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ABSTRACT

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We provide empirical evidence on the impact of IT diffusion on the stability of employment relationships. We document the evolution of different components of job instability over a panel of 348 local labor markets in France, from the mid-1970s to the early 2000s. Although workers in more educated local labor markets adopt IT faster, they do not experience any increase in job instability. More specifically, we find no evidence that the diffusion of IT increases job-to-job transitions, and we find that it tends to reduce transitions to non-employment among high-school dropouts. Overall, the evidence goes against the view that the diffusion of IT has spurred job instability. Combining local labor market variations with firm data, we argue that these findings can be explained by French firms' strong reliance on training and internal promotion strategies in order to meet the new skills requirement associated with IT diffusion.

JEL Classification: J23, J24, J41

Keywords: technical change, labor turnover, skill bias, job security, internal labor markets

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Introduction

Among the questions raised by IT-based technical change among labor economists, one remains unsettled: to what extent has the diffusion of IT over the past decades modified the stability and the security of employment relationships?

Several theoretical arguments predict that a rapid diffusion of IT should result in higher job instability. In Schumpeterian models, IT-based technical change, just like any form of technical change, goes through a creative destruction process. The reallocation of workers across sectors or firms is part of that process. In a frictionless labor market, this may simply result in more frequent job-to-job transitions; in the presence of matching frictions, it may also create job insecurity, characterized by transitions from employment to unemployment.[2] This first argument is not specific to IT. A second argument is related to the role of IT in the "new economy", where firms create more value by the rapid introduction of new products and services rather than by the continuous improvement of production processes. The perpetual re-composition of the firms' workforce is part of this post-Fordist model, as a way to introduce new talent and to develop creative approaches (Reich, 2001). IT diffusion may facilitate it by allowing firms to codify their processes, making it easier for new workers to adapt quickly, and limiting the knowledge loss associated with the exit of more experienced workers (Caroli, 2007). Yet, balancing these two arguments, there are also theoretical reasons to believe that stable employment relationships are compatible with IT diffusion. The external labor market is only one source at which firms may find the skills they need; internal labor markets are another one. As argued by Mincer (1989), the long-run response to technical change and the need for new skills may well be on-the-job training rather than costly worker flows.

[2] Following the literature, we define job instability as the sum of voluntary and involuntary job exits, and define job insecurity as involuntary worker flows only, which we characterize through transitions from employment to unemployment (Mottschalk and Moffit, 1999).

In this paper, we provide empirical evidence on the impact of IT diffusion on the stability of employment relationships. We document the evolution of different components of job instability over a panel of 348 local labor markets in France, from the mid 1970s to the early 2000s. Although workers in more educated local labor markets adopt IT faster, they do not experience any increase in job instability. More specifically, we find no evidence that the diffusion of IT increases job-to-job transitions, and we find that it tends to reduce transitions to non employment. Overall, the evidence goes against the view that the diffusion of IT has spurred job instability. In a second part of the paper, we combine the local labor market variations with firm data. We argue that the persistence of stable employment relationships can be explained by French firms' strong reliance on training and internal promotion strategies in order to meet the new skills requirement associated with IT diffusion.

The first contribution of our analysis is to rely on differences in IT adoption across labor markets, an unusual source of variation to study the impact of IT on employment relationships.[3] Other papers have used comparisons across industries (Neumark and Reed, 2004; Givord and Maurin, 2004) or across firms (Bauer and Bender, 2004; Behaghel, Caroli and Walkowiak, 2011), yielding quite contrasted results. We discuss the differences that may explain these discrepancies.

Our second contribution is to connect this empirical investigation of the *impact* of IT to the theoretical and empirical literature on the *causes* of IT adoption. Pursuing a tradition in the economic history literature (Habakkuk, 1962; Goldin and Sokoloff, 1984), Caselli (1999) and Acemoglu (2007) have stressed the endogeneity of IT adoption and more particularly the role of initial factor endowments. Such models have been extended and applied to local labor markets

[3] An exception is Neumark and Reed (2004) who (among other things) investigate the prevalence of contingent and alternative employment relationships in high-tech cities.

by Beaudry, Doms and Lewis (2010), who show that the adoption of PCs across U.S. cities is significantly driven by the initial skill mix. We find similar results for France: a worker located in a local labor market with an initial high supply of skills tends to adopt IT faster, even after controlling for his own education and for the firm's characteristics. We argue that these local patterns in IT adoption are plausibly exogenous to the evolution of employment stability and use them to estimate a causal, aggregate impact of IT diffusion on employment stability. We find evidence that differences in the initial skill mix do not lead to increases in job instability, suggesting that the adoption of IT has not considerably affected job instability.

Last, we analyze firm human resource strategies as a first step in uncovering the mechanisms through which technical change modifies the employment relationship. Our results support Mincer's insight that the effects of technical change are mediated by firms' adaptation strategies. More precisely, and consistently with results at the worker level, we find that the adoption of IT does not increase worker flows in and out of the firm. However, it leads to an upgrading of the occupational structure through training and promotions.

The first section of the paper describes our empirical approach and relates it to the literature. The second section presents the data and displays graphical evidence. The next two sections detail the results, using two different perspectives: section 3 shows the net impact of IT diffusion on labor market transitions at the local labor market level, while section 4 offers a first pass on mechanisms, analyzing human resource strategies at the firm level. The last section offers some concluding comments and underlines remaining questions.

1. Related literature and empirical strategy

Over the past few years, the micro-econometric literature on technical and organizational changes has made considerable progress in understanding patterns of IT adoption. Even though the main driving source of IT-based technical change – the dramatic fall in the real cost of computers – is an economy-wide force, IT adoption patterns significantly differ across firms, industries, and places.[4] At the firm level, recent papers have shown that the type of ownership matters, with family-owned businesses less likely to adopt new organizational methods, and the opposite being true for multinationals (Bloom and Van Reenen, 2010). At the industry level, the share of routine tasks in 1960 is a strong predictor of subsequent IT adoption (Autor, Levy and Murnane, 2003); international trade, particularly import competition from China, may also have induced technical change (Bloom, Draca and Van Reenen, 2009). Lastly, at the city (or local labor market) level, the local supply of skilled labor predicts substantial differences in computer usage rates (Doms and Lewis, 2006; Beaudry, Doms and Lewis, 2010).

All these findings are interesting *per se*: they reveal comparative advantages for IT, which may have large consequences on inequalities across individuals, sectors and areas. But they are also disturbing findings for the empirical literature that attempts to measure the *consequences* of IT adoption. Take the consequences of IT on wage inequalities, for instance. All of the above factors – firms' ownership and management type, competitive pressure from imports, trade and immigration shocks – confirm that the adoption of IT is endogenous, motivating the search for instruments; but none of these factors can directly be considered as a plausible instrument. Indeed, the exclusion restriction does not hold: wage policies are likely to be directly impacted by firms' management types and ownership; import

[4] At the worker level, the finding that unskilled workers have a lower propensity to use computers has been a major ingredient in the empirical literature on skill-biased technical change.

competition puts pressure on wages in a way that may directly impact wage inequalities; and the local supply of skilled labor has equilibrium effects on relative wages. The literature on IT adoption has therefore been particularly careful not to claim that these sources of variations provide valid instruments to explore the wage effects of IT. This has led to a somewhat disturbing split between the strand of research that documents the endogeneity of IT adoption and a second strand of the literature exploring IT impacts under exogeneity assumptions that appear more and more fragile.

Our hypothesis is that the first strand of the literature, although it does not provide bullet-proof instruments, may be used to build plausible difference-in-difference strategies. Take the papers by Beaudry, Doms and Lewis on the impact of local differences in skilled labor supply. In an earlier version of their paper, the authors document the negative correlation between the relative wage and the relative supply of educated workers across cities in the U.S., as of 1970. This negative correlation is consistent with the expected equilibrium effect. That correlation diminishes over time until it becomes almost 0 in 2000 (Beaudry, Doms and Lewis, 2006, figures 8a to 8d). Whether the change in the correlation can be attributed to differential patterns of PC diffusion depends on a standard difference-in-difference assumption: to the extent that local labor markets with different skills endowments would have witnessed parallel trends in equilibrium relative wages in the absence of IT diffusion, the relative increase in the wage of more educated workers in areas with a more educated workforce can be attributed to computer adoption. Even though it is conditional, this statement is informative, given the absence of other fully conclusive evidence.

The strategy we propose in this paper is similar: we use initial differences in skilled labor endowments across local labor markets to perform two difference-in-difference analyses. Did local labor markets with a more educated workforce adopt computers faster? Did the same local labor markets witness a larger increase in job instability? If yes, and to the extent that these local labor markets would have displayed similar trends without IT diffusion, differential evolutions in job instability can be attributed to the diffusion of PCs. Let IT_c be a measure of IT use in local labor market c, $Educ_{c0}$ the initial supply of skilled labor, and T_c^e job instability in education group e.[5] Our strategy amounts to estimating two reduced-form equations, looking at differences in evolutions across local labor markets:

$$\Delta IT_c = \beta_0^e + \beta_1^e \; Educ_{c0} + \beta_2^e \; \Delta X_c + \varepsilon_c, \tag{1}$$

$$\Delta T_c^e = \alpha_0^e + \alpha_1^e \; Educ_{c0} + \alpha_2^e \; \Delta X_c + v_c. \tag{2}$$

If the "parallel trend" assumption holds, then $\gamma_1^{ed} \equiv \alpha_1^{ed} / \beta_1^{ed}$ is the impact of IT diffusion on labor market transitions, among workers with education level e. This difference-in-difference approach can be rephrased as an IV approach. The equation of interest can be written as:

$$\Delta T_c^e = \gamma_0^e + \gamma_1^e \; \Delta IT_c + \gamma_2^e \; \Delta X_c + m_c. \tag{3}$$

Then, the parallel trend assumption amounts to the exclusion restriction $E(m_c \, Educ_{c0})=0$ and γ_1^e can be consistently estimated by 2SLS using $Educ_{c0}$ as an instrument.[6]

Clearly, this empirical strategy is not immune to criticism. There may be reasons why the parallel trend hypothesis would not hold. It is however, a clear improvement over a direct estimation of equation (3) by OLS. Indeed, any idiosyncratic shock that affects a given local labor market – say, a positive demand shock on the market for goods – is likely to impact the ability of firms to invest in IT and to retain their workforce. This creates a bias in the OLS estimate,

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[5] In our empirical analysis, we will distinguish high-school graduates from high-school dropouts.

[6] The appendix provides a derivation of equation (3) based on the different mechanisms hypothesized in the literature relating technical change and job instability.

but not on the IV as long as demand shocks are evenly distributed across initially more or less educated local labor markets.

