tested in the paper.

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[1]   It is worth noting that most studies aggregate workers into two groups – production vs. non-production, skilled vs. unskilled, information vs. non-information, and so on. In this paper, high-skilled workers are not exclusively related to a single category, that is, knowledge workers. In our study, skilled workers are composed of workers from the data and knowledge categories and, to a lesser extent, management workers such as will be presented in the next section. For more details on the classification of workers used in this paper, we refer the reader to Lavoie, Roy (1998).

[2]   See Lavoie, Roy (1998) for a description of the dynamics of increasing complexity and uncodifiable tasks as well as Levy, Munrane (1996) who clearly describe uncodifiable tasks as those that involve "making judgment calls" as opposed to routinized tasks, which hardly require judgment and can be performed at low cost. OECD (1996) is another important source.

[3]   Braverman (1974) was the one who introduced the concept of de-skilling of work, meaning essentially that the skill content of people's jobs is decreasing considerably. Under this label, we also include the upgrading effect. For example, it is likely that secretaries have had to improve their skills over the last few decades to keep abreast of the changes brought by computerization, even though there has been no change in the number of secretaries required in the economy. In other words, the content of the secretary's job has probably changed but followed an upgrading instead of a de-skilling process (Spenner: 1990). In this paper, we do not examine the content of individual occupations but rather the change in the number of different occupations.

2.   CLASSIFICATION SCHEME

The occupational classification used in this paper aggregates all occupations (499 occupations in 4 digit SOC-1980 codes for years prior 1996 and 514 occupations in 4 digit SOC-1991 codes for 1996) into five broad occupational categories – knowledge, management, data, services and goods[4]. The knowledge category is made up of workers whose core tasks are to produce new ideas; consequently, the role of creativity is important and the computer could hardly serve as a substitute. However, the complementary tasks of these workers are frequently supported by the computer and computerization has even indirectly helped knowledge workers with their core activities by speeding up and facilitating calculations, and so on. For data workers, on the other hand, core tasks include data storage and retrieval, which are amenable to computerization given their codifiable nature. Unlike knowledge workers, data workers have routinized core activities and tacit complementary activities, including, for example, judgment activities.

The core tasks of a manager are hardly routinized, as they require judgment and some creativity for planning, directing, reading reports, and so on. The complementary tasks could nonetheless be more routinized as they might consist in writing up bills and invoices which can be made a standard procedure with computerization. The core tasks of service workers, which consist in providing personal services, are built on experience in a sort of learning-by-doing process and, consequently, are highly tacit. Finally, goods workers' core tasks are composed of highly routinized activities, especially in the manipulation and production of goods, and are good candidates for expert systems software. However, this is less true for those goods workers who are involved in transportation. In general, the complementary tasks of these workers are minimal.

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[4]   The classification used in this paper is inspired from that of Wolff, Baumol: 1989 and is the same than the one used in Lavoie, Roy, Therrien (2003), Lavoie, Roy (1998) and Lavoie, Therrien (1999). Worth noting that in those previous papers, the knowledge category was disaggregated into 4 sub-groups, namely, sciences, engineering, computer science, and social sciences and humanities.

3.   TRANSFORMATION OF THE CANADIAN EMPLOYMENT STRUCTURE

Looking at the employment intensity of industrial sectors by occupation, we see that different sectors lean more heavily toward different categories of workers. First of all, goods workers remain the most important group in manufacturing and their concentration in 1996 is still significant (63 percent). This is also the most important group in the primary sector with a substantial 81 percent of total employment.

TABLE 1
Industrial Employment by Category of Occupations, 1971-1996

Primary

	Knowledge		Management		Data		Service		Goods	
	#	*%*	*#*	*%*	*#*	*%*	*#*	*%*	*#*	*%*
1971	15	2,0	3	0,4	33	4,4	9	1,2	682	91,9
1981	27	3,5	14	1,8	62	8,1	11	1,4	652	85,2
1991	34	4,3	21	2,7	76	9,7	15	1,9	642	81,5
1996	26	3,6	18	2,5	76	10,7	15	2,1	580	81,1

Manufacturing

	Knowledge		Management		Data		Service		Goods	
	#	*%*	*#*	*%*	*#*	*%*	*#*	*%*	*#*	*%*
1971	78	4,5	34	2,0	389	22,6	47	2,7	1174	68,2
1981	99	4,8	121	5,9	400	19,5	43	2,1	1385	67,7
1991	128	6,9	175	9,4	390	21,0	37	2,0	1128	60,7
1996	133	7,1	139	7,4	386	20,5	36	1,9	1190	63,2

