Technological Innovation and Employment Reallocation

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ABSTRACT

The paper describes the dynamics of employment at a firm and sector level in the French industry and examines how far technological innovation can give account of it. We use a firm sample of 15,186 firms, over the 1986-1990 period. The two facts we want to explain at a firm level and a sector level are the net change in employment and the micro turmoil (transfers between competing firms). Innovating firms and sectors create jobs more than others over medium run (5 years). Process innovation is more job creating than product innovation at the firm level, but the converse is true at the sector level. This puzzle is probably be due to substitution effects (creative destruction).

Key words : job flows, technological innovation, empirical study

INTRODUCTION

Reallocation of jobs between firms is a massive phenomenon, which has attracted recently a great deal of attention from economists. Some firms increase their labour force while, at the same time, other firms reduce their employment. These divergent dynamics generate a high jobs turnover, as workers switch firms. The consequences on this turnover are striking. As workers move from job to job they frequently have some time of unemployment. Actually or potentially moved workers have a feeling of insecurity reflected in opinion polls (OECD, 1996). Moreover, this temporary unemployment can get permanent when there are rigidities in the allocation of labour as in European countries. Another consequence is a loss in skills, especially skills which are specific to a precise job or to a firm. Jobs instability also results in deficient training practices since firms are likely not to get the return when workers move. As emphasised below, however, reallocation of jobs is a direct consequence of the competitive process, which delivers many beneficial outcomes.

The puzzling fact is that turnover at a micro level, seems to be much higher than aggregate adjustment requires. In other words, jobs are created and destroyed by very similar firms, at least with respect to well identified criteria such as size and industry. Reallocation cannot be explained only by macroeconomic shocks (although an asymmetry in the reaction of firms to such shocks may matter). No satisfactory explanation of this phenomenon has hitherto been provided and checked against actual data. The issue is to find out factors that generate heterogeneity in firms employment trajectory. The present study focuses on one such factor, technological innovation. It explores the effects of various types of innovation on the creation and destruction of jobs by firms and at the industry level.

The pioneer works of Leonard (1987) and Davis and Haltiwanger (1989) emphasised the great heterogeneity of plant-level employment dynamics within sectors, even when using a very detailed sector nomenclature. What kind of explanations can give account of these job transfers ? Davis and Haltiwanger (1992) underline four main hypotheses. First, transfers are due to a selection effect associated with passive learning about initial conditions (a cost parameter or the level of efficiency). Second, differences in initial conditions or uncertainty about future conditions drive firms towards distinct choices of production techniques, which, in turn, leads to heterogeneity in response to demand or cost disturbances. Third, the existence of idiosyncratic cost disturbances influenced by local conditions (tax burdens or energy costs for example) may generate transfers. The last explanation is technical change, because the replacement of old plants by technologically superior one involves idiosyncratic disturbances. These four hypotheses are tested in a very indirect fashion by Davis and Haltiwanger, using the age, the size or the location of the plant as proxies for heterogeneity factors.

Also Baldwyn et al. (1998) find a primary role of technology in the reallocation of jobs. They observe a striking similarity between US and Canada sectoral patterns of jobs reallocation over the 1975-1993 period. They conclude that the explanation which fits best with this similarity is technology -which is common to the two countries: technological change, but also technology used (e.g. sunk costs).

It is the purpose of the present study to analyse the effect of technical change on job flows in a direct way, using indicators of technical change at the firm level and relating them to patterns of jobs creation and destruction.

The impact of technical change on employment can be analysed at three distinct (and complementary) levels, and may differ depending on the process or product orientation of innovation. At the firm level, innovation is a source of “creative destruction”, in the words of Joseph Schumpeter. Firms which innovate successfully take an advantage over their competitors in terms of market share or in terms of profits (higher margins). Whether this advantage results in more or less jobs depends in turn upon the type of innovation. A product innovation will have a positive effect on the market share of the firm that innovates and thus on its employment when productivity is held constant. Only high substitutability with other goods provided by the same firm (“cannibalism”) can limit the positive effect on its employment level. The effect of a process innovation is ambiguous. On the one hand, the market share of the firm increases thanks to the reduction in price (due to higher productivity). On the other hand, the productivity of labour increases too, generating a reduction in labour demand for a given production level. The resultant effect depends crucially on the price elasticity of demand. If it is high, the effect of cost reductions on sales will be strong, hence boosting employment. If it is low the "Ludd effect" dominates, the machine kills jobs. Econometric evidence presented below shows that innovating firms create jobs, and they create more jobs when they implement new processes.

At a sector level, one must take into account the effect of innovation by one firm on employment in other firms. If other firms do not innovate, this effect is negative since all non innovating firms are loosing market shares. This is the schumpeterian process of creative destruction -innovating firms displace jobs from non innovating ones. The total effect (innovating firm plus non innovating ones) depends on the within and between sector elasticities of substitution. For instance a high within substitution coupled with low between substitution will limit the effect of innovation on job creation within the industry. To what extent does the price reduction or the supply of a new good allow the sector to increase its share in total demand (at the expense of other sectors)? A reasonable guess (which we verify later) is that product innovation should have a more positive effect than process innovation for the concerned sector, since it extends the market more than a reduction in price (within sector cannibalism is lower). This guess is confirmed by econometric evidence presented herein.

Finally, at a macro level, if goods and factors markets are competitive, the "compensation effect" implies that technological innovation should not modify total employment. Transitory unemployment due to friction may appear. As mentioned above unemployment can become permanent as soon as rigidities on the labour market impede the reallocation process. Increases in productivity result in destruction of jobs in innovating sectors, but firms in other sectors do not create jobs: due to low or uncertain demand conditions, or to high costs of creation (direct or indirect, such as the cost of firing). If markets are not competitive, especially if the markets for goods are constrained by demand, then product innovation could generate an increase in demand which would in turn foster jobs creation. This mechanism has been explored in depth by Pasinetti.

The present study deals with job reallocations between firms and sectors, not with the macro level. Taking innovation as exogenous, we explore its effects on firms and industries employment trajectories. We use data on employment French manufacturing firms between 1984 and 1991, along with data on technology from an "Innovation survey" carried out in 1991 in firms over 20 employees.

In France, two empirical studies have investigated the reallocation of jobs. Nocke (1994) worked on a data file at the firm level[1] and explored the impact of the life cycle of the firm (i.e. its age) on reallocations. Morin, Torelli and Lagarde (1994), using another data file

[1] He used an exhaustive data file of government origin on company accounts, called the BIC data file ("déclarations de Bénéfices Industriels et Commerciaux").

at the establishment level[2] analysed the links between job reallocations and the macroeconomic cycle. They also measured net employment flows, using a breakdown of the establishment workforce into six job categories. These two studies do not assess the influence of technological change on job reallocation.

At the firm level, the employment effect of innovation has been mainly investigated through case studies of particular firms. They generally conclude that innovation has a negative effect on employment growth. Nevertheless, these studies generally focus on process innovation (automation for example), on a time period that does not allow to capture output growth driven by innovation. Furthermore, case studies are not able to assess what would have happened if the firm had not innovated. Only few empirical studies use innovation surveys or available data on patents or innovation counts to analyse the employment effect of innovation. Doms, Dunne and Roberts (1994) exploit data on U. S. manufacturing establishments to examine the effect of the number of advanced manufacturing technologies used by plants on employment growth and survival. They find both effects positive. Van Reenen (1997) uses innovation count data from the Science Policy Research Unit (SPRU) innovation data base matched with a panel of 600 U. K. manufacturing firms listed in the London Stock Exchange over the 1977-1982 period. He finds a positive effect of the number of product and process innovations on short term employment growth (first differences), but a stronger effect for product than for process innovation. In this paper, we test the same type of relationship, at the firm level, in a somewhat different framework, due to the nature of available information on innovation in French manufacturing industry. As in the preceding studies, we find a positive effect of innovation on employment growth, but we find a different result as Van Reenen (1997) for the respective effects of product and process innovation.

[2] They used a data file of government origin giving the job structure of establishments over 20 employees, called

The paper is organised as follows. In section 1-1 we discuss the data and results on job reallocations at the sector level. This is especially important in a field of studies where results are sensitive to the data used (as the diversity of conclusions in this literature shows it). Moreover the indicators deserve careful examination since, as we show it, they convey some biases mainly due to the size structure of the sample. These methodological warnings apply as well to previous studies in the field. In section 1-2 we describe the data on technical innovation and we present a sector-based econometric study on the links between innovation and employment. Then we adopt a firm level approach, which is descriptive in a first step (section 2-1), and more structural in a second step (section 2-2). We conclude on the consistency of the results obtained on these two levels of analysis.

1: TECHNOLOGY AND EMPLOYMENT AT THE SECTOR LEVEL

1-1 : Job reallocations : an assessment for the 1984-1991 period

The data we use is a French annual business survey, called EAE (Enquête Annuelle d'Entreprise) carried out in all the establishments of firms over 10 employees in the manufacturing industry. We chose this data source because a supplement to the survey, on technological innovation, has been conducted in 1991, at the firm level. This allows to match information on employment net flows with direct measures of technical change.

The employment variable we use is the average level of employment for one year, calculated according to the time spent by every employee in the establishment. It includes short term and long term contracts, apprentices and temporary workers. We aggregated this

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the ESE data file ("Enquête sur la Structure des Emplois").

information over all the establishments of a firm so as to obtain a firm level indicator of employment. The period of time that we consider runs from 1984 to 1991.

We excluded firms that were not present for 4 years or more between the dates when they appear and disappear in the file. Otherwise, we corrected missing values through interpolation. This leads to a sample of 97,347 establishments and 55,519 firms present at least one year during the 1984-1991 period.

The last problem concerns creation and destruction of firms, which is partly disconnected from the presence of firms in the file because of the size threshold (a firm appears in the file when it crosses the threshold, not when it is created). To deal with it, we used information on the presence of the firm in the BIC data file (which is exhaustive) over the 1970-1992 period. For the firms existing in the BIC data file, but absent from the EAE survey, we assumed that the employment level of the firm was 9 employees. This operation allows to get the actual dates of creation and destruction of firms.

