The Shelf-life of Incumbent Workers in Times of Accelerating Technological Change: Evidence from a Reform of a Mandatory Training Regulation.

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Preliminary version.

Abstract:

In periods of accelerating technological change, incumbent workers must steadily update their skills to remain productive. In contrast, young graduates who just entered the labor market often acquired modern skills in school or university. We investigate how incumbent workers' careers respond to an increasing labor supply of graduates with modern IT skills during a period of accelerating technological change. We identify a supply shock of IT-skilled graduates by exploiting a reform of a mandatory training regulation that obligated all new apprentices in a large German manufacturing occupation to acquire in-depth IT skills. We use a difference-in-differences approach to analyze how this supply shock of IT-skills affected the careers of incumbent workers. The results show that even young incumbents experienced long-lasting earnings losses in form of lower wage growth after the IT-skilled graduates entered the labor market. Detailed analyses of the mechanisms reveal that IT-skilled graduates crowded incumbent workers out of their occupation, and suggest that incumbents forwent promotions in favor for IT-skilled graduates. However, incumbents experienced only little unemployment during a transition period after the supply shock and mostly resumed a stable career in other occupations and sectors.

Keywords: skill-biased technological change, wage adjustments, supply shock, apprenticeship
JEL codes: J24, J64, O30

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I. INTRODUCTION

Changing technologies have a substantial impact on labor markets (e.g., Acemoglu, 2015; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2016; Acemoglu and Restrepo, 2017; Michaels *et al.*, 2014), because they change the demand for skills (e.g., Autor, 2013; Autor *et al.*, 2003; Goos and Manning, 2007; Goos *et al.*, 2014; Michaels *et al.*, 2014; Spitz-Oener, 2006).[1] As a result of new emerging technologies, such as cyber-physical systems and artificial intelligence, a public debate has evolved about the importance of live-long learning to ensure that employees can maintain and update their skills. For example, Randell Stephenson, CEO at AT&T, has argued that workers who do not spend five to ten hours a week in online learning will become obsolete with technology (NYT, Feb. 13, 2016).[2] Yet, incumbent workers incur high opportunity costs for continuously updating their skills—specifically, those who work full-time and have a high earnings capacity.[3] In contrast, students can undertake large human capital investments at low opportunity costs, and they learn how to handle new technologies in school or university. Thus, incumbent workers may have a disadvantage relative to recent graduates when new technologies fundamentally change the demand for skills, and this disadvantage may manifest in negative long-term consequences for their careers.

However, micro evidence on the long-term dynamics of workers' careers during periods of fundamental technological change is surprisingly scarce. While the general relationship between job tasks, workers' skills, and changes in employment stocks and the wage distribution is relatively well understood,[4] only two recent papers have analyzed the relationship between changing technologies and workers' careers. First, Cortes (2016) who has studied the relationship between routine-biased technological change and individual workers' wages and employment Second, El-Sahli and Upward (2017) who analyzed how the technology of containerization affected the employment patterns of UK dockworkers. Most other studies have analyzed repeated cross sections of aggregated measures to provide macroeconomic evidence on the effects of technological change on labor markets.

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[1] See Akerman *et al.* (2015), Autor *et al.* (2002), Brynjolfsson and Hitt (2000), Brynjolfsson and Hitt (2003), Bresnahan *et al.* (2007), Doms *et al.* (1997) and Caroli and Van Reenen (2001) for evidence on the firm level. Chin *et al.* (2006) and Hynninen *et al.* (2013) provide historical evidence from the introduction of steam engines.

[2] Also a number of scientific studies have shown that firms invest more in training of their workers after they have adopted new technologies (Bresnahan *et al.*, 2007; Sieben *et al.*, 2009).

[3] This argument follows simple human capital theory (Becker, 1962). Indeed, already Mincer (1974) argued that incumbent workers' opportunity costs increase to a point at which they have no incentives to undertake human capital investments that are large enough to compensate the depreciation of their existing human capital. Moreover, incumbent workers are more likely to have families, such that they have to devote more time to home production.

[4] For example, Autor (2015), Acemoglu and Autor (2011), Autor *et al.* (2008), Autor *et al.* (1998), Acemoglu (2002), Acemoglu (1998), Dustmann *et al.* (2009).