Service

	Knowledge		Management		Data		Service		Goods	
	#	*%*	*#*	*%*	*#*	*%*	*#*	*%*	*#*	*%*
1971	218	5,5	79	2,0	1664	41,6	706	17,6	1335	33,4
1981	384	6,5	439	7,4	2406	40,8	1040	17,6	1634	27,7
1991	638	8,2	760	9,7	3027	38,8	1497	19,2	1876	24,1
1996	744	8,8	875	10,4	3302	39,2	1718	20,4	1777	21,1

Public Sector

	Knowledge		Management		Data		Service		Goods	
	#	*%*	*#*	*%*	*#*	*%*	*#*	*%*	*#*	*%*
1971	121	7,4	81	4,9	804	49,1	470	28,7	162	9,9
1981	175	8,7	130	6,4	1028	50,8	522	25,8	168	8,3
1991	260	10,1	217	8,5	1252	48,9	639	24,9	194	7,6
1996	288	12,5	153	6,6	1223	53,1	511	22,2	128	5,6

Total

	Knowledge		Management		Data		Service		Goods	
	#	*%*	*#*	*%*	*#*	*%*	*#*	*%*	*#*	*%*
1971	433	5,3	197	2,4	2889	35,7	1232	15,2	3353	41,4
1981	685	6,4	703	6,6	3896	36,3	1615	15,0	3839	35,7
1991	1059	8,1	1173	9,0	4745	36,5	2187	16,8	3840	29,5
1996	1192	8,9	1185	8,9	4989	37,4	2277	17,1	3676	27,6

Note: Numbers (#) are expressed in thousands

Source: Census

Data workers are highly concentrated in the service sector, with a share of 39 percent, and compose 53 percent of the public sector. Finally, it is worth emphasizing that knowledge workers still represent only a small proportion of workers in all sectors, ranging from 12 percent for the public sector to 4 percent in the primary sector with mid-range numbers of 7 and almost 9 percent respectively for the manufacturing and service sectors.

A glance at the composition of the employment structure reveals that the share of goods workers in the economy decreased considerably between 1971 and 1996, that is, from 41 percent to 28 percent while all other categories of occupation increased though at a different pace. Management occupations had the strongest increase over time (from 2 percent in 1971 to 9 percent in 1996) followed by the knowledge workers (5 and 9 percent in 1971 and 1996)[5]. Data and service occupations increased their relative share in the economy between the whole period studied, but at a much lower pace – from 36 percent in 1971 to 37 percent in 1996 for Data and from 15 percent to 17 percent for service.

Looking more closely at the industrial disaggregation, we can see the emergence of different growth patterns for each of the occupational groups.

3.1.   Management Workers' Employment

As expected, the management group increased its relative employment share in all industrial sectors between 1971 and 1996. During this period, the most important concentration of managers shifted from the non-business (public) sector to service sectors. It should also be noted that the increasing demand of manager occupations ended in 1991 where its share in the whole economy slightly decreases between 1991 and 1996 in all sectors except in the service industry.

3.2.   Knowledge Workers' Employment

The most knowledge-intensive sector is the public sector, followed by the service sector, while the primary sector comes last. The growth for these workers was fairly stable for all industrial categories over the period studied, with the only exception being the primary sector between 1991 and 1996, where knowledge workers experienced a slight decrease returning to 1981 levels.

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[5] Although some portion of the increase in the share of management occupation is real, it is however important to note the bias introduced by the coding changeover from OCM to SOC between 1971 and 1981. We refer the reader to a Statistics Canada staff report (Montigny: 1988), entitled *An Evaluation of Occupational Data from the 1981 Census,* by the Labour and Household Surveys Analysis Division, which explains the reasons behind the rapid rise in management-related occupations between the two censuses. Suffice it to say for now that the main reasons were (*i*) a change in administrators' tasks which led to more frequent use of the term "manager" and (*ii*) less restrictive use of salary limits in 1981 than in 1971. In this report, it is also reported that the French version of the coding manual introduced a bias as well.

3.3. Data Workers' Employment

Data workers are at the heart of the information technologies revolution, as their tasks are mainly designed to store and retrieve data. In the public sector, in 1996, data workers made up 53 percent of total employment while between 1971 and 1996 they accounted for only an average 40 percent of the service sector[6]. This occupational group represents a substantially smaller proportion of total employment in the primary sector – 4 percent in 1971 and 11 percent in 1996 – while in the manufacturing sector it accounts for 23 and 21 percent respectively in 1971 and 1996. The largest concentration of these workers is therefore in the public and service sectors.

3.4. Service Workers' Employment

While the largest concentration of service occupations is in the public sector, the growing importance of these workers in service industries, combining with a decreasing trend in the public sector, results in a similar concentration of these workers in the service and public sectors in 1996. Although small, the concentration of these workers in the primary sector is growing while their number decreased in the manufacturing sector between 1991 and 1996.