Job flow indicators

This data source does not give complete information on all the employment flows that transit through the establishment or the firm. We only measure the net flows which are the employment variations between two dates. We used the same indicators of job flows as those constructed by Davis and Haltiwanger (1992). They are the following:

Let E_{et} be the size of the firm or the establishment *e* at a date *t*. We measure x_{et}, which is the average employment between t and t-1:

$$x_{et} = \frac{E_{et} + E_{et-1}}{2}$$

Let g_{et} be the time *t* growth rate of employment:

$$g_{et} = \frac{E_{et} - E_{et-1}}{x_{et}}$$

This growth rate measure is symmetric about 0 and its values lie between -2 and 2. The two extreme values correspond to the death and the birth of the firm. The advantage of this measure is that it allows an integrated treatment of birth, life and death in the empirical analysis, with an indicator which is increasing in the traditional growth rate measure.

We then have four different measures of job flows within a given category *s* that can be the sector, age, size categories etc.:

$$g_{st}^{pos} = \sum_{\substack{e \in E_{st} \\ g_{et} > 0}} \frac{x_{et}}{x_{st}} g_{et}$$

$$g_{st}^{neg} = \sum_{\substack{e \in E_{st} \\ g_{et} < 0}} \frac{x_{et}}{x_{st}} \left| g_{et} \right|$$

$$g_{st}^{net} = g_{st}^{pos} - g_{st}^{neg}$$

$$g_{st}^{exc} = (g_{st}^{pos} + g_{st}^{neg}) - \left| g_{st}^{net} \right| = 2\min(g_{st}^{pos}, g_{st}^{neg})$$

The first measure is a job creation rate within a category *s* and the second one is a job destruction rate. These two measures are size weighted means of positive (respectively negative) growth rates of employment over a category s. They are lower bounds for the true creation and destruction rates since they do not take into account simultaneous jobs creation and destruction in a same firm, but only their difference. The third measure is the aggregated net employment growth rate of category *s*. The fourth measure is the "excess job reallocation rate", which is computed as the difference between the sum of creation and destruction rates within category s and the net growth employment rate of s. If there was no heterogeneity in employment dynamics between firms within a category s, each firm would register the same net growth rate as the aggregated one and the excess job reallocation rate would be nil. A positive excess job reallocation rate for one category signals the existence of job transfers between firms belonging to a same category. They appear to be "in excess", because they where not needed to reach the overall net growth employment rate of s[3].

The use of these indicators must be very cautious. First, an employment flow has two dimensions. An employee can change from one *job* to another and/or from one *firm* to another. As it is shown below, the size of the firm has a strong mechanical impact on flows which can be misleading. When an employee changes his job, his probability of changing firm by the same token is higher if he works initially in a small firm than if he works in a large firm. In other words, when one changes one's job, the probability of changing firm is higher when the firm is smaller. If one moves from establishment A to establishment B, he may or may not change firm depending on the ownership structure of these establishments. If the establishments are self owned (the "two small firms" case) there is reallocation in the present definition. If they merge in one big firm, there is no reallocation. Because of this effect, job creation and destruction rates reach higher level when they are calculated over small size categories as compared to big size categories. The same phenomenon appears when rates are computed on sectors with more small firms as compared to highly concentrated sectors. We do not mean here that the fact of changing firm has no importance for the employee, but only that the fact that transfers are more frequent in small size categories has, for one part of it, a purely mechanical, non economic, reason. As a result, in descriptive statistics, we have to control for this effect, something which was not done in previous studies in the field.

[3] This concept is similar to the "intra-industry trade" used in international trade economics, which captures this

A second reason for cautiousness concerns specifically the excess job reallocation rate. The analysis of job transfers within a category is hazardous if the category has no economic meaning. There is no reason for expecting homogeneity of behaviour in a set of firms when they do not face similar shocks. As a consequence, such kind of heterogeneity cannot be interpreted as transfers, which suppose some causal relationship between gains and losses. For example, transfers between age categories are bound to be erroneously interpreted because there is no reason why job transfers should take place between firms of a same age. On the other hand, the sector or the location are relevant categories, the sector because it is a proxy of markets where firms are competing on sales or competencies, the location because if the workforce is not perfectly mobile, there is competition for hiring people on the local labour market.

Job Reallocations in industry: General Trends

Figures 1 and 2 plot frequency distributions for the net growth rate of employment in our seven years' sample of firms (1985-1991). Figure 1 displays unweighted rates whereas figure two displays weighted rates. The distributions have a peak in the interval surrounding zero and two accumulation points at the tails which correspond to creation and destruction of firms. On figure 1, we see that firm destruction are slightly less frequent than firm creations. But 85% of firm creations and 74% of firm destruction concern firms with less than 20 employees -created firms are overall more numerous, but are smaller than destroyed ones. Finally, figure 2 shows that creations and destruction of firms represent a very small share, of about the same amplitude, of employment creation and destruction.

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part of trade which comes in addition to trade explained by the factors allocation theory.

Distributions displayed in the two figures are both asymmetric, but the small asymmetry that can be seen in figure 1 is reversed and becomes much stronger in figure 2. This means that firms with growing employment are more numerous than firms with declining employment, but they are also smaller. More employment is destroyed than created because firms creating jobs are much smaller than firms loosing jobs.

All in all, manufacturing employment has been shrinking during the period. Table 1 reports that the mean annual loss rate is -1.3%. In our sample, approximately 270,000 jobs have been destroyed between 1985 and 1991. Industry lost employment nearly every year except in 1989-1990, with a magnitude that follows the macroeconomic cycle. Job transfers within manufacturing industry are intense. They reach an annual average of 16.2% of current employment. Excess job reallocation rate is positively correlated with net employment growth rates, which suggests that more jobs are transferred between firms in years where job creation exceeds job destruction. The pro-cyclical dynamics of jobs reallocation is consistent with the view that economic growth favours the renewal of industry, as opposed with the view which underlines the “cleansing effect” of recessions. The first view relies on the higher incentive to innovate when market conditions are favourable, whereas the latter emphasises the lower opportunity cost of restructuring when demand is gloomy. It would be interesting to relate this finding to data on innovation, in order to assess the dynamics of innovative activities along the business cycle. But the data on innovation that we have do not allow such an investigation (only one point in time is available).

Table 2 reports the same indicators as table 1, but for a breakdown of industry into 18 sectors. The indicators are annual averages for each sector, calculated over seven years. This table shows that there is a great variability in net employment growth rates across sectors, and that even when rates are alike, they can come out of job reallocation rates of very different level (ferrous ores and metal, first stage steel processing and non ferrous ores, metals and semi-manufactures for example). The excess job reallocation rates range between 5.3% and 22.1%. A few sectors increase their labour force (glass, foundry work and metal work, rubber and plastics, printing, press and publishing), but most of them loose jobs and in some cases the loss is quite important (ferrous ores and metal, first stage steel processing, non ferrous ores, metals and semi-manufactures, leathers and footwear). Another noteworthy fact, also pointed out by Davis and Haltiwanger (1992) and Nocke (1994), is that sectors which have high job creation rates, also have high job destruction rates: The cross section correlation between these two rates is strong and very significant. However, when the structure of sectors by firm size is taken into account, the relationship is much weaker (table 3). The cross sectors correlation for firms of a same size category is positive and significant for two categories only, it is negative and significant for one category, and non significant for the three categories of smaller firms. The positive correlation is for a large part a result of the size bias mentioned above. The remaining correlation, weaker but more robust, can be attributed to creative destruction: Some jobs are created in firms to the detriment of others.

The influence of firm size[4] on job flows, which we measure in table 4, appears powerful. Small firms create jobs whereas big ones tend to destroy them[5]. This result contradicts the findings of Davis, Haltiwanger and Schuh (1993) for U. S. manufacturing but it is in agreement with Nocke (1994) for the case of France. The positive evolution of employment in small businesses may be linked to a life cycle effect, whereas the contraction of employment in large firms may reflect downsizing practices, that may also have some

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[4]The size categories are measured with the current size of the firm, that is the average of the firm's current employment and of its employment twelve month before to avoid the "size distribution fallacy" resting on base year measure of size category and illustrated by Davis, Haltiwanger and Schuh (1993).

[5]We observe a non linearity in net employment growth rates : firms between 500 and 999 employees are characterised by a lower job contraction than firms between 200 and 499 employees.

impact on the creation of jobs in small size categories through the creation of new firms (outsourcing).

Another striking feature of table 3 is the decreasing pattern of job creation and job destruction[6] rates across size categories from the smaller one to the bigger one. As underlined before, this is due in a first place to a purely arithmetic size effect: When a job is reallocated in a small firm, the probability for an employee to pass the frontier of the firm (that is to be hired or fired) is higher than in a big firm. A large firm can be seen as a collection of establishments or activities between which jobs can be reallocated when economic conditions make it necessary.

Table 5 reports simulations which capture this pure size effect. In this table, we first compute job flow rates for 1985 on the subsample of firms present in the file in 1984 or 1985 (top of the table). We then extract the firms with 10 to 19 employees (current size in 1985), and aggregate them randomly, making first groups of 2 firms, then groups of 3 firms etc. until we reach groups of 100 firms. We keep these groups as new entities, generating the same size distribution as in 1985 but with fictitious firms and compute job flow rates by firm size on this new population. We do the same operation for another random draw, now using the population of firms between 20 and 49 employees. Table 5 shows that net growth employment rates are not affected by aggregation, but that job creation and job destruction rates are strongly influenced by it. Both simulations generate a decreasing pattern, as the one observed on the real sample of firms, although there is here clearly no economic factor behind that. We can also notice that creation and destruction rates decrease more sharply according to size in the simulations than in the real world. This suggests that although big firms create and destroy a lower portion of their jobs than small firms, they do it more than what they would do according to a pure size effect. As a result, contrary to what table 4 seems to tell in a first analysis, big firms seem to have a more active employment policy than small firms, in the sense that they create and destroy more jobs after controlling for the relevant factors. This result contradicts previous finding in the literature. Large internal labour markets, far from exempting large firms from the need to hire and fire employees, seem to encourage them to do it more actively.