The parameter of interest γ_1^e combines several effects that can take place at the workplace, at the firm, or at the local labor market level. Effects at the workplace level take place when a worker starts using IT herself. This should directly increase her own productivity; whether it increases the probability of staying in the firm depends on how the outside options of the worker and the firm evolve. Moreover, the effect on productivity is partly endogenous, as it depends on whether and how the worker is trained to use the technology. A second type of effect is driven by the diffusion of IT in the firm (or more broadly in the city), independently from the adoption by the worker herself. There may be a positive impact of IT on all production factors (e.g., more efficient processes). There may also be complementarity or substitutability effects – one important hypothesis in the literature is that IT will tend to substitute for unskilled labor as it is concentrated in routine tasks. Another hypothesis is that IT will substitute for specific human capital, through the codification of firm implicit knowledge. The goal of the econometric analysis will be to evaluate this net impact, but the different mechanisms will not be identified separately.[7] However, given the evidence that IT-based technical change is biased against unskilled labor, we will distinguish impacts on high-school graduates (or more educated workers) and high-school dropouts. Furthermore, following the literature, we will distinguish two types of job instability: job insecurity (proxied by transitions from employment to non employment[8]) and job-to-job transitions. This distinction is made since increases in the outside option of the worker could generate job-to-job

[7] In particular, we will not be able to distinguish between the impact of IT adoption at the workplace and at the firm level: this would require exogenous sources of variation in the adoption of IT by individual workers.
[8] Transitions from employment to unemployment yield qualitatively similar results.

transitions, while increases in the outside option of the firm generate job insecurity. However, changes in the match productivity may induce job-to-job transitions as well as transitions to non employment.

It is useful to relate this strategy to the emerging literature on the impact of IT-based technical change on job instability. Firm-level variations have been used in particular by Bauer and Bender (2004) for Germany, and Behaghel, Caroli and Walkowiak (2012) for France. A necessary identifying assumption is that firm heterogeneity (for instance, unobserved managerial capacity) that drives the adoption of IT has no direct impact on worker flows. Bauer and Bender (2004) use lagged values of the adoption of IT or innovative workplace practices to mitigate endogeneity concerns; however, as they acknowledge, this does not reduce the risk of spurious correlation due to either permanent unobserved heterogeneity, or to the fact that technical and organizational changes may be introduced in reaction to anticipated shocks.[9]

Variations across sectors are used in Givord and Maurin (2004), for France. They study the evolution of involuntary job loss in France between 1982 and 2002, with the French Labor Force Survey. Their results indicate that job insecurity is higher in the 1990s than in the 1980s. This increase in job loss rates appears to be more important in sectors where workers use new technologies more intensively.[10] They conclude that technological change contributes to increasing job insecurity. The underlying assumption is that without the adoption of new technologies, the

[9] Contrasting results are obtained by the two papers. Bauer and Bender (2004) find that new technologies increase churning rates for skilled and unskilled workers. On the other hand, Behaghel et al. (2012) find that, although the introduction of new IT is associated with an upward shift of the occupational structure within firms, about two-third of it occurs through promotion rather than through the entry and exit of workers. Moreover, IT adoption is not associated with excess turnover. Behaghel et al. (2012) argue that this is consistent with the large diffusion of internal labor markets in France, whereas occupational labor markets are dominant in Germany (Marsden, 1999).

[10] Givord and Maurin use a classification with 38 sectors.

evolution of job insecurity across sectors would have been identical. This assumption is violated if shocks at the sector level affect job security in some sectors and not in others, or if macroeconomic shocks have a differentiated impact across sectors. Another limitation has to do with the direct comparison of sectors with high and low IT adoption patterns, regardless of the reasons for differential adoption. It is plausible that some sectors respond to shocks like import competition by adopting new technologies more aggressively (as argued by Bloom et al., 2010) and by changing their human resource management practices (for instance, switching from long-term employment relationship to short-term ones, as shown by Bertrand, 2004).

Lastly, Neumark and Reed (2004) have contrasted results for the U.S. They find a significantly greater use of contingent and "alternative" [11] employment relationships in jobs located in cities classified as high-tech. They also use cross-industry variations, with differing results: a greater use of contingent and alternative employment relationships was found in fast-growing industries, compared to a *lesser* use of this type of contracts in high-tech industries.

Overall, the picture is mixed enough to warrant a different look at the evidence comparing trends in job instability across local labor markets with a varying education levels among their workforce.

2. Data and graphical evidence

Our test of the impact of local skill endowment requires data at the local labor market level over a sufficient time span. We created a database at the level of the *zones d'emploi* ("employment areas"). The 348 *zones d'emploi* constitute a

[11] Those include independent contractors, on-call workers, temporary help agency workers, and workers provided by contract firms.

partition of the French territory; they were delimited by the French statistical institute (INSEE) and the Ministry of Labor on the basis of commuting data from the 1990 population census; we use this partition throughout the period. The working age population of a given *zone d'emploi* can be thought of as the potential labor supply faced by local firms. In what follows, we will use the term "local labor market" for *zone d'emploi*.

Measures of the initial skill mix come from the 1975 population census, through our access to tabulations from the complete data. As a measure of the initial skill endowment for a given local labor market, $Educ_{c0}$, we use the share of the working age population (aged 20 to 59) holding a high-school degree or more. Variations in $Educ_{c0}$ are substantial: the (unweighted) mean across local labor markets is 12.9%, with a standard deviation of 4.5%. The gap between the 9th and the 1st deciles is about 10 percentage points (pp) (=18.6-8.7). As shown on figure 1, more educated workers are concentrated in the South and the greater Paris area. Spatial correlations are strong (22 regional dummies explain 27% of the variance over the 348 local labor markets). Moreover, differences in skill mix are correlated with differences in population density (figure A1). However, the correlation is far from perfect: for instance, although the North is densely populated, its population has relatively low educational attainment. Another feature of the data is the remarkable stability of endowment differences over time, as shown by comparing the maps in 1975 and 1999 (figure A2). The correlation coefficient between skill endowments at these two dates is as high as .9. Overall, there is a strong and stable dispersion in skill endowment over the French territory. Only part of it can be explained by the presence of cities and variation in population density. A likely hypothesis is that, similar to the US experience (Moretti, 2004), a significant determinant of these local differences has to do with the expansion of education in France in the late 19th – early 20th centuries.

Consistent series on technology usage at the local level are rare in France. Firm surveys asking for information on software and hardware investments only started in the late 1990s and often have data at the firm rather than at the plant level, making it hard to analyze geographical repartitions. We therefore rely on supplements to the French Labor force survey (*Enquête Emploi*, thereafter called the LFS) in 1987, 1991, 1993 and 1998. These supplements ask workers detailed questions on their working conditions and the tools they use at work. Given our focus on IT, we construct two main indicators, one for the use of a personal computer at work (from 1987 to 1998), and the other for the use of the Internet (for 1998).

Lastly, we rely on the 1975 to 2002 issues of the French LFS to compute year-to-year transition rates on the labor market. Over that period, the French LFS takes place each year in March as a 3-year rotating panel with a 1/300 sampling rate.[12] Following the literature, we compute indicators for job instability and job insecurity based on transition rates out of a given job. Specifically, for job insecurity we consider transitions from employment to non employment based on transitions between year *t* and *t+1* among all wage earners aged 20 to 59. This indicator includes both transitions to unemployment and transitions out of the labor force[13]; the key reason for including transitions out of the labor force is the prevalence of early retirement schemes for workers above 55. Workers in early retirement will mostly declare themselves as out of the labor force (although some of them are technically receiving unemployment benefits). Early retirement schemes have been widely used as a less painful way for firms to adjust their

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[12] From 1968 to 2002, the households included in the Labor Force Survey sample were interviewed in March of three consecutive years with one-third of the households replaced each year. Since 2003, the households included in the French LFS are interviewed six consecutive quarters with one-sixth of the households replaced each quarter. To avoid the break in series, we stop the analysis in 2002. This covers the main period of diffusion of the PC.

[13] Transitions toward retirement are not included: the minimal retirement age is 65 until 1982 and 60 afterwards.

workforce, often leaving workers with no better choices; it is therefore warranted to include these forced transitions in the job insecurity indicator.[14] As an indicator of job instability, we consider yearly job-to-job transitions. A complete measure of worker flows (at a yearly frequency) can be obtained by adding the job-to-job and the employment to non employment transition rates.

In contrast to the persistent debate in the US (see Stevens, 2005, and Farber, 2007 and 2010), there is little doubt on the existence of a long-term trend in rising job insecurity in France (see Givord and Maurin, 2004). In our data, transitions from employment to unemployment and from employment to non employment appear to rise significantly over the period, despite pauses in years of economic expansions (late 1980s, late 1990s) (see Figure A3). On average, transition rates appear to increase by more than 2 pp for high-school dropouts and by about 1.5 pp for high-school graduates between 1975 and 2002. This roughly corresponds to a multiplication by a factor of 2. In contrast, job-to-job transitions display no clear trend, and are strongly procyclical. Overall, the strong increase in job insecurity motivates digging further into the potential explanatory role of IT adoption.

We now turn to graphical evidence on the link between skilled labor endowment and the adoption of IT. To do so, we split the 348 local labor markets into 4 quartiles in terms of $educ_{c0}$.[15] Q4 corresponds to the quartile with the highest skilled labor endowment, and Q1 to the quartile with the lowest endowment. We then compute usage rate within each quartile, in various years.[16][17] As shown by

[14] Nonetheless, this may overstate job insecurity as it also includes, for instance, women who stop working to raise their children. Restricting job insecurity to transitions toward unemployment yields qualitatively similar results.
[15] Local labor markets are weighted by the size of their working age population, as of 1975.
[16] The French LFS is a clustered sample, so that some local labor markets are present in some years, and not in the others. Regression analysis with local labor market dummies in the next section will control for possible composition effects due to local labor markets entering and exiting the sample.

figures 2a and 2b, there is a clear correlation between $Educ_{c0}$, the initial endowment of skilled labor, and the adoption of computers and the Internet. This correlation holds even after controlling for the worker's education by looking separately at high-school dropouts and high-school graduates. Interestingly, differences in usage rates are higher for high-school dropouts than for high-school graduates, in absolute as well as in relative terms. In 1993, for instance, the probability that a high-school dropout located in a local labor market with a low endowment in educated labor (1st quartile) uses a PC at work is only 10%. It is almost 15 pp higher for a high-school dropout located in a well-endowed local labor market (4th quartile). The same difference is closer to 10 pp for high-school graduates, on a basis of 40%. This first pass at the data seems to confirm the hypothesis that the local supply in educated labor may be a driver of IT adoption (even after controlling for the individual worker's education).

