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Contribution of ICT on Labor Market Polarization: an Evolutionary Approach

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Contribution of ICT on Labor Market Polarization: an Evolutionary Approach

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Abstract: This paper analyses the role of Information and Communication Technologies (ICT) on the job market polarization. We rely on an evolutionary framework by applying a "distance from mean approach". Using data for 8 industrialized economies, we account for probable heterogeneous and time-varying effects through the estimation of a semiparametric smooth coefficient model. Our results show a significant contribution of ICT on polarization dynamics with some differences between countries and industries. We also find evidence that diffusion of ICT is initially accompanied by a Skill Bias Technological Change (SBTC), then contributing to job market polarization. Finally, our findings highlight a progressive weakening of the positive link between ICT diffusion and the increasing demand for high-skilled workers over time.

Keywords: ICT, Evolutionary economics, Polarization of labor market, Semi-parametric Smooth Coefficient Model

JEL Classification: C14, E11, J21, O33

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1 Introduction

The impact of technology diffusion on the labor market is a long-standing issue that has been discussed since classical economists like Ricardo (1821). This question has known a renewed interest due to the diffusion over the last decades of computer tools. According to Vivarelli (2011), the impact of technology diffusion on the labor market should be apprehended both quantitatively and qualitatively. Analyzing the qualitative impact amounts to investigating whether technology diffusion has an influence on labor market structure by fostering or disadvantaging some categories of workers depending on their level of qualification. From this perspective, many authors suggest the existence of a technological bias in favor of the most skilled workers. In other words, capital accumulation is positively correlated with demand growth and/or an increase of wages for this kind of workers.[1] In this sense, technology can be viewed as complementary to the most educated workers, and as a substitute for the low and middle-skilled workers. This relation called "Skill Bias Technological Change" (SBTC), was initially investigated by Nelson and Phelps (1966) and has received some empirical support from Griliches (1969), Welch (1970) or Tinbergen (1974, 1975).[2]

Other authors have reconsidered this issue by taking into account the diffusion of Information and Communication Technologies (ICT) and shown that there is also a complementarity between these technologies and the high-skilled workforce. Berndt et al. (1992), by analyzing data from the US industry for the period 1968-1986, identify a positive correlation between the enrichment of capital in new technologies and the increase in the amount of work for highly qualified workers. Krueger (1993) shows that the growth in the use of computers in the 1980s counts for between one third and half of the rise in the rate of return to schooling. Berman et al. (1994), using data from 450 US manufacturing sectors over the period 1979-1987, show that investment in computers and R&D induces a shift in employment structure in favor of skilled workers. Autor et al. (1998) provide detailed arguments regarding the SBTC hypothesis in the US economy. They find evidence of a positive correlation, over the period 1979-1993, between the increase of computer use and the demand of skilled workers. They also obtain some empirical arguments in line with an acceleration of this dynamics. Using only data on retail

[1] Vivarelli (2011) argues that the wage effect is more pronounced in countries which have high level of flexibility (USA, UK), while countries having a rigid labor market are more subject to the employment effect. In this paper, we pay particular interest in the employment effect.

[2] For a historical perspective on SBTC, see Goldin and Katz (1998).

industry and assuming the existence of a causal relationship, these authors suggest that computer capital growth has contributed for about one third to the dynamics of qualification rise during the 1970 and 1980 decades.
One explanation to this favorable coevolution -diffusion of ICT and increasing demand for more educated workers- lies in the fact that production of technological products needs high skills, and that their introduction and their use require also high competences (Chun, 2003). On the other hand, many authors as Askenazy and Gianella (2000), Caroli and van Reenen (2001), Brynjolfsson et al. (2002) link the existence of SBTC with organizational changes. Indeed, the adoption and the utilization of ICT produce a large amount and flows of data ("information overload", Bresnahan et al. (2002)). This requires new kind of organization within firms with the gradual shift from a vertical to a more horizontal organization. In the latter case, the authority is more distributed and needs the most skilled workers.

Retaining a different framework, the link between ICT diffusion and labor market changes has also been investigated by Autor et al. (2003) who formulate the "ALM hypothesis" (or "routinization hypothesis"[3]). They argue that in the production process, there are some routine tasks "that can be accomplished by following explicit rules" and some nonroutine tasks that cannot. The workers that carry out the first type of tasks are logically threatened by ICT because they are in direct competition with machines. Conversely, given that nonroutine tasks are difficult to conduct by computer tools, the workers assigned to these operations have not to face to this constraint.[4] Morever, they can have a complementary role with these technologies. Autor et al. (2003) build a theoretical model based on the assumption that the decline in price of computer capital determines the magnitude of the substitution process. Using data on the US economy over the period 1960-1998, Autor et al. (2003) obtain empirical evidence in favor of their model. A similar approach is adopted by Maurin and Thesmar (2004) on the French economy, leading to similar results.
On this basis, Goos and Manning (2003) formulate the "polarization hypothesis".[5] These authors go further than the ALM analysis by showing that routine tasks are mainly located in the intermediate ranges of the distribution of wages and qualifications. The diffusion of ICT should thus have a negative impact on the intermediate workforce (due to a substitution dynamic) and,

[3]Acemoglu and Autor (2010)

[4]Bresnahan et al. (2002) refer to "limited substitution" in the sense that some workers are less subject to capital-labor substitution.

[5]This labor market polarization due to ICT diffusion has been anticipated by Leontieff and Duchin (1986).

conversely, a positive impact for the more skilled workers through a complementarity relation. The less skilled workers should be positively affected by ICT because they carry out an important share of nonroutine tasks. Additionally, new service jobs (jobs that include mainly nonroutine tasks) are created under the influence of ICT diffusion. Goos and Manning (2003) bring some econometric evidence for the UK labor market in favor of their assumption. Other studies have also obtained some results in line with the polarization hypothesis: Goos et al. (2009) on a sample of sixteen OECD countries, Michaels et al. (2010) on eleven industrialized economies and Autor et al. (2008) and Autor and Dorn (2013) on the US economy.

Falling into this stand of the litterature, the purpose of our paper is to assess the exact role played by ICT in the dynamics of polarization by considering the probable heterogeneity in this process. More specifically, we aim at grasping the magnitude of ICT impact and the differences that may exist in space (ie between countries) and relative to the nature of economic activities (type of industry). We also investigate the question of the stability in time of the relation between ICT and labor market changes by seeking to identify some temporal dynamics. This question is indeed highly relevant because some authors (Autor et al. (2008); Acemoglu and Autor (2010)) have suggested the existence of variations in the polarization movement, a way that has not been much explored.

The contribution of this paper is twofold. First, it relies on an evolutionary perspective, specifically used in population analysis. Indeed, we resort to the "distance from mean approach" to model the evolution of the share of categories of workforce in all population of workers. For each kind of workforce, these changes depend on its ability to adapt to a common selective pressure (here, ICT diffusion) and on the adaptability of other categories in responding to this constraint. This methodology permits to take into account the interdependencies between different types of workers in the form of a dynamic system. Second, from a methodological viewpoint, we consider a SemiParametric Smooth Coefficient Model (SPSCM) allowing coefficient variation in accordance with several selected variables such as industry, country and time. To the best of our knowledge, the evolutionary approach and SPSCM models have never been applied to investigate the contribution of ICT to the polarization of labor market.
The rest of this paper proceeds as follow. In Section 2, we describe the data and our methodology. Section 3 presents the results of the empirical analysis and Section 4 concludes the paper.

2 Data and Methodology

2.1 Data

Data come from the EU Klems database[6] (2008 release). They are available for 240 industries[7] from 8 industrialized economies: Austria, Denmark, Finland, Italy, Japan, the Netherlands, the United Kingdom, and the United States over the period 1981-2005.
Turning to the labor market, we use shares of hours worked in the total of hours worked for each type of workers: high-skilled (HS), medium-skilled (MS), and low-skilled (LS). These categories are defined by school achievement. High-skilled workers are those who have a university degree. The case of the middle-skilled workers is more complicated given the different definitions between countries. In the EU Klems database, people with a high school degree or a professional degree are included in this category. The last category is composed by the other workers. Data regarding Information and Communication Technologies are capital share in total of capital stock (ICT). The panel is balanced with 6000 observations for each variable. Summary statistics are reported in table 1.

