The long-lasting effect of technological change on the careers of young workers: Evidence from changes of mandatory training regulations

Simon Janssen (IAB Nürnberg, IZA)

Jens Mohrenweiser (ZEW, Mannheim)

Abstract

This paper investigates how the increasing labor supply of fresh graduates with modern IT (information technology) skills impacts the careers of incumbent workers during periods of fundamental technological change. To identify the causal effect within a difference-in-difference framework, we exploit a regulatory change in a mandatory German apprenticeship training regulation that obligated fresh graduates of a large manufacturing occupation to acquire modern IT skills. The paper shows that fresh graduates with modern IT skills crowd incumbent workers out of their jobs and occupations. As a result, even young incumbent workers, who lack modern IT skills, experience long-lasting earnings reductions. The earnings effects prevail for more than 20 years and incumbent workers are more likely to leave their occupation or to become unemployed.

Keyword: skill-biased technological change, wage adjustments, supply shock, apprenticeship

JEL Classification: J24, J64, O30

I. Introduction

According to standard human capital theory, incumbent workers are more productive than similarly educated fresh graduates, simply because incumbent workers have relatively more work experience. However, a number of empirical studies suggest that skill-biased technological change relates to a steadily increasing productivity of fresh graduates (e.g. Card and Lemieux, 2001 and Bowlus and Robinson, 2014).[1] Fresh graduates commonly acquire the newest knowledge in school, and they can make large investments to become proficient in the use of modern technologies. In contrast, incumbent workers, who are involved in the production process, must incur substantial opportunity costs to accumulate the most recent knowledge. Thus if groundbreaking new technologies substantially change the demand for skills,[2] incumbent workers may have a comparative disadvantage in the use of recent technology relative to similarly educated fresh graduates. Particularly, younger incumbent workers with little work experience, who often must compete with fresh graduates for jobs and promotions, may incur substantial and long-lasting adjustment costs, because firms have incentives to replace them with workers who have a comparative advantage in the use of modern technologies (e.g. Acemoglu and Autor, 2011[3]).

This paper is the first to analyze how the careers of young incumbent workers respond to a shock in the supply of modern-skilled fresh graduates during a period of fundamental technological change. By doing so, we complement a long strand of previous studies, which analyze the impact of technological change on workers' labor market outcomes. Some of these previous studies provide evidence for the negative impact of technological change on the careers of older workers.[4] Under the implicit assumption of most studies that similarly educated workers are substitutes, it appears intuitive that young workers are better in coping with the changing demand for skills than older workers. But fresh graduates may become ever more productive than previous generations (for example, because policy makers change school curricula) such that firms have incentives to replace particularly young incumbent workers with fresh graduates. Therefore, our study goes beyond previous studies and analyzes whether even young workers incur long-lasting adjustment costs in times of fundamental technological change.

[1]These empirical studies assume that college graduates of different cohorts are imperfect substitutes and show that changes in the relative supply of college graduates can explain a substantial part of the increased college-high school gap over the last decades.

[2] A huge literature documents that technological change alters the demand for skills and changes the wage structure. See, for example, Autor et al. (1998); Autor et al. (2003); Autor et al. (2008); Dustman et al. (2009); Dustman et al. (2009)

[3] Acemoglu and Autor (2011) argue that in equilibrium firm assign more tasks to workers with a comparative advantage in the use of modern technologies such that workers with a comparative disadvantage in the use of modern technologies crowded into lower paying jobs or even become unemployed.

[4]Some earlier studies argue that human capital depreciates in response to technological change, because experience-earnings profiles are u-shaped (e.g. Ben-Porath (1976); Neuman and Weiss (1995)). Some newer studies show that firms' computer use relates to the retirement decision and wages of older workers (e.g. Aubert al al. (2006))

While most previous papers relate time trends of income developments to periods of technology progress, we can identify a skill shock in a quasi-experimental setting. The quasi-experimental setting allows us to analyze the long-term adjustment processes of incumbent workers in response to the increasing labor supply of modern-skilled graduates during a period of groundbreaking technology change. We find that incumbent workers experience substantial and long-lasting earnings losses (i.e. 3 percentage points per year) in response to the increasing supply of modern-skilled workers. The effect persists for more than 20 years. Moreover, incumbent workers experience a higher probability to switch their occupation and to become unemployed.

Our quasi-experimental setting is based on mandatory training regulations of the German apprenticeship system. The training regulations provide detailed information about the training content such that we can identify when cohorts of apprenticeship graduates with modern skills enter the labor market. In contrast to other countries, apprenticeship training is the main route for school-leavers in Germany, and about two thirds of young Germans follow an apprenticeship training program. As apprenticeship training commonly last between three and three and a half years, apprentices are skilled workers and, therefore, comparable to college educated blue-collar workers in the U.S. Most importantly, the mandatory training curricula define the training content very precisely for more than 350 training occupations, and all German training firms and vocational schools must obey to these curricula. The curricula are enforced by independent institutions, which monitor apprenticeships and carry out occupation-specific final exams for all apprentices.

Our identification strategy exploits a mandatory change of one such apprenticeship training regulation that lead to a substantial increase in the labor supply of modern-skilled workers in the manufacturing sector. By analyzing the careers of incumbent workers who graduated shortly *before* the mandatory change in the training regulation occurred, we can investigate how incumbent workers respond to the increasing supply of modern-skilled fresh graduates. We separate the causal effect from differences in unobserved ability, unrelated institutional changes, and macroeconomic developments by using a difference-in-differences approach. Thus we compare wage trajectories of incumbent workers in the affected occupation to wage trajectories of incumbent workers of a comparable occupation, which was not affected by a similar regulatory change in their training occupation. As workers of both occupations learned and work in the same firms, have otherwise similar training contents, general schooling requirements, produce similar goods, and are represented by the same unions, both groups are exposed to exactly the same labor market institutions and macroeconomic conditions.

In more detail, we exploit a major regulatory change that occurred in the training curriculum of machining metal operators. Machining metal operators are very important for the production of metal parts in one manufacturing sector that produced world-leading products. Because of the occupation's technological content, the relatively good pay, and the secure employment perspectives, many young men with a medium level of general education choose to become machining metal operators. In the late 1980's, the training curriculum of machining metal operators was changed in response to the invention of a groundbreaking new technology: the computer numerical control machine (CNC). The introduction of CNC machines substantially changed the nature of work and the necessary skills (Bartel et al., 2007; Dunne and Schmitz, 2005; Lewis, 2011). Before the introduction of CNC machines, workers performed processes such as drilling, turning, and milling on specific manual machines. Afterwards, CNC machines integrated all of these machining processes in one machine that workers controlled via a computer system.

Although CNC technology was available a few years before the regulatory change of the training curriculum, incumbent workers did not learn modern CNC skills as part of their regular apprenticeship training program. Nonetheless, even before the regulatory change of the training program, some workers may have acquired CNC skills. But the training mostly took place as unstructured on-the-job training. In contrast, after the reform of the training curricular all apprenticeship graduates had to acquire CNC skills in the form of a structured and elaborated training program that often took place in external training centers. Thus on average incumbent workers, who graduated before the reform of the training program, had a comparative disadvantage in the use of CNC technology relative to apprenticeship graduates who underwent the structured CNC apprenticeship training after the reform.

In sum, our design allows us to identify a change in the supply of modern CNC skills in a narrowly defined treatment occupation in response to a fundamental technological innovation. This quasi-experimental design permits analyzing how the careers of these incumbent workers respond to the increasing supply of young graduates with modern skills.