Are these systematic differences in the diffusion of IT paralleled by systematic differences in the evolution of job instability and its components? Figures 3-5 display graphical evidence. In each figure, the top two graphs display transition probabilities, comparing local labor markets in the upper or lower half of the initial skill mix ($Educ_{c0}$) The bottom two graphs display the gap in transition probabilities for cities in the lower half of the initial skill mix controlling for observable differences between the two groups in terms of location (region dummies), industry composition, and the distribution of workers' age, tenure and gender.[18]

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[17] Unfortunately, due to the break in the LFS between 2002 and 2003, we were not able to retrieve data by local labor markets in 2005. We therefore only have one data point – 1998 – for the use of the Internet.

[18] We estimate a linear probability model on these controls plus a dummy for cities with initial skill mix above median, separately for each year. We use the estimated coefficient on that dummy to predict the gap between cities with low or high initial skill mix. The impact of the controls varies year by year, because the estimated coefficients on the control may differ, but also because

Figure 3 considers all separations (i.e. the probability that a given worker is not in the same firm the next year). We focus on the bottom graphs, which control for differential evolutions due to changes in the composition of the two comparison groups. Patterns for high-school graduates are fairly similar in the two groups of local labor markets. For high-school dropouts, the graphs suggest a slight relative decrease in their transition rate in more educated job markets. Figure 4 considers transitions to non employment as a first component of total job instability. There is no clear difference in the trends for high-school graduates. For high school dropouts, starting in the mid 1980s, transitions to non employment tend to become less frequent in local labor markets with a higher initial skill mix (bottom graph in the left). If we attribute this difference to more rapid diffusion of IT, it would imply that IT has reduced transitions to non employment for high-school dropouts.[19] Job-to-job transitions are highly pro-cyclical (figure 5). However, the evolutions are remarkably parallel across local labor markets, for high-school graduates as well as for high-school dropouts.

The graphical analysis can be used to assess the validity of the parallel trend assumption: if one believes that there were no differences in technology adoption before, say, the mid 1980s, our identifying assumption implies that the trends in job-to-job transitions and in job insecurity should be parallel between 1975 and 1984. This holds for job-to-job transitions, which in fact stay parallel over the whole period. It is also true for employment to non employment transitions. Transition rates diverge for high-school dropouts after 1985, but they are parallel before that date. One might argue that IT was already diffusing before 1985, so that parallel trends before may reflect offsetting effects. This specification test however adds credit to the identifying strategy.

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of changing composition differences between the two comparison groups, due to the French LFS sampling frame.

[19] Figure A4 in the appendix displays qualitatively similar results using transition rates from employment to unemployment as a measure of job insecurity.

Overall, the graphical analysis confirms that the adoption of IT is predicted by the initial supply of skilled labor. There is however no evidence that the diffusion of IT results in less stable employment relationships. If anything, patterns for transitions to non employment suggest that the adoption of new technologies has been associated with *less* job insecurity for high-school dropouts. The next two sections use regression analysis to explore these apparent relationships further. We first use the exact same data as in the graphical analysis to estimate equation (3). We then introduce firm data to get some more insight on the mechanisms underlying the results.

3. Impact of IT diffusion on job instability: city-level evidence

Table 1 displays 2SLS estimates of the impact of IT diffusion on job instability overall and on its two components.[20] Although workers in more educated local labor markets adopt IT faster, they do not experience any increase in job instability. More specifically, our estimates are all negative which suggests that, if anything, the adoption of IT tends to reduce job instability. This decrease in job instability is particularly significant for high-school dropouts. Controlling for local labor market characteristics and region dummies (column 3), a 10 percentage point increase in PC usage rate reduces job instability by 0.85 percentage point. This effect corresponds to both a decrease in transitions to non employment (0.59 percentage point) and an (insignificant) decrease in job-to-job transitions (0.26 percentage point). For high-school graduates, the corresponding estimates are also negative but smaller and insignificant. A 10 percentage point increase in PC usage rate reduces job instability by 0.13 percentage point in total. It is worth noting however that these differences between high-school graduates

[20] The number of observations is lower than the total number of local labor markets in France. This is due to the Labor Force Survey sampling scheme.

and high-school dropouts are not significant. All in all, we find no evidence that the diffusion of IT increases job-to-job transitions, and we find that it tends to reduce transitions to non employment for high-school dropouts. Our results suggest that the diffusion of IT has not spurred job instability.

These results suggest that productivity gains associated with the development of IT compensate the induced loss in specific human capital which could increase worker flows. A complementary explanation could be that firms adapt to the new skill requirements by upgrading the skills of their existing workforce through training instead of resorting to the external labor market. This investment in training could be especially relevant for individuals with low qualifications thus explaining that IT diffusion particularly reduces transitions of high-school dropouts. Our investigations in the next section appear to confirm this scenario.

Table 2 provides the first stage estimates and shows that our set of instruments (skill mix in 1975 and its square) is not weak. The F-stats are 19.55 and 32.52 respectively for high-school graduates and high-school dropouts which is larger than the standard requirement of 10 (columns 3 and 6). More precisely, an increase in the skill mix in 1975 from the 1st to the 9th decile increases the PC usage rate by about 18 percentage points.[21] The first stage effects are similar for high-school graduates and high-school dropouts suggesting that variations in the 2SLS estimates are not due to differences in the first stage. Comparing the 2SLS with OLS estimates (table A2), the results suggest that the OLS tend to underestimate the decrease in job instability caused by the development of IT. In all cases, 2SLS estimates are more negative than their OLS counterparts. While differences between OLS and 2SLS are not significant for high-school graduates, they are in the case of job instability and job insecurity for high-school dropouts.

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[21] For instance, for high-school dropouts (1st column), $2.804 \times 0.186 - 3.524 \times 0.186^2 - [2.804 \times 0.087 - 3.524 \times 0.087^2] \approx .18.$

This suggests that the OLS estimates are biased toward IT increasing job instability. This could reflect the fact that firms impacted by adverse shocks (e.g., a negative demand shock) react by simultaneously reducing their workforce and take advantage of the changes to introduce IT, implying that the OLS estimates are biased by a reverse causality impact.

Interestingly, all our results are confirmed when Internet is used as the IT measure instead of PC usage (table A3). Results indicate that a 10 percentage point increase in Internet usage rate reduced job instability (by 1.5 percentage point) and job insecurity (by 1.6 percentage point) for high-school dropouts. These effects are also negative for high-school graduates, but they are smaller and insignificant. As for PC usage, the effects on job-to-job transitions are not significant for both subpopulations.

4. Evidence on mechanisms: the role of training and promotions

The city-level results of the previous section imply that the adoption of IT reduces turnover[22] in firms: indeed, job-to-job transitions are stable but transitions to non employment decrease. This may seem at odds with the literature on skill-biased technical change: if the adoption of IT is associated with a renewal of the workforce in order to meet the associated skills requirement, we would expect higher job instability, i.e. higher turnover. As noted in the introduction though, firms need not rely on the external labor market (and increased churning rates): the alternative is to rely on internal labor market responses, typically by training and promoting incumbent workers. This, in turn, can result in lower job

[22] In what follows, we characterize the firm's turnover by the workers' exit rate, i.e. the ratio of workers exiting the firm in a given period over the initial size of the workforce. This is equivalent, from the worker's perspective, to job instability, characterized by the probability of exiting the firm (either to another job, or to non employment). Given the focus on job instability, we do not detail results on hiring here. Adding hiring rates to the analysis does not modify the overall picture (see Behaghel et al., 2012).

instability, if the joint investment in human capital and IT makes the employment relationship more profitable. This second interpretation is in line with the empirical evidence in Behaghel et al. (2012). In this section, we link the local labor and worker level data used in the previous sections with the same firm-level data they use.[23] The purpose is to analyze to what extent the evidence that IT adoption does not increase worker flows can be explained by the firms' human resources strategies.

We start by replicating the 1-stage analysis of the previous two sections on the firm data. IT adoption level is measured in firm *j* located in local labor market *c* through a firm survey conducted in 1998. The survey provides information on the proportion of workers using the Intranet[24] and the Internet in 1998 (no use, less than 5%, 5 to 19%, 20 to 49%, 50% and more). We define a dummy variable IT_{jc98} equal to 1 if at least 5% of the workers use the Internet or at least 20% of the workers use the Intranet. With this definition, 33% of plants in the sample are "adopters" (meaning that IT_{jc98} is equal to 1). We estimate the following adoption equation:

$$IT_{jc98} = a\ Educ_{c0} + b\ Educ_{c0}^2 + m\ X_{jc98} + \varepsilon_{jc98}, \qquad (4)$$

where Educ_{c0} is the local labor market skill mix in 1975 (defined and measured as above), and X_{jc98} are control variables at the firm or at the local labor market level.[25] Results are in table 3. They are fully consistent with the predictions of

[23] See the data appendix for a presentation of the data.

[24] The exact phrasing is 'Intranet and computer networks'.

[25] We control for plant size (dummy variable for plants with more than 200 employees), being located on a labor market whose density is higher than the median, multi-establishment firms, public sector companies, listed companies, presence of union delegates, share of women in the labor force, part-time work (dummy variable for firms with more than 5% of workers being part-time) and 15 sectors. The estimation uses robust standard errors, clustered at the local labor market level. About 250 local labor markets are represented in the sample.

endogenous technology adoption and with the worker-level evidence of table 2.[26] Estimates of *a* and *b* are jointly statistically significant and imply large effects: the probability of using advanced IT is 22 percentage points higher in firms located in local labor market that were at the 9th decile of the skill distribution 25 years earlier, compared to those at the 1st decile. This is a very large effect given that the average adoption rate in the sample is around 1/3.