Table 1: Summary statistics

Variables	Minimum	Mean	Median	Maximum	Standard Deviation
HS	0.001	0.129	0.085	0.716	0.127
MS	0.158	0.654	0.657	0.984	0.170
LS	0.001	0.217	0.197	0.836	0.155
ΔHS	-0.086	0.003	0.002	0.064	0.008
ΔMS	-0.010	0.004	0.004	0.158	0.014
ΔLS	-0.150	-0.008	-0.008	0.095	0.013
ICT	0	0.060	0.028	0.894	0.089

In terms of level, the middle-skilled workers represent on average the largest share in the entire population, while the low-skilled workers are more numerous than the most educated workers. The variables in difference show different paths. The two higher categories of workers (HS, MS) are mainly affected by positive variations, but the low-skilled workforce is subject to negative evolution.

[6] http://www.euklems.net/

[7] The list of industries is available in results in tables 4, 5, 6. It includes for each country, 17 industries belonging to the manufacturing sector and 13 to the services sector.

2.2 An evolutionary view: Distance from mean approach

The evolutionary framework finds its roots in the works of Veblen (1898, 1908) and Schumpeter (1934), and has been developed in its modern form by Nelson and Winter (1982). According to the evolutionnary approach, economy can be viewed as a dynamic system composed of heterogeneous agents with bounded rationality and subject to constraints. The evolutions of the system are determinated by the qualitative changes of entities and by the pressure of several selection processes.
Within this framework, we resort to population analysis by using the distance from mean approach derived from the work of Fisher (1930); which is based on three theoretical elements:

- A population of individuals evolving in the same environment.
- This population is divided into homogeneous subgroups differentiated by specific characteristics.
- A constraint applies to all individuals and acts as an instrument of selection.

The reactions of each subgroup face to this constraint determine the evolutions of respective shares in the total population. This reaction is called "fitness" and can be interpreted in several ways according to the considered problematic. It can be seen as a brute survival rate, as a differential growth or as ability to adapt through innovation (Metcalfe, 2008). Given our topic of investigation, we retain here the last interpretation. This theoretical framework is formalized by the following simple "replicator equation":

$$\frac{\partial x_i}{\partial t} = \dot{x}_i = (F_i - \bar{F})x_i \tag{1}$$

where i is the category index (subgroup of the population), t denotes time, x_i is the share of category i in the total population, n being the size of the population, F_i is the fitness of the category i and $\bar{F}$ is the weighted average fitness of the entire population:

$$\bar{F} = \sum_{i=1}^{n} F_i x_i$$

Changes in the share of each category of population depend on its own reaction to the constraint and to level of its reaction compared to other subgroups. This interdependence is represented by the term $F_i - \bar{F}$, denoting the distance from mean. In this way, we obtain a dynamic perspective that reflects the interactions between categories over time.[8]

This replication process can be adapted to our problematic by identifying the population with labor force, the subgroups with the categories of workers differentiated by the levels of skill, and the constraint with the diffusion of ICT. Because it exists a historical trend of increase of qualification in industrialized countries, we also add a term (c_t^i) to capture this long-run evolution. Considering discrete-time, we can rewrite equation (1) for high-skilled workers:

$$\Delta HS_t = c_t^{HS} + (F_t^{HS} - \bar{F}_t)HS_t \tag{2}$$

where

$$F_t^{HS} = \alpha_t^{HS} ICT_t$$

and

$$\bar{F}_t = F_t^{HS} HS_t + F_t^{MS} MS_t + F_t^{LS} LS_t$$

where $F_t^i = \alpha_t^i ICT_t$ is the fitness with $i =$ HS, MS, LS, and α_t^i is a coefficient specific to each subgroup that can be estimated. Here, we interpret the fitness value as the capacity to adapt to diffusion of ICT. By rearranging some terms, we get:

$$\Delta HS_t = c_t^{HS} + \lambda_t^{HS} HS_t ICT_t \tag{3}$$

with

$$\lambda_t^{HS} = \alpha_t^{HS} - (\alpha_t^{HS} HS_t + \alpha_t^{MS} MS_t + \alpha_t^{LS} LS_t)$$

For the two other categories of labor force, we have:

$$\Delta MS_t = c_t^{MS} + \lambda_t^{MS} MS_t ICT_t \tag{4}$$

$$\Delta LS_t = c_t^{LS} + \lambda_t^{LS} LS_t ICT_t \tag{5}$$

Considering equations (3), (4) and (5), our aim is to estimate the differences λ_t^{HS}, λ_t^{MS}, λ_t^{LS}, the individual coefficients α_t^{HS}, α_t^{MS}, α_t^{LS} and the trends c_t^{HS}, c_t^{MS}, c_t^{LS}.

[8] This approach has been used in economics by several authors as Silverberg and Verspagen (1994), Saviotti and Mani (1995) and Metcalfe (1994, 2008).

2.3 A semiparametric smooth coefficient model

In order to estimate the coefficients, we consider a SemiParametric Smooth Coefficient Model (SPSCM) allowing coefficient variations in accordance with many variables.[9][10] This model doesn't make any assumptions on the shape of the relation between variables such as linearity or strict parametric form. This means that intercept and slope coefficients are varying and are unknown smooth functions of some selected variables. This approach is particularly suitable for panel data because it can grasp the probable heterogeneity between individuals more precisely than the classical methods (fixed effect, panel smooth transition regression model (PSTR)...).
Li and Racine (2010) have improved this approach by including continuous and categorical variables in the SPSCM. This method is appealing and highly relevant in our case because the series display pronounced heterogenity and strong temporal variations.
We rewrite equation (3) in a SPSCM form. In our panel, industries are individuals indexed by k, and denoting ϵ_{kt} as an iid error term, we have:

$$\Delta HS_{kt} = c_{kt}^{HS}(Z_{kt}) + \lambda_{kt}^{HS}(Z_{kt})HS_{kt}ICT_{kt} + \epsilon_{kt}^{HS} \tag{6}$$

The coefficients are some unknown functions of the vector of Z variables Z_{kt} =(industry, country, time). For the two other categories of labor force, we have:

$$\Delta MS_{kt} = c_{kt}^{MS}(Z_{kt}) + \lambda_{kt}^{MS}(Z_{kt})MS_{kt}ICT_{kt} + \epsilon_{kt}^{MS} \tag{7}$$

$$\Delta LS_{kt} = c_{kt}^{LS}(Z_{kt}) + \lambda_{kt}^{LS}(Z_{kt})LS_{kt}ICT_{kt} + \epsilon_{kt}^{LS} \tag{8}$$

In this way, it is possible to grasp probable differences between industries, countries, and according to time regarding the impact of ICT.

To estimate $\hat{\beta}(Z_{kt)} = (\hat{c}_{kt}^{i}(Z_{kt}), \hat{\lambda}_{kt}^{i}(Z_{kt}))$, we use the local constant estimator developed by Li and Racine (2010) that can be written as follows:

$$\hat{\beta}(Z_{kt)} = \left[\sum_{j=1}^{N}\sum_{\tau=1}^{T} X_{j\tau}X'_{j\tau}K(Z_{j\tau}, Z_{kt)}\right]^{-1}\sum_{j=1}^{N}\sum_{\tau=1}^{T}X_{j\tau}Y_{j\tau}K(Z_{j\tau}, Z_{kt}) \tag{9}$$

[9] This type of model was discussed by Hastie and Tibshirani (1993) and generalized by Li et al. (2002).