Our results show that incumbent workers incur substantial adjustment costs when groundbreaking technologies change the demand for skills. In contrast to the inherent assumption of many policy makers and researchers, who presume that only old workers, who are close to retirement, must fear the competition of young workers with modern skills, we show that also young incumbent workers experience relative earnings losses when modern technologies change the demand for skills. Therefore, our study provides important insights for policy makers, who are interested in updating and maintaining the skill level of a country's workforce.

In a more general sense, we contribute to the literature on the "skill biased technological change". In contrast to many prior studies, we are able to provide micro-evidence based on a quasi-experimental setting. Because quasi-experiments are hard to find, and data sources that are informative about the content of workers' skills are scarce, most existing studies had to rely on descriptive investigations, which relate the timing of important technological innovations and relative changes in the level of skills to macroeconomic trends in wage inequality. But these approaches have been criticized, because the timing of such events may coincide with other important institutional and macroeconomic changes (e.g. Card and DiNardo, 2002; DiNardo and

Pischke, 1997). In contrast, we can show the consequences of technological change in a more controlled setting, which allows us to isolate the effects from common confounding factors.

The remainder of the paper is organized as follows. Section 2 describes the theoretical background, and section 3 presents the institutional details. Section 4 describes the methods and the data. Section 5 presents the results, and section 6 concludes.

II. Background

II.A. The influence of CNC technology on the nature of work

An extensive literature on the "skill biased technological change" suggests that workers whose skills complement modern technologies benefit from technological change at the expense of workers, whose skills complement older technologies. A very distinct example for a skill-biased technology is the introduction of computer numerical control machines (CNC). Beginning in the late 1970s, CNC technology revolutionized the manufacturing industry; particularly, machining metalworking processes. Prior to the introduction of CNC machines, very specialized workers had to perform different machining process such as milling, turning, and drilling on separate manual machines. In contrast, CNC machines are able to run different processes and integrate several manual machines into one machine. While older manufacturing technologies required almost exclusively manual skills, CNC machines are operated by computer systems, and CNC operators must possess programming skills, use new tools, and handle more different manufacturing processes at a time.

A very detailed paper of Bartel et al. (2007) shows, for example, that the introduction of CNC technology is related to an increasing productivity on the firm level, and an increasing demand for computer, programing, and problem solving skills on the worker level. Moreover, firms which provided formal CNC training to their workers were much more productive than firms with comparable CNC technology that did not provide formal CNC training. In line with the SBTC hypothesis, firms replaced multiple manual machines with CNC technology. This substitution leads to an increasing employment of workers with modern CNC skills at the expense for non-CNC workers. Other studies, such as Brynjolfsson and Hitt (2003) show that firms with CNC technology hire more skilled workers; in particular, if they combine introduction of CNC technology with complementary work place practices.

II.B.CNC skilled graduates and incumbent workers' careers

In the first place, firms adopt new CNC technology to become more productive. However, to operate CNC machines, firms must somehow meet the new skill requirements coming along with the adoption of CNC technology. To do so, firms can either hire CNC experts on the market or train their own incumbent workers. As this decision largely depends on the disparity between further training costs for incumbent workers and hiring costs of external candidates, the general supply of CNC skilled workers determines whether firms will train their incumbent workers or hire external candidates. The supply increase of CNC skilled workers leads to decreasing hiring costs of external CNC-skilled workers as relative wages of CNC skilled workers decrease. Moreover, firms have lower search costs because firms are more likely to encounter workers with CNC skills on the labor market. Therefore, firms should become more reluctant to train incumbent workers if the supply of CNC-skilled workers increases and firms may decide to replace the incumbent workers by CNC-skilled graduates.

However, a firm's decision to replace incumbent workers by external CNC skilled graduates may not only depend on the quantity of CNC skilled workers on the market, but also on the quality of external CNC skilled workers. While recent graduates invest large shares of their schooling investments to become proficient in every detail of CNC technology, incumbent workers are commonly involved in the production process and earn high wages such that the training of incumbent workers may produce high opportunity costs for workers and firms. In consequence, firms may hire recent graduates with a comprehensive CNC training at the expense of incumbent workers—even if those incumbent workers possess some CNC skills.

But the increasing supply of CNC-skilled graduates may not only influence firms' decision to train incumbent workers, the increasing supply of CNC-skilled workers may also directly influence firms' adoption of CNC technology (Acemoglu, 1998; Machin and Manning, 1997). Since CNC skilled workers complement CNC technology, the investment in the new technology becomes cheaper and firms should be more likely to invest in the new technology. A number of studies suggest that firms' technology adoption is endogenous and particularly depends on the relative supply of skilled in local markets. Prior empirical evidence supports this idea. For example, Lewis (2011) shows that changes in the regional skill level foster firms' adoption of CNC technology. In our case, firms may produce with older technologies as long as relatively few workers on the market possess CNC skills. Firms may adopt CNC technology if they expect the supply of CNC-skilled workers to increases in the near future.

Finally, CNC skilled workers may directly spread the knowledge about CNC technology across firms. An important argument in the management and personnel economics literature postulates that hiring recent graduates is beneficial for firms if recent graduates are able to bring new skills and ideas from their general education into firms. According to this idea, high-tech industries that undergo rapid technological change should benefit by hiring recent graduates. In our case, CNC-skilled workers may be those who bring CNC technology into firms in the first place. Graduates with CNC skills may, for example, convince employers, who were skeptical about CNC, to implement modern CNC technology.

If the increasing supply of CNC skilled workers either reduces firms' CNC training for incumbent workers and/or directly influence firms' adoption of CNC technology, recent graduates with modern CNC skills become a serious threat for the careers of incumbent workers. Thus increasing adoption of CNC technology lowers the demand for incumbent workers and firms become less willing to train incumbent workers for the use of CNC. This leads to shrinking average wages of incumbent workers. Moreover, those firms should become more likely to reallocate incumbent workers or lay them off entirely. Therefore, incumbent workers should be more likely to switch their occupation or become unemployed if the supply of CNC skilled workers increases.

III. Identification strategy and methods

III.A. The German Apprenticeship Training System

Our identification strategy exploits a unique institutional setting of the German labor market: the apprenticeship training system. The German apprenticeship training system traditionally provides the highest education degree for about two thirds of the German workforce (Harhoff and Kane, 1997; Ryan, 2001). In contrast to other countries, apprenticeship training in Germany is organized as a dual track, which provides formal schooling and on-the-job training alongside. Most apprentices start their training right after high school at the age of 16 and work full-time after finishing their training program such that youth unemployment is very low among the group of apprenticeship graduates.

The training system is highly regulated. The “Vocational Training Act” and occupation-specific training curricula are mandatory for all firms and vocational schools in the country. For each occupation, training curricula precisely define the training content and describe the skills and tasks that have to be learned in each training period. Moreover, independent institutions monitor the apprenticeship training of all German firms and ensure that all firms obey by the training regulations. These independent institutions also administer and carry out the final exams. The training regulations give firms no leeway to design an apprenticeship so that it mostly entails firm-specific skills. Thus apprenticeship graduates in each single occupation acquire the same comparable minimum level of general and occupation-specific skills at the same point in time. Skills and tasks are comparable between firms and transferable and visible by outsider firms. Moreover, apprentices usually start their training at the same point in time and the apprenticeship contract ends at the day after their final exam which is the same day within one occupation and region. Hence, initial conditions and macroeconomic conditions are fixed within each training cohort.

Importantly for our design, training curricula are closely aligned to the technological development because they are defined and can be changed by a board comprised of members from employer associations, trade unions, and the government. The board is interested that young workers acquire up-to-date skills to assure their employability and adequate labor supply for firms. The board decides on new training curricular and changes existing curricular. This process is controlled by governmental institutions. All updated training curricula are published in the Federal Law Gazette (FN mit Internetadresse).