A last set of indicators proposed by Davis and Haltiwanger (1992) reports whether the reallocation process corresponds to transitory of persistent changes in employment levels. They allow to characterise the stability over time of the employment trajectories of firms, be it positive or negative. These indicators are one-year or two-year persistence rates. The one-year positive persistence rate gives the proportion of jobs created between *t* and *t+1* that still exist at *t+2*. Symmetrically, the one-year negative persistence rate gives the proportion of jobs destroyed between *t* and *t+1* that have not been replaced at *t+2*. The two-year persistence rates, Perpos2 and Perneg2, are defined analogously.

Tables 6 reports these indicators. We see that negative persistence rates are higher than positive persistence rates (respectively 93.4% and 76.9% for one-year persistence), which suggests a higher irreversibility in job destruction than in job creation. This result is trivial when job destruction is associated with firm destruction. In order to find out if these differences are due to the irreversibility of firm destruction, we computed the same indicators for 1985, over the subsample of firms continuously present between 1984 and 1991, so as to leave out firms that are destroyed during the period. We still find a higher level of negative persistence even though the indicator drops down (77.3% against 89.3% for one-year persistence). Firm destruction explains part of the asymmetry between positive and negative

[6]Except for firms over 1,000 employees, which have a higher job destruction rate than the preceding size

persistence. The rest of it could come from the negative trend in manufacturing employment. We also notice than two-year persistence rates are lower that one-year persistence rates, which is mechanical, but that the discrepancy is bigger for positive persistence.

To understand better which phenomenon lies behind these aggregated indicators, we analyse persistence at the level of the firm. Between *t* and *t+1*, a firm may have stable, growing or declining employment. If it is growing or declining the firm may be characterised between *t+1* and *t+n* by, either total persistence (all the jobs created or destroyed in *t+1* are kept or remain destroyed in *t+2* or *t+3*), or partial persistence (only a fraction of the newly created or destroyed jobs is kept or remain destroyed), or by an inversion in employment trajectory (all the newly created jobs are destroyed or all the newly destroyed jobs are created back again). The aggregated persistence indicators do not only reflect partial persistence in each firm, they also give a mixed image of the distribution of firms in the 3 categories (total persistence, partial persistence and inversion).

This distribution is reported in table 7 (unweighted and size weighted) for 1986 as base year *t*. It is striking in this table that when we add up total persistence in growth with total persistence in decline, which is the proportion of firms (or of employment in firms) with straightforward trajectories, we take into account a very big portion of firms and employment (respectively 44% and 66% for one-year persistence). If we look at total two-year persistence, figures are still quite high (respectively 37% and 58%).

As compared with one-year total persistence, two-year total persistence (positive or negative, weighted or unweighted) records a decline of approximately 4%, whereas inversion is higher and partial persistence remains unchanged, this pattern being stronger for positive persistence than for negative persistence. Figures in table 6 derive more from this uneven

category that may be linked to a downsizing effect.

distribution of trajectories than from high partial persistence rates equally distributed among firms (partial persistence only concerns 10% of firms and 11% of employment). This confirms high irreversibility in the employment behaviour of firms, against the thesis of "fine tuning" in employment practices through temporary layoffs. Mixed aggregate figure reflect differences between firms trajectories rather than changes over time in each firm trajectory.

Another set of results stems from the comparison between unweighted and size weighted distributions. First, firms with declining employment are rather big ones (they represent 32.7% of firms and 60.8% of employment), whereas firms with stable or growing employment are smaller. The comparison between the share in the total of firms and the share in the total of employment also shows that total positive persistence (unchanged trajectory) takes place in small firms, whereas bigger firms display partial positive persistence and radical change. This relation is reversed for negative persistence, total persistence takes place in firms with an average size that is twice as big as the average size on the whole sample. To check the impact of firm destruction on total negative persistence, we broke down this category according to the date of destruction when it occurs. It turns out that destruction represents only a very small share of firms and employment change. The core of the result on total negative persistence lies in the behaviour and size of firms with continuous presence.

Three main findings reported above are of interest for the following. First there is a high heterogeneity in firms employment dynamics, even within narrowly defined classes. The next section aims at highlighting this result. Second, there are biases due to firms size in some of the indicators used. It is therefore crucial to control for this effect in the econometric study, so as to isolate the factors of interest. Third, most firms display employment trajectories that are quite stable over time. Firm's employment behaviour is characterised by a weak time variability. We then loose few information in working at a more than yearly time interval when we try to explain heterogeneity.

1-2: Technological Innovation and Jobs Reallocation

We analyse the effect of technological innovation on job reallocation through the use of a supplement to the EAE survey called the Innovation Survey. This survey was carried out by the Ministry of Industry among 20,000 French manufacturing, with 20 employees and more. It deals with their innovative activity during the 1986-1990 period[7]. We use a set of questions on technical achievements, which are of the type: "Has your firm implemented, at least once during the 1986-1990 period, the following kind of innovation?" Five kinds are proposed: three of them are product innovations (improvement in existing products, imitation from a competitor, new product for the market), two are process innovations (process improvement and technical breakthrough). These questions allow to identify firms that have implemented at least one kind of innovation (Inno), at least a product innovation (prod) and at least a process innovation (Proc) between 1986 and 1990.

The Innovation survey has the advantage of giving direct measures of technical change for a large number of firms, that can be matched with other data (the matched sample with employment data includes 15,186 firms). However they have some limitation. First, it is qualitative information, which does not tell the number of innovations achieved by the firm, but only the existence of at least one innovation, which is likely to encompass a size bias. Second, we do not know the year when innovation(s) took place, which limits the study of the impact of innovation on firms’ short term employment behaviour. Third, only firms still alive in 1991 were surveyed. This selection generates a bias since technical dynamics may have

[7]See SESSI (1994) for more details and descriptive results about this survey.

some influence on the death of firms during the 1986-1990 period. On the one hand firms may have disappeared because of innovation performed by their competitors, on the other hand there are innovating firms among those which disappeared.

When information is aggregated at the sector level, only a summary of it is used, but it allows to go beyond some of the preceding limits. At the sector level, annual data on job reallocation can be analysed in terms of innovation, under the assumption that innovation is equally distributed in time between 1986 and 1990 for all sectors. Sector-based analysis also limits the biases due to the absence of firm destruction in the sample of the Innovation survey, if we assume that the differences in innovative behaviour between firms destroyed and firm continuously present over the period are alike in all sectors.

Product and process innovations and sector-based employment shifts

Does technical change contribute to explain between and within sector job reallocations? To answer this question, we calculated three indicators of innovation at the sector level: $Proc_S$, $Prod_S$ and $Inno_S$ that measure respectively the intensity of process innovation, of product innovation and of innovation (be it product or process). These variables are the share, in the sector employment, of firms that have implemented at least one process innovation ($Proc_S$), or one product innovation ($Prod_S$), or one innovation of either type ($Inno_S$), between 1986 and 1990. These indicators are calculated for a breakdown of manufacturing industry into 37 sectors. There mean for manufacturing is 0.82 for $Inno_S$, 0.72 for $Proc_S$ and 0.76 for $Prod_S$.

The variables that we want to explain in a first step are the job creation rate, the job destruction rate and the net growth employment rate (g^{pos},g^{neg}, and g^{net}). These indicators have been computed for a crossing of 7 size categories and 37 sectors, so as to control for the size bias underlined in section 1-1. They are annual means over the period. The exogenous variables that we consider are the sector-based innovation variables (no size criterion is used in constructing these variables because technology needs to be associated with the type of good produced rather than to the size of productive units), and size dummies.

Table 8 reports the results of this first set of regressions. The effect of $Inno_S$ is positive on job creation rate, negative on job destruction rate and positive on net employment growth rate : taken in its broader definition, innovation is significantly favourable to the expansion of sector employment. When we break down the intensity of innovation into two components, $Proc_S$, $Prod_S$, we find some further results. Sectors with more process innovation have a higher job destruction rate and a lower net employment growth rate (but not significant), while sectors with more product innovation have a higher job creation rate and a lower job destruction rate. Thus sector level employment seems to benefit more from product innovation than from process innovation, which tends to confirm previous theoretical results (Katsoulacos, 1994). The positive influence of the intensity of innovation on sector-based employment growth is related to the fact that in most sectors, product innovation dominates process innovation. This is also noticed by Van Reenen (1997) when he examines the U. K. innovation count data.

Orientation of innovation and life cycle of the product

In order to go one step further in the interpretation of the preceding result and to investigate its robustness, we calculated "reduced variables", that separate the intensity of innovation ($Inno_S$) from the orientation of innovation (process dominated or product dominated). The variable that measures the orientation of innovation, called Innorel, is the sector ratio of $Prod_S$ on $Proc_S$. When Innorel is greater than one, product innovation prevails in the concerned sector. Its mean value over manufacturing sectors is 1.04.

Columns 1 of table 9 gives the results of the regression of Innorel on the sector-size-based employment variables. It shows that Innorel gives the same information on employment dynamics as $Proc_S$ and $Prod_S$ do (compare table 8 with table 9). An orientation of innovation towards product increases the job creation rate and reduces the job destruction rate.

In order to assess the respective influence of innovation intensity and innovation orientation, we have to control for the fact that these two variables are positively correlated as showed in table 10. To do so, we estimate a second set of regressions where the exogenous variables are $Inno_S$ and the component of the orientation of innovation that is independent from the intensity of innovation, Innorel1 (It is estimated as the residual of the regression of Innorel on $Inno_S$ displayed in table 11). The results of these regressions are reported in columns 2 of table 9. We find that a high intensity of innovation is associated with higher job creation and lower job destruction, whereas a product oriented innovation reduces job destruction. Both the intensity and the orientation of innovation towards products have a positive impact on net employment growth.

However we must be careful with such results. The orientation of innovative activity may be correlated with other variables that directly influence employment dynamics and would be the true factors hidden behind an apparent relationship. To get rid of this effect we must identify these factors. The "product cycle" theory (Vernon 1967) provides a useful framework for that. This theory states that any product or sector follows a life cycle. Product innovation initiates the cycle since it creates the good or the activity itself. Process innovation becomes more important as the sector becomes mature, since the products are stabilised and price competition takes place among firms. Sector maturity is the key variable that determines the relative weight of product and process innovation. Following the previous results on employment dynamics, we expect that less mature sectors create more jobs than mature ones, and that they display higher within sector job transfers, reflecting their lower degree of stabilisation. Maturity is also related to the dynamics of demand. Younger sectors face faster increasing demand since consumers are not yet equipped. Therefore, a younger sector has a growing share in total employment that is partly independent of innovation. We want to get rid of this effect to assess the pure effect of technology, that is the effect of product Vs process innovation in a sector with given maturity.