Therefore, this study contributes to the literature by analyzing whether and how incumbent workers responded to the market entry of graduates whose modern IT skills complement a fundamental technological innovation that substantially changed the demand for skills in the manufacturing sector. Our study is unique for at least two reasons. First, we use a quasi-experimental setting that exploits a large training reform that led to a shock in the relative supply of graduates with modern IT skills in the German labor market. Second, we provide micro evidence on workers' careers by using highly precise register data that allows us to follow the careers of incumbent workers for more than 25 years.

The labor supply of graduates with modern IT skills may influence the careers of incumbent workers through at least three channels: First, incumbent workers may have to compete with modern-skilled graduates in internal labor markets, such that they forgo promotions during early stages of their careers. Second, firms may become less likely to (financially) support the training of incumbent workers if the external supply of modern skills rises, such that hiring modern-skilled workers becomes cheaper than training incumbent ones.[5] Third, the increasing supply of modern skills may directly impact firms' decision to adopt modern technologies. As the theory of endogenous technological change implies, firms become more likely to adopt modern technologies if workers whose skills complement the new technology are cheap and available. As a result, the supply of modern-skilled graduates may create its own demand at the expense of the demand for incumbent workers with outdated skills (e.g., Acemoglu, 1998; Beaudry *et al.*, 2010; Caselli and Coleman II, 2001; Lewis, 2011; Machin and Manning, 1997).

This paper analyzes how the careers of incumbent workers respond to the increasing supply of graduates with modern IT skills. Therefore, we exploit a reform of a mandatory apprenticeship training regulation for a large manufacturing occupation in Germany that led to a substantial shock in the relative supply of graduates with modern IT skills. We analyze the response of incumbent workers' careers to this supply shock by using a difference-in-differences approach with a comparison group of incumbent manufacturing workers from an unaffected occupation. As workers of both occupations had a similar level of general education, were trained in the same firms, and were exposed to the same institutions, we can isolate the causal effect from influences of unrelated institutional changes, and macroeconomic developments.

[5] Some studies have shown that firms that adopt new technologies hire more skilled workers, others show that they become more likely to train their incumbent workers (e.g., Akerman *et al.*, 2015; Bartel and Sicherman, 1998; Bresnahan *et al.*, 2007; Brynjolfsson and Hitt, 2000; Brynjolfsson and Hitt, 2003; Sieben *et al.*, 2009).

In contrast to other countries, apprenticeship training is the main school-to-work route in Germany, and about two thirds of the German workforce has been participating in apprenticeship training. Apprenticeship graduates are skilled workers who are comparable to U.S. workers with a medium level of college education, because apprenticeship training programs last between three and three and a half years. Apprenticeship training is regulated at the federal level and mandatory training curricula define the skills that have to be trained for more than 350 training occupations. Independent institutions monitor apprenticeship training programs and carry out occupation-specific final exams to enforce these curricula (Acemoglu and Pischke, 1998; Dustmann and Meghir, 2005; Dustmann and Schönberg, 2009; Harhoff and Kane, 1997; Ryan, 2001). Thus, all apprentices, who successfully graduate from their training program, possess at least the skills that are required by their current training regulation. As a result, we can use reforms of training curricula to infer when entire cohorts of graduates enter the labor market with fundamentally new skills. We exploit this unique feature to analyze how the careers of incumbent workers, who have been trained *before* the reform, respond to the reform-induced supply shock of workers who possess modern IT-skills, because they have been trained after the reform.[6]

We analyze a particular reform in the occupation of machining metal operators. Machining metal operators produce metal parts, such as precision parts for cars and heavy machinery. Given the occupation's technological content, the relatively good pay, and the long-term employment perspectives in Germany, many young men with a medium level of general education chose to become machining metal operators. Until the mid-1980's machining metal operators performed processes such as drilling, turning, and milling on several specific manual machines. In the mid 1980's computer numerical control machines (CNC), a groundbreaking new technology, spread across the industry (see Figure 1). CNC technology integrated most manual machining processes in one machine that workers control via a computer system. Therefore, CNC machines have substantially changed the nature of work and the necessary skills in the occupation (Bartel *et al.*, 2007; Lewis, 2011).