3.5. Goods Workers' Employment

In the sectors most intensive in goods workers – primary and manufacturing – negative growth on average was registered between 1971 and 1996, although there was positive growth between 1991 and 1996 in the manufacturing sector. It is worth noting that, in 1996, goods workers still accounted for 81 percent of total employment in the primary sector and 63 percent of total employment in the manufacturing sector.

In the service and public sectors, which are very low-intensive in goods workers, goods employment experienced a decrease in their share of workers to make up 21 percent in the service sector and more than 5 percent in the public sector.

Overall, there was a declining demand for goods workers while knowledge workers, though still a very small proportion of total employment constituted a growing group. We assume these trends to be associated with technological change and, in particular, computerization.

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[6] It is worth emphasizing the fairly heterogeneous composition of the industries included in our service category. Comparing the construction industry with FIRE, both in the service category, shows a rather low concentration of data workers in the former and a significant one in the latter (not shown on the tables).

4.   METHODOLOGY

In this paper, we attempt to correlate the diffusion of computers at the industry level with the employment shares of different categories of workers between 1971 and 1996. In the literature, there are many variants of this structure[7]. The most common are employment share and cost share. We use the former because, as Chennels and Van Reenen state, "although less appropriate from a theoretical point of view, this clearly has the advantage that it allows a statistical decomposition of the effects of technology into a relative wage component and a relative employment component" (Chennells, Van Reenen: 1999).

The econometric specification used in this paper is typically derived from a restricted translog cost function (assuming symmetry and homogeneity of degree one in price) with five variable factors – wages of knowledge, management, data, service and goods workers – and a quasi-*f*ixed factor – capital stock. The wage bill equation for a given type of workers, Pi is as follow :

$$(1) \qquad P_i = \alpha_i + \gamma_{ii} \ln W_i + \Sigma_j \gamma_{ij} \ln W_j + \gamma_{iK} \ln K + \gamma_{iY} \ln Y + e_i, \quad i \neq j$$

Where subscript i = kn, m, d, s, g refers to knowledge, management, data, service and goods occupations. Pi is the wage bill of occupation i relative to the total wage bill and Ln Wi is the log of the relative wage of the ith occupation. The terms ln K and ln Y are respectively the logs of capital stock and value added.

Using appropriate approximations[8] to transform a wage bill equation in an employment equation and using the wage of service workers (W_s) as a baseline, equation (1) becomes:

$$(2) \qquad S_i = \delta_i + \rho_{ii} \ln\left[\frac{W_i}{W_S}\right] + \Sigma_j \rho_{ij} \ln\left[\frac{W_j}{W_S}\right] + \beta_{iK} \ln K + \beta_{iY} \ln Y + u_i, \; i \neq j$$

Where S_i is the employment share of occupation *i*.

Finally, imposing a homogeneity restriction of the structure of production ($\gamma_{iY} + \gamma_{iK} = 0$) and adding the computer investment intensity variable (C/I), we end up with the following system of equations :

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[7]   See Chennells and Van Reenen (1999) for an exhaustive review of the studies using the same structure and the variants.
[8]   See Klein (1953) for formal demonstration.

Management workers

$$(3.a) \quad S_{m_n} = \delta_m + \rho_{mm} \ln\left[\frac{W_{m_n}}{W_{s_n}}\right] + \Sigma_j \rho_{mj} \ln\left[\frac{W_{j_n}}{W_{s_n}}\right] + \beta_{m\,tech} \ln(C/I)_n + \beta_{m\,K} \ln(K_n/Y_n) + u_{m_n}$$

Knowledge workers

$$(3.b) \quad S_{kn_n} = \delta_{kn} + \rho_{knkn} \ln\left[\frac{W_{kn_n}}{W_{s_n}}\right] + \Sigma_j \rho_{knj} \ln\left[\frac{W_{j_n}}{W_{s_n}}\right] + \beta_{kn\,tech} \ln(C/I)_n + \beta_{kn\,K} \ln(K_n/Y_n) + u_{kn_n}$$

Data workers

$$(3.c) \quad S_{d_n} = \delta_d + \rho_{dd} \ln\left[\frac{W_{d_n}}{W_{s_n}}\right] + \Sigma_j \rho_{dj} \ln\left[\frac{W_{j_n}}{W_{s_n}}\right] + \beta_{d\,tech} \ln(C/I)_n + \beta_{d\,K} \ln(K_n/Y_n) + u_{d_n}$$

Goods workers

$$(3.d) \quad S_{g_n} = \delta_g + \rho_{gg} \ln\left[\frac{W_{g_n}}{W_{s_n}}\right] + \Sigma_j \rho_{gj} \ln\left[\frac{W_{j_n}}{W_{s_n}}\right] + \beta_{g\,tech} \ln(C/I)_n + \beta_{g\,K} \ln(K_n/Y_n) + u_{g_n}$$

Subscript n indexes industry. A positive coefficient on β_{itech} denotes a complementarity or labour-using technological change while a negative coefficient indicates a substitution or labour-saving technological change. Complementarity (substitution) between capital and employment would imply a positive (negative) correlation between the capital ratio and employment (coefficient β_{ik}). The coefficients ρ_{ii} and ρ_{ij} also provides the same complementarity/substitution pattern of relative wage intensity in relation to employment.