The firm data thus confirms the adoption pattern found with worker data. But its true value is to uncover some of the mechanisms through which firms adapt their workforce to the skill requirements associated with IT. In what follows, we adopt the same approach as Behaghel et al. (2012) in order to assess whether firm human resources strategies can explain the absence of increase in job instability. Skill-biased technical change is often documented by changes in the occupational structure of adopting firms, estimating the following model on firm data:

$$\Delta S_{jcp} = x_{jc}\beta_p + IT_{jc}\delta_p + \varepsilon_{jcp}\,, \qquad (5)$$

where ΔS_{jcp} is the change in the share of occupation *p* in firms *j* located in local labor market *c*. Typically, one expects positive δ_p in skilled occupations, and negative ones in less skilled ones. This upward shift can be approximately decomposed into two parts: changes in the occupational structure that result from the entry and exit of workers (which we denote $\Delta\tilde{S}_{jcp}$) and changes that result from internal promotions and demotions (which we denote $\Delta\hat{S}_{jcp}$). Holding the occupational structure constant, another channel could be the acquisition of new skills through the addition of fresh workers in a given occupation. Following the literature on worker flows (see in particular Davis and Haltiwanger, 1999), this

[26] Tables 2 and 3 differ by the IT indicators used (PC usage rate vs. Internet/intranet usage, measured in two independent surveys) and by the controls (the same as those of the 2SLS estimations, in tables 1 and 4 respectively).

can be measured as excess turnover, et_{jcp}, i.e. flows in excess of the minimum worker flows needed to adjust the size of occupation *p* in firm *j*. Last, we consider training T_{jcp}, measured in two ways: number of trainees per 100 workers, and training hours per worker. To summarize, and following Behaghel et al. (2012), firm strategies associated with IT-based technical change can be analyzed by weighting "internal labor market responses" (promotions and training), estimated by:

$$\Delta\hat{S}_{jcp} = x_{jc}\hat{\beta}_p + IT_{jc}\hat{\delta}_p + \hat{\varepsilon}_{jcp} \qquad (6)$$

and

$$T_{jcp} = x_{jc}\beta_L{}^T + IT_{jc}\delta_p{}^T + \varepsilon_{jcp}{}^T, \qquad (7)$$

against "external labor market responses" (hiring workers in higher skill groups or relying on excess turnover), as estimated by

$$\Delta\tilde{S}_{jcp} = x_{jc}\tilde{\beta}_p + IT_{jc}\tilde{\delta}_p + \tilde{\varepsilon}_{jcp}, \qquad (8)$$

and

$$et_{jcp} = x_{jc}\beta_L{}^{et} + IT_{jc}\delta_p{}^{et} + \varepsilon_{jcp}{}^{et}., \qquad (9)$$

Estimating equations (6)-(9), Behaghel et al. (2012) acknowledge that their estimates should not necessarily be interpreted causally. Indeed, the endogeneity of the technology adoption variable remains an issue. Here, the variations provided by skill mix differences across local labor market and the strong and significant results obtained from estimating equation (4) suggest using $Educ_{c0}$ as an instrument for IT_{jc}. The exclusion restriction is that unobserved determinants of firms' human resources policy (as of 1998) should not be correlated with the skill mix of the local labor market (as of 1975). While this restriction is not above criticism, it is weaker than assuming the exogeneity of IT_{jc}. The 2SLS results are given in table 4. The first panel shows the overall impact of IT adoption on the firms' occupational structure: the share of managers and professionals increases significantly at the expense of lower occupations. The increase is sizeable: a 5.6 percentage point increase. This is more than the OLS estimate (1.3 pp) reported in Behaghel et al. (2012). This can be due to either measurement error (if the Internet/intranet variable is an imperfect proxy for the firm's technology level) or to downward biases affecting the OLS estimates. Note however that the 2SLS effect is imprecisely estimated, so that the difference between the two estimations should not be overstated. Panels B-F show that internal labor market responses can account for most of the skill upgrading. The upward shift in the occupational structure can almost fully be explained by higher promotion rates (panel B), while worker flows explain at most 25% of the change (panel C). Excess turnover increases only for clerks (panel D), but this is not robust to other specifications of the first stage (see tables A4 and A5). Conversely, though they are not precisely estimated, effects on training measures tend to be positive (panels E and F), and are statistically significant for clerks and blue collars.[27] This increase in the training of clerks and blue collars is consistent with our results in the previous section showing that the adoption of IT reduces job instability for high-school dropouts. To sum up, there is little evidence that firms adopting IT rely upon the external labor market to upgrade their workforce, while there is consistent evidence that they use internal labor market mechanisms, such as training and promotions. This could explain the absence of increases in job instability found in the worker data.[28]

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[27] These estimates are qualitatively similar to the OLS results in Behaghel et al. (2012) , but quantitatively larger.

[28] We perform various robustness checks on table 4. In particular, using a binary instrument or adding local labor market controls (density of the labor supply or regional dummies) does not change the results qualitatively (see tables A4 and A5 in the appendix).

5. Conclusion

Based on two different sources on IT usage, we find that workers and firms located in more educated labor markets tend to adopt IT faster. This is consistent with models of endogenous adoption of new technologies. However, workers do not experience less job stability, and firms do not display larger workers' flows. This is at odds with a Schumpeterian model of creative destruction, or with "post-Fordist" theories. These findings can be explained by the firms' human resource strategies in which internal labor markets' mechanisms, namely firm-provided training and internal promotions, still play a large role.

The results have to be interpreted within the French context. The persistence of internal labor markets in France may be the exception. By international standards, France is indeed still characterized by strict employment protection legislation (Venn, 2009): firms perhaps rely on internal adjustments because going on the external labor market is simply too costly. Replicating the analysis in other institutional contexts may be particularly valuable. LFS data, provided that workers can be located, enable the replication of the main analyses of this paper; we believe that similar work using local labor markets as a source of variation in other countries could yield additional useful insights.

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Table 1: Impact of IT diffusion on job instability

	High-school dropouts			High-school graduates		
	A. Job instability (all transitions)					
PC usage rate in 1998	-0.085***	-0.081**	-0.085**	-0.070***	-0.056	-0.013
	(0.022)	(0.032)	(0.035)	(0.024)	(0.041)	(0.059)
	B. Transitions to non employment					
PC usage rate in 1998	0.020	-0.066***	-0.059**	-0.032**	-0.022	-0.008
	(0.016)	(0.025)	(0.028)	(0.013)	(0.023)	(0.036)
	C. Job-to-job transitions					
PC usage rate in 1998	-0.105***	-0.015	-0.026	-0.039**	-0.034	-0.005
	(0.014)	(0.023)	(0.023)	(0.020)	(0.033)	(0.046)
# of cities	269	269	269	268	268	268
Controls for composition changes	No	Yes	Yes	No	Yes	Yes
Region dummies	No	No	Yes	No	No	Yes

Each cell displays results from a separate 2SLS regression with PC diffusion instrumented by initial skill mix (share of high-school graduates in the city and its square, as of 1975). Dependent variables are changes in transition rates between the late 1970s and the late 1990s (1975-81 and 1995-2001). Observations are at the city level; they are weighted by the geometric mean of the number of observations in Labor Force Surveys in the two periods. Columns 2, 3, 5 and 6 control for changes in the composition of the local labor force: share of female workers, share of the different age groups (5-year groups), distribution of tenure in firms, share of the different occupations groups (6 categories), sector (16 industries), distribution of plant size (5 dummies). Columns 3 and 6 introduce 22 region dummies. Levels of significance: *: 10% **: 5% ***: 1%

SAMPLE: individuals aged 20 to 59

READING: a 10 pp increase in PC usage rate at the city level reduces job instability for high-school dropouts by 0.85 percentage point.

SOURCES: Population census (1975), Labor Force Surveys (1998), Working Conditions survey (1998)

Table 2: Initial skill mix and computer use in 1998
(1^{st} stage equation)

	High-school dropouts			High-school graduates		
Skill mix in 1975	2.804***	2.367***	3.129***	2.826***	2.581***	3.272***
	(0.571)	(0.740)	(0.851)	(0.509)	(0.575)	(0.622)
(Skill mix in 1975)²	-3.524**	-2.651	-5.025**	-3.754***	-3.431**	-5.397***
	(1.474)	(1.994)	(2.312)	(1.264)	(1.434)	(1.524)
F-stat	125.1	21.40	19.55	137.6	53.22	32.52
# of cities	269	269	269	268	268	268
Controls for composition changes	No	Yes	Yes	No	Yes	Yes
Region dummies	No	No	Yes	No	No	Yes

Each column displays results from a separate OLS regression (1^{st} stage of table 1). The dependent variables are PC usage rates among high-school dropouts (columns 1-3) and among high-school graduates (columns 4-6). Observations are at the city level; they are weighted by number of observations in the 1998 Labor Force Survey. Columns 2, 3, 5 and 6 control use the same controls as table 1. Levels of significance: *: 10% **: 5% ***: 1%

SAMPLE: individuals aged 20 to 59

SOURCES: Population census (1975), Labor Force Surveys (1998), Working Conditions survey (1998)

Table 3: Initial skill mix and Internet/Intranet adoption by firms in 1998 (1st stage equation)

	Dependent variable: Internet/intranet			
Skill mix in 1975	2.830***	2.619**	1.975*	1.612
	(1.016)	(1.114)	(1.168)	(1.288)
(Skill mix in 1975)²	-2.157	-2.232	-1.179	-0.136
	(2.499)	(2.860)	(2.912)	(3.270)
Number of plants	1,109	1,109	1,109	1,109
R^2	0.054	0.133	0.136	0.153
Firm controls	no	yes	yes	yes
Labor market density	no	no	yes	yes
Region dummies	no	no	no	yes
F-stat instruments	110.3	29.45	16.27	10.32

Each column displays results from a separate OLS regression (1st stage of table 4). The dependent variable indicates whether the firm uses the Internet or an intranet. Firm controls are: plant size (dummy variable for plants with more than 200 employees); indicators for multi-establishment firms, public sector companies, listed companies, presence of union delegates; share of women in the workforce, part-time work (dummy variable for firms with more than 5% of workers being part-time) and 15 sector dummies. Levels of significance: *: 10% **: 5% ***: 1%. Robust standard errors clustered at the local labor market level.
SOURCES: Population census (1975); REPONSE firm survey.

Table 4: IT adoption and skill upgrading channels: 2SLS estimates

	Managers and professionals	Technicians and supervisors	Clerks	Blue collars
	A. Overall changes in the occupational structure			
Internet/Intranet	5.59***	-1.48	-1.94	-2.18
	(1.26)	(1.11)	(1.73)	(1.50)
Obs	1,109	1,109	1,109	1,109
	B. Internal movements			
Internet/Intranet	4.45***	-0.66	-1.91	-1.88
	(1.19)	(1.69)	(1.61)	(1.48)
Obs	1,109	1,109	1,109	1,109
	C. External movements			
Internet/Intranet	1.36	-0.86	0.29	-0.78
	(1.26)	(1.25)	(0.74)	(1.15)
Obs	1,109	1,109	1,109	1,109
	D. Excess turnover			
Internet/Intranet	3.70	15.95	71.39**	150.61
	(14.74)	(15.49)	(32.52)	(126.28)
Obs	1,085	1,090	1,099	1,041
	E. Number of trainees (per 100 workers)			
Internet/Intranet	-3.84	21.83	13.72	38.83***
	(10.82)	(25.16)	(10.69)	(13.77)
Obs	1,092	1,047	1,082	905
	F. Training hours per worker			
Internet/Intranet	0.34	-0.64	8.40**	10.48***
	(5.09)	(5.55)	(4.27)	(3.61)
Obs	1,090	1,037	1,078	903

Each cell displays results from a separate 2SLS regression with Internet/Intranet usage instrumented by initial skill mix (share of high-school graduates in the city and its square, as of 1975). The corresponding first stage is in table 3. Each regression includes controls for plant size (dummy variable for plants with more than 200 employees), being located on a labor market whose density is higher than the median, multi-establishment firms, public sector companies, listed companies, presence of union delegates, share of women in the labor force, part-time work (dummy variable for firms with more than 5% of workers being part-time) and 15 sectors. Levels of significance: *: 10% **: 5% ***: 1%

READING: The adoption of Internet/Intranet leads to a 5.6 percentage point increase in the share of managers and professionals.