—Figure 1 about here—

In the late 1980's, policy makers have reformed the training curriculum of machining metal operators in response to the invention of CNC technology. Until then, machining metal

[6] We emphasize here that we do *not* compare those who have been trained before the reform with those who have been trained after the reform. Instead, our interest is to understand how incumbent workers respond to the increasing competition of modern-skilled workers.

operators were required to learn how to use one of the traditional manual machines during apprenticeship training. After the reform, all machining metal operators in the entire country had to learn in-depth CNC skills in a structured and elaborated training program, which often took place in specialized training centers. The training program provided very sophisticated CNC skills, such as coding and debugging CNC programs. Of course, CNC technology was already available before the reform, but the reform accelerated the supply of workers with sophisticated CNC skills within a very narrow window of time. In contrast, apprentices who have graduated before the reform did not receive extensive CNC training as mandatory element of their apprenticeship training, such that these incumbent workers were, on average, less proficient in the use of CNC technology than apprentices who graduated after the reform.

We analyze how the careers' of incumbent machining metal operators[7] *without* modern CNC skills responded to the increasing supply of CNC-trained graduates by identifying the effect of the reform-induced supply shock in a difference-in-differences approach. More specifically, the reform-induced supply shock of CNC-skilled apprenticeship graduates is the treatment. The treatment group consists of incumbent machining metal operators who graduated shortly before the reform and, therefore, did not receive CNC training as mandatory element of their apprenticeship training.

The comparison group consist of incumbent workers from a similar occupation that was not exposed to groundbreaking technological innovation leading to a reform-induced supply shock of graduates with modern IT-skills. More specifically, the comparison group consists of incumbent *non-machining* metal mechanics from the same graduation cohorts as our treatment group. In contrast to machining metal operators, non-machining metal mechanics assemble parts and do not use CNC technology. Otherwise, non-machining metal mechanics are very similar to machining metal operators, because both groups have learned and worked in the same firms, produced similar final goods, and were represented by the same unions. As a result, both groups were exposed to exactly the same labor market institutions, macroeconomic conditions, and employers applied similar selection criteria to hire them.

Our analyses relies on register data from the Federal Employment Agency of Germany that allows us to follow our treatment and comparison group for more than 25 years, i.e., before and after the supply shock. The data contains highly accurate information about workers' wages, employment status, and common demographic characteristics, such as age, nationality, and education. Moreover, the data allows us to link the worker to the firm, such that we can

[7] In the following, the term „incumbent workers" always refers to worker who graduated before the apprenticeship training reform and did not receive CNC training as mandatory element of their apprenticeship training.

account for unobserved heterogeneity of the training quality by matching workers from the treatment and comparison group who have been trained in the same firms at the same time.

Our results show that incumbent workers experienced long-lasting earning losses in response to the market entry of graduates with modern CNC skills. Over the observation period of more than 25 years, total earnings losses amounted to about 70% of an average workers' annual pre-treatment earnings. Earnings losses were largely related to reduced real daily wage growth. In contrast, we found only small effects on the extensive margin. On average, incumbent workers have only experienced transitory unemployment during a short period immediately after the market entry of CNC-skilled graduates and resumed a stable employment path in the long run.

A detailed analysis of the mechanisms suggests that incumbent workers forwent crucial promotions in favor for the modern-skilled graduates, i.e., their lower wage growth appears to be partly the consequence of a less favorable career path within firms. Moreover, incumbent workers have adjusted to the competition of CNC-skilled graduates by switching to other occupations, even within firms.

In line with existing evidence on job polarization, we find that incumbent machining metal operators became significantly less likely to remain in the metal working sector and significantly more likely to enter the service sector, particularly, low-wage service jobs. However, in contrast to evidence from the U.S., our results suggest that many incumbent workers remained in the metal working sector. One potential reason is that employment in German manufacturing has evolved more stable than the employment in U.S. manufacturing as a result of the East-European trade integration (Dauth *et al.*, 2014). Thus, affected workers potentially had more opportunities to remain in the sector than in U.S. workers.