Data from the five censuses – 1971, 1981, 1986, 1991 and 1996 – are pooled together[9]. Time dummies are added in the equations to control for institutional change or other non-specified change, while industry dummies are added to control for fixed effects.

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[9]   See the Annex I for details regarding data sources and Annex II for descriptive statistics.

The model presented above does not depart from the literature, using a typically production function as the general framework. However, it contains some particularities, which are worth clarifying.

First, as discussed earlier, dependent variables are employment shares of 5 broad categories of occupations – knowledge, management, data, service and goods– and are measured as the share of employment of a given type of occupation out of total employment by industry. Using the classification with 5 categories of occupation allows us to capture a greater variety of relationships between occupational categories and use of computer than the conventional skilled/unskilled classification of occupations.

Second, several studies, following Berman, Bound, Grilliches (1993), took for granted the non-variation of relative wages across industries. In this paper, we adopted a different track and included relative wages in the model. This inclusion allows us to determine whether the effect of technology is driven by relative wage movements or by relative employment movements. More plausibly, the effect of technology is a combination of both movements. Wages represent the average annual income earnings for full-time/full-year workers. This also includes wages and salaries of self-employed people who worked more than 30 hours per week for more than 49 weeks. Relative wages are those of the knowledge, management, data and goods occupations relative to the wages of the service occupations. Since the service category is regarded as relatively exogenous in terms of technological change (due to the highly tacit nature of these occupations), it is a relatively good benchmark for other occupations.

Third, the model uses, as an explanatory variable, the capital stock intensity. This variable was constructed as capital stock over value added. Value added is preferred from other output measures (such as shipments) because it gives precise information on the true production of an industry since it removes purchases (material cost) from other industries. Capital stock intensity approximates the productivity of equipment and machinery as well as providing indirect information on the state of technology, which proves extremely useful in an inter-industrial analysis.

Finally, computer investment intensity – constructed by dividing computer investment by investment in machinery and equipment – is used in this paper, as the technology variable[10]. For the purpose of this study, we seek to know what share of employment is associated with a given level of computer investment intensity regardless of computer performance in a given period (current dollars) and see how this has evolved over time. Computer investment intensity allows us to appraise, at the same time, the evolution of the ratio of computers to machinery and equipment, in other words, the increasing level of computerization.

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[10]   Ideally, stock of computer investment is what we would have liked to use but the poor reliability of computer capital stock data in Canada, prevented us from doing so. The problem mainly lies in the depreciation index, which does not really represent the true value of the computer despite the amount of work done on this lately. It is especially hard to find a fair representation of the real cost of computers over time in relation to performance. We refer the reader to Lavoie, Therrien (1999) for an exhaustive explanation regarding this issue.

Since we have data on employment (the dependent variable) and wages for census years only, average computer investment and machinery and equipment investment variables were constructed using a three years moving average around the census years. In this way, we can somewhat avoid the problem related to the volatility of investment[11]. Moreover, as computer life expectancy is approximately four years, the capital stock problem is less important here than it would be for another commodity.

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[11] Since the series of computer investment data begins in 1971, as an exception, average computer investment was calculated on a two year basis, that is, 1971 and 1972.

5.   EMPLOYMENT STRUCTURE TRANSFORMATION: SOME EXPLANATIONS

In the following section, empirical results are described and analysed. It is composed of three parts corresponding to the analysis of the three independent variables included in our model – relative wages, capital intensity and computer investment intensity. Two sets of regressions are reported and analysed. Under the first regression, we estimate the effect of computer investment intensity for the whole economy disaggregated over time (1971, 1981, 1986, 1991, and 1996) and that of capital intensity. The second regression disaggregates employment effects of computer intensity over time and capital intensity into three broad industrial sectors — primary, manufacturing and service[12].

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[12]   It is worth noting that the public sector is excluded from the second equation because the computer investment variable for this sector is an industrial average and therefore constitutes a single observation.