Because of this high level of regulation, which manifests in the mandatory training regulations, the German apprenticeship system provides an ideal setting to identify skills of recent graduates and infer points in time when cohorts of graduates enter the labor market with novel skills. Our paper exploits this particularity to identify a comparative disadvantage of incumbent workers when graduates with CNC skills in a specific occupation of the German manufacturing sector enter the market. We describe the skills of a specific occupation, the machining metal operators, in the next section, as well as the skill changes due to the training curriculum adjustment in response of a fundamental technological innovation. Afterwards we describe the control occupation of metal mechanics and the estimation strategy.

III.B. Treatment group

We exploit a mandatory change in the specific training curriculum of machining metal operators that lead to a supply shock of workers with modern CNC skills in the labor market of machining metal operators.

Machining metal operators are responsible for manufacturing precision parts out of metal billets, such as gearing wheels, screws, or threads. Before the change of their training curricular in 1987, machining metal operators were trained to manufacture these metal parts by using manual machines such as drilling, turning and milling machines. But in 1987, policy makers reformed the apprenticeship training in the manufacturing sector to adjust the training content to meet new technological developments. As part of this reform, they introduced the training of CNC skills in the training curriculum of machining metal operators. Thus all apprentices who started their apprenticeship training according to the new curriculum in 1987 had to become proficient in the use of modern CNC skills in order to obtain their apprenticeship degree 3 ½ years later; regardless of whether their firms actually used CNC technology or not.

Since CNC technology was available before the curriculum changed, a number of firms just used the technology before but many did not. The introduction of CNC technology in several European countries has been described by Backes-Gellner (1996). The first introduction in Germany took place in 1983, but CNC introduction peaked in 1987.

Nonetheless, the new curriculum was not mandatory right from the beginning of 1987. While firms could easily train their apprentices on-the-job to learn the old manual machines, the training of CNC programming skills required more formal training methods. Therefore, firms had to hire professional instructors, sent their trainees to external training centers or larger firms, which could afford to set up their own internal training centers. To facilitate the transition between the old and the new training requirements, policy makers gave firms a grace period until the year of 1989 to adjust their apprenticeship training to the new training requirements. During this period, firms could either organize their own CNC training or arrange for external training institutes to train their apprentices in using the new technologies.

As table 1 shows firms relied heavily on this option. In 1987 only about 55 per cent of all apprentices were trained according to the new curriculum. This number substantially increased to 89 per cent in 1988. In 1989—a year before the new curriculum became mandatory—almost all firms trained their apprentices according to the new curriculum. Of course, CNC technology was available before 1987 and some firms probably trained their apprentices even before the change in the curriculum on CNC. Unfortunately, we can neither observe the use of skills nor the further training activities. But the steep increase in table 1 suggests that many firms did not train CNC before 1987 Moreover, because we know that all apprentices were able to use CNC after the change in the training curriculum, we can estimate a lower bound of the effects of the skill-shock. Prior dissemination rather leads to a downward biased point estimator.

—Table 1 about here—

Finally, the opt-out period leads us to the following definition of cohorts. Apprenticeship entry cohorts before 1987 belong to the incumbent workers that do not learn CNC skills during apprenticeship. The first cohort with CNC skills, the 1987 cohort graduates in 1991. This is the year when the treatment starts. In the following, we will speak about graduation cohorts. Hence, each cohort graduating before 1990 was trained according to the old curriculum. However, we cannot be sure whether graduates of the 1987 cohort learn CNC skills or not but expect changed skills one year later.

III.C Control group

The occupational structure of the metal working industry provides a suitable control group. Metal working firms that employ machining metal operators mostly also train and employ metal mechanics. While machining metal operators produce gear wheels or cranks, metal mechanics assemble these parts to a machine, a gearbox or a motor. Metal mechanics commonly neither used manual drilling machines nor CNC technology. Importantly, the training curriculum of metal mechanics was also updated in 1987 but does not adapt to a fundamental technological innovation.

Apprenticeships for machining metal operators and metal mechanics occupations have the same training duration. Both occupations share the first training year when they learn basic metal working techniques but the curricula separates later. Both occupations are frequently trained in the same training firms and have the same selection criteria. This allows us to control for establishment-level effects, i.e. we compare apprentices in both occupation who are equally treated by the same training center, training instructors, wage setting rules and selection criteria. Moreover, both occupations experience the same macroeconomic shocks because both work in the same firms.

III.D. Difference-in-differences estimation

To isolate the effect of the supply shock from confounding factors such as differences in unobserved ability, unrelated institutional changes, and macroeconomic developments, we use a difference-in-differences approach with a comparable control group of apprentices from the manufacturing occupation of non-machining metal mechanics, who were not affected by a comparable change in their training curriculum.

In more detail, our treatment group consists of 6 graduation cohorts of machining metal operators, who graduated between 1984 and 1989, shortly before CNC was a mandatory part of the apprenticeship training for machining metal operators, i.e. the cohort of 1989 started their apprenticeship training in 1986. We can follow these workers until the year of 2010. Thus we are able to observe the careers of incumbent workers for up to 6 years before the treatment and 19 years after the treatment. Our control group consists of non-machining metal mechanics of the same 6 graduation cohorts between 1984 and 1989. Non-machining metal mechanics commonly assemble machines, but they do not manufacture parts. We specifically restrict our control group to only those machining metal mechanics who were trained in firms in which also members of our treatment group were trained at the same time and vice versa. In other words, we only compare members of the treatment and control group who were trained at the same firms.

Based on this sample, we estimate equations of the following form:

$$lny_{ijt} = \alpha + \beta_1 D_{TG} + \beta_2 D_{t\geq 1991} + \delta D_{TG} \cdot D_{t\geq 1991} + \gamma_t + \theta_j + \epsilon_{ijt} \quad (1)$$

lny_{ijt} represents the log of worker i 's daily earnings at year t. The subscript j denotes the training firm. α is a constant. θ_j and γ_t are training firm and year fixed effects. ϵ_{ijt} is a normally distributed error term. The dummy variable D_{TG} is one if a worker belongs to the treatment group and holds an apprenticeship degree as machining metal operator and zero if the worker belongs to the control group and holds an apprenticeship degree as non-machining metal mechanic. The dummy $D_{t\geq 1991}$ indicates the treatment and is one if the observation year is greater or equal than 1991. The year of 1991 is the year when the first large cohort of machining metal operators with modern CNC skills entered the market, i.e. the year of 1991 indicates the supply shock of workers with modern skills (treatment). We emphasize again that our sample only consists of workers who graduated in the years *before* 1989, because we are interested in analyzing how a shock in the supply of workers with modern skills influences the career path of incumbent workers, who on average have less modern skills. Our coefficient of main interest is δ. The coefficient estimate δ of the interaction term between $D_{t\geq 1991}$ and D_{TG} measures the average treatment effect on the treated (ATT). The treatment is the supply shock of workers with modern skills and the treatment effect indicates how incumbent workers' earnings respond to the supply shock.

The identification of δ requires in particular one critical assumption: workers of the treatment and control group would follow the same trends in the absence of the treatment, i.e. regulatory change in the training curricula.

Although we cannot test this assumption, we can provide evidence to justify the assumption by comparing earnings trajectories of both occupations before the curriculum changed (compare figure 1 und 2 discussed in the findings). Moreover, both occupations are covered by the same collective agreement so that comparable wages and dismissal rules exist. All remaining concerns about the identifying assumption would lead to a bias towards zero. This means that we may estimate an upper bound if we nevertheless identify some patterns.