In the most general sense, we provide causal micro-evidence for a long-term adjustment process of labor markets to the consequences of technological change. Thus, our results contribute to at least four strands of literature. First, previous studies showed that the adverse consequences of routine-biased technological change were most substantial for medium-educated workers, in particular, for medium-educated production workers (Goos *et al.*, 2014). Our paper supports these findings and, additionally, shows that wage losses persist over workers' entire careers. However, our evidence also shows that workers adjust to the consequences of technological change, for example, by switching to other occupations and sectors. This result is consistent with recent studies suggesting that occupational mobility contributes to changes in the wage structure (e.g., Kambourov and Manovskii, 2009) and with empirical finding suggesting that the decline of employment in technology-intensive sectors is offset by an increase of employment in other sectors, such as the service sector (e.g., Gregory *et al.*, 2016).

Second, quasi-experiments are hard to find, and only few data sources provide micro-level information about workers' careers, their skills, and the changing nature of individual jobs. Therefore, most existing studies had to rely on aggregate measures that only allow to infer time-trends of descriptive associations between changes in the content of job tasks, computer usage, employment, and wage rates. But as these descriptive associations often do not allow to infer precise mechanisms, a number of researchers have criticized that they merely reflect other institutional and macroeconomic changes and cannot necessarily be interpreted as evidence for skill-biased technological change (Card and DiNardo (2002); DiNardo and Pischke (1997)). Our design allows us to identify a change in the supply of modern IT skills for a narrowly defined treatment occupation in response to a fundamental technological innovation. Thus, we are able to provide micro-level evidence on a specific mechanism that accounts for the relationship between technological change and changes wage and employment structure.

Third, we complement a number of studies that have argued that human capital depreciates with technological change. For example, a number of older studies have associated u-shaped wage profiles with depreciating human capital (Ben-Porath (1967); Neuman and Weiss, 1995). Others analyzed whether older workers decide to retire early, after firms have implemented modern computer technology (Aubert *et al.*, 2006). Yet others have argued that workers of different age groups are imperfect substitutes, because their human capital is specific to different vintages of technology[8] to explain occupational mobility, college wage premiums, and changes in the wage structure (Bowlus and Robinson, 2012; Card and Lemieux, 2001; Violante, 2002). Our results contribute to that literature, because we identify such vintage effects in a clean setting. Moreover, we show that human capital depreciation may even affect relatively young workers with substantial long-term consequences for their careers.

Fourth, while most existing studies have analyzed effects of labor market programs, training and schooling reforms for those who benefit from the programs and reforms (Harmon and Walker, 1995; Heckman *et al.*, 1999; Pischke and von Wachter, 2008), some recent papers have highlighted important displacement effects for those who did not benefit from the labor market programs (Crépon *et al.*, 2013). Our study shows the long-term consequences from such displacement effect.

[8] Neuman and Weiss (1995) and Weiss and Lillard (1978) have used the term vintage human capital to explain cross-sectional wage patterns as a consequence of technological change.

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

II. CNC TECHNOLOGY AND TRAINING IN THE MANUFACTURING SECTOR

This chapter describes the role of the CNC technology in the German manufacturing sector and the institutional background in more detail. The first subsection describes how CNC technology has influenced the nature of work in the manufacturing sector. The second subsection presents the German apprenticeship system.

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

CNC technology is a very distinct example of a skill-biasing technology that revolutionized the manufacturing industry; particularly, machining metalworking processes. Although CNC technology was invented in the 1970s, the technology became a common standard in Germany between the late 1980s and early 1990s (Backes-Gellner, 1996). Before the age of CNC machines, specialized workers had to perform machining processes, such as milling, turning, and drilling on separate manual machines. In contrast, CNC machines are able to run several machining processes by integrating the manual machines into one single 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 different manufacturing processes simultaneously. CNC technology increased the demand for computer, programing, and problem solving skills (Bartel et al., 2007) and is a strong complement to medium and high skills (Lewis, 2011).

Until the late 1990’s, programming and trouble-shooting CNC machines was very complex, and CNC operators needed sophisticated skills to write, edit, and debug CNC programs. During this period, even slight mistakes in complex CNC programs could cause substantial interruption in the production process and even damage the CNC machines. Thus, the reform of the training curriculum occurred in a period when sophisticated knowledge about CNC machines became more important to guarantee a smooth and fast production process. Afterwards, in the late 1990’s and early 2000’s, advances in software, fusion control technologies, and three dimensional computer aided designs (3D CAD) made CNC programming more conversational and more simple to complete and execute.