[10] This specific methodology was applied for example for the study of the role of institutional quality on the firm performances (Bhaumik et al., 2012), of the productivity in US electricity generating plants by Kumbhakar and Sun (2012) or in the Korean electric power plants by Heshmati et al. (2013).

with N and T being respectively the number of cross-section and periods. $K(Z_{j\tau}, Z_{kt})$ is the "Generalized Product Kernel Function" (Li and Racine, 2004).

$$K(Z_{j\tau}, Z_{kt}) = \prod_{r=1}^{2} K(Z^d_{rj\tau}, Z^d_{rkt}, \theta_r) K^w(Z^w_{rj\tau}, Z^w_{rkt}, \phi) \tag{10}$$

where K^d and K^w are respectively the Aitchison and Aitken (1976) and the Wang and van Ryzin (1981) kernels.

$$K^d(.) = \begin{cases} 1-\theta_r & \text{if } Z^d_{rj\tau} = Z^d_{rkt} \\ \dfrac{\theta_r}{(1-c)} & \text{otherwise} \end{cases}$$

$$K^w(.) = \begin{cases} 1-\phi & \text{if } |Z^w_{rj\tau} - Z^w_{rkt}| = 0 \\ \dfrac{(1-\phi}{2}\phi^{|Z^w_{rj\tau} - Z^w_{rkt}|} & \text{if } |Z^w_{rj\tau} - Z^w_{rkt}| > 1 \end{cases}$$

c denotes the number of levels of the variables, θ_r are bandwidths for unordered categorical variables, namely industry and country, and $\phi \in [0, 1]$ is bandwidth for time, which is the ordered categorical variable. The optimal bandwidths are selected by cross-validated bandwidth selection (Li and Racine (2010)).

After estimating the differences λ^{HS}_{kt}, λ^{MS}_{kt}, λ^{LS}_{kt}, we obtain for each date, industry and country, a system of equations which can be solved to get the individual coefficients α^{HS}_{kt},α^{MS}_{kt}, α^{LS}_{kt}, the individual fitnesses F^{HS}_{kt}, F^{MS}_{kt}, and F^{LS}_{kt} and the distances from mean.[11]

3 Results

Implementing the SPSCM produces a lot of results because estimated coefficients are observation-specific. For the sake of simplicity and brevity, we do not report all estimation results but only the most interesting ones.[12] In commenting our results, we mainly pay attention to the means of the distribution of all functional coefficients estimated, as suggested by Racine (2008). We also add medians for more accuracy.

[11] These systems can be singular, we thus rely on pseudoinverse matrix (Moore-Penrose).
[12] All results are available upon request to the author.

3.1 Mean Results

First, we focus our attention on mean results of the trends. As shown in table 3, we obtain results in line with the historical trend of increasing qualification in industrialized countries (ie positive signs for the high and middle-skilled workers and negative sign for the low-skilled workers). For the fitness and the distance from mean over all the period (tables 3, 4, 5, 6), there is generally a positive correlation between ICT diffusion and variations of the share of high-skilled workers, whilst there is a negative relation with the share of middle and low-skilled workers. In other words, our results show the existence of a skill biased technological change (SBTC). In terms of magnitude, the strongest effect is related to the high-skilled workers, while we observe a clear negative effect for the middle-skilled workers and a smaller impact on the low-skilled workers. We show in the next section that behind these results several temporal dynamics are hidden.

Our model takes into account interdependencies between all categories of labor force, as illustrated by looking at the difference between the values of the distance from mean and the fitness, or between the fitness and the average fitness. Indeed, in most cases, the fitness coefficient for the high-skilled workers is highly positive but less than the distance from mean due to the level of the fitness mean. In fact, the positive relationship is amplified by the relative performance of each subgroup. The inverse situation is observed for the middle-workers. The negative impact of ICT diffusion is sharply reduced by the fact that the mean fitness is negative. Furthermore, the performances of the low-skilled are also positively influenced by their distances from mean.

Although it is possible to draw general conclusions, there is heterogeneity across industries and countries.

We first observe variability in the industries probably due to their differences in terms of specialization and labor force dotation. In most of industries and regarding the high-skilled workers, a positive relationship is observed and the fitness values are close to the mean of the sample. However, some industries have magnitudes which are markedly different from the overall average. This is the case for electrical and optical equipment, post and telecommunications, real estate activities and renting of machinery and equipment sectors.

In a similar way, the distributions of fitness for the middle-educated workers and low-skilled workers are centered on the mean but large deviations can be identified. These deviations have a tendency to be the inverse of those identified for the HS fitness. The sectors already mentioned above show contrary movements. For the low-skilled workers, in most cases, the fitnesses are negative but it is possible to discern two activities concerned by a mean positive fitness, namely the financial intermediation and renting of machinery and equipment sectors. In terms of distance from the mean, at the industry level, and given the value of average fitness, the specific ability of high-skilled workers is amplified by the interdependencies, while the negative impact is minimized for the two other subgroups, particularly for the less skilled workers whose some fitness values become slightly positive.

On the other hand, we observe that ICT impact is not homogeneous across countries. For the high-skilled workers, the average fitness is higher in the Netherlands, Italy or in the UK. These values are lower in countries such as Austria, Denmark or USA. These results then have a different real impact due to relative performance. The effects of ICT are clearly strengthened since the mean value of fitness is in most cases less than zero.
For the middle-educated workers, the fitnesses are negative on average but the values can be markedly distinct depending on the country. For example, it is strongly negative in Denmark, the USA or in Japan while it is slightly negative in Austria and positive in Italy. Heterogeneity is also observable in the impact on low-skilled workers. For example, the ability to adapt to ICT diffusion for this kind of labor force in Finland and Japan is positive while it is very low in Italy or in the UK. For the last two categories of workers, the net impact on the share of each type of labor is modified by the average fitness in the same way that at the industry level.

3.2 Dynamics of functional coefficients

The mean results may suggest that ICT diffusion produces only a SBTC, meaning that these technologies increase the demand for high-skilled workers and decrease the demand for middle and low-skilled workers. However, behind these summary observations, we can identify several temporal dynamics consistent with a contribution of ICT to labor market polarization. All variations are displayed in figures 1, 2, 3, 4, 5, 6. We plot the smooth means by year of the fitnesses and distances from mean.[13]
First, we note a specific trajectory for the high-skilled labor force, indicating a decrease of the positive impact of ICT after having reached a peak in the first part of the 1990s. Indeed, most industries and countries suffer from a decline of the fitness from this period. Nevertheless, these trends are often compensated by the distance from the mean. The situation is different with regard to middle-skilled workers. Changes over time are less pronounced but

[13] The reader should keep in mind that the scales are different in each figure because we concentrate our attention on the evolutions (the levels are already presented in tables 3, 4, 5, 6).

in most cases, we observe an aggravation of the negative effect of computer tools. This evolution is more noticeable by looking by industry. However, there are exceptions in some countries. In Finland, the fitness is growing but clearly negative while in Italy, it is most of the time slightly positive. For the low-skilled workers, we observe a very clear path which most often takes the form of a U-shaped curve. In the first part of the period studied, we often see a more and more negative effect until the beginning of the 1990s. After this date, we are noticing a progressive recovery of the fitness values which, finally, become in most cases positive.
These results are consistent with previous literature (see references in section 1), reflecting a contribution of ICT to polarization of the labor market. Furthermore, our findings allow clarification on the timing of the changes observed. The diffusion of computer technologies has led, in 1980s and until the beginning of 1990s, to a technological bias promoting the most educated workers (SBTC) and then a weakening of this positive relation accompanied by a progressive growth of demand for low-skilled workers (polarization).