SOURCES: Population census (1975); REPONSE survey, EMMO, DMMO, ESE and 24-83.

Figure 1: Share of high-school graduates and above in 1975

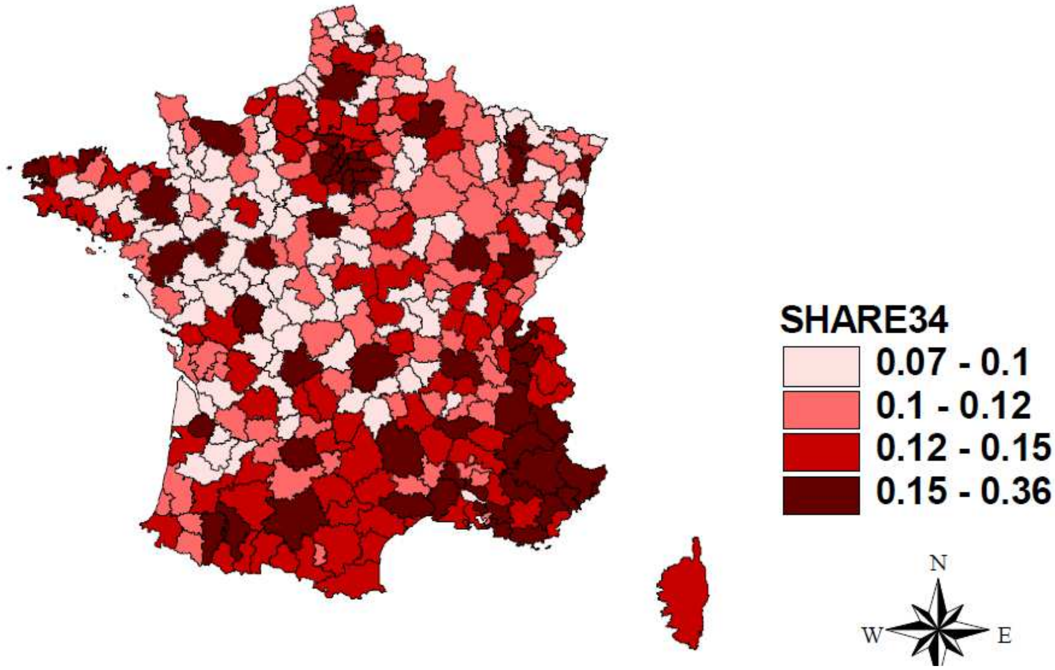


Figure 2a: PC adoption by initial skill mix

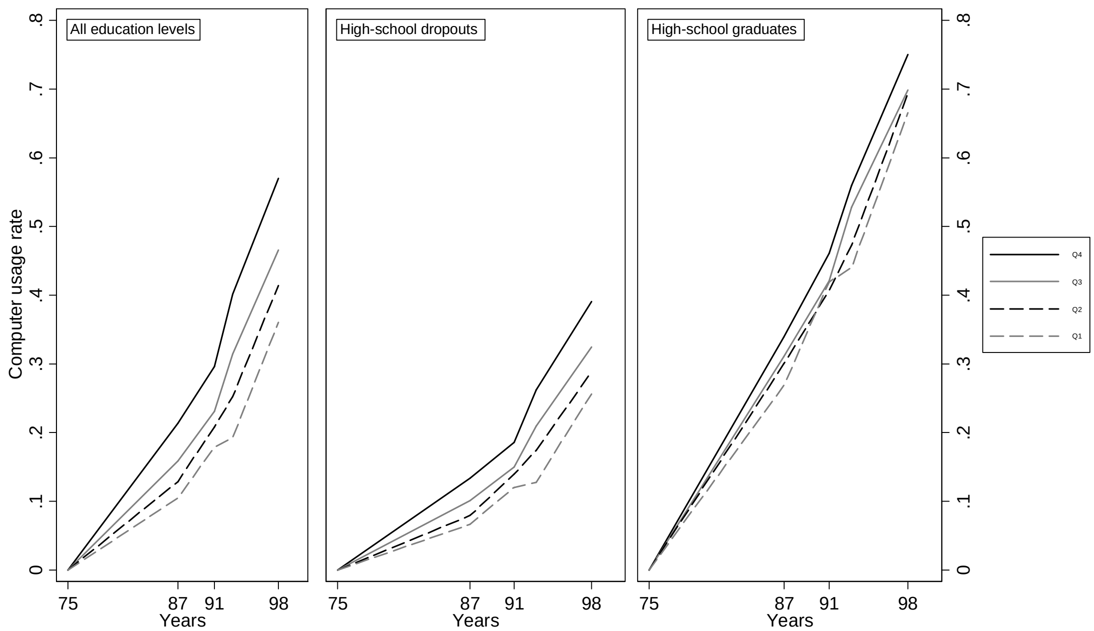


Figure 2b: Internet adoption by initial skill mix

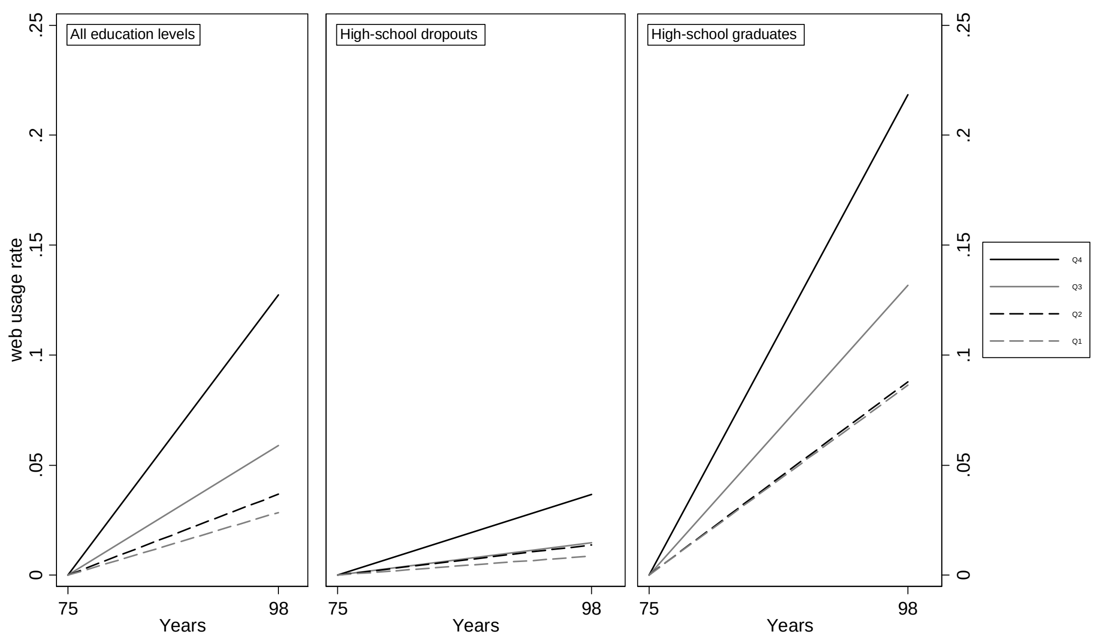
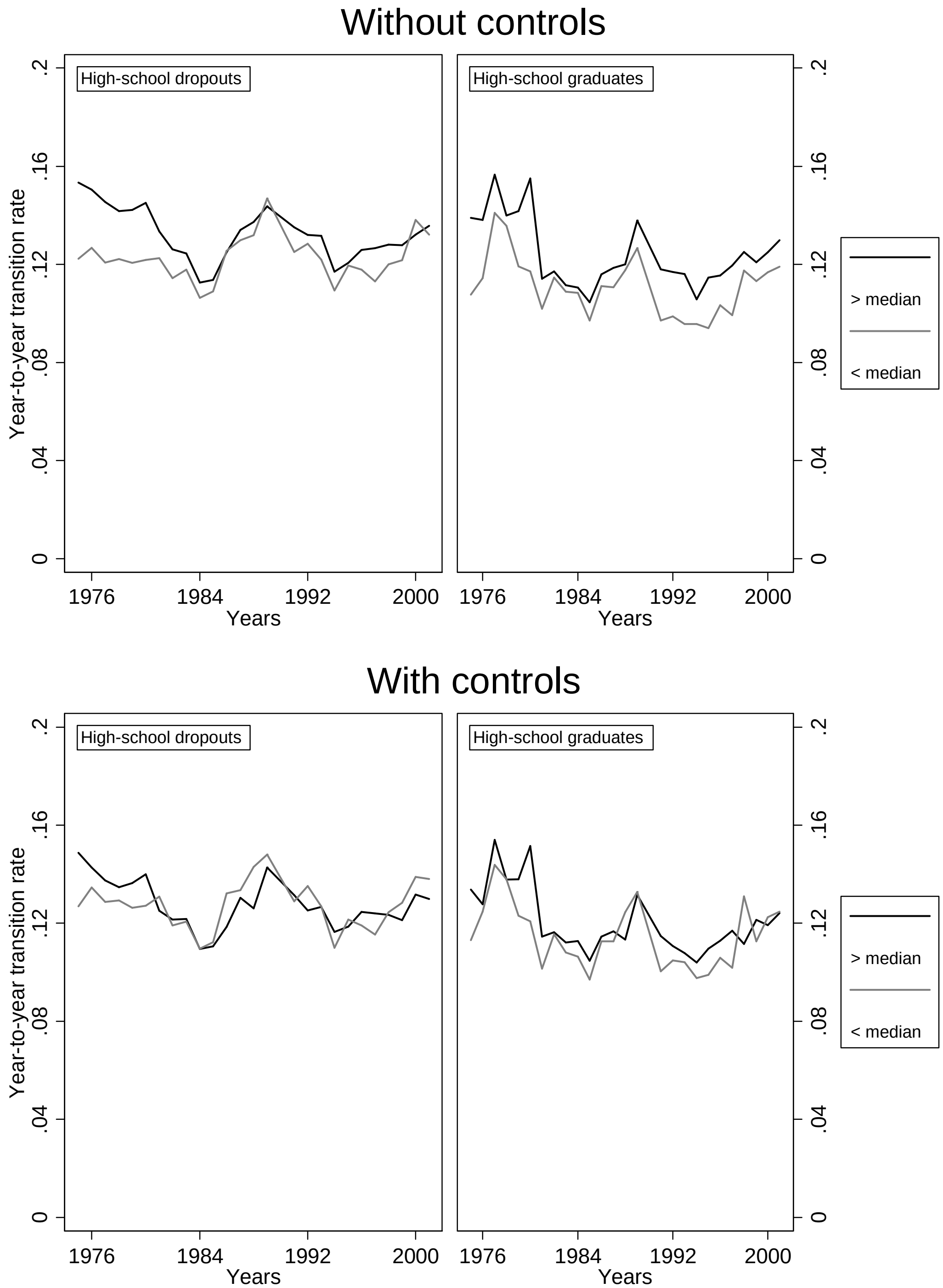
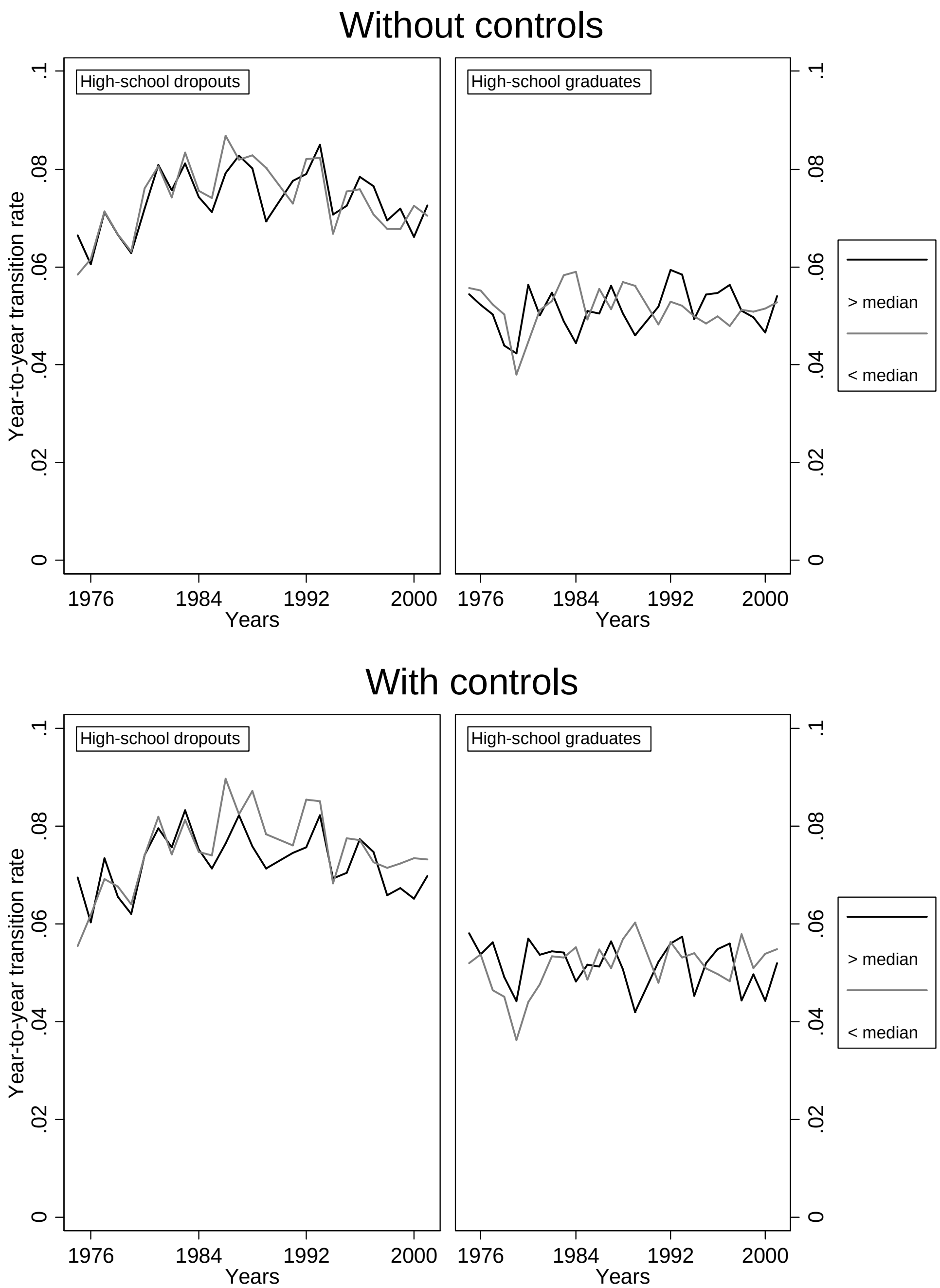


Figure 3: Job instability by initial skilled labor endowment



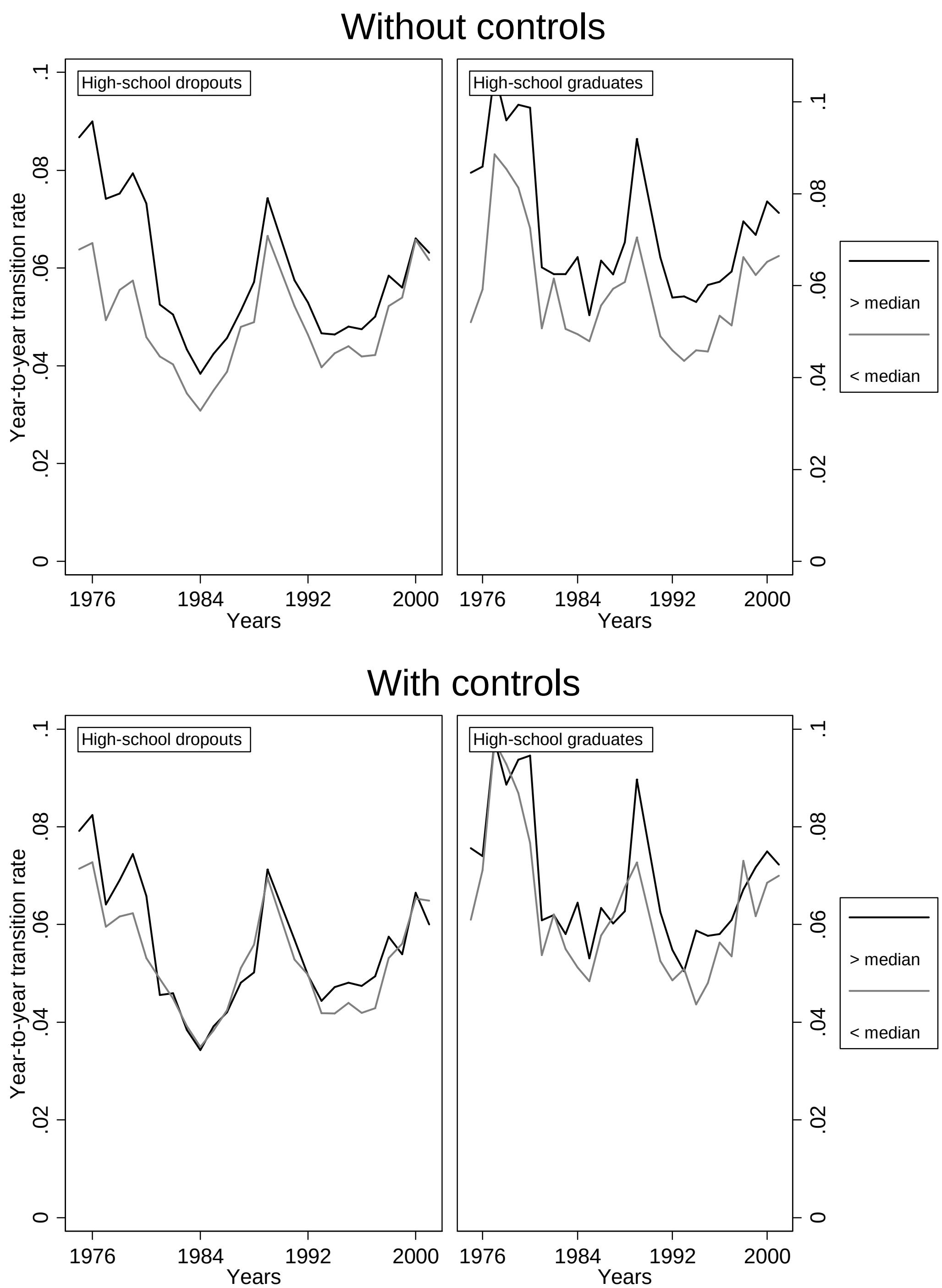
Note: Year-to-year transition rates from a firm to non employment or to a new firm, computed separately for high-school dropouts and high-school graduates. Local labor markets are split into 2 groups depending on their initial skill mix. Bottom graphs: the difference between local labor markets with lower and higher initial skilled mixes are net of differences in composition in terms of workers' gender, age and years of tenure; sector; firm size.

Figure 4: Transitions from employment to non employment, by initial skilled labor endowment



Note: Year-to-year transition rates from employment to non employment, computed separately for high-school dropouts and high-school graduates. Local labor markets are split into 2 groups depending on their initial skill mix. Bottom graphs: the difference between local labor markets with lower and higher initial skilled mixes are net of differences in composition in terms of workers' gender, age and years of tenure; sector; firm size.

Figure 5: Job-to-job transitions by initial skilled labor endowment



Note: Year-to-year transition rates from employment to non employment, computed separately for high-school dropouts and high-school graduates. Local labor markets are split into 2 groups depending on their initial skill mix. Bottom graphs: the difference between local labor markets with lower and higher initial skilled mixes are net of differences in composition in terms of workers' gender, age and years of tenure; sector; firm size.

Data appendix: Firm-level data and measure of firm strategies to upgrade the skill level of their workforce

The data used in section 4 is from Behaghel et al. (2012). For convenience, this appendix summarizes the presentation of the data and of variables used in section 5, but a more detailed description is in the original paper.

The information on IT comes from the REPONSE survey (RElations PrOfessionnelles et NégocationS d'Entreprise). In 1998, 2978 establishments were surveyed with senior managers being asked questions about industrial relations, implementation of new technologies and reorganisations.