II.B. 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 vocational education and training for about two thirds of the German workforce (Harhoff and Kane, 1997; Ryan, 2001). In contrast to many other countries, apprenticeships in Germany are organized as dual tracks that simultaneously provide formal schooling at state funded vocational schools and extensive on-the-job training in firms. The typical apprenticeship training program lasts three or three and half years, and apprentices are commonly school-leavers in their late teens who directly apply for an apprenticeship in training firms. Firms are free to decide whether and how many apprentices to train if they fulfill the training requirements stated in the Vocational Training Act.

Each training occupation has a specific training curriculum that precisely defines the training content for each training year, and independent institutions monitor apprenticeship training and administer and carry out final exams, such that all firms have to comply with the training regulations. Thus, firms have no leeway to design their apprenticeship training in a way that it mostly contains firm-specific skills. As a result, apprenticeship graduates in each occupation acquire a comparable level of general and occupation-specific skills that are visible to all firms in the market (Dustmann and Meghir, 2005; Dustmann and Schönberg, 2009; Mohrenweiser *et al.*, 2013).

For two reasons, the German apprenticeship system is ideal to identify curriculum-induced skill shocks between cohorts. First, training curricula are closely aligned to technological developments. More specifically, a board of members from employer associations, trade unions, and the government defines and changes training curricula. The board’s two main objectives are to ensure that young workers are employable and to provide an adequate labor supply for firms. Therefore, the board has a strong interest to provide apprentices with up-to-date skills. Public institutions govern the entire curriculum updating process and publish all new and updated training curricula in the Federal Law Gazette. Second, apprentices usually start and finish their training at the same time, i.e., apprenticeship contracts legally end a day after the final exam, which commonly takes place at the same day within each occupation and region in the first half of a calendar year. Apprenticeship contracts are legally distinct from employment contracts. Thus, initial macroeconomic conditions are similar for all members of the same training cohort.

Overall, the high level of regulation of the German apprenticeship system provides an ideal setting to identify skills of recent graduates and to infer when cohorts of graduates enter the labor market with novel skills.

III. TRAINING REFORM AND IDENTIFICATION STRATEGY

The goal of this paper is to analyze how the careers of incumbent machining metal operators without modern CNC skills responded to the increasing labor supply of graduates with modern CNC skills. Therefore, we exploit a reform of an apprenticeship training curriculum that led to a substantial labor supply shock of graduates with modern CNC skills in the labor market of machining metal operators. The next subsections present the reform and our identification strategy in more detail.

III.A. The reform of the training curriculum

Our identification strategy exploits a specific reform of a training curriculum that led to a supply shock of graduates with modern CNC skills in the labor market of machining metal operators. Machining metal operators produce precision parts out of metal billets, such as gearing wheels, screws, or threads. Before the reform, firms could choose between several specializations of manual machines, e.g., drilling, turning, or milling machines (see Figure 1 for an example of a drilling machine). To use those machines, apprentices had to learn manual precision skills, but they did not have to learn any IT or programming skills.

In 1987 policy makers implemented a new training curriculum that combined several machining metal occupation into one and introduced in-depth CNC training (first red vertical line in Figure 2). As a result, all machining metal operators who started their apprenticeship training under the new curriculum had to become proficient in using modern CNC machines to obtain their apprenticeship degree. More specifically, the new curriculum required all apprentices to devote at least eight weeks of training to CNC programming. Throughout this period, they had to learn how to write and code new programs, how to debug and change existing ones, and how to produce their own goods on CNC machines. They also had to work for at least 26 weeks on non-manual machines. Finally, during their final examination, apprentices had to produce a metal good on a CNC machine to obtain their degree. As depicted by the second red line in Figure 2, the new training curriculum extended the training duration from three to three and a half years, such that the first cohort of CNC-skilled machining metal operators graduated in the beginning of 1991.

—Figure 2 about here—

Previous evidence suggests that the sophisticated CNC training under the new curriculum has indeed had an effect on the organization of work in Germany. In the 1990s, many German firms programed their CNC machines in-house, while firms in countries without a comparable apprenticeship system largely contracted external specialist to program their CNC machines. More specifically, while 66% of German firms programmed their CNC machines in-house, only about 8% of French and UK firms programmed their CNC machines in-house (Backes-Gellner, 1996). Moreover, some existing evidence from the U.S. suggests that formal CNC training is productivity enhancing even in countries without a structured apprenticeship training program. For example, Bartel et al. (2007), who analyzed U.S. manufacturing firms during the late 1990s, show that firms that provided formal CNC training were able to reduce the setup and run time of CNC machines by about 50% in comparison to firms with comparable CNC technology that did not provide formal CNC training.