IV. Data and sample selection

We use a special draw of the German Social Security Records (BEH, Beschäftigtenhistorik Panel). The data extraction was conditioned on individuals with an apprenticeship spell in metal-working occupations between 1983 and 1996. The apprenticeship spell had to last at least for two years. From those individuals, the sample includes an 80 per cent draw of apprentices in the treatment group (machining metal operators) and a 50 per cent sample in the control group (metal mechanics). For each individual, we merge the Unemployment Insurance Records (LEH, Leistungsempfängerhistorik Panel).

For the analysis, we focus on apprentices who graduate between 1984 and 1989, the years before the treatment (change of the training curricula). We do not use apprentices graduating in 1990 because training firms had an opt-out clause and could still follow the old curricula (compare III.B). Moreover, we use only apprentices with employment spells before and after 1991 and do not use those with earnings above or below the Social Security thresholds because these seem to be misreports. Finally, we use only apprenticeship graduates in the treatment occupation for which we find a peer in the control group who graduates in the same establishment and year and vice versa (compare III.C). These definitions reduce our initial sample from 15,641 to 9,075 individuals in the treatment occupation and from 51,979 to 10,846 in the control occupations (compare Table 2).

—Table 2 about here—

We define the graduation cohort as the year of the last apprenticeship training spell. However, reporting the transition from apprenticeship to work was not mandatory in the 1980's and reported apprenticeship termination also accumulates at December 31th in each year. This happens because a number of firms report only once a year to the Social Security Administration; even if the employee works the entire year in the establishment. In these cases, establishments usually report the actual status of an employee (apprentice or skilled worker) at December 31th. Thus we redefine individuals with final apprenticeship spell on December 31th to the graduation cohort of the following year. This misreport leads us further to start our analysis after the first year in employment as a skilled worker. Finally, we use real earnings and adjust the earnings with the consumer price index from the national statistical office.

Table 3 provides descriptive statistics for workers in the treatment and control group before the treatment in 1991. In detail, we calculated averages for the key variables, on a sample of the workers' first observation after the apprenticeship training. The table shows no significant differences between the treatment and control group for daily earnings and age. Although neither the treatment nor the control group contain a large number of women and foreigners, the control group contains slightly fewer females and foreigners than the treatment group, and the differences are significant at reasonable confidence levels.

—Table 3 about here—

V. Results

V.A. Descriptive results

Figure 1a graphically presents the key results of the paper exemplified for the graduation cohort of 1987. The figure follows earnings trajectories of the treatment group (solid line) and the control group (dashed line) from the year of their graduation until the year of 2010. The vertical solid lines mark the market entry of the first large cohort of machining metal operators with CNC programming skills in 1991. Figure 1b presents the results separately for each subfigure each single graduation cohort between 1985 and 1989.

—Figure 1a and 1b about here—

The key identifying assumption of our difference-in-difference approach is that earnings trends of machining metal operators and non-machining metal mechanics would be the same in the absence of the introduction of CNC technology in training curriculum of machining metal operators. Although we cannot test this assumption, we can investigate it's plausibility by analyzing earnings trends for both groups before the treatment occurred. If earnings trends would be parallel before the treatment in 1991, we still could not completely rule out that the identifying assumption is valid. But if wage trends would not even be parallel before the treatment, we should be extremely concerned of whether they would be parallel in the absence of the treatment.

Figure 1a clearly shows that earnings trajectories of machining metal operators (solid lines) and non-machining metal mechanics (dashed lines) were not only parallel, but almost identical before 1991. This result is the same for each of the six graduation cohorts (figure 1b). In contrast, earnings trends diverge substantially after 1991, and the treatment occupation ended up on an inferior earnings path than the control occupation. Therefore, the results suggest that the market entry of CNC-skilled machining metal operators had an adverse effect on the labor market careers of incumbent workers.

Table 4 quantifies the results in more detail and provides average real earnings of the treatment and control occupation before and after the treatment. The first row of table 4 provides average real earnings differences for the overall sample. Individuals in the treatment occupation earn 4.271 log daily earning before the treatment and individuals in the control occupation 4.267 log daily earnings. The difference between both occupation is 0.7 percentage points and insignificant. After the treatment, log daily earning of both occupation increase but the earnings growth is stronger for individuals in the control occupation. The difference in log daily earnings increase to 3.1 percentage points after the treatment and becomes significant. Table 4 rows 2 to 7 present the results separately for each of the six graduation cohorts. We do not find any significant earnings differences before 1991. After 1991 earnings differences range between 6.3 and 1.9 percentage points and are highly significant. Moreover, earnings differences decrease slightly between the graduation cohort of 1984 and 1989.

—Table 4 about here—

If the effect of figure 1 and table 4 is indeed related to the introduction of CNC skills in the curriculum of machining metal operators, we should not find similar effects for graduation cohorts after 1991. Because machining metal workers, who graduated after 1991, have the relevant CNC skills, they should at least be as well of as non-machining metal mechanics. Figure 2 presents earnings trajectories for six graduation cohorts after 1991. The solid lines present again the daily earnings of the treatment occupation and the dashes lines of the control occupation. In contrast to figure 1, figure 2 now shows parallel trends for each graduation cohort after treatment over the entire observation period. Thus the results do not suggest that the effect shown in figure 1 is generic, and thus unrelated to the increased supply of CNC workers in the occupation of machining metal operators. The descriptive findings suggest that the market entry of CNC-skilled machining metal operators had an adverse effect on the labor market careers of incumbent workers.

—Figure 2 about here—

V.B. Regression results: Daily earnings

Table 5 presents the core results of our difference-in-difference approach specifications with the log of real daily earnings as dependent variable. All regressions contain training firm and year fixed-effects, and each regression controls for age, gender, and nationality. Standard errors are clustered at the level of the training establishment.

—Table 5 about here—

Column 1 presents the earnings regression for our entire sample of machining metal operators and non-machining metal mechanics who graduated between 1984 and 1989. The remainder columns show the results separately for each graduation cohort. Before we describe our coefficient estimate of main interest, we briefly discuss the remainder coefficients. As the variable “After 1991” in the first row of table 5 shows, all workers earned on average about 2.3 percentage points more in real earnings during the post-treatment period after 1991 than before. The variable “Machining Occupations” in the second row shows a small and insignificant coefficient estimate which is close to 0, indicating that earnings trajectories between our treatment and control occupation did not differ before the year 1991. The third row “treatment effect” presents the coefficient estimate of main interest. The average treatment effect on the treated (ATT) amounts to 3.3 percentage points and is precisely estimated at the 1 percent level. Thus the results suggest that the earnings growth of our treatment occupation of machining metal operators slowed down after the supply of workers with CNC skills increased in their occupation. The remainder specification in table show average treatment effects per graduation cohort. The treatment effects are between 5.9 and 2 percentage points. The effects become smaller for younger cohorts such as indicated by the descriptive results in the previous section.

The treatment effects are not extremely large, but figure 1 suggests that the effects persist for about 20 years. Table 6 analyses the persistence of the effect in more detail. The estimations in table 6 replace the single interaction term by a set of interaction terms measuring the effect 5, 10 and 20 years after the first cohort of machining metal operators with formal CNC training entered the market. The results show a precisely estimated negative effect for all three interaction terms. The effect increases from 2.9 to 3.6 percentage points in in later years of our observation period. Hence, the earnings disadvantage is not only significant but also long-lasting and can be measured 20 years after the supply shock.

—Table 6 about here—

V.C. Regression results: Occupational changes and unemployment

The increasing supply of machining metal operators with modern CNC skills leads firms to lower earnings trajectories for incumbent workers. If firms adopt modern technologies and/ or reduce their training intensity for incumbent workers, firms should also be more likely to reallocate or dismiss incumbent machining metal operators after the shock in the supply of workers with modern CNC skills increased. Hence, we proceed and analyze whether the curriculum change affects the probability of an occupational change and an unemployment incidence.