Let us now provide some economic interpretation for these evolutions. As stressed above, the positive relationship between the diffusion of ICT and the share of high-skilled workers in the total labor force (fitness > 0) has weakened over time over time, among most of the industries and countries. This trend may also be associated with the diffusion of specific skills in computer technology. Indeed, at the beginning of the sample, these technologies were difficult to use and required specific competences (knowledge on software, programming…). On this basis, only very educated workers could carry out tasks with computer tools. Progressively, ICT facilities have spread and known simplification of their use, and thanks to learning processes, the number of users has risen dramatically. In this perspective, in addition to a probable long-term effect, the diffusion of ICT produces a positive short-term impact on the demand of high-skilled workers to make easier the introduction of these technologies (Bartel and Lichtenberg 1987; Chun 2003). So, we can think that, as time goes, the specificity of the high-skilled workers is becoming less obvious (it is not the case for some very difficult tasks) which may have contributed to a weakening of the positive relationship that existed with ICT. In other words, we interpret this evolution (reduction of the fitness) as an erosion of the monopole of the most educated workers on computer skills.

Another way to explain the weakening of complementarity between high-skilled workers and ICT diffusion is to make a link with the increasing performance of computer tools. Over the period analyzed, there was a considerable improvement in the capacity of ICT. One example is the increase of computing power. Using data compiled by McCallum[14] and completed by Nordhaus (2007), we show that over the period studied (1981-2005), the performance in computation by second has been multiplied approximately by 43000, which is equivalent to an annual growth equal to 56%. Even if it is only one indicator, it supposes that the number and the type of tasks that can be achieved by ICT are growing over time. So, a part of tasks traditionally carried out by high-skilled workers is gradually realized by specialized softwares or machines. In addition, this augmentation in performance is associated with a very strong fall in prices of these technologies. The cost per computation by second has been divided by 100000. This corresponds to an annual decline equal to 38%. Autor et al. (2003) have shown that the decline in price is a major engine of ICT capital-labor substitution. To sum up, the decrease in the fitness for the more educated workers can be explained by the fact that an increasing share of tasks realized by such workers is carried by computers tools due to progressive improvement of capacities and large decline in the prices of these technologies. From this perspective, the concept of "limited substitution" (Bresnahan et al. (2002)) becomes less meaningful.

Furthermore, considering the ALM hypothesis and by referring specifically to the work of Goos and Manning (2003), we see that the workers situated in the top of the distribution of wages (ie the most skilled workers) mainly carry out nonroutine tasks, but are also concerned about the accomplishment of routine tasks. For example, in the UK, 43% percent of workers in the highest-paid occupations are in jobs that need above-average nonroutine cognitive skills. We can think that, as time goes (and that the ICT capital grows), this type of tasks is executed by computer tools, weakening the positive relation existing between ICT and the demand for high-skilled workers.

The middle-skilled workforce is also subject to temporal variations, with a global decreasing fitness overtime. The simpliest way to interpret this path is to link it to the level of ICT stock. In the perspective of ALM hypothesis and Goos and Manning's analysis, this group of workers is the most vulnerable face to the spread of computer technologies. So, it seems logical that, as the amount of ICT capital grows, the negative effect on middle-skilled workers becomes more and more important (due to labor-saving process).

[14] http://www.jcmit.com/cpu-performance.htm

Another major dynamics identified concerns the fitness of the low-educated workers, taking a U-shaped form. Generally, there is a progressive diminution of the fitness denoting a growing difficulty to adapt to ICT diffusion until the middle of 1990s and then an inversion of this movement. Frequently, the fitness becomes positive at the end of the period studied. These variations can be explained by the fact that during the first interval, ICT capital is constituted at the expense of the less educated workers. The period is probably dominated by capital-labor substitution, the workers carrying out routine tasks being progressively replaced by ICT capital.
In the second part of the period studied, the relation between this category of workers and ICT tools becomes complementary. Indeed, a classical argument in favor of labor market polarization is that the development of services (which includes an important share of nonroutine tasks) promotes the hiring of low-skilled employees. From an empirical perspective, since the mid-1990s in the countries of our sample, in addition to the long-run trend favoring the increase of service sector, new products and activities related to ICT have emerged. This concerns directly ICT sectors such as mobil phone or Internet and other activities reorganized under the technological pressure. These new activities and new organizational dispositions require less educated workforce for non-routine tasks as sell, telephone support service, transport... It seems plausible to link the emergence of these activities to the evolution of the fitness value for low-skilled workers.

3.3 Robustness checks

Our framework being semiparametric, we assess the robustness of our estimates using "wild bootstrap" (Härdle and Mammen, 1993). This procedure permits to construct a confidence interval ("Percentile Bootstrap") and evaluate the significance of estimates (Efron and Tibshirani, 1994). In our case, we can evaluate the robustness of the λ^i estimates. Given the type of model and the bootstrap procedure that we use, the confidence intervals are observation-specific so we choose to specify in table 2 for each variable the proportion of cases significantly different from zero.
For the three trends, we have a large proportion of significant values whilst we obtain values between 29% and 69% for the λ^i coefficients. These results can be explained by the fact that this type of model has a non-negligible proportion of insignificant coefficients in the total sample.[15] Moreover, since this robustness check deals with distances, it is logical to have insignificant values when the λ^i coefficients are very close to zero.

[15]see for example Kumbhakar and Sun (2012).

Table 2: Proportion of significant coefficients (5%)

Variable	%	Variable	%
c^{HS}	92	λ^{HS}	69
c^{MS}	66	λ^{MS}	38
c^{LS}	88	λ^{LS}	29

bootstrap n=1000.

4 Conclusion

The aim of this paper is to investigate the contribution of ICT to the labor market polarization. To this end, we adopt an evolutionary view by applying a "distance from mean approach". Our model is estimated with a SemiParametric Smooth Coefficient model (SPSCM) which makes it possible to identify the heterogeneity of impact of ICT on labor market and its variation over time. Our results show a sharp contribution of ICT to job market changes with some differences according to the industries and the countries. In addition, the temporal dynamic evidenced suggests that ICT tools are biased towards high-skilled workers, therefore acting in favor of labor market polarization. Finally, we find evidence of weakened of positive relation between high-skilled workers and ICT diffusion over time.

Appendix

Table 3: Mean / Median results by country

Country	c^{HS}		c^{MS}		c^{LS}		Mean Fitness	
	mean	median	mean	median	mean	median	mean	median
Austria	0.003	0.002	0.006	0.006	-0.008	-0.008	-0.103	-0.016
Denmark	0.002	0.002	0.008	0.009	-0.010	-0.011	-0.183	-0.108
USA	0.003	0.003	0.002	0.002	-0.004	-0.004	-0.136	-0.049
Netherlands	0.003	0.002	0.004	0.005	-0.006	-0.006	-0.136	-0.073
Finland	0.004	0.004	0.006	0.006	-0.012	-0.012	-0.042	-0.026
Italy	0.002	0.002	0.000	0.000	-0.002	-0.001	0.078	0.028
UK	0.003	0.003	0.008	0.008	-0.011	-0.013	-0.117	-0.073
Japan	0.003	0.003	0.008	0.008	-0.011	-0.011	-0.146	-0.060
All sample	0.003	0.003	0.005	0.005	-0.008	-0.008	-0.098	-0.040

Country	Fitness HS		Distance HS		Fitness MS		Distance MS		Fitness LS		Distance LS	
	mean	median	mean	median	mean	median	mean	median	mean	median	mean	median
Austria	0.195	0.050	0.297	0.076	-0.115	-0.011	-0.013	0.001	-0.079	-0.033	0.023	-0.012
Denmark	0.191	0.141	0.374	0.247	-0.415	-0.247	-0.232	-0.130	0.224	0.036	0.407	0.162
USA	0.192	0.096	0.328	0.184	-0.309	-0.122	-0.173	-0.075	0.116	0.016	0.252	0.058
Netherlands	0.365	0.218	0.502	0.307	-0.157	-0.062	-0.021	-0.010	-0.208	-0.103	-0.072	0.003
Finland	0.213	0.136	0.255	0.150	-0.236	-0.120	-0.194	-0.090	0.023	-0.008	0.065	0.009
Italy	0.520	0.303	0.441	0.235	0.064	0.023	-0.015	-0.001	-0.583	-0.338	-0.662	-0.374
UK	0.356	0.237	0.473	0.316	-0.143	-0.040	-0.026	-0.005	-0.212	-0.107	-0.095	-0.015
Japan	0.245	0.111	0.391	0.180	-0.312	-0.136	-0.166	-0.071	0.067	-0.002	0.213	0.041
All sample	0.285	0.144	0.383	0.205	-0.203	-0.073	-0.105	-0.032	-0.082	-0.031	0.017	0.002