TABLE 2

Employment Effects of Computerization

	KNOWLEDGE				MANAGEMENT				DATA				GOODS			
	(1)		(2)		(1)		(2)		(1)		(2)		(1)		(2)	
	Coeff	Std-Err	Coeff	Std-Err	Coeff	Std-Err	Coeff	Std-Err	Coeff	Std-Err	Coeff	Std-Err	Coeff	Std-Err	Coeff	Std-Err
Time dummies	YES		YES		YES		YES		YES		YES		YES		YES	
Industry dummies	YES		YES		YES		YES		YES		YES		YES		YES	
Log(K/VA)	1,2428**	(0,30)			0,0697	(0,14)			3,8849**	(0,77)			-3,8989**	(0,99)		
Log(K/VA)*Pri			1,8529**	(0,77)			0,6032	(0,57)			1,9540	(1,81)			-5,1313**	(1,13)
Log(K/VA)*Man			-0,0639	(0,36)			0,2002	(0,16)			1,3563*	(0,70)			-0,5007	(0,48)
Log(K/VA)*Ser			1,3649**	(0,35)			-0,4777	(0,30)			-4,5051	(6,18)			0,1265	(4,65)
Log(Wk/Ws)	-2,1848	(2,01)	-1,5395	(1,89)												
Log(Wm/Ws)	-1,0826	(0,85)	0,3085	(0,95)	-1,1648*	(0,62)	-1,1129	(0,76)								
Log(Wd/Ws)	-11,4220**	(2,17)	-7,2301**	(2,16)	0,7110	(1,30)	-0,1956	(1,49)	-5,2755	(4,17)	-2,4444	(3,65)				
Log(Wg/Ws)	10,7955**	(1,81)	6,6643**	(1,46)	3,1831**	(1,00)	3,8949**	(1,09)	14,7545**	(3,70)	6,0391**	(2,50)	-26,9686**	(6,93)	-8,4582**	(3,14)
1971 and 1981																
Log(C/I)	1,2221**	(0,24)			0,2749**	(0,09)			4,1635**	(0,68)			-4,4563**	(0,80)		
Log(C/I)*Pri			2,1122**	(0,47)			0,8272**	(0,33)			3,0956**	(1,31)			-8,0956**	(0,80)
Log(C/I)*Man			0,1476	(0,23)			0,3232**	(0,12)			2,3331**	(0,66)			-0,9953**	(0,39)
Log(C/I)*Ser			2,1462**	(0,45)			0,8491**	(0,25)			5,4134**	(2,30)			-3,4116*	(1,84)
1986 and 1991																
Log(C/I)	3,1325**	(0,42)			1,4188**	(0,33)			6,2595**	(0,87)			-9,6201**	(1,37)		
Log(C/I)*Pri			3,1554**	(0,59)			2,1053**	(0,47)			2,8696*	(1,60)			-**	(0,95)

							10,090
							1
Log(C/I)*Man	1,5204** (0,41)		1,3481** (0,39)		3,2272** (0,75)		-4,0142** (0,73)
Log(C/I)*Ser	4,4091** (0,72)		2,6026** (0,62)		8,0538** (3,25)		-8,2789** (2,51)
1996							
Log(C/I)	2,5124** (0,65)		1,2193** (0,33)		5,4502** (0,76)		-8,7352** (1,54)	
Log(C/I)*Pri		3,3553** (0,77)		1,4698** (0,49)		1,3435 (1,64)		-8,1759** (1,09)
Log(C/I)*Man		1,5545** (0,56)		1,0254** (0,40)		2,7674** (0,60)		-3,8287** (0,70)
Log(C/I)*Ser		5,0022** (1,08)		1,4706* (0,74)		7,6861** (3,50)		-8,1280** (2,82)
System R square	0,9072	0,9777	0,9072	0,9777	0,9072	0,9777	0,9072	0,9777
Obs	145	140	145	140	145	140	145	140

Notes: Dependent variables are employment share (x100) for the Knowledge,
Management, Data, and Goods occupations.

K=Capital Stock, VA=Value Added, C=Computer investment, I=M&E investment, Wk= average income earnings for Knowledge, Wm= average income earnings for Management,

Wd= average income earnings for Data, Wg= average income earnings for Goods, Ws= average income earnings for Service, Pri=primary sector, Man=manufacturing sector.

Coefficients are produced by SUR estimation. Standard errors are heteroscedastic consistent.

5.1.   **Wages and the Employment Structure**

Although it is worth examining the role of relative wages in some occupations, the analysis is complex given the number of categories of occupations involved in the present study as compared with other studies, which generally deal with, at most, two categories, that is, skilled vs. unskilled. The first observation of interest concerns the fact that for management and goods workers, when there is a relative increase in their wages, we find a decrease in their employment share ; for knowledge and data workers categories, the effect of wages is not significant. Though we cannot conclude that a premium is given to these workers, these results nonetheless reveal something quite interesting in that the wages of knowledge and data workers are probably more flexible than those of other workers. However, more work should be done to understand what differentiates knowledge workers' wage mechanism from that for other categories of workers.