The first specification of Table 7 shows regression results for linear probability models with the dependent variable of a dummy that is 1 if the individuals remain in his or her training occupation and 0 otherwise. The control variables are the same as in the previous Tables. The first specification shows that incumbent machining metal operators became about 5.9 percentage points more likely to switch their occupation after the shock in the supply of CNC-skilled machining metal operators. The increasing likelihood to leave the training occupation might be one important driving factor for the lower earnings trajectories.

—Table 7 about here—

Moreover, if the increasing supply of machining metal operators did indeed alter the demand for tasks in the occupation of machining metal operators, the supply shock should only affect incumbent workers' likelihood to change their occupation. In contrast, we should not find that the increasing supply of CNC-skilled workers leads machining metal operators to switch their firms but remain in their occupation. Table 7 specification 2 and 3 investigate this argument more carefully. Specification 2 presents a linear probability model with a dependent variable indicating whether workers remain in their training firm. We do not find any evidence, that the change in the curriculum leads to a change in the probability to switch the training firm. Specification, 3 shows a linear probability model for occupational stayers as in specification 1 but for a subsample of workers who remain in their training firm. This specification shows that workers become more likely to switch their occupation even within their firm. This result indeed suggests that the increasing supply of CNC-skilled machining metal operators changed the demand for skills in that occupation making it more difficult for incumbent workers to remain in their jobs.

Table 8 analyses whether the shock in the supply of CNC-skilled workers increased the likelihood of machining metal operators to become unemployed, the first specification for the entire sample and the second for the occupational movers only. The table shows that incumbent machining metal operators are indeed about 1 percentage point more likely to become unemployed after the supply of CNC-skilled workers increased in their occupation. The effect seems not be particularly large but unemployment is generally very low among machining metal operators. The effect is precisely estimated at the 1 percent level. The supply increase of CNC skilled workers leads to a higher probability to switch the training occupation and to become unemployed. The increasing probability to switch the occupation holds even for employees who stay in their training firm.

—Table 8 about here—

V.D. Regression results: Mechanisms

If the increasing supply of machining metal operators with modern CNC skills stimulates firms' adoption of CNC technologies but reduces the CNC training for incumbent workers, incumbent machining metal workers should either become unable to perform their job and leave their occupation, or learn the relevant skills and manage to remain in their occupation. Therefore, incumbent machining metal operators who stay in their occupation are more likely to learn CNC skills in further training courses and should therefore experience less or no earnings losses. In other words, the negative earnings effect of subsection V.B should largely be related to incumbent machining metal workers who leave their occupations.

Table 9 investigates this idea more closely and analyses earnings regressions as in Table 5 but for several particular sub-samples. The first column replicates the estimation of Table 5 model 1, the earnings regression for the entire sample. The second column presents results for a subsample of incumbent workers who switch their occupation at some instant. In contrast the third column presents results for a subsample of workers, who work in their occupation in 2010. We indeed find a larger negative effect of 4.1 percentage points for those machining metal operators who leave their occupation (model 2). In contrast, we even find a positive significant effect for those machining metal workers who never leave their occupation and may have learned the CNC skills in further training courses (model 3).

—Table 9 about here—

V.E. Regression results: Robustness checks

We test the robustness of our results regarding ability upgrading in the occupation of machining metal operators after the change in the curriculum.

First, the new cohorts of machining metal operators may be a better selected group and, therefore, of higher ability than incumbent workers of older cohorts. In this case, firms may simply decide to replace incumbent workers with lower abilities by recent graduates with higher abilities. Of course, we cannot observe a worker's ability, but if firms selectively dismiss incumbent workers' with low abilities, we should find wages of movers to be lower before they move. The first column of table 10 shows a specification for which we restricted our sample to observations of movers before they actually move. We cannot find evidence that movers have lower wages even before they move.

—Table 10 about here—

Second, we test whether the treatment effect may be rather related to the mobility of incumbent workers from the control group of non-machining metal mechanics than to the mobility of the treatment group of machining metal operators. To check for this possibility, the second specification of table shows results for which we compare stayers of the treatment group to movers of the control group, while the third specification compares stayers of the control group to movers of the treatment group. As expected, we find no significant effect for the second but a significant negative effect for the third specification.

Third, we include also those individuals of the treatment occupation in the sample who do not have a peer in the control occupation and vice versa. This increases the number of observation for the costs that we are now unable to include training establishment fixed effects. This test provides the last specification of table 10. The results remain qualitatively the same.

Conclusion

The present paper exploits a quasi-experimental setting to analyze how young incumbent workers' careers respond to a supply shock of fresh graduates with modern IT skills during a period of fundamental technological progress. The papers shows that incumbent workers experience long lasting earning losses, and they are more likely to leave their training occupations and become unemployed after the supply of modern-skilled fresh graduates increased. Therefore, the paper provides causal evidence that even young workers incur substantial adjustment cost if groundbreaking new technologies change the demand for skills.

The paper contributes on the literature on the "skill-biased-technological change" by providing micro-evidence on the long lasting impacts of fundamental technological innovation. Moreover, the results point to important implications for policy makers who wish to update and maintain the skill level of their countries' workforce.

References

Acenoglu D (1998). Why do New Technologies Complement Skills? Direct Technical Change and Wage Inequality, *in Quarterly Journal of Economics 113*: 1055-1089.

Acemoglu D and Pischke J-S (1998). Why Do Firms Train? Theory and Evidence, *in Quarterly Journal of Economics 113*: 79-119.

Acenoglu D (1999). Changes in Unemployment and Wage Inequality: An Alternative Theory and Some Evidence, *in American Economic Review 89(5)*:1259-1278.

Acemoglu D (2002). Technical Change, Inequality, and the Labor Market, *in Journal of Economic Literature 40*: 7-72.

Acemoglu D (2003). Cross-Country inequality trends, *in Economic Journal 113*: F121-49.

Acemoglu D. and Finkelstein A (2008). Input and Technology Choices in Regulated Industries: Evidence from the Health Care Sector, *in Journal of Political Economy, 116(5):* 837-880.

Acemoglu D and Autor D (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings, *in Handbook of Labor Economics 4B*: 1043-1171.

Autor DH, Katz LF and Krueger AB (1998). Computing Inequality: Have Computers Changed the Labor Market?, *in Quarterly Journal of Economics 113*: 1169-1213.

Autor DH, Levy F and Murnane RJ (2003). The skill content of recent technological change: an empirical exploration, *in Quarterly Journal of Economics 118 (4)*: 1279-1333.

Autor DH, Katz LF and Kearney MS (2008). Trends in US wage inequality: re-assessing the revisionists, *in Review of Economics and Statistics 90(2):* 300–323.

Autor DH, Handel M (2009). Putting tasks to the test: human capital, job tasks and wages, NBER working paper No. 15116.

Autor DH and Dorn D (2009). The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market, NBER working paper 15150.

Aubert P, Caroli E and Roger M (2006): New technologies, organisation and age: firm-level evidence*, *in The Economic Journal 116(509):* F73-F93.

Ben-Porath Y (1967). The Production of Human Capital and the Life Cycle of Earnings*, in Journal of Political Economy 75:* 352-365.

Bartel A, Ichniowski C and Shaw K (2007). How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills. *in The Quarterly Journal of Economics* 122(4): 1721-1758.

Brynjolfsson E and Hitt L (2003): Computing productivity: Firm-level evidence, *in Review of economics and statistics 85(4):* 793-808.