The indicator of maturity that we compute (Youth) is the long term growth rate of nominal demand for the sector (production + imports - exports on the French internal market, in nominal value for 1977-1994). We chose internal demand rather than production because the latter is affected by international trade and national specialisation, which are not relevant here. We preferred a value rather than a volume measure because relative price changes reflect changes in the quality of goods, which are relevant here and should not be left aside. We take a longer time period than that over which we observe employment dynamics (1977-1994 vs. 1986-1990) in order to ensure the exogeneity of the indicator. A high level for Youth reads as low maturity. Its average value for manufacturing is 1.87. Simple correlation analysis (table 10) shows that the pattern of innovation is related to maturity (significant at a 10% level). As assumed in the product cycle model, less mature sectors favour product innovation relative to process innovation.

Columns 3 of table 9 reports the results of the regressions that include Inno_S, Youth and Innorel2, which is Innorel controlled by Youth and Inno_S (the residual of the regression of Innorel on the two variables given in table 11). Youth has a positive impact on job creations and a negative impact on job destructions. The results of this regression are made more clear by computing the effect of a change of each exogenous variable of one standard deviation on the employment variables (table 12).

The main conclusion is that sectors that create more jobs are those with a higher innovation intensity, an innovation pattern oriented towards products rather than processes and a lower maturity.

Innovation and job transfers within sectors

Explaining job transfers within sectors has been a major challenge for previous studies on job reallocation. For dealing with this issue, we compute sector values for g^{exc} and perform various econometric regressions with the same variables as above and a sector size indicator, which is the number of firms in the sector[8].

The result of this regression is reported in table 13. It shows that the orientation of innovation is the only variable that affects significantly excess job reallocation rate, the influence being positive. Product innovation contributes to reallocate the labour force within sectors presumably by reallocating market shares between competing firms. At first glance, this result seems at odds which economic theory that predicts a higher substitution between firms belonging to a same sector when process innovation is dominating. Nevertheless, we have to keep in mind that until now, we examined short term employment reallocation (yearly), that may differ from medium term employment adjustments. We will come back on this topic in the following sections.

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[8]Here, the excess job reallocation rate is not a size-sector-based variable like in the other regressions, because it would have no economic meaning as stressed in section 1-1. We introduce an indicator of the sector size to control the size bias that affects this rate, like the job creation and destruction rates.

Sector-based analysis of the links between innovation and employment leads to two main results. First, the sectors that create more employment and/or that destroy less employment are those marked by an intense innovative activity, oriented towards product innovation and with a lower degree of maturity. Second, orientation towards product innovation increases short term job transfers within sectors.

2: INNOVATION AND EMPLOYMENT DYNAMICS AT THE FIRM LEVEL

What is the micro background under these aggregate level results? The firm level analysis complements the sector-based analysis as it rests on a different use of the available information. It takes into account firm's dynamics, but, since we do not have annual data on innovation, we have to work on medium term employment dynamics (5 years).

Moreover, the firm level allows to go beyond a descriptive approach, towards the estimation of a model including all the variables affecting labour demand, notably costs, because this information can be captured by merging the core firm sample from the Innovation survey with other data sources. In a first section, we carry on a descriptive approach which is analogous to our sector-based approach, except that we work on medium term employment growth. The second section is dedicated to the presentation and testing of an economic model that gives more insight into our descriptive results.

2-1 : A descriptive approach

At the firm level, we measure innovation through dummies signalling the implementation of at least one innovation during the 1986-1990 period. The variable we want to explain is the annual mean of the five years change in employment (expressed in Log differences). We use, on one hand a sample of firms continuously present over the period

(13 126 firms), on the other hand the total sample from the Innovation survey (15 186 firms). On this second sample, the annual mean of employment growth is calculated over a period of time that is shorter than five years for those firms created after 1985. Exogenous variables are either the primary variables from the Innovation survey, or an innovation dummy (Inno), or process and product innovation dummies (Proc and Prod). Moreover, initial size and sector (respectively, 7 and 19 categories) are added in the regression to control for potential biases, as well as the date of creation for the total sample.

As all exogenous variables are of a discrete type, we perform estimations with variance analysis. The results, which are presented in table 14, can be read as average differences in growth rate of employment, the reference situation being that of non innovative firms, with more than 1 000 employees in 1985 (or at their date of creation for the total sample), belonging to the sector of rubber and plastics and created before 1985 for the total sample. The average employment growth for the reference population is given by the intercept.

The first striking result, on the smallest sample, is the strong positive relationship between technological innovation and employment change. Firms that innovate create more jobs than other ones, or at least they destroy fewer jobs (since the overall change in manufacturing industry is a reduction of jobs): the average annual employment growth rate over the 1985-1990 period is higher by 1.6% in innovative firms as compared to the reference population.

The second fact is that, although this relationship holds for all types of innovation, its size is uneven. Firms that perform process innovation face a higher net change than firms implementing product innovation (1.3% compared with 0.6%). The difference is statistically significant and remains unchanged when we consider the total sample of firms.

Van Reenen (1997) finds a rather different result as far as the orientation of innovation is concerned. He finds that both types of innovation influence positively employment growth, but product innovation is associated with a stronger impact. Nevertheless he tests separately the influence of a growth in the number of product innovation or process innovation on short term (yearly) employment growth, controlling for various sources of biases, while we work on medium term employment growth (5 years), using innovation dummies rather than innovation counts that are not available in French data bases. Thus, the two results are not directly comparable.

2-2 : Employment and innovation : a simple model

The aim of this section is to give an economic interpretation to the results found in our descriptive approach. Innovation is positively correlated, at the firm level, with medium term employment growth, and the positive correlation is stronger for process innovation than for product innovation. This seems to contradict our sector-based results. We will interpret the discrepancy in sector-based and firm-based results in the conclusion of this paper. Here, we propose a simple structural model that will allow us to test empirically the idea that process innovation works as a supply shock that changes the production function, whereas product innovation works as a demand shock that changes the demand function. Our guess is that this difference in the way process and product innovation affects activity may explain the difference found in their respective impact on employment. Structural modelling allows to go beyond the observation of equilibrium outcome provided by the descriptive analysis, and identifying various underlying mechanisms at work.

An economic model

To start with, we consider that firms operate under a Cobb Douglas technology with two inputs, labour (L) and capital (K), and a Hicks neutral technical change parameter A:

$$Ys = AK^{\alpha_1}L^{\alpha_2} \qquad (1)$$

Ys is the (homogenous) good supply. We assume that the technical parameter A represents the state of techniques and has two components, A', the general state of techniques in the economy and T, the technological level of processes used by the firm. A' is given to all firms, it is exogenous, while T is chosen by the firm:

$$A = A'T^{\alpha_a} \qquad (2)$$

So, any improvement in the technological level of the processes used by the firm, increases productivity with elasticity α_a: Process innovation works as a supply shock. If W represents the cost of labour and R the cost of capital, the cost function writes:

$$C = ZA'^{-\frac{1}{e}}T^{-\frac{\alpha_a}{e}}R^{\frac{\alpha 1}{e}}W^{\frac{\alpha 2}{e}}Ys^{\frac{1}{e}} \qquad (3)$$

with $Z = \left[\frac{\alpha_1}{\alpha_2}\right]^{\frac{\alpha 2}{e}} + \left[\frac{\alpha_1}{\alpha_2}\right]^{\frac{-\alpha 1}{e}}$ and $e = \alpha_1 + \alpha_2$, returns to scale. If e=1 we have constant returns to scale.

We model demand (Yd), using a constant elasticity demand function, with price elasticity of demand, β, higher than 1:

$$Yd = BP^{-\beta} \qquad (4)$$

B represents the degree of novelty or quality of the goods sold on the market. It has also two components, B' the technological level of goods in the economy (given to all firms) and G the degree of novelty or quality of the goods supplied by the firm:

$$B = B' G^{\alpha_b} \qquad (5)$$

Any increase in the degree of novelty of products available on the market, increases demand for a given price: Product innovation works as a demand shock, a new product being more attractive for the consumer that an old, standardised one.

We don’t model the decision by the firm to innovate or not. As we are interested in the employment impact of process and product innovation and that we believe that innovation is predetermined to employment decisions. Moreover, we assume that the firm behaves as a monopole and sets price (P) with a constant mark-up over marginal cost:

$$P(Y) = \frac{C'(Y)}{1 - \frac{1}{\beta}} \qquad (6)$$

This assumption means that firms, especially when they change their process, are able to change their price policy. Price is a decision variable. Monopolistic competition would be a weaker assumption but would not lead to a testable model, since prices are not available in most firm level data bases.