Table 4: HS Mean / Median results by industry

Sector	Industry	Fitness		Distance	
		mean	median	mean	median
	Agriculture, hunting, forestry and fishing	0.017	0.010	0.024	0.015
	Mining and quarrying	0.057	0.052	0.077	0.065
	Food products, beveradges and tobacco	0.136	0.140	0.192	0.185
	Textiles, textile products, leather and footwear	0.124	0.097	0.164	0.155
	Wood and products of wood and cork	0.193	0.114	0.234	0.165
	Pulp, paper, printing and publishing	0.306	0.285	0.432	0.400
	Coke, refined petroleum and nuclear fuel	0.254	0.085	0.336	0.129
Manufacturing	Chemicals and chemical products	0.266	0.189	0.317	0.240
Activities	Rubber and plastics products	0.138	0.123	0.189	0.157
	Other non metallic mineral product	0.143	0.148	0.199	0.183
	Basic metals and fabricated metal	0.134	0.132	0.195	0.179
	Machinery not elsewhere classified	0.371	0.340	0.536	0.503
	Electrical and optical equipment	0.852	0.807	1.123	1.053
	Transport equipment	0.210	0.181	0.299	0.262
	Manufacturing not elsewhere classified and recycling	0.214	0.165	0.287	0.253
	Electricity, gas and water supply	0.068	0.049	0.093	0.068
	Construction	0.207	0.187	0.302	0.283
	Sale, maintenance and repair of motor vehicles and motocycles; retail sale of fuel	0.320	0.324	0.464	0.443
	Wholesale trade and commission trade, except of motor vehicles and motocycles	0.408	0.395	0.595	0.511
	Retail trade, except of motor vehicles and motorcycles, repair of household goods	0.360	0.354	0.507	0.434
	Transport and storage	0.143	0.117	0.197	0.145
	Post and telecommunications	0.405	0.131	0.433	0.208
Services	Real estate activities	1.598	1.385	2.115	1.906
Activities	Renting of machinery and equipment and other business activities	0.563	0.585	0.737	0.676
	Hotels and restaurants	0.009	0.002	0.009	0.003
	Financial intermediation	0.325	0.289	0.534	0.425
	Public administration and defence, compulsory social security	0.137	0.100	0.181	0.124
	Education	0.111	0.085	0.116	0.086
	Health and social work	0.154	0.129	0.186	0.169
	Other community, social and personal services	0.312	0.258	0.409	0.338
	Manufacturing industries	0.217	0.131	0.294	0.186
	Services industries	0.373	0.178	0.499	0.249

Table 5: MS Mean / Median results by industry

Sector	Industry	Fitness		Distance	
		mean	median	mean	median
	Agriculture, hunting, forestry and fishing	-0.018	-0.008	-0.011	-0.002
	Mining and quarrying	-0.051	-0.028	-0.031	-0.010
	Food products, beveradges and tobacco	-0.107	-0.079	-0.051	-0.028
	Textiles, textile products, leather and footwear	-0.078	-0.041	-0.039	-0.013
	Wood and products of wood and cork	-0.089	-0.048	-0.047	-0.018
	Pulp, paper, printing and publishing	-0.238	-0.142	-0.112	-0.067
	Coke, refined petroleum and nuclear fuel	-0.116	-0.065	-0.034	-0.035
Manufacturing	Chemicals and chemical products	-0.136	-0.121	-0.085	-0.077
Activities	Rubber and plastics products	-0.101	-0.056	-0.049	-0.022
	Other non metallic mineral product	-0.113	-0.079	-0.057	-0.027
	Basic metals and fabricated metal	-0.118	-0.079	-0.056	-0.027
	Machinery not elsewhere classified	-0.296	-0.232	-0.131	-0.073
	Electrical and optical equipment	-0.541	-0.490	-0.270	-0.167
	Transport equipment	-0.167	-0.097	-0.077	-0.037
	Manufacturing not elsewhere classified and recycling	-0.146	-0.085	-0.073	-0.034
	Electricity, gas and water supply	-0.047	-0.030	-0.022	-0.012
	Construction	-0.177	-0.077	-0.082	-0.021
	Sale, maintenance and repair of motor vehicles and motocycles; retail sale of fuel	-0.231	-0.146	-0.087	-0.044
	Wholesale trade and commission trade, except of motor vehicles and motocycles	-0.324	-0.237	-0.137	-0.118
	Retail trade, except of motor vehicles and motorcycles, repair of household goods	-0.277	-0.169	-0.131	-0.062
	Transport and storage	-0.126	-0.042	-0.072	-0.010
	Post and telecommunications	-0.076	-0.079	-0.048	-0.023
Services	Real estate activities	-0.772	-0.478	-0.255	-0.194
Activities	Renting of machinery and equipment and other business activities	-0.611	-0.438	-0.437	-0.159
	Hotels and restaurants	-0.002	-0.001	-0.002	-0.001
	Financial intermediation	-0.585	-0.413	-0.376	-0.184
	Public administration and defence, compulsory social security	-0.122	-0.070	-0.078	-0.030
	Education	-0.104	-0.084	-0.099	-0.090
	Health and social work	-0.103	-0.083	-0.071	-0.055
	Other community, social and personal services	-0.218	-0.169	-0.121	-0.081
	Manufacturing industries	-0.149	-0.063	-0.072	-0.026
	Services industries	-0.273	-0.090	-0.147	-0.045

Table 6: LS Mean / Median results by industry

Sector	Industry	Fitness		Distance	
		mean	median	mean	median
	Agriculture, hunting, forestry and fishing	0.001	-0.005	0.001	0.007
	Mining and quarrying	-0.006	-0.013	0.002	0.014
	Food products, beveradges and tobacco	-0.029	-0.037	0.014	0.028
	Textiles, textile products, leather and footwear	-0.046	-0.021	0.007	-0.007
	Wood and products of wood and cork	-0.104	-0.019	0.007	-0.063
	Pulp, paper, printing and publishing	-0.068	-0.071	0.011	0.058
	Coke, refined petroleum and nuclear fuel	-0.139	-0.027	0.002	-0.057
Manufacturing	Chemicals and chemical products	-0.130	-0.042	0.005	-0.079
Activities	Rubber and plastics products	-0.037	-0.036	0.008	0.015
	Other non metallic mineral product	-0.031	-0.034	0.006	0.025
	Basic metals and fabricated metal	-0.016	-0.036	0.006	0.045
	Machinery not elsewhere classified	-0.075	-0.115	-0.001	0.091
	Electrical and optical equipment	-0.311	-0.288	-0.015	-0.040
	Transport equipment	-0.043	-0.044	0.006	0.047
	Manufacturing not elsewhere classified and recycling	-0.068	-0.047	0.007	0.004
	Electricity, gas and water supply	-0.022	-0.019	0.000	0.003
	Construction	-0.030	-0.044	0.004	0.064
	Sale, maintenance and repair of motor vehicles and motocycles; retail sale of fuel	-0.089	-0.060	0.009	0.055
	Wholesale trade and commission trade, except of motor vehicles and motocycles	-0.085	-0.143	0.011	0.102
	Retail trade, except of motor vehicles and motorcycles, repair of household goods	-0.083	-0.134	0.001	0.064
	Transport and storage	-0.016	-0.026	0.008	0.038
	Post and telecommunications	-0.328	-0.042	0.011	-0.300
Services	Real estate activities	-0.826	-0.278	0.022	-0.310
Activities	Renting of machinery and equipment and other business activities	0.048	-0.216	-0.073	0.221
	Hotels and restaurants	-0.008	0.000	0.000	-0.008
	Financial intermediation	0.261	-0.055	0.000	0.470
	Public administration and defence, compulsory social security	-0.016	-0.038	-0.013	0.028
	Education	-0.007	-0.015	-0.021	-0.002
	Health and social work	-0.051	-0.043	0.000	-0.019
	Other community, social and personal services	-0.095	-0.062	-0.003	0.002
	Manufacturing industries	-0.068	-0.028	0.003	0.009
	Services industries	-0.100	-0.036	0.000	0.026