Card, D and DiNardo J (2002). Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles, *in Journal of Labor Economics 20(4*)

Card D, Heining J and Kline P (2012): Workplace Heterogeneity and the Rise of West German Wage Inequality, NBER working paper 18522.

Caselli F (1999). Technological Revolutions, *in American Economic Review 89(1)*: 78-102.

DiNardo, J and Pischke J (1997). The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure Too?, *in The Quarterly Journal of Economics 112(1):* 291-303.

Dunne T and Schmitz JA (1995). Wages, Employment Structure and Employer Size-Wage Premia: Their Relationship to Advanced-technology Usage at US Manufacturing Establishments, *in Economica 62*: 89-107.

Dustmann C, Ludsteck J and Schönberg U (2009). Revisiting the German wage structure, *in Quarterly Journal of Economics 124 (2)*, 843–881.

Franz W and Soskice D (1995). The German Apprenticeship System, in Buttler F, Franz W, Schettkat R and Soskice D (Eds.), *Institutional Frameworks and Labor Market Performance: Comparative Views on the U.S. and German Economies* (pp. 208-234). London: Routledge.

Fitzenberger B and Kohn K (2006). Skill wage premia, employment, and cohort effects: are workers in Germany all of the same type?, ZEW discussion paper.

Galor O and Moav O (2000). Ability-Biased Technological Transition, Wages and Economic Growth, *in Quarterly Journal of Economics 115*: 469-497.

Goos M, Manning A. and Salomons A. (2009). The polarization of the European labor market, *in American Economic Review Papers and Proceedings 99(2)*: 58-63.

Gordon RJ (1990). The Measurement of Durable Good Prices, NBER Monograph Series (Chicago: University of Chicago Press, 1990

Harhoff D and Kane TJ (1997). Is the German apprenticeship system a panacea for the U. S. labor market?, in Journal of Population Economics 10:171–196.

Katz L and Autor D (1999). Changes in the wage structure and earnings inequality, in Ashenfelder O. and Card D (Eds.) *Handbook if Labor Economics Vol 3* (Chap. 26: 1463-1455). Elsevier, Amsterdam.

Kiley MT (1999). The Supply of Skilled Labour and Skill-Based Technological Progress*, in Economic Journal 109:* 708-724.

Krugman P (1995). Growing World Trade: Caises and Consequences, *in Brooking Papers and Economic Activity 1995:* 327-362.

Laing D, Palivos T and Wang P (2003). The economics of 'new blood', *in Journal of Economic Theory 112*: 106–156

Lewis E (2011). Immigration, Skill Mix, and Capital Skill Complementarity, *in Quarterly Journal of Economics* 126(): 1029-1069.

Lindbeck A and Snower DJ (2001). Insiders vs. Outsiders, *in Journal of Economic Perspectives 15* 165-188.

Ludwig V and Pfeiffer F (2006). Depreciation Rates of General ad Vocational Training Capital – Evidence Based on Subjective Ratings, *in Journal of Economics and Statistics 226*: 260-284.

Machin, S and Manning A (1997): Can supply create its own demand? Implications for rising skill differentials, *in European Economic Review 41(3)*: 507-516.

Machin S and van Reenen J (1998). Technology and changes in Skill Structure: Evidence from seven Countries, *in Quarterly Journal of Economics 113 (4):* 1215-1244.

Manning A (2004). We can work it out: the impact of technological change on the demand for low-skill workers, *in Scottish Journal of Political Economy 51(5)*, 581–608.

Mohrenweiser J, Zwick T and Backes-Gellner U (2011). Poaching and Firm-Sponsored Training: First Clean Evidence, *in Economic of Education working paper No. 51*.

Mortensen DT and Pissarides CA (1999). Unemployment Responses to Skill-Biased Technology Shocks: The role of Labour Market Policy, *in Economic Journal 109 (455):* 242-265.

Neuman S and Weiss A (1995): On the effects of schooling vintage on experience-earnings profiles: theory and evidence. *in European economic review 39(5)* : 943-955.

Rosen R (1975). Measuring the Obsolescence of Knowledge, in Juster FT (Ed.) *Education, Income and Human Behaviour*, NBER: 199-232.

Ryan P (2001). The School-to-Work Transition: A Cross-National Perspective, *in Journal of Economic Literature 39*: 34-92.

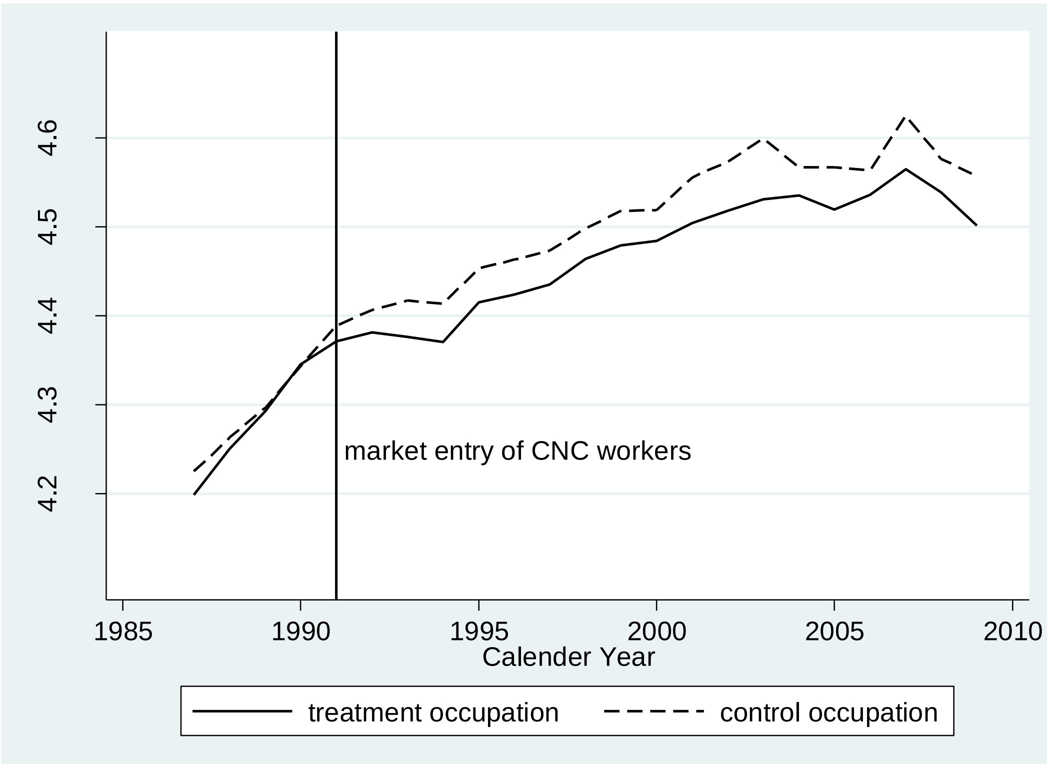
Spitz-Oener A. (2006). Technical Change, Job Tasks and Rising Educational Demands: Looking Outside the Wage Structure, *in Journal of Labor Economics 24*, 235-270.

Violente G (2002). Technological Acceleration, Skill Transferability, and the Rise in Residual Inequality, *in Quarterly Journal of Economics 117(1)*: 297-338.

Weiss M. and Garloff A. (2011): Skill-biased technological change and endogenous benefits: the dynamics of unemployment and wage inequality, *in Applied Economics, 43:* 811-821.