Rearranging (6) according to (3) leads to:

$$P(Y) = \frac{\beta}{e(\beta - 1)} ZA'^{-\frac{1}{e}} T^{-\frac{\alpha_a}{e}} R^{\frac{\alpha 1}{e}} W^{\frac{\alpha 2}{e}} Y^{\frac{1-e}{e}} \qquad (7)$$

The firm determines its supply by producing the amount demanded by consumers at the price it has set. [4] and [7] imply:

$$Y = \frac{B' G^{\alpha_b}}{\left[1 - \frac{1}{\beta}\right]^{-\beta}} \left[\frac{1}{e} ZA'^{-\frac{1}{e}} T^{-\frac{\alpha_a}{e}} R^{\frac{\alpha 1}{e}} W^{\frac{\alpha 2}{e}} Y^{\frac{1-e}{e}}\right]^{-\beta} \qquad (8)$$

Factors demand directly comes from cost minimisation :

$$L = A'^{-\frac{1}{e}}\,T^{-\frac{\alpha_a}{e}}\left[\frac{\alpha_1 W}{\alpha_2 R}\right]^{-\frac{\alpha_1}{e}} Y^{\frac{1}{e}} \qquad (9)$$

$$K = A'^{-\frac{1}{e}}\,T^{-\frac{\alpha_a}{e}}\left[\frac{\alpha_1 W}{\alpha_2 R}\right]^{-\frac{\alpha_2}{e}} Y^{\frac{1}{e}} \qquad (10)$$

We can write down the reduced forms of (7), (8), (9) and (10), taking Logarithms (x=Log(X)) and differentiating ($\dot{x} = \frac{dx}{dt}$):

$$\dot{y} = c_y + \frac{e\alpha_b}{\theta}\dot{g} + \frac{\beta\alpha_a}{\theta}\dot{t} - \frac{\beta\alpha_1}{\theta}\dot{r} - \frac{\beta\alpha_2}{\theta}\dot{w} \qquad (11)$$

$$\dot{p} = c_p + \frac{(1-e)\alpha_b}{\theta}\dot{g} - \frac{\alpha_a}{\theta}\dot{t} + \frac{\alpha_1}{\theta}\dot{r} + \frac{\alpha_2}{\theta}\dot{w} \qquad (12)$$

$$\dot{l} = c_l + \frac{\alpha_b}{\theta}\dot{g} - \frac{(1-\beta)\alpha_a}{\theta}\dot{t} + \frac{(1-\beta)\alpha_1}{\theta}\dot{r} - \frac{(1-\beta)\alpha_1 + \beta}{\theta}\dot{w} \qquad (13)$$

$$\dot{k} = c_k + \frac{\alpha_b}{\theta}\dot{g} - \frac{(1-\beta)\alpha_a}{\theta}\dot{t} - \frac{(1-\beta)\alpha_2 + \beta}{\theta}\dot{r} + \frac{(1-\beta)\alpha_2}{\theta}\dot{w} \qquad (14)$$

with $\theta = e + \beta(1-e)$. Note that if returns to scale are constant, then $\theta = e = 1$.

Equation (11) to (14) represent the behaviour of the firm. The firms chooses its level of production (11), its price (12), its labour demand (13) and its capital demand (14) by maximising its profits, taking into account its innovation records relative to its competitors and the prices of inputs. In this model, the influence of process innovation on labour demand passes through its effect on productivity, which, in turns, influences firm's price competitiveness and thus supply. Product innovation affects the non price-competitiveness of the firm, allowing to increase sales without any change in price, thanks to higher demand at this price.

An econometric approach

We now try to estimate econometrically the above model. A first difficulty is that we don't have price data at the level of the firm: we only have information on the *value* of production (or value added), that is P.Y. Knowing that $\dot{py} = \dot{p} + \dot{y}$, we write down how $\dot{py}$ changes for a change of the exogenous variables:

$$\dot{py} = c_p + c_y + \frac{\alpha_b}{\theta}\dot{g} - \frac{(1-\beta)\alpha_a}{\theta}\dot{t} + \frac{(1-\beta)\alpha_1}{\theta}\dot{r} + \frac{(1-\beta)\alpha_2}{\theta}\dot{w} \qquad (15)$$

The influence of product and process innovation on the technological dynamics of the firm may be tested through the estimation of (13), (14) et (15) (adding disturbance terms) that are reduced forms, non linear in their parameters. We use Prod and Proc as proxies to the increase in the technological level of products ($\dot{g}$) and processes ($\dot{t}$) respectively.

The variables of interest being those concerning technological innovation, the time structure of the model takes into account the constraints imposed by the nature of information given by the Innovation survey: This survey measures changes over a 5 years time period. Nevertheless, estimating the model in long differences allows to control for fixed effects and thus leads to more robust results. Moreover, working on a five years time period allows to neglect adjustment costs that are not negligible on a short time period as far as employment is concerned.

Endogenous variables are the growth rates expressed in Log-differences, cumulated over five years (1985-1990), of value added (expressed in value, $\dot{py}$), of the volume of labour ($\dot{l}$) and of the volume of capital ($\dot{k}$). Exogenous variables are the existence of at least one product or one process innovation, and the cumulated growth rate of labour cost (average cost calculated as the ratio of aggregate remuneration, including social contributions, on the number of employees) and of capital cost (average cost depending on the structure of the firm's balance sheet). Details on the construction and value of these different variables are given in appendix.

Estimations are conducted on a subsample of 5,919 firms continuously present between 1985 and 1990, that remain after the Innovation survey is merged with the INSEE firm data base[9] and controls for outliers are implemented.

In order to have a first idea on the matching between our theoretical expectations and empirical evidence, we estimated equations (13), (14) et (15) separately, using ordinary least squares. Results are given in table 15. Table 16 reports the relations between estimated coefficients and parameters of the model, when returns to scale are constant and non constant.

A first result is the proximity of estimated coefficients for process and product innovation when the three regressions are compared. This is consistent with our theoretical framework. We also observe that, as compared with our preceding variance analysis (table 14), the coefficients associated with innovation are weaker (to be compared with table 14, they need to be divided by five) and less significant. Nevertheless, we have to take into account the fact that the subsample here is much smaller. The same variance analysis as in table 14, performed on the 5,919 firm sample gives:

Demp = 0.101 + 0.008 Proc + 0.002 Prod + sector and size dummies

(10.33) (4.34) (1.17) R^2=0.08

[9]The INSEE firm data base is constructed from "SUSE": "Système unifié de statistique d'entreprises" which combines the information of the annual business surveys ("Enquête Annuelle d'Entreprise", EAE) and of the firm fiscal declarations ("Déclarations de Bénéfices Industriels et Commerciaux", BIC) that gives firms' balance sheets.

where Demp in the annual mean of employment growth over the period (in Log differences). The signs of the coefficients remain unchanged but their level and significance are lower. Table A2, in appendix shows that more small firms are excluded when we pass from the total sample to our subsample.

We also observe that the estimation associated with the variation of capital stock is of lesser quality (the corresponding R-square statistic is weaker). Moreover, if the cross-constraints associated with costs that are presented in table 16 are approximately respected in the first two equations, they are not so for the capital equation. We can relate this with the fact that the measure of capital stock evolution raises more problems than that of employment or of value added.

Finally, the values of the coefficients associated with costs are not acceptable. If we calculate the parameters of the structural model using estimated coefficients under the constant returns to scale hypothesis[10], we obtain a price elasticity of demand that is less than 1 in absolute value and a negative influence of process innovation on productivity. This is contrary to our theoretical expectations: According to these results, firms that make process innovations create more jobs because they are less productive. As to the sign associated with product innovation, it matches with what we were expecting.

More generally, from table 16, if the coefficient associated with process innovation is positive (a result that comes out of all the regressions) and if, according to theory, price-elasticity of demand is higher than 1 in absolute value, then process innovation increases productivity when θ is positive. This condition is fulfilled when the coefficients of factor costs

[10]In order to identify 4 parameters on the basis of the estimation of 3 equations, we have to make a supplementary assumption on returns.

are negative in equation (13), and when the coefficients of the cost of capital in equation (14) and of the cost of labour in equation (15) are also negative. Table 15 shows opposite results.

This kind of results is frequently obtained on firm data, when costs are used. A possible reason is that costs are observed with measurement errors. Company accounts do not give a measure of the marginal cost of labour, only a measure of the average cost, based on the ratio of aggregate compensation on the number of employees. We use the same measure of the number of employees to calculate employment growth, which may generate a fallacious correlation. The high Student statistic associated with labour cost growth in labour equations confirm that we have to face a problem of this type. As far as the cost of capital is concerned, measurement errors are also obvious. The cost of capital, as it is described by theory, is observed nowhere in statistical systems. As a result, it has been constructed through a series of approximations. This measure is also more of an average cost type than of a marginal cost type.

If cost variables are measured with errors and if measurement errors are correlated with the disturbance terms of the model, parameter estimates are biased. The implementation of the Hausman test rejects the exogeneity of $\dot{r}$ and $\dot{w}$. Consequently, in table 17 both costs are instrumented, using the level of the cost variables in 1984 (r84, w84), the location of the firm (18 regions) and the innovation variables that we assume exogenous. The signs of the estimators associated with cost variables are now consistent with what we expected, while the coefficients associated with innovation variables are little affected. Like in the preceding estimations, cross-constraints on capital demand do not seem fulfilled.

The last step consists in identifying the parameters. We do it directly, by estimating the system, using non linear two-stages least squares, under three different assumptions on returns to scale (e=0,9 ; 1 ; 1,1). Results are reported in table 18. The price-elasticity of demand (β) is low, but higher than 1 in absolute value, and the output elasticity of capital (α_1) is satisfactory. Finally, estimated parameters associated with innovation (α_a for process and α_b for product) are positive and significant. This is concordant with what we expected, given the value of other parameters.

Estimations show that under a constant returns to scale assumption, a firm implementing process innovation reduces its price by 14% on average on a five years time period ($-\alpha_a$). This leads to a 19% increase in demand ($\beta\alpha_a$). If demand had remained unchanged, the firm would have reduced its employment by 14%, according to the "productivity" effect ($-\alpha_a$). Nevertheless, the combination of the "productivity" effect and of the "demand" effect leads to a 5% increase in employment. On the other hand, product innovation generates a 1.5% increase in demand (α_b) that in turn generates an increase in employment by the same amount.

These results confirm those of the descriptive approach : innovation has a positive influence on employment at the firm level. They also give some insight into the mechanisms through which innovation influences employment. Process innovation has a positive impact on employment that is stronger than product innovation, because the productivity gains that it generates are largely balanced, in terms of employment, by an increase in demand due to price reduction.

CONCLUSION: THE CONSISTENCY OF THE SECTOR AND OF THE FIRM LEVELS

We still have to understand what kind of links relates the sector level analysis and the firm level analysis. At the sector level like at the firm level, innovation is positively correlated with employment : sectors as well as firms who are more innovative are able to avert jobs destruction or to create more jobs those who don't innovate. This result contradicts the pessimistic view of technical progress as destroying jobs in places were it is implemented.

This general result becomes more subtle when we distinguish product and process innovations. At the sector level, process innovations are far less favourable to employment than product innovation, whereas the opposite holds at the firm level. We can solve the puzzle with the following explanation. Process innovation generates job creation in the firms that perform it, but at the expense of their competitors. It does not enlarge directly the market size, but only the market share of its performer. On the other hand, product innovation increases only moderately the sales of the firm, but it does not harm so much the competitors. Substitution with existing goods on the market is lower.