There are some other interesting findings if we look more specifically at the effect of relative wages on the employment shares of different categories of workers. However, it would require careful handling since this is not a direct cause-and-effect relationship. The first point of interest regards the role of relative data wages in the share of knowledge workers. We find that when there is an increase of 1 percent in relative data wages, we see a decrease in the share of knowledge workers[13]. It is also interesting to observe that when there is an increase of 1 percent in relative wages of goods workers, the picture is reversed for all other employment shares.

In general, we can see that the inclusion of relative wages in the model does not show any fundamental change in the relationship between a category of workers and computer investment intensity[14].

5.2.   **Capital/Skill Complementarity**

We assume that capital intensity is complementary to certain skills and could therefore explain part of the employment composition shift. As stated by Goldin and Katz, "physical capital and skill have been shown to be relative complements both today and in the recent past". They also argue that "the shift to a more advanced technology is associated with increases in both capital intensity and the relative employment of more-skilled workers" (Goldin, Katz : 1998).

Estimates from Table 2 (equation 1) show a complementarity effect between capital and knowledge workers as well as with data workers, while the association between goods workers

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[13]   The analysis of the effect of relative wages on the employment structure, such as done in this section, does not imply a causality link between the relative wages of one category of workers and the share of another category of workers. The situation pictured can be due to a multitude of other variables and does not simply involve a substitutive relationship between one category of workers and another.

[14]   That is, even after our regressions with and without relative wages, the magnitude and trends of the computer investment coefficients remain the same.

and capital is a substitutive one. Finally, there is no association between management workers and physical capital and, therefore, the rapid increase of these workers cannot be related to physical capital[15].

A glance at cross-industry comparisons, under estimate 2, reveals different patterns of relationships between categories of workers and capital. For example, we can see that the substitutive relationship between goods workers and capital is present in the primary sector but, quite surprisingly, not significant in the manufacturing sector. When our results are disaggregated across industries, the complementarity found between data workers and capital in the economy as a whole is only significant for manufacturing (at around 10 percent). Finally, knowledge workers and capital remain complementary in primary industries as well as in service industries.

The interesting point to make here is that while the effect of capital intensity was no different from that of computer intensity in 1971 and 1981, the relationship with computer intensity was the stronger of the two for 1986 and 1991 and remains quite strong in 1996. Therefore, in these later years, we can clearly observe a more dominant computer effect than in 1971 and 1981 with a peak between 1986 and 1991 for all categories of employment. The evolution of the impact of computers will be examined in further detail in the following section.

5.3.   Computer Technology/Skill Complementarity

Despite the predictions of the automation debate of the 1950s, according to which computerization would inevitably lead to mass unemployment, something more complex is happening in the current labour market in relation to the diffusion of information and communication technologies, in general, and computers, in particular. Computers and computerized equipment have, instead, eliminated occupations requiring physical effort and replaced them with occupations depending more on mental ability.

In this section, we examine the evolution of the level of complementarity between computer intensity and various occupations across industrial sectors. As explained above, the nature and characteristics of the tasks accomplished by a worker are important elements to take into account in order to determine how computerization may have changed the employment structure. In other words, the less tacit and, therefore, the more codifiable the tasks, the more likely that they could be replaced by a computer. On the other hand, the more tacit these tasks, the less likely that a computer will be able to substitute for them. However, it may be that only some of the tasks are codifiable and, therefore, replaceable ; in this case, with the support a computer can provide, the focus of the job may shift from core activities to complementary ones. Whether activities are core or complementary to the job will also play an important role in the process of employment creation/destruction. For example, a computer can reduce the complexity of calculations a scientist has to do as a complementary activity as well as speed up these calculations; this results in a new

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[15] Tests that we performed show that the effect of capital intensity remained constant all over the period (though not reported in these tables).

level of complexity of the core activities moving the search process forward, so that the judgement skills essential to the core activities to analyze and interpret the results of these complex calculations may become even more important, thereby reducing the productivity of a scientist and thus increasing the rate of employment of this category of workers. Although the role of the computer in this example is accessory, it can ultimately change the number of scientists required to do a job, given that it helps to precipitate a considerable complexity in the search process, pushing back the frontiers of knowledge. In the light of the above analysis, we will do a detailed examination of occupations.

5.4.   Knowledge Workers

The strong increase in knowledge workers over the 1971-1996 period led us to assume that a technological shock had occurred. Moreover, given the pervasive nature of the computer, which invaded all spheres of private and professional life, and considering the simultaneity of events, we also assumed that the computer *per se* might have been an important determinant in this increasing trend.

According to our findings, as shown in Table 2, there is, in general, a significant complementarity between knowledge workers and the computer though the magnitude differs slightly when disaggregated by industrial sector over time. As early as 1971, there is a complementarity association in the primary and service sectors. There is also a fair complementarity in both the primary and service sectors in 1971 and 1981, while in 1986 and 1991, this is outpaced by complementarity in the service sector and still more in 1996. Overall, the findings mean that where there is a knowledge worker, there should be a computer. However, the computer *per se* could not replace the tasks of the knowledge worker *per se*; it is mainly a tool used to assist the worker in his (her) job.