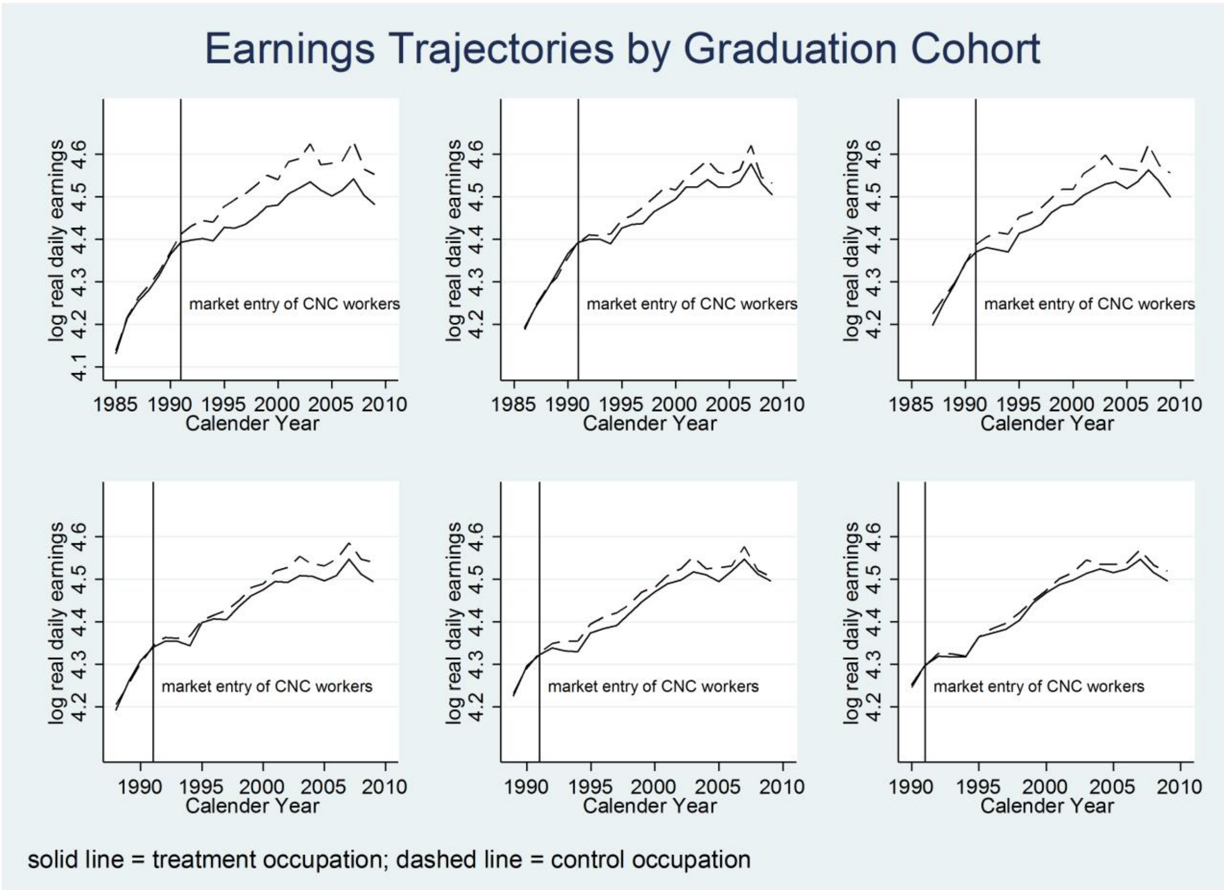
Wälde K (2000). Egalitarian and elitist education systems as the basis for international differences in wage inequality, in European Journal of Political Economy 16: 445–468.

Figure 1a: Earnings trajectories of treatment and control occupations: 1987 cohort before treatment



(1987) N = 58150

Figure 1b: Earnings trajectories of treatment and control occupations: all cohorts before treatment



N = 76,548 (1984); N = 67,132 (1985); N = 61,979 (1986); N = 60705 (1987) N = 58150 (1988); N = 55,230 (1989); Source BEH 1984-2010

Figure 2: Earnings trajectories of treatment and control occupations: all cohorts after treatment

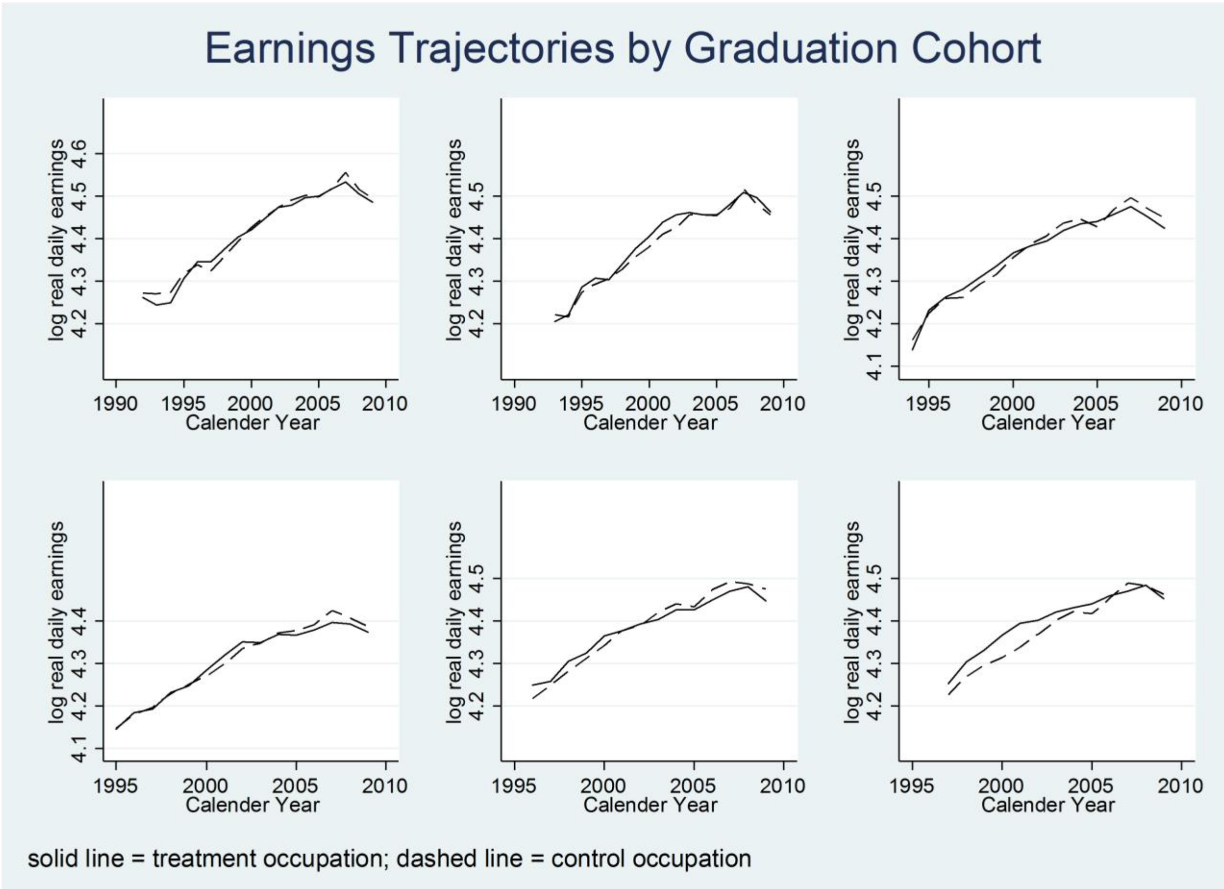


Table 1: Apprenticeship training during the grace period (1987-1989)

	Training curricula	
	without CNC (old)	With CNC (new)
1987	55 %	45 %
1988	11%	89%
1989	5%	95%

Percentage of apprentices trained according to the old/new training scheme during the grace period.