As a result, we expect process innovation to generate more job transfers within sectors that product innovation, which seems at odds with the sector level result on excess job reallocation. However, the time horizon is not the same. At the firm level we observe a medium run (5 years) employment change, whereas at the sector level we observe annual, short run transfers. We solve the puzzle by guessing that product innovation creates more jobs in the short run in firms that perform it[11], and destroys more jobs in their competitors, but the effect is transitory. In other words, job transfers generated by product innovation are higher but less durable than those generated by process innovation. Table 19 gives a numeric example showing this mechanism.

The story could be the following: Product innovation creates more uncertainty that process innovation in the short run. The reaction of consumers to a new product is more uncertain that their reaction to a change in price for an existing good. This, in turns, entails a

[11] This guess is in accordance with the results found by Van Reenen (1997).

higher dispersion of firms' expectations (hence decisions with regards to employment) when they launch new products, and a bigger proportion of firms facing difficulties due to irrelevant decisions.

On the consumer side, we can represent what happens with a product innovation as an experiment: Consumers that move from the competitor's old good to the firm's new good, do it without knowing how well the new product fits their needs. After the trial, part of them moves back to the old good. In such a framework, uncertainty associated with product innovation from the consumer's point of view generates time instability in market shares, and thus short time job transfers.

On the other hand, firm level analysis suggests that process innovation generates more job transfers within sectors when a longer time horizon is considered. This is not easy to test in a Davis and Haltiwanger framework, which is adapted to the analysis of yearly employment flows.

A further step in the analysis will be to endogenise technical change, having in mind that it is probably not independent from job reallocation, being influenced to some extent by the same variables, notably factor prices. A previous study (Greenan and Guellec, 1998) has shown that firms performing process innovation have a higher capital/ labour ratio than other firms. In such a case, the relative price of labour and capital could be a main contributor to the choice made by firms in the trade-off between product and process innovation. The link between innovation and skills has been investigated by Duguet and Greenan (1997) on French micro data. They find evidence of a skill bias in innovation resulting from the aggregation of biases that differ according to the type of innovation considered. Notably, radical product innovation favours skilled labour, but this effect is partially offset by weak innovations (product and process) that favour unskilled labour. A further step would be to merge the approach through skill mix and the approach through employment level and job reallocation.

Overall, the results of this study on French data confirm previous findings on other countries. However, there are some discrepancies, especially with regards to the respective effects of product and process innovation. It will be necessary to perform similar analysis on a broader range of countries in order to know to which extent these differences are due to methodological choices or to country specificities.

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Figure 1 : Unweighted Growth Rate of Employment Distribution at the Firm Level

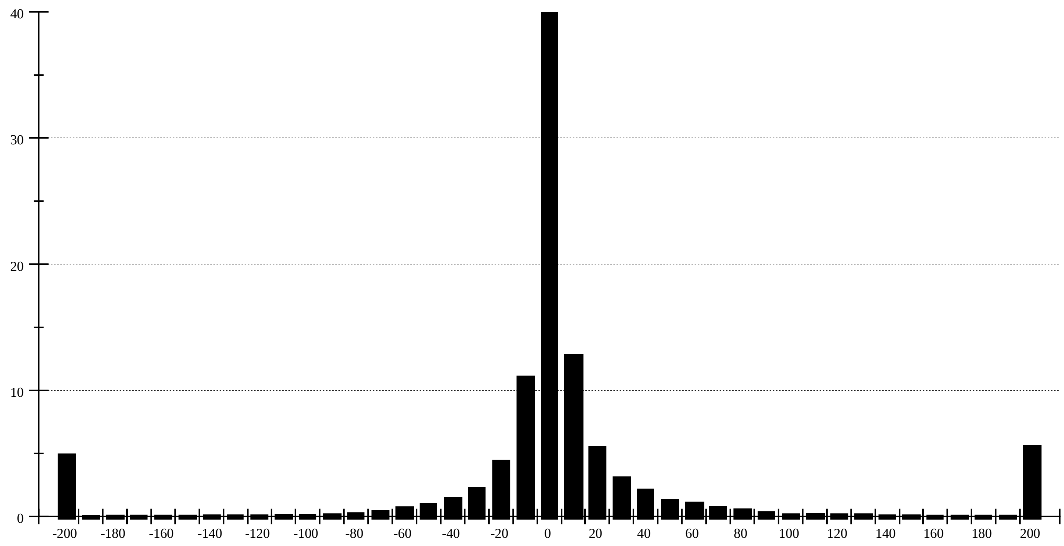
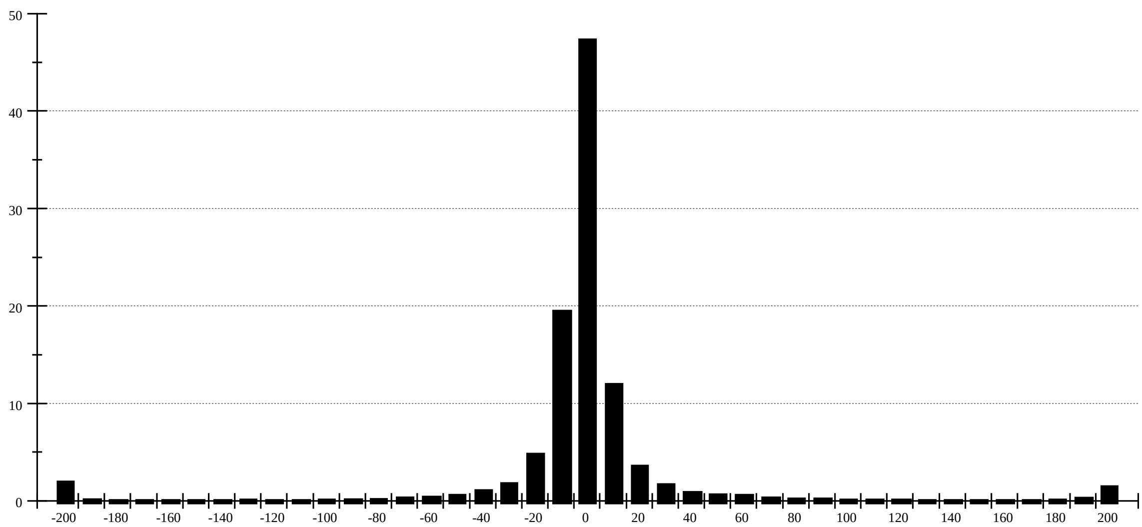


Figure 2 : Size Weighted Growth Rate of Employment Distribution at the Firm Level



<u>Table 1</u> - Job flow rates in French industry 1985-1991

Year	g^{pos}	g^{neg}	g^{net}	g^{exc}	Employment level
1985	0.083	0.097	-0.014	0.165	3390753
1986	0.071	0.110	-0.039	0.142	3302822
1987	0.078	0.104	-0.027	0.156	3196368
1988	0.077	0.088	-0.011	0.154	3136647
1989	0.100	0.095	0.004	0.190	3126542
1990	0.078	0.078	-0.000	0.156	3133395
1991	0.082	0.088	-0.006	0.164	3123454
Total	**0.081**	**0.094**	**-0.013**	**0.162**	**3201426**

Reported values are size-weighted means.

<u>Pearson correlations (1985-1991)</u> :

$p(g_t^{pos}, g_t^{neg})$ = -0.1649 (0.7239)

$p(g_t^{net}, g_t^{exc})$ = 0.7455 (0.0544)

Table 2 - Job flows rates, by industry

Industry	g^{pos}	g^{neg}	g^{net}	g^{exc}	Employment share	Mean size
Intermediate Goods Industries						
[T07] Ferrous ores and metals, first-stage steel processing	0.111	0.161	-0.050	0.221	3.67	475
[T08] Non ferrous ores, metals and semi-manufactures	0.027	0.073	-0.047	0.053	1.49	351
[T09] Building materials and miscellaneous ores	0.073	0.084	-0.011	0.146	3.44	48
[T10] Glass	0.064	0.049	0.014	0.098	1.49	140
[T11] Basis chemicals, artificial and synthetic yarns and fibers	0.078	0.108	-0.030	0.156	3.28	272
[T13] Foundry work and metal work	0.100	0.091	0.010	0.181	9.79	40
[T21] Paper and card board	0.074	0.074	-0.001	0.147	2.85	94
[T23] Rubber and plastics	0.079	0.069	0.010	0.138	5.54	82
Equipment Goods Industries						
[T15A] Professional electrical and electronic equipment	0.093	0.110	-0.018	0.186	12.83	120
[T15B] Household capital equipment	0.071	0.096	-0.025	0.142	1.53	260
[T14] Mechanical engineering	0.089	0.093	-0.004	0.179	11.17	55
[T16] Motor vehicles and other inland transport equipment	0.040	0.074	-0.035	0.079	11.34	367
[T17] Ships, aircraft and weapons	0.070	0.078	-0.008	0.140	4.10	495
Consumer Goods Industries						
[T12] Parachemicals and pharmaceuticals	0.062	0.067	-0.005	0.125	5.27	148
[T18] Textiles and clothing	0.092	0.125	-0.033	0.184	9.63	52
[T19] Leathers and footwear	0.070	0.112	-0.042	0.140	2.20	65
[T20] Timber, wood, furniture and miscellaneous industries	0.100	0.102	-0.002	0.199	5.38	38
[T22] Printing, press and publishing	0.099	0.087	0.012	0.174	5.02	37
Total	**0.081**	**0.094**	**-0.013**	**0.162**	**100.00**	**75**

Reported values for rates are size-weighted annual means.