Worker flows, are from two different sources. The DMMO (Données sur les Mouvements de Main-d'Oeuvre) has exhaustive data on entries and exits of workers in and out of establishments with 50 employees or more. The data is broken down into four occupational categories: managers and professionals,[29] technicians and supervisors, clerks and blue-collars. The EMMO (Enquête sur les Mouvements de Main-d'Oeuvre) has identical information on a representative sample of firms with less than 50 employees. We use this data to compute counterfactual changes in labor shares over 1996-1998, i.e. changes that are due only to entries and exits (resp. promotions) in the various occupations over the period. We also use information on the level of employment in each occupational cell at the beginning and at the end of the period. This information is provided by the French survey of employment structure: the ESE (Enquête Structure des Emplois), as of December 31st 1995 and 1998.

Last, the so-called 24-83 fiscal records provide firm-level data on the number of workers receiving training and the volume of training hours.[30] This only refers to continuous and formal training. In particular, apprenticeship and informal on-the-job training are excluded. Using the information available in the 24-83, we compute both the proportion of workers receiving some training and the average number of training hours per worker for four occupational categories - identical to those in the DMMO-EMMO database. These are averaged over 1996-1998.

[29] This category also includes engineers.

[30] The 24-83 records provide firm rather than plant-level data on training. Matching them with establishment-level data generates some measurement error that is likely to raise the standard errors in our estimates.

Matching the four datasets and cleaning out establishments with implausible values for skill upgrading reduces our sample to 1,114 establishments. The low matching rate is primarily due to the fact that the EMMO and 24-83 sources are not exhaustive (respectively, not systematically coded).

The share of occupational group *p* in the workforce of firm *i* is computed as*:*

$$\Delta S_{ip} = \frac{L_t^{ip}}{L_t^i} - \frac{L_{t-1}^{ip}}{L_{t-1}^i}.$$

The counterfactual changes in labor shares ($\Delta\tilde{S}_{ip}$) describing what would have happened to the occupational structure if there had only been entries and exits at the different occupational levels, but no internal movement (promotion or demotion) is computed as:

$$\Delta\tilde{S}_{ip} = \frac{L_{t-1}^{ip} + H_t^{ip} - E_t^{ip}}{L_{t-1}^i + H_t^i - E_t^i} - \frac{L_{t-1}^{ip}}{L_{t-1}^i}$$

where L_{t-1}^{ip} is the number of workers in occupation *p* in firm *i* at time *t-1*, H_t^{ip} is the number of entries in occupation *p* in firm *i* between time *t-1* and *t* and E_t^{ip} is the number of workers formerly employed in occupation *p* leaving firm *i* between time *t-1* and *t*. Similarly, L_t^i, H_t^i, and E_t^i respectively denote the total number of workers, entries and exits in firm *i* at time *t*.

Changes in the occupational structure through promotions only ($\Delta\hat{S}_{ip}$) are defined as the changes in the occupational structure that would have occurred if there had been none of the entries or exits that we observe in the data:

$$\Delta\hat{S}_{ip} = \frac{L_t^{ip} - H_t^{ip} + E_t^{ip}}{L_t^i - H_t^i + E_t^i} - \frac{L_{t-1}^{ip}}{L_{t-1}^i}$$

where L_t^{ip} is the number of workers in occupation *p* in firm *i* at time *t*.

Excess turnover *et* in plant *i* and for group *p* is defined as:

$$et_{ip} \equiv \frac{H_{ip} + E_{ip}}{L_{ip}} - \left| \frac{H_{ip} - E_{ip}}{L_{ip}} \right|.$$

Table A1 (replicating table A1 in Behaghel et al., 2011) displays descriptive statistics on the firm sample.

Table A1: Descriptive statistics on the firm sample

	All plants	Internet/Intranet=0	Internet/Intranet=1	Manufacturing	Services
Change of labor share (in %)					
Managers and professionals	0.77	0.33	1.65	0.93	0,54
Technicians and supervisors	0.56	0.63	0.44	0.72	0,36
Clerks	-0.38	-0.15	-0.84	-0.27	-0,53
Blue collars	-0.95	-0.81	-1.24	-1.38	-0,37
Change of labor share through internal movements (in %)					
Managers and professionals	0.92	0.60	1.55	0.90	0,93
Technicians and supervisors	0.79	0.73	0.92	0.96	0,56
Clerks	-0.64	-0.38	-1.16	-0.41	-0,95
Blue collars	-1.07	-0.95	-1.31	-1.46	-0,55
Change of labor share through entries and exits (in %)					
Managers and professionals	-0.07	-0.18	0.15	0.07	-0,26
Technicians and supervisors	-0.13	0.00	-0.41	-0.17	-0,09
Clerks	0.18	0.13	0.29	0.14	0,25
Blue collars	0.02	0.04	-0.02	-0.04	0,10
Excess turnover (in %)					
Managers and professionals	24.12	25.04	22.29	18.54	31,89
Technicians and supervisors	25.13	27.38	20.67	13.95	40,55
Clerks	61.10	61.07	61.16	30.13	102,88
Blue collars	49.93	53.38	42.79	27.21	84,89
Number of trainees per 100 workers					
Managers and professionals	59.60	56.71	65.38	60.58	58,27
Technicians and supervisors	59.59	55.47	67.94	60.94	57,62
Clerks	41.27	37.88	48.06	43.82	37,83
Blue collars	34.18	32.04	39.14	34.17	34,22
Hours of training per worker					
Managers and professionals	21.45	19.54	25.24	22.70	19,75
Technicians and supervisors	19.45	17.55	23.30	19.97	18,69
Clerks	12.07	10.87	14.47	13.08	10,70
Blue collars	9.49	8.27	12.31	10.31	7,63
Internet/Intranet	0,33	0.00	1.00	0.34	0.32
Indicator for plant with more than 200 workers	0,53	0.48	0.62	0.62	0.40
Indicator for dense local labor market	0,25	0.21	0.34	0.20	0.32
Indicator for service sector	0,42	0.43	0.41	0.00	1.00
Indicator for multi-establishment firm	0,60	0.57	0.66	0.63	0.56
Indicator for public sector	0,03	0.03	0.05	0.02	0.05
Indicator for listed company	0,43	0.38	0.54	0.55	0.27
Indicator for presence of union delegates	0,77	0.76	0.81	0.84	0.69
Share of women (%)	35,13	35.91	33.54	25.98	47.53
Indicator for part-time work (>5% of workforce)	0,37	0.37	0.38	0.22	0.58
Number of observations	1114	747	367	641	473

ADDITIONAL FIGURES AND TABLES

(NOT FOR PUBLICATION)

Table A2: IT diffusion and Job instability (OLS regressions)

	High-school dropouts			High-school graduates		
	Job instability (all transitions)					
PC usage rate in 1998	0.009	-0.004	-0.005	0.051**	0.004	0.004
	(0.012)	(0.008)	(0.008)	(0.022)	(0.011)	(0.011)
	Transitions to non employment					
PC usage rate in 1998	-0.004	-0.002	-0.001	-0.005	-0.012	-0.005
	(0.008)	(0.008)	(0.007)	(0.008)	(0.009)	(0.009)
	Job-to-job transitions					
PC usage rate in 1998	0.013*	-0.002	-0.004	0.056***	0.016*	0.009
	(0.007)	(0.006)	(0.006)	(0.017)	(0.009)	(0.009)
# of cities	271	271	271	271	271	271
Controls for composition changes	No	Yes	Yes	No	Yes	Yes
Region dummies	No	No	Yes	No	No	Yes

Each cell displays results from a separate OLS regression of transition rates on PC usage rate (as of 1998). Dependent variables are changes in transition rates between the late 1970s and the late 1990s (1975-81 and 1995-2001). Observations are at the city level, weighted by the number of observations.
Columns 2, 3, 5 and 6 control for differences in the composition of the local labor force: share of female workers, share of the different age groups (5-year groups), distribution of tenure in firms, share of the different occupations groups (6 categories), sector (16 industries), distribution of plant size (5 dummies). Columns 3 and 6 introduce 22 region dummies. Levels of significance: *: 10% **: 5% ***: 1%
SAMPLE: individuals aged 20 to 59
READING: a 10 pp increase in PC usage rate at the city level reduces job instability for high-school dropouts by 0.05 percentage point. The coefficient is not statistically different from 0.
SOURCES: Population census (1975), Labor Force Surveys (1998), Working Conditions survey (1998)

Table A3: Impact of the diffusion of the Internet on job stability

	High-school dropouts			High-school graduates		
	A. Job instability (all transitions)					
Internet usage rate in 1998	-0.144**	-0.146**	-0.146*	-0.100***	-0.104**	-0.106
	(0.057)	(0.074)	(0.087)	(0.037)	(0.048)	(0.074)
	B. Transitions to non employment					
Internet usage rate in 1998	0.035	-0.139***	-0.155**	-0.047***	-0.033	-0.056
	(0.030)	(0.049)	(0.061)	(0.017)	(0.032)	(0.054)
	C. Job-to-job transitions					
Internet usage rate in 1998	-0.178***	-0.007	0.009	-0.053*	-0.071*	-0.050
	(0.036)	(0.046)	(0.049)	(0.029)	(0.039)	(0.063)
# of cities	269	269	269	268	268	268
Controls for composition changes	No	Yes	Yes	No	Yes	Yes
Region dummies	No	No	Yes	No	No	Yes

Each cell displays results from a separate 2SLS regression with Internet usage instrumented by initial skill mix (share of high-school graduates in the city and its square, as of 1975). Dependent variables are changes in transition rates between the late 1970s and the late 1990s (1975-81 and 1995-2001). Observations are at the city level; they are weighted by the geometric mean of the number of observations in the two periods.

Columns 2, 3, 5 and 6 control for changes in the composition of the local labor force: share of female workers, share of the different age groups (5-year groups), distribution of tenure in firms, share of the different occupations groups (6 categories), sector (16 industries), distribution of plant size (5 dummies). Columns 3 and 6 introduce 22 region dummies. Levels of significance: *: 10% **: 5% ***: 1%

SAMPLE: individuals aged 20 to 59

READING: a 10 pp increase in Internet usage rate at the city level reduces job instability for high-school dropouts by 1.46 percentage point.