5.5.   Management Workers

If there is one category of workers for which the relationship with the computer is close but not simultaneous, this would be management. One core activity of these workers is planning, including the planning of computer adoption. We do find some degree of increasing closeness in all sectors up to 1991 slightly decreasing in 1996. This less strong complementarity between the computer technology and this category of workers, when compared with knowledge and data workers, might be the result of a certain lag effect between the adoption of computers and the activity of planning it.

5.6.   Data Workers

It appears that the strongest complementarity between computer technology and skills is among data workers in the service sector. There is also a complementarity in manufacturing for all years. As a whole, data workers, whose core tasks consist in using data, can hardly do without a computer. Although less significant than the increase in knowledge workers, there has been an increase in these workers, leaving us to assume that no major substitution took place for this group of workers. This is confirmed in research by Hunt and Hunt, reported by Cyert and Mowery: " They argued that these flaws led the studies to overstate the job-displacing impact of technological change on clerical workers " (Cyert, Mowery : 1987).

5.7.   Service Workers

This category of workers is neither substituted nor complemented by the computer (not shown on the tables). This is not surprising since their tasks are not only uncodifiable but rarely require the use of a computer, and, if then, only for supporting complementary tasks. For example, it would be rather unusual to find a hairdresser doing his or her tasks with the support of a computer.

5.8.   Goods Workers

The association between the computer and goods workers goes only in one direction, that is towards substitution, as shown by the negative coefficient of $ß_{tech}$ for all industries. The strongest and most steadily growing computer substitution relationship for goods workers is in the primary sector. It is interesting to observe that as early as the first decade, substitution took place in this sector while it is only in the second decade that manufacturing began to experience a stronger substitutive relationship.

Essentially, this means that the work of goods workers has become increasingly obsolete and, furthermore, that this rate of obsolescence is similar to the rate of computer investment. In other words, the greater the investment there was in computers, the more the employment share of goods workers tended to decrease. The routinized nature of core tasks accomplished by goods workers certainly explains much of the substitution. More than likely it is the CAD/CAM and CAD/CAE software portion of computer investment which has had the strongest effect.

In general, we found that computer diffusion favours professional and technical (knowledge, management, data) workers as opposed to manual (goods) workers. However, a variety of industrial patterns emerged and these differences have been analysed.

The conceptual framework developed above is useful in interpreting our results. For example, it helps to explain the differences between the data and goods categories of workers. The core tasks

of a goods worker are characterized by their codifiability which explains the high level of replacement of goods workers by the computer (in this case, it is probably the expert systems software component which is responsible). Let us compare it with the tasks of a secretary – included in the data category. While manual and secretarial workers both have codifiable core activities, the secretary has multiple-task core activities as well as tacit complementary activities (such as dealing with people and thus using judgment) ; manual workers, on the other hand, have, in general, specialized core tasks with minimal complementary tasks. As a result, if a secretary's core activity is replaced by a computer, the content of the job will be transformed, forcing a change in the secretary's tasks – from typing to editing, for example (since computers are widespread, people who write papers and reports now do their own typing). In other words, while the secretary was able to shift from a core activity to another and even from one core activity to a complementary activity, the narrowly specialized competencies of a goods worker may prevent him/her from doing the same.

CONCLUSION

There is increasing empirical evidence of a shift from unskilled workers towards skilled workers in Canada and elsewhere (Berman, Bound, Griliches : 1993, Lavoie, Roy, Therrien : 2003, Lavoie, Roy : 1998, Osberg, Wolff, Baumol : 1989). While many factors are probably responsible for the trend, technology has been singled out as the main determinant. This paper has provided an analysis of the employment effects of computerization across industrial sectors. In presenting these results, we have attempted to go beyond simple description and offer explanations for the various impacts the computer has had on diverse categories of workers and industries. We developed an analytical framework which proved very useful for understanding occupational diversity in relation to computerization. Basically, we assumed that the association of workers with the computer is defined by the nature of the knowledge – tacit vs. codified – required by an occupation and the inherent character of the tasks – core vs. complementary – related to this occupation.