Pearson correlation cross industries :

$$p(g_t^{pos}, g_t^{neg}) = 0.6174\ (0.0063)$$

$$p(g_t^{net}, g_t^{exc}) = 0.1065\ (0.6740)$$

Table 3 - Cross industries correlation between jobs creations and jobs destructions, by size category

Number of employees	Pearson correlation	significance
10-19	-0.16	0.35
20-49	0.07	0.68
50-199	-0.05	0.75
200-499	0.40	0.02
500-999	-0.32	0.06
1 000 +	0.61	0.00

Table 4 - Job flow rates by firm size

Number of employees	g^{pos}	g^{neg}	g^{net}	Employment level	Employment share
10-19	0.188	0.151	0.037	146470	4.73
20-49	0.118	0.109	0.009	411830	13.29
50-199	0.091	0.094	-0.003	607692	19.61
200-499	0.067	0.079	-0.012	413325	13.34
500-999	0.066	0.067	-0.001	304855	9.84
1 000 +	0.046	0.081	-0.034	1213964	39.18
Total	**0.081**	**0.094**	**-0.013**	**3098136**	**100.00**

Reported values for rates are size-weighted annual means. The difference in the total of employment between this table and table 1 is due to the fact that firms with less than 10 employees have been excluded.

<u>Table 5</u> - Simulations of the arithmetic effect of size on job flow rates

Number of employees	g^{pos}	g^{neg}	g^{net}	Employment level
Observed job flow rates in 1985				
10-19	0.183	0.163	0.020	147,794
20-49	0.116	0.126	-0.010	394,293
50-199	0.090	0.119	-0.028	607,982
200-499	0.061	0.082	-0.021	434,269
500-999	0.099	0.073	0.026	337,402
1 000 +	0.055	0.082	-0.027	1,387,763
Simulation on firms with 10 to 19 employees, first draw				
10-19	0.183	0.163	0.019	148,014
20-49	0.148	0.127	0.022	297,508
50-199	0.098	0.079	0.019	1,583,426
200-499	0.064	0.045	0.019	3,175,358
500-999	0.046	0.026	0.020	5,283,205
1 000 +	0.037	0.018	0.019	4,291,891
Simulation on firms with 10 to 19 employees, second draw				
10-19	0.183	0.163	0.020	147,983
20-49	0.149	0.126	0.023	296,689
50-199	0.096	0.076	0.020	1,584,722
200-499	0.062	0.043	0.020	3,173,000
500-999	0.046	0.027	0.020	5,276,202
1 000 +	0.039	0.020	0.019	4,300,805
Simulation on firms with 20 to 49 employees, first draw				
20-49	0.117	0.126	-0.009	429,888
50-199	0.083	0.095	-0.011	1,822,230
200-499	0.057	0.066	-0.009	3,703,633
500-999	0.039	0.049	-0.010	6,209,488
1 000 +	0.023	0.033	-0.010	27,264,012

Table 6 - Persistence rates for jobs creation and destruction, 1985-1990

Year	One-year persistence		Two-year persistence	
	PERPOS1	**PERNEG1**	**PERPOS2**	**PERNEG2**
1985	0.775	0.939	0.576	0.895
1985(*)	0.773	0.893	0.643	0.811
1986	0.767	0.936	0.667	0.909
1987	0.764	0.920	0.648	0.882
1988	0.761	0.907	0.657	0.871
1989	0.833	0.926	0.719	0.897
1990	0.758	0.916	-	-
Total Firms	**0.779**	**0.925**	**0.655**	**0.892**

Reported values are size-weighted means. (*) the persistence rates have been calculated over the subsample of firms continuously present between 1984 and 1991 (28,011 firms).

Table 7 - Persistence at the firm level

	One-year persistence		Two-year persistence	
	unweighted	**size weighted**	**unweighted**	**size weighted**
Stability	32.2	7.4	32.2	7.4
Growth	35.1	31.7	35.1	31.7
Total persistence	20.9	16.1	16.8	12.1
Partial persistence	5.8	5.7	5.9	5.6
Inversion	8.4	9.9	12.4	14.0
Decline	32.7	60.8	32.7	60.8
Total persistence	23.4	49.6	20.4	45.8
with continuous presence	17.3	44.5	12.7	38.6
with destruction 1986	4.1	2.2	4.1	2.2
with destruction 1987	2.0	2.9	2.0	2.9
with destruction 1988	-	-	1.6	2.1
Partial persistence	3.8	4.9	4.0	5.1
Inversion	5.5	6.3	8.3	9.9

Persistence rates are computed for firms continuously present either in 1985 or in 1986 (41821 firms). The reference variation of employment occurs between these two dates. The 1986 current level of employment (x_{et}) is used for the size weighted distribution.

Table 8 - The impact of technological innovation on job flows

	g^{pos}	g^{neg}	g^{net}
$Inno_S$	0.070 (2.35)	-0.091 (-2.21)	0.161 (3.15)
R2	0.37	0.30	0.12
$Proc_S$	-0.014 (-0.25)	0.250 (3.38)	-0.264 (-2.88)
$Prod_S$	0.078 (1.71)	-0.279 (-4.53)	0.357 (4.69)
R^2	0.38	0.35	0.18

The endogenous variables are the annual mean values of flows computed over the period 1986-1990 by industry (37 categories) and size (7 categories) which leads to 255 observations. The exogenous variables are the industry level share of employment in firms which have achieved at least one type of innovation ($Inno_S$) and size dummies in the first model ; the industry level shares of employment in firms which have achieved at least one process innovation ($Proc_S$), one product innovation ($Prod_S$) and size dummies in the second model. Between brackets are Student statistics.

Table 9 - Innovation and maturity : an econometric analysis

	g^{pos}			g^{neg}			g^{net}		
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
Youth			0.010 (2.14)			-0.020 (-3.34)			0.030 (4.03)
$Inno_S$		0.075 (2.52)	0.067 (2.26)		-0.118 (-3.00)	-0.103 (-2.63)		0.193 (3.96)	0.170 (3.53)
Innorel	0.057 (2.18)			-0.207 (-6.08)			0.264 (6.23)		
Innorel1		0.041 (1.49)			-0.203 (-5.61)			0.244 (5.43)	
Innorel2			0.031 (1.10)			-0.190 (-5.16)			0.220 (4.87)
R2	0.37	0.37	0.38	0,38	0.38	0.39	0.21	0.22	0.24

Notes of table 8 apply. Moreover, the variable Innorel, when regressed together with $Inno_S$ is in fact Innorel1, the residual of a regression of Innorel on $Inno_S$; and when regressed together with Inno and Youth it is Innorel2, the residual of a regression of Innorel on $Inno_S$ and Youth (both regressions are reported in table 10b). Between brackets are Student statistics.

<u>Table 10</u> - Correlation between innovation and maturity at the industry level

	Innorel	$Inno_S$
Youth	0.28 (0.09)	NS
$Inno_S$	0.40 (0.01)	1

Between brackets is the significance of coefficients.

<u>Table 11</u> - The pattern of innovation controlled by the intensity of innovation and maturity of the sector

	$Inno_S$	Youth	R2
Innorel1	0.514 (2.61)		0.16
Innorel2	0.484 (2.50)	0.047 (1.59)	0.22

The regression has been performed at the sector level (37 sectors). Innorel is the endogenous variable. The residual of the regression reported in line 1 is referred as Innorel1, and in line 2 as Innorel2. Between brackets are Student statistics.

<u>Table 12</u> - Simulated effects of changes in variables on sector employment dynamics

	Mean	**Stand. dev.**	**Innorel**	**Inno$_S$**	**Youth**
g^{pos}	0.116	0.096	0	0.012	0.012
g^{neg}	0.132	0.127	-0.037	-0.018	-0.023
g^{net}	-0.016	0.140	0.043	0.030	0.035

The values in columns 3 to 5 report the effect on the employment variables of a change in each exogenous variable of amplitude equal to one standard deviation.

<u>Table 13</u> - Innovation and job transfers within sectors

	g^{exc}
Inno$_S$	-0.067 (1.13)
Innorel1	0.101 (2.11)
Sector size	0.000 (0.72)
R2	0.22

Between brackets are Student statistics

Table 14 - Innovation and employment growth, at the firm level

Employment Log differences	Firms present over the 1985-1990 period	Total Sample of firm
Intercept	-0.036 (-6.88)	-0.058 (-5.99)
Inno	0.016 (11.72)	0.019 (7.74)
R2	0.48	0.39
Intercept	-0.041 (-7.79)	-0.066 (-6.70)
U1	0.000 (0.03)	-0.006 (-1.92)
U2	0.003 (1.90)	0.009 (2.98)
U3	0.006 (3.80)	0.007 (2.43)
U4	0.010 (5.26)	0.009 (2.77)
U5	0.011 (7.24)	0.019 (6.90)
R2	0.49	0.39
Intercept	-0.037 (-7.10)	-0.061 (-6.25)
Proc	0.013 (8.48)	0.019 (6.93)
Prod	0.006 (3.54)	0.005 (1.68)
R2	0.49	0.39
Number of Firms	13,126	15,186

The endogenous variable is the mean annual employment growth computed in Log differences. In column 2, it is calculated over different periods of time depending on the presence of the firm in the EAE file. Some dummy variables are introduced into the regression to control for this. The exogenous variables are dummy variables for innovation, dummy variables for size (7 categories) and for industry (19 categories). Between brackets are Student statistics.

The innovation variables have the following meaning :
Inno : The firm has introduced at least one innovation during the period.
U1 : The firm has substantially improved existing products
U2 : The firm has invented a product that is new for the market
U3 : The firm has invented a product that is new for her, but already present on the market
U4 : The firm has invented a new process
U5 : The firm has substantially improved existing processes
Proc : The firm said yes at either U4 or U5
Prod : The firm said yes at either U1, U2 or U3

<u>Table 15</u> - Separate estimations with ordinary least squares

N=5,919	$\dot{py}$	$\dot{l}$	$\dot{k}$
Intercept	0.200 (20.61)	0.155 (18.70)	0.049 (3.90)
Proc	0.043 (3.91)	0.036 (3.71)	0.032 (2.29)
Prod	0.017 (1.55)	0.014 (1.48)	0.025 (1.76)
$\dot{r}$	0.215 (10.09)	0.165 (9.14)	-0.098 (-3.62)
$\dot{w}$	0.397 (15.22)	-0.548 (-24.67)	0.114 (3.41)
R2	0.064	0.103	0.007

Between brackets are Student statistics.