Figure 1: Fitness by country

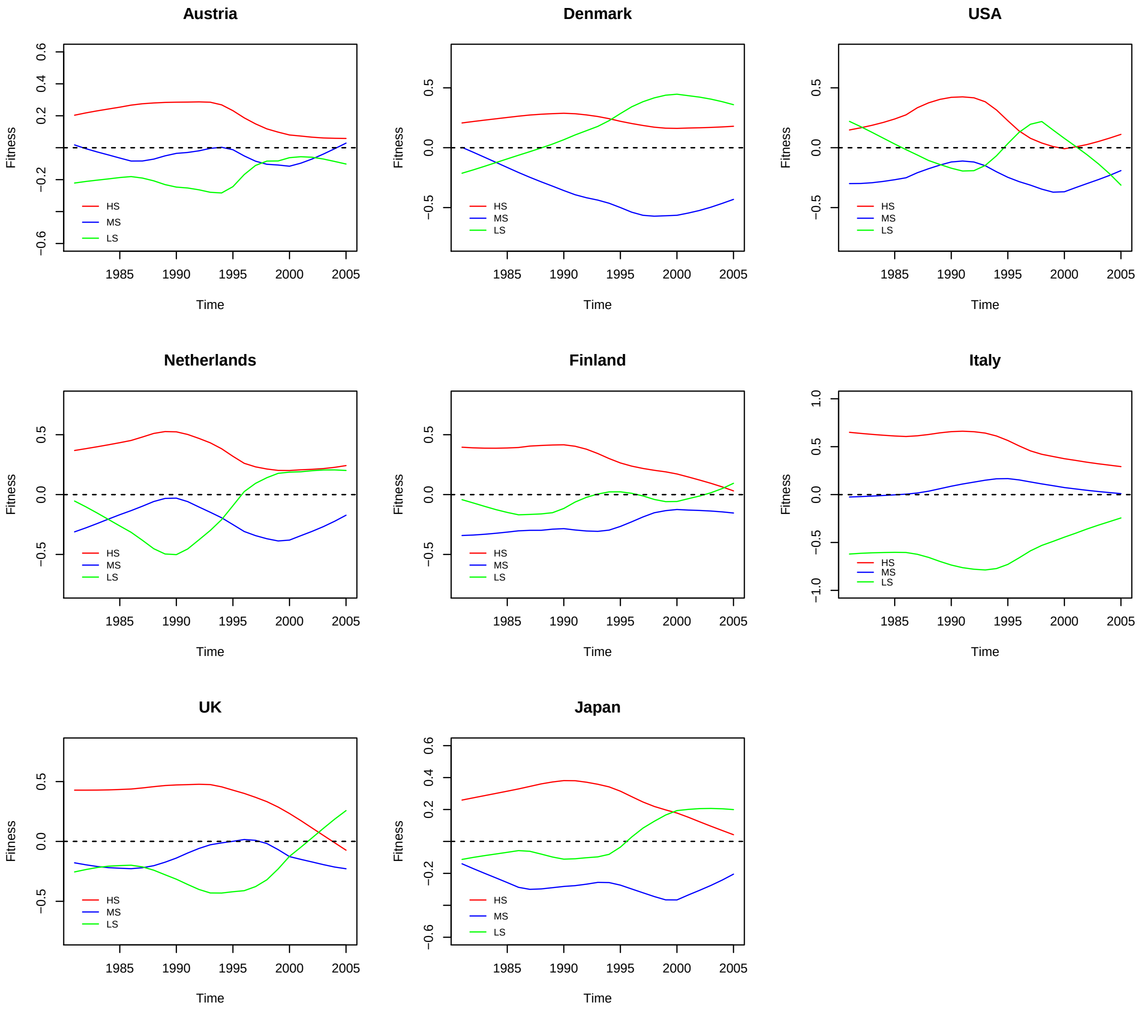


Figure 2: Distance from mean by country

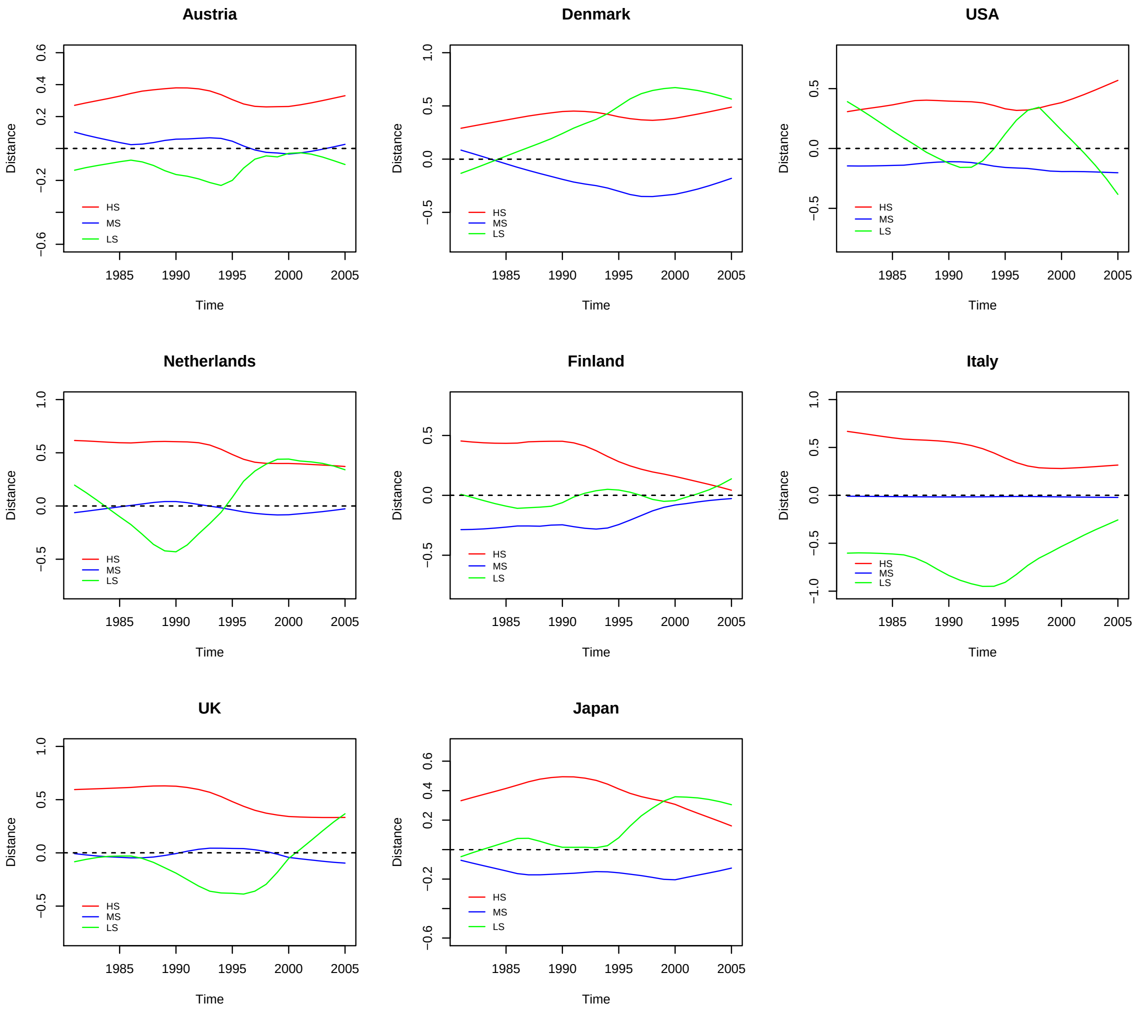


Figure 3: Fitness by industry 1