Table 2: Sample selection

	Treatment Group machining metal operators		Control Group non-machining metal mechanics	
	80% sample	Estimation sample	50% sample	Estimation sample
1984	2,617	1,654	7,912	2,001
1985	2,472	1,504	8,155	1,804
1986	2,410	1,452	8,855	1,741
1987	2,548	1,484	9,050	1,777
1988	2,629	1,454	8,989	1,807
1989	2,965	1,526	9,018	1,716
Total	**15,641**	**9,075**	**51,979**	**10,846**

Source: BEH 1984-2010.

Table 3: Differences between treatment and control occupation

Variable	Treatment occupation (machining metal operators)	Control occupation (metal mechanics)
Log daily earnings	4.191	4.203
Female	0.046	0.014
Foreigner	0.089	0.064
Age	21.97	22.52
Observations	9.075	10.846

Only the first observation per individual after graduation before treatment; Source BEH 1984-2010.

Table 4: Descriptive log earnings differences between treatment and control occupation by cohort

	Before 1991		After 1991		First Difference	
	Treatment occupation	Control occupation	Treatment occupation	Control occupation	Before 1991	After 1991
Overall	4.271	4.267	4.461	4.492	0.007	-0.031
By cohort						
1984	4.263	4.273	4.469	4.532	-0.010	-0.063
1985	4.280	4.279	4.480	4.506	0.001	-0.026
1986	4.272	4.284	4.471	4.513	-0.012	-0.042
1987	4.254	4.254	4.452	4.476	0.000	-0.024
1988	4.259	4.261	4.446	4.465	-0.002	-0.019
1989	4.252	4.245	4.443	4.464	0.007	-0.021

All individual/ year observations; Source BEH 1984-2010.

Table 5: Impact of supply increase on earnings: cohort effects and yearly regressions

	All	1984	1985	1986	1987	1988	1989
After 1991	0.229*** (0.009)	0.357*** (0.076)	0.411*** (0.079)	0.129*** (0.011)	0.118*** (0.012)	0.291*** (0.065)	0.084*** (0.009)
Machining occupations	-0.001 (0.004)	-0.004 (0.007)	0.003 (0.007)	-0.005 (0.008)	-0.004 (0.007)	-0.003 (0.007)	0.005 (0.007)
Treatment Effect	**-0.033*** (0.004)**	**-0.059*** (0.008)**	**-0.031*** (0.007)**	**-0.036*** (0.007)**	**-0.028*** (0.008)**	**-0.020** (0.008)**	**-0.022** (0.008)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.275	0.331	0.311	0.309	0.307	0.317	0.323
Number of observations	379,717	76,548	67,132	61,979	60,705	58,150	55,203

Dependent variable log daily earnings, OLS regressions with standard errors clustered on training establishment level, standard errors in parenthesis; Control variables: age, female, foreigner, training establishment fixed effects, year fixed effects; * p < 0.1; ** p >0.05; *** p < 0.01; Source: BEH 1984-2010.

Table 6: Long-lasting effects on earnings and probability to stay in the occupation.

	Earnings
Treatment 91-95	-0.020*** (0.003)
Treatment 96-00	-0.029*** (0.004)
Treatment 01-05	-0.037*** (0.005)
Treatment 06-10	-0.036*** (0.005)
Controls	Yes
R-square	0.255
Number of observations	379,717

Dependent variable log daily earnings (Column 2) and Dummy equals 1 if the observation is a respective stayer (Column 3), OLS regressions with standard errors clustered on training establishment level, standard errors in parenthesis; Control variables: age, female, foreigner, training establishment fixed effects, year fixed effects; # measured as occupational stayer/ mover in 2010; * p < 0.1; ** p >0.05; *** p < 0.01; Source: BEH 1984-2010.

Table 7: Impact of supply increase on mobility

	Occupational Stayer	Establishment Stayer	Occupational stayer within establishment
After 1991	0.153*** (0.051)	-0.225*** (0.045)	0.222*** (0.088)
Machining occupations	0.138*** (0.014)	0.006 (0.011)	0.152**** (0.022)
Treatment Effect	**-0.059*** (0.010)**	**-0.002 (0.012)**	**-0.034** (0.016)**
Controls	Yes	Yes	Yes
R-square	0.155	0.404	0.281
Number of observations	379,717	379,717	140,894

Dependent variable: Dummy equals 1 if the observation is a respective stayer, OLS regressions with standard errors clustered on training establishment level, Control variables: age, female, foreigner, training establishment fixed effects, year fixed effects; * p < 0.1; ** p >0.05; *** p < 0.01; Source: BEH 1984-2010.

Table 8: Impact on supply increase on unemployment incidence

	Unemployment incidence	
	Mover and Stayer	Mover only
After 1991	0.083*** (0.010)	0.137*** (0.009)
Machining occupations	-0.0028* (0.002)	-0.001 (0.002)
Treatment Effect	**0.007*** (0.004)**	**0.009*** (0.002)**
Controls	Yes	Yes
R-square	0.044	0.049
Number of observations	409,057	356,597

Dependent variable Dummy variable equals one if the observation is unemployed and zero otherwise (Column 2 and 3); uninterrupted days in one unemployment spell (Column 3 and 4); OLS estimation with standard errors clustered on training establishment level, Control variables: age, female, foreigner, training firm fixed effect, year fixed effect; * p < 0.1; ** p >0.05; *** p < 0.01; Source: BEH 1984-2010.

Table 9: Impact of supply increase on log earnings

	Mover only[#]	Stayer only[#]	Mover within establishments	Firm switch within occupations
After 1991	0.248*** (0.021)	0.260*** (0.035)	0.242*** (0.018)	0.272*** (0.019)
Machining occupations	0.001 (0.004)	-0.011 (0.008)	0.005 (0.005)	0.006 (0.006)
Treatment Effect	**-0.041*** (0.004)**	**0.021*** (0.006)**	**-0.0143*** (0.007)**	**-0.001 (0.004)**
Controls	Yes	Yes	Yes	Yes
R-square	0.269	0.530	0.607	0.424
Number of observations	328,731	50,986	140,894	167,014

Dependent variable log daily earnings, OLS regressions with standard errors clustered on training establishment level, standard errors in parenthesis; Control variables: age, female, foreigner, training establishment fixed effects, year fixed effects; [#] measured as occupational stayer/ mover in 2010; * p < 0.1; ** p >0.05; *** p < 0.01; Source: BEH 1984-2010.

Table 10: Robustness checks: Movers before they move, Do movers of the control group drive the results, Relax training firm composition

	(1)	(2)	(3)	(4)
After 1991	0.179*** (0.031)	0.282*** (0.029)	0.191*** (0.023)	0.219*** (0.012)
Machining occupations	0.014*** (0.005)	-0.047*** (0.007)	0.046*** (0.006)	-0.001 (0.003)
Treatment Effect	-0.003 (0.006)	-0.004 (0.006)	-0.016*** (0.006)	-0.030*** (0.003)
Controls	Yes	Yes	Yes	Yes
R-square	0.465	0.291	0.306	0.347
Number of observations	56,476	165,728	213,989	1,152,360

Dependent variable log daily earnings, OLS regressions with standard errors clustered on training establishment level, standard errors in parenthesis; Restrictions: (1) follows all moving individuals until they move the occupation; (2) compares those staying in the treatment occupation in 2010 with those who move out of the control occupation (3) compares those who move out of the treatment occupation with those who stay in the control occupation until 2010; (4) relaxes condition that two apprentices have to graduate from the same training establishment (or uses the complete sample shown in Table 1); Control variables: age, female, foreigner, training establishment fixed effects, year fixed effects; * p < 0.1; ** p >0.05; *** p < 0.01; Source: BEH 1984-2010.