<u>Table 16</u> - relations between estimated coefficients and the parameters of the model

Constant returns to scale			
	$\dot{py}$	$\dot{l}$	$\dot{k}$
Proc	$-(1-\beta)\alpha_a$	$-(1-\beta)\alpha_a$	$-(1-\beta)\alpha_a$
Prod	α_b	α_b	α_b
$\dot{r}$	$(1-\beta)\alpha$	$(1-\beta)\alpha$	$(1-\beta)\alpha-1$
$\dot{w}$	$(1-\beta)(1-\alpha)$	$(1-\beta)(1-\alpha)-1$	$(1-\beta)(1-\alpha)$
Non constant returns to scale, $\theta = e + \beta(1-e)$			
	$\dot{py}$	$\dot{l}$	$\dot{k}$
Proc	$-(1-\beta)\alpha_a/\theta$	$-(1-\beta)\alpha_a/\theta$	$-(1-\beta)\alpha_a/\theta$
Prod	α_b/θ	α_b/θ	α_b/θ
$\dot{r}$	$(1-\beta)\alpha_1/\theta$	$(1-\beta)\alpha_1/\theta$	$-[(1-\beta)\alpha_2+\beta]/\theta$
$\dot{w}$	$(1-\beta)\alpha_2/\theta$	$-[(1-\beta)\alpha_1+\beta]/\theta$	$(1-\beta)\alpha_2/\theta$

<u>Table 17</u> - Separate estimations, with two stage least squares

N=5,919	$\dot{py}$	$\dot{l}$	$\dot{k}$
Intercept	0.375 (8.32)	0.305 (7.81)	0.129 (2.34)
Proc	0.055 (4.82)	0.040 (4.06)	0.051 (3.63)
Prod	0.014 (1.25)	0.011 (1.13))	0.020 (1.43)
$\dot{r}$	-0.211 (-3.27)	-0.261 (-4.67))	-0.960 (-12.13)
$\dot{w}$	-0.304 (-1.66)	-1.149 (-7.21)	-0.182 (-0.81)
R2	0.009	0.016	0.027
Hausman	211.15	336.77	5.48

Between brackets are Student statistics.
Instruments : location (18 categories), r84, w84, Proc, Prod.

<u>Table 18</u> - Estimations of the system, under non linear form

N=5,919	e=0.9	e=1	e=1.1
Int. py	0.354 (12.60)	0.354 (12.60)	0.353 (12.59)
Int. l	0.311 (11.11)	0.311 (11.11)	0.313 (11.16)
Int. k	0.144 (5.07)	0.144 (5.07)	0.144 (5.06)
α_b	0.016 (2.15)	0.015 (2.15)	0.017 (2.22)
α_a	0.123 (2.84)	0.137 (2.84)	0.148 (2.85)
α_1	0.364 (2.79)	0.404 (2.79)	0.443 (2.80)
β	1.412 (9.74)	1.356 (11.27)	1.315 (12.82)

Between brackets are Student statistics.
Instruments : location (18 categories), r84, w84, Proc, Prod.

Table 19 - A numeric example of the time pattern of innovation

Type of innovation	Firm	Period 1	Period 2	Period 3
Process innovation	Firm 1	10	15	15
No innovation	Firm 2	10	4	4
Product innovation	Firm 1	10	19	13
No innovation	Firm 2	10	3	9

Figures are the employment level of each firm at each period. Firm 1 performs an innovation whereas firm 2 stands by. Our two firms belong to the same sector. The aggregated indicators NET and EXC (for the sector) can be computed in each case. Moreover EXC can be computed two ways: for the whole period (period 3 compared to period 1) or as the mean two one period indicators (EXC1 and EXC2 respectively). Results are the following:

Process innovation:

NET=-0.05 ; EXC1= (5+6-1)/20 = 0.50; EXC2= ((5+6-1)/20+0)/2 = 0.25.

Product innovation:

NET= 0.10; EXC1= (3+1-2)/20= 0.05; EXC2= ((9+7-2)/20)+(6+6-0)/22)/2 = 1.25.

As pointed out in the text we have EXC1(process) > EXC1(product), but EXC2(process) < EXC2.(product).

APPENDIX

1) Construction of the variables for estimating the structural model

The supplementary variables needed for estimating the structural model (value added, volume of labour, labour cost, volume of capital stock, cost of capital) are constructed from the firms' fiscal declaration present in the INSEE firm data base. They are constructed as follows:

Value added (Y)

The measure used is that of value added "at factor costs":

Y = production **-** intermediate consumption **+** subsidies **-** production-linked taxes

Volume of labour (L)

The same measure of the volume of labour is used throughout the whole study. It is the average level of employment for one year, calculated according to the time spent by every employee in the establishment. It includes short term and long term contracts, apprentices and temporary workers. We aggregated this information over all the establishments of a firm so as to obtain a firm level indicator of employment

Labour cost (W)

The measure used is an average cost:

W = (aggregate remuneration + social contributions) / L

Volume of capital stock (K)

The value of capital stock is measured, using the book gross value of fixed assets given by the firm's balance sheet. Knowing that this value is measured at historic costs, the volume of capital stock is estimated, using the price of investment that corresponds to the average age of capital. This average age is constructed as follows:

age = 16 ***** (cumulated fiscal depreciation / gross value of fixed assets)

This age is estimated according to an assumption of 16 years' life duration. We then make a correction, taking into account usual methods for fiscal depreciation.

corrected age = age / 2 if age <= 8

= age **-** 4 otherwise

This age represents the average age of firm's capital stock. We then use investment deflators from national account for manufacturing industry (base year: 1980). The price corresponding to t **-** corrected age is used for deflating the value of capital stock:

K(**t**) = gross value of fixed asset(**t**) / investment deflator (**t - corrected age**)

Cost of capital (R) :

The measure of the cost of capital is a weighted average cost measure, taking into account the financial structure of capital. It is constructed as follows:

R = IDS [(1 - FISTRU) * CEQ + (FISTRU * CDEBT) + DEPR - INFL]

IDS= investment deflator from national account for a breakdown of industry into 41 sectors (base year: 1980)

FISTRU = financial structure of capital
= financial debts / (financial debts + equity)

CEQ = cost of equity
= return required by stockholders knowing the fiscal policy /
(1 - tax rate on profits)

CDEBT = apparent cost of debt
= financial costs / financial debts

DEPR = depreciation rate
= current fiscal depreciation (corrected for economic life duration) /
gross value of fixed assets

INFL= growth rate of IDS

According to these measures, the cost of equity only varies in the time dimension, when the cost of debt varies in time and from one firm to the other. This is because we can isolate from the balance sheet only one component of this cost, dividends paid to stockholders, that concerns only 30% of the firms in our sample, whereas all firms pay interests on financial debts. Our measure of the cost of capital relies on strong assumptions and on a series of approximations, but its main aim is to give an acceptable measure, taking fiscality into account, as well as the financial structure of capital and its physical structure (through individual depreciation rates).

Table A1 gives the average value and standard deviation for the components of the cost of capital and for labour cost on our subsample of 5,919 firms.

2) From the total sample to the sample of 5,919 firms

The first part of the study is based on a sector aggregation of the French annual business survey ("Enquête annuelle d'entreprise") for the manufacturing industry (carried out at the establishment level) and of its supplement on innovation carried out only for the manufacturing industry at the firm level. The EAE sample is the biggest, grouping 97,347 establishments and 55,519 firms present at least one year during the 1984-1991 period. 15,721 firms answered correctly the Innovation survey. The discrepancy between the EAE sample and the Innovation survey sample comes from the fact that first survey concerns all establishments over 10 employees, when the second one was directed towards firms over 20 employees.

When we work at the firm level, in the second part of the study, we use the sample of firms from the Innovation survey. We left out firms only present in the EAE data file in 1990, 1990-1991, as well as firms that had extreme employment dynamics over the period. This leads to 15,186 firms (13,126 if we take only the firms continuously present over the period).

When we estimate the structural model, we go to an even smaller sample, of 5,919 firms. This is because we merge firms from the Innovation survey with the INSEE firm data base. This data base is constructed from "SUSE", "Système unifié de statistique d'entreprises", which combines the information of the EAE and of the firm fiscal declarations ("Déclarations de Bénéfices Industriels et Commerciaux", BIC) that gives firms' balance sheets. We keep firms that are continuously present in the two files, and for which the variable of interest do not take extreme values.

What kind of distortion is generated when we switch to the sample of 5,919 firms? Mainly a size distortion. The sector structure of the sample remains stable but the size structure evolves in favour of firms over 50 employees in 1985 and to the detriment of firms with less than 20 employees (table A2).

<u>Table A1</u> : components of capital cost and labour cost

	FISTRU	CDEBT	CEQ	DEPR	R	W
1984	0.263 (0.182)	0.459 (0.291)	0.248	0.069 (0.033)	0.405 (0.117)	128.900 (37.830)
1985	0.273 (0.178)	0.414 (0.277)	0.259	0.067 (0.030)	0.452 (0.114)	138.897 (40.949)
1986	0.260 (0.174)	0.386 (0.268)	0.161	0.067 (0.029)	0.364 (0.111)	147.820 (59.676)
1987	0.248 (0.169)	0.365 (0.263)	0.180	0.067 (0.029)	0.405 (0.103)	155.732 (68.058)
1988	0.240 (0.165)	0.345 (0.256)	0.156	0.066 (0.027)	0.389 (0.102)	164.215 (117.021)
1989	0.236 (0.164)	0.344 (0.256)	0.152	0.066 (0.026)	0.385 (0.100)	171.106 (107.400)
1990	0.233 (0.165)	0.352 (0.259)	0.196	0.067 (0.027)	0.458 (0.104)	177.346 (52.243)
1991	0.228 (0.169)	0.352 (0.258)	0.168	0.068 (0.030)	0.488 (0.924)	187.686 (156.890)

Between brackets are standard deviations. The cost of equity has no standard deviation as it is the same for all firms every year. Labour cost is expressed in thousand francs per year and per employee, the cost of capital is expressed in francs, for owning one franc of capital (price of 1980) during one year.

<u>Table A2</u> : Evolution of the size structure of the sample

size categories in 1985	13,126 firms	5,919 firms
less than 9 employees	9.9	0
10 to 19 employees	9.0	0.7
20 to 49 employees	42.1	42.8
50 to 199 employees	26.0	33.7
200 to 499 employees	7.9	12.2
500 to 999 employees	2.8	5.0
more than 1 000 employees	2.2	5.6
Total	100	100