The major findings include the following :

i)   In general, the association between workers and physical capital was not significantly different from their relationship with the computer in the first decade, but the impact of computers outweighed the effect of capital in 1986 and 1991 as well as in 1996. This clearly reflects the significant diffusion of computers from the mid-1980s onwards ;

ii)   There are some important differences across industrial sectors in the computer intensity level as well as in the skill composition, leading to differences in the cross-sectoral impacts of computerization on different occupational categories. It is in the service industries that the computer effect is the strongest and most pervasive for knowledge, management and data occupations. This effect is however stronger in the primary sector for goods workers ;

iii)   A complementarity between computers and the data and knowledge categories of workers was established in this paper. While for the knowledge category the use of a computer is mainly a complementary activity (supporting the core activities), except perhaps for computer scientists, it more frequently constitutes a core activity for data workers who are forced to redefine the content of their jobs on the basis of their largely tacit complementary activities. As a result, there is a shift from codifiable core tasks to tacit complementary tasks ;

iv)   Given the strongly tacit nature of the service category of workers, we found no association with the computer, meaning that computer use is essentially non-existent for this category of workers given the nature of their core and complementary activities ;

v)   The category of goods workers has a strong substitutive relationship with the computer especially in the primary and manufacturing sectors over time. This effect is most certainly related to expert systems software included in the computer investment data ;

vi)   In general, however, computerization does not appear to be a labour-saving process but is instead a labour-using one, which partly explains the shift in the composition of labour over the last two decades. This confirms the findings of other studies.

These findings raise additional questions as to the role of computerization in the general shift from a manufacturing to a service-related base economy. For example, to what extent is the role of computerization in the declining relative demand for goods workers independent of an increase in the relative demand for knowledge workers ? It would be interesting, then, to assess whether the degree of international competition intensity across industries partly explains the skill upgrading, since, as emphasized by Berman, Bound and Griliches, "the uniqueness of the computer revolution" should not be exaggerated (Berman, Bound, Griliches : 1993).

Another question is related to the direction of the causality link between high-skilled workers and adoption of technology. The most likely interpretation would be that new technologies will be adopted once some high-skilled workers are in place – with high-skill workers encouraging the adoption of technological change and vice versa (technological change requiring the skills of these workers). This starts a virtuous circle, as more technological change takes place and more high-skilled workers are hired to deal with the new equipment. This is of course only one interpretation and we think that the direction of the relationship depends on the industrial sector and the nature of the technology being adopted.

We found a complementarity between knowledge, management and data workers and the computer but is it enough to affect skill demand ? We believe that the computer investment variable captures the general technology trend and that other technology variables would be required to capture all technology effects and even purify the computerization one.

ANNEX I

DATA SOURCES

Data used in this paper are drawn from Statistics Canada. Data on employment and wage come from the last five Canadian censuses (1971, 1981, 1985, 1991 and 1996). From one census to another, occupational and industrial classifications were not directly comparable and required some reconciliation work (Lavoie, Roy, Therrien : 2003) for explanation regarding matrices reconciliation). Data on value added (Statistics Canada, Catalogues 15-201 and 15-202) and capital stock (Statistics Canada, Cat. 13-568) are expressed in 1986 constant dollars for the entire period. Capital stock is constructed using a perpetual inventory combined with a geometric depreciation method. Finally, data on computer investment come from the Input-Output Division, while data on machinery and equipment investment are drawn from Cat. 61-2051.

Regarding data on computer investment, we have to account for the fact that the computing machine referred in 1971 is completely different from the computer referred to in 1991. We used input-output commodities 346 (1971-1986) and 359 (1986-1996) which include the computer *per se*, that is, the hardware plus some software component. A strict delimitation of the different types of software included in our data is rather difficult to establish precisely. However, it would be quite fair to say that "marketed software products" embedded in computer equipment are included and that "custom designed software" is excluded. From 1971 to 1981, computer investment was not surveyed in the input-output tables and approximations of this investment were derived from American imports since almost all computer equipment was imported.

ANNEX II
DESCRIPTIVE STATISTIQUES BY INDUSTRY, 1971 AND 1996

INDUSTRY	EAR	n %)	g %)	t %)	v %)	d %)	/I x100)	M$)	M$)	K/VA	k/Ws	m/Ws	d/Ws	g/Ws	MPLOY %)
PRIMARY	971	,98	,45	,45	,18	1,95	,12	3,9	239,2	,21	,10	,62	,28	,07	,15
	996	,65	,51	0,68	,05	1,11	,51	2,6	798,3	,25	,31	,18	,33	,06	,37
MANUFACTURING	971	,54	,00	2,56	,73	8,15	,92	3,3	166,3	,60	,70	,42	,28	,14	1,25
	996	,06	,37	0,49	,89	3,16	,64	08,9	5268,6	,56	,67	,30	,23	,10	4,14
SERVICE	971	,45	,97	1,58	7,64	3,35	,36	65,4	171,5	,88	,00	,81	,12	,38	9,38
	996	,84	0,40	9,23	0,41	1,11	6,70	218,5	1249,5	,04	,24	,15	,34	,42	3,19
PUBLIC SERV.	971	,42	,92	9,06	8,70	,90	5,19	2,6	78,1	,65	,48	,72	,36	,36	0,21
	996	2,52	,62	3,10	2,18	,57	3,33	371,7	115,3	,67	,86	,78	,90	,13	7,29

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