SOURCES: Population census (1975), Labor Force Surveys (1998), Working Conditions survey (1998)

Table A4: IT adoption and skill upgrading channels: 2SLS estimates (instrument: *above median initial skill mix* 1($Educ_{c0}$>median))

	Managers and professionals	Technicians and supervisors	Clerks	Blue collars
	A. Overall changes in the occupational structure			
Internet/Intranet	4.73***	-0.49	-2.28	-1.96
	(1.23)	(1.55)	(1.49)	(1.80)
Obs	1,109	1,109	1,109	1,109
	B. Internal movements			
Internet/Intranet	4.02***	0.43	-2.74	-1.71
	(1.28)	(1.71)	(1.68)	(1.78)
Obs	1,109	1,109	1,109	1,109
	C. External movements			
Internet/Intranet	1.06	-0.59	0.48	-0.95
	(0.98)	(1.30)	(1.09)	(1.39)
Obs	1,109	1,109	1,109	1,109
	D. Excess turnover			
Internet/Intranet	-20.67	25.85	37.95	156.79
	(18.71)	(26.34)	(38.01)	(114.22)
Obs	1,085	1,090	1,099	1,041
	E. Number of trainees (per 100 workers)			
Internet/Intranet	11.60	51.01*	27.07**	50.73**
	(13.08)	(27.27)	(13.12)	(20.82)
Obs	1,092	1,047	1,082	905
	F. Training hours per worker			
Internet/Intranet	2.78	6.11	9.79**	10.01**
	(6.55)	(6.84)	(4.68)	(4.15)
Obs	1,090	1,037	1,078	903

See notes to table 4. The instrument is an indicator variable for initial skill mix above median.

Table A5: IT adoption and skill upgrading channels: 2SLS estimates (instrument: *above median initial skill mix* 1($Educ_{c0}$>median); local labor market controls: region dummies and labor market density)

	Managers and professionals	Technicians and supervisors	Clerks	Blue collars
	A. Overall changes in the occupational structure			
Internet/Intranet	5.55**	1.36	-1.52	-5.38
	(2.47)	(3.08)	(2.66)	(3.82)
Obs	1,109	1,109	1,109	1,109
	B. Internal movements			
Internet/Intranet	3.99	1.95	-2.34	-3.60
	(2.81)	(2.78)	(3.67)	(3.24)
Obs	1,109	1,109	1,109	1,109
	C. External movements			
Internet/Intranet	1.91	-0.20	-0.64	-1.07
	(1.72)	(2.62)	(2.35)	(3.21)
Obs	1,109	1,109	1,109	1,109
	D. Excess turnover			
Internet/Intranet	-26.76	99.44	93.94	232.50
	(37.77)	(79.65)	(65.95)	(166.22)
Obs	1,085	1,090	1,099	1,041
	E. Number of trainees (per 100 workers)			
Internet/Intranet	43.38	66.93	52.40*	49.96*
	(30.23)	(52.59)	(30.14)	(26.19)
Obs	1,092	1,047	1,082	905
	F. Training hours per worker			
Internet/Intranet	8.29	-0.72	19.19**	8.55
	(14.32)	(13.38)	(9.32)	(7.23)
Obs	1,090	1,037	1,078	903

See notes to table 4. The instrument is an indicator variable for initial skill mix above median. Region dummies and labor market density are included as additional controls.

Figure A1: Population density in 1975

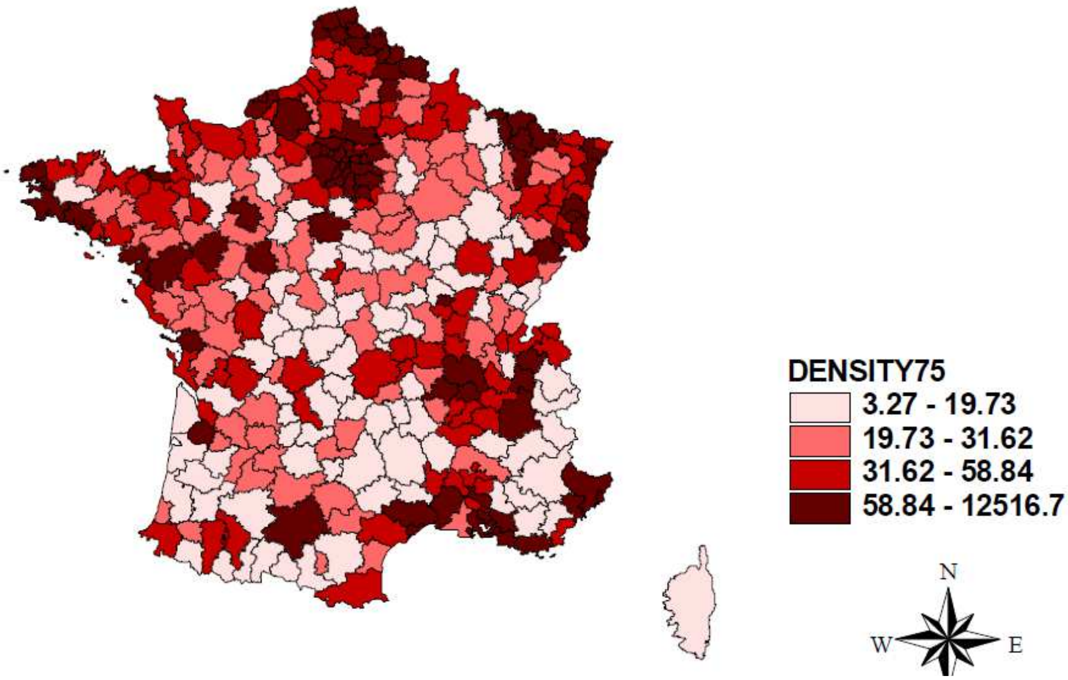


Figure A2: Share of high-school graduates and above in 1999

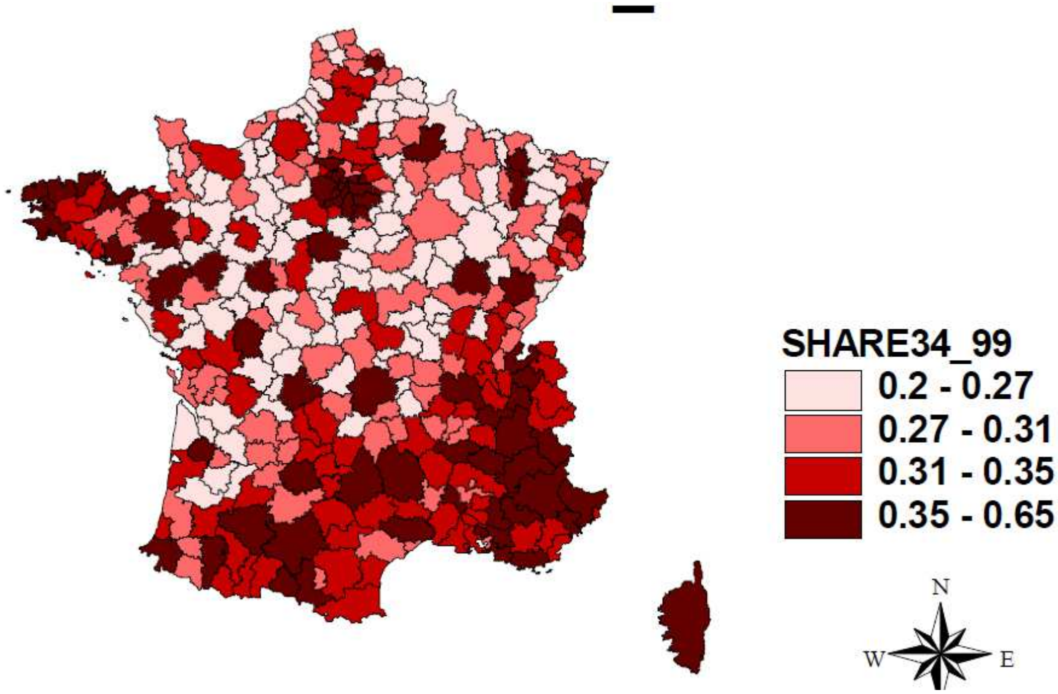


Figure A3: Transitions from employment

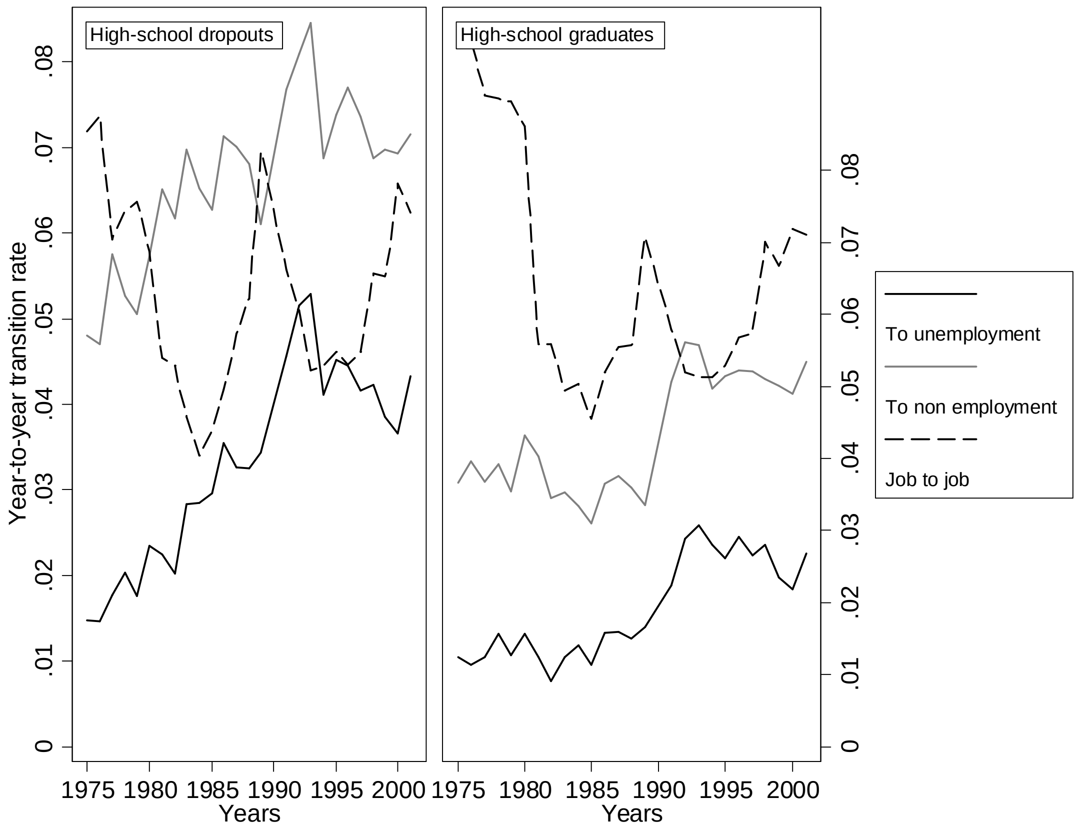


Figure A4: Transitions from employment to unemployment, by initial skilled labor endowment