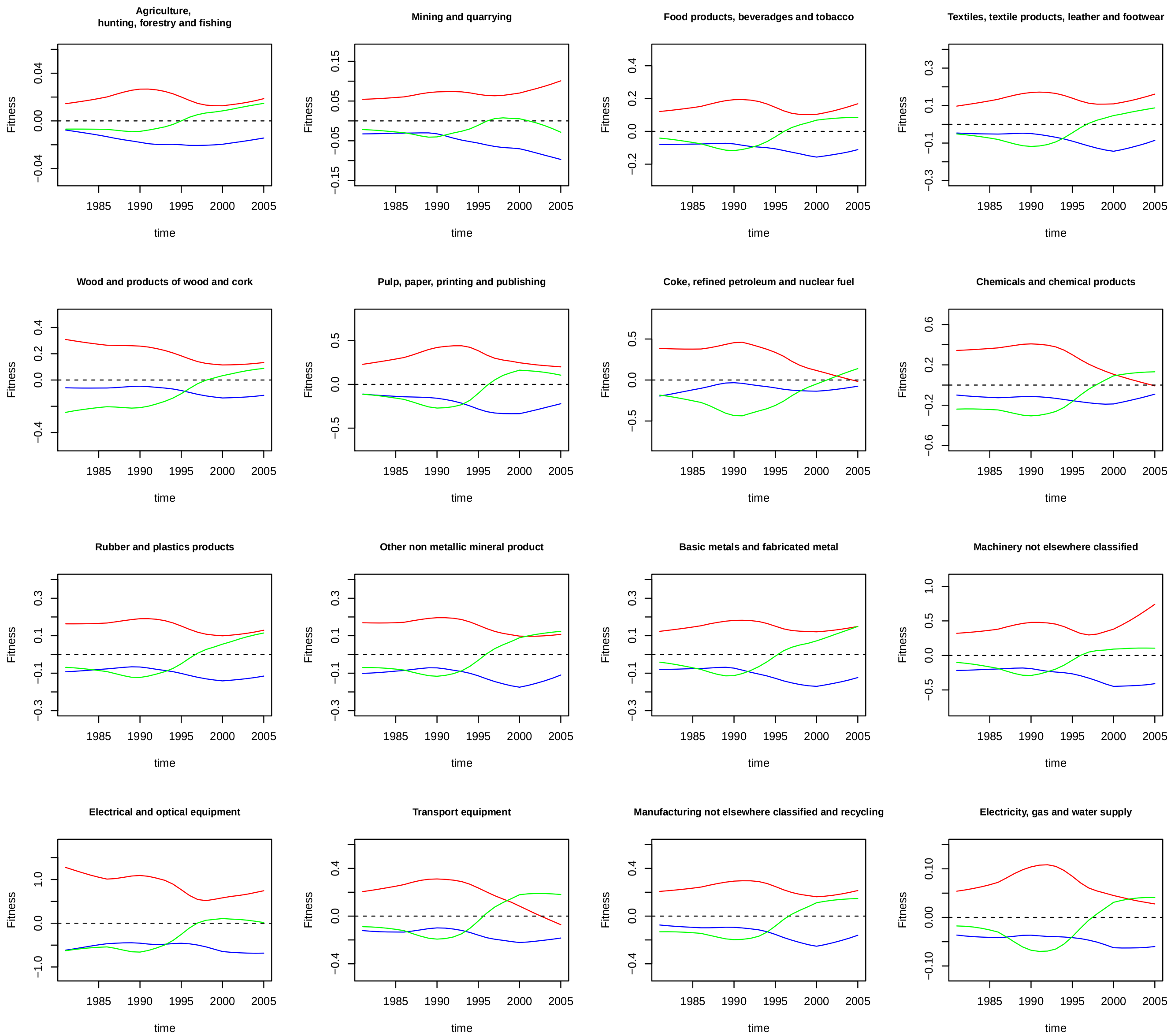


Figure 4: Fitness by industry 2

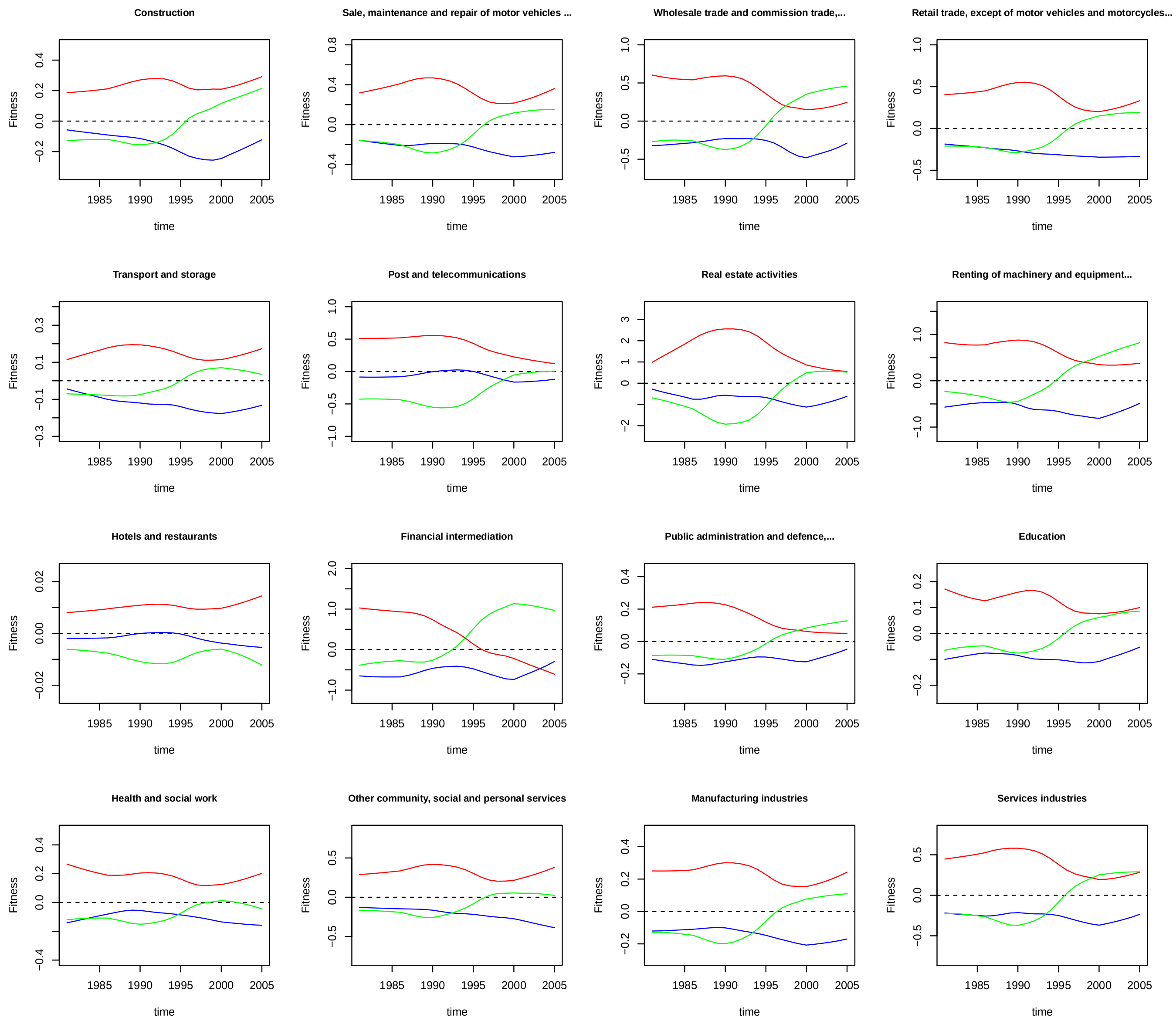


Figure 5: Distance from mean by industry 1

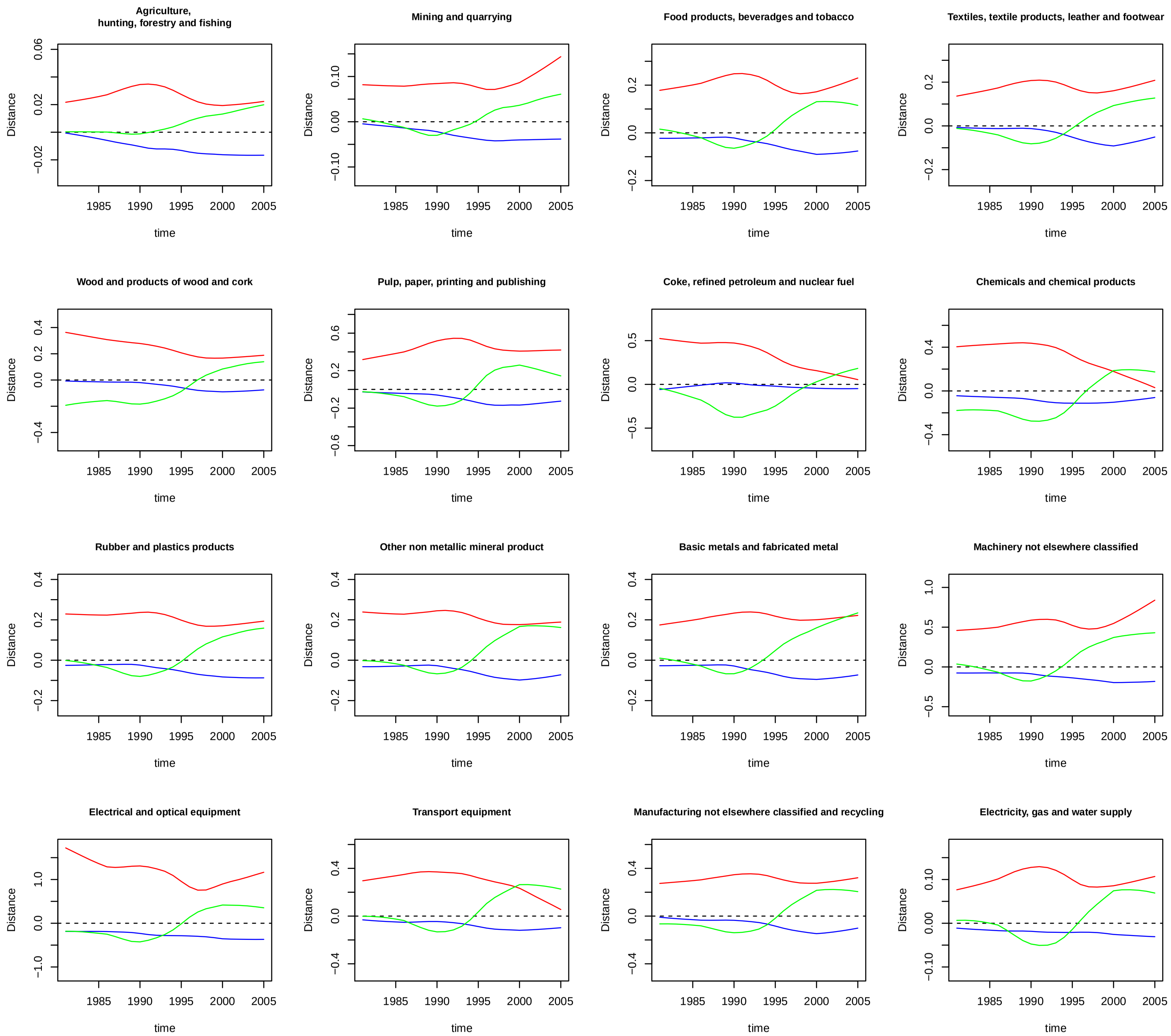
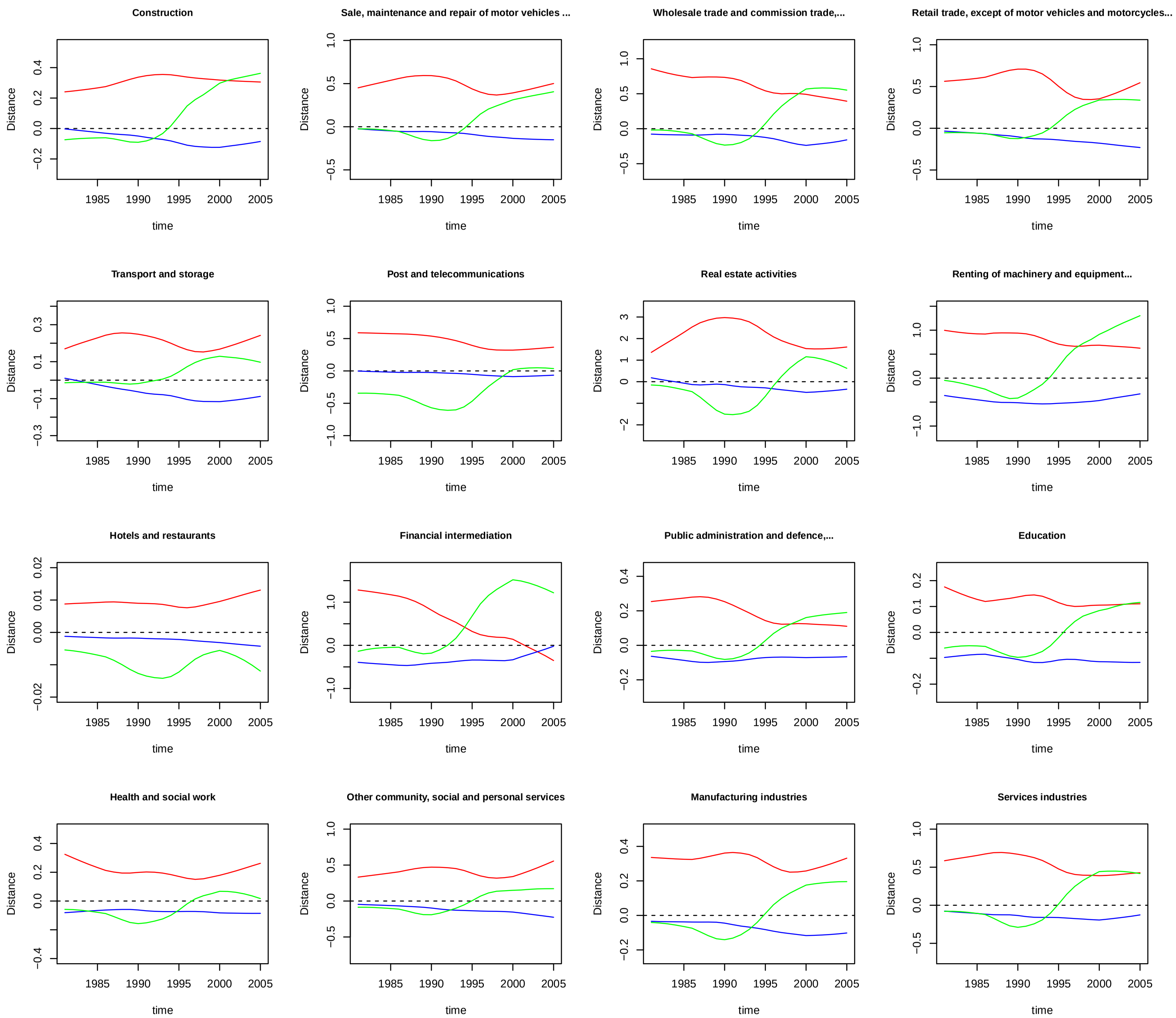


Figure 6: Distance from mean by industry 2



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