As CNC technology was available even before the reform, most firms might already have trained their workers on CNC machines, such that the reform was merely a legal manifestation of a process that had occurred long before the actual reform. However, the reform required a very extensive and structured CNC training that challenged apprenticeship training firms, because they had to have specialized instructors and spare CNC machines to fulfil the extensive training requirements imposed by the new curriculum. As many firms were unable to provide such an extensive training program, the government subsidized and set-up special programs to help firms to cope with the change and to cooperate in the training of machining metal operators (Freding, 1992). Moreover, many firms started to send their apprentices to specialized CNC training centers or larger firms that were able to run their own training centers. Thus, even if some apprentices had already received CNC-training before the reform, the reform substantially changed the average level of CNC skills that apprentices had to acquire.

Table 1 and Figure 3 document the impact of the reform on firms' training programs. Table 1 presents descriptive statistics for the registered training contracts of machining metal operators who started their apprenticeship training between 1987 and 1989 (see dashed line in Figure 2). During this period, policy makers implemented a grace period to facilitate the transition between the old and the new training curriculum. Thus, firms had the option to still follow the old training curriculum instead of applying the new one. As row 1 of Table 1 shows, only about 45% of the apprentices who started their apprenticeship training in 1987 had been registered under the new curriculum. If most firms had extensively trained their workers on CNC machines even before the reform of the training curriculum, almost all firms should have immediately applied the new curriculum. However, throughout the grace period, the share of apprentices who were trained according to the new curriculum rapidly increased to 95% suggesting that virtually all training firms applied the new training curricula before the end of the grace period. Although these results cannot rule out that some firms have provided CNC training even before the reform, the results support that a substantial number of firms only introduced CNC training in response to the reform.

—Table 1 about here—

Figure 3 presents descriptive statistics about the relative size of graduation cohorts and the size of training firms over time. The figure shows a sharp decline in the number of apprenticeship graduates between 1990 and 1992. Of course, the size of graduation cohorts mechanically decreased between 1990 and 1991, because the reform extended the apprenticeship duration from 3 to 3.5 years. More specifically, those firms who used the grace period to opt for the old curriculum in 1987, the first year of the reform, finished their apprenticeship in summer 1990, while those who immediately followed the new curriculum finished their apprenticeship in January/ February 1991. However, even the graduation cohort of 1992 was still smaller than the pre-reform cohorts and the cohort size only resumed its pre-reform level in 1993.

Moreover, the median firm size of training firms increased shortly in 1991 and declined afterwards. This results suggests that specifically smaller firms took a short break in their training activities. Most likely, because they have faced problems to quickly implement the new training program—particularly, the CNC training requirements. However, at the end of the grace period when the new training program became mandatory, the median size of training firms decreased and the number of apprenticeship graduates rose again showing that small firms quickly resumed apprenticeship training according to the new curriculum. Thus, overall Figure 2 provides additional evidence that the reform of the training curriculum had indeed changed the skills of apprenticeship completers. Nevertheless, the number of apprenticeship graduates declined again for the graduation cohort of 1995 and 1996 because a severe recession affected the manufacturing sector with unemployment rates of about 12% in 1996.

—Figure 3 about here—

III.A. Identification strategy

We exploit the training reform to estimate how the supply shock of modern-skilled workers impacted the careers of incumbent machining metal operators by using a difference-in-differences approach comparing the careers of incumbent machining metal operators to the careers of incumbent non-machining metal mechanics, who were not exposed to a supply shock of modern-skilled workers in response to a skill-biased technological innovation. We define the treatment, the treatment group, and the comparison group according to Figure 2 as follows:

(I) The treatment is the supply shock of modern skilled CNC workers. The supply shock started in 1991 with the market entry of the first cohort of machining metal operators who were trained according to the new curriculum (see the second red line in Figure 2). Thus, the treatment indicator simply divides the observation period in the pre-treatment period before 1991 and the post-treatment period after 1991.

(II) The treatment group includes six cohorts of incumbent machining metal operators who graduated between 1984 and 1989. All of them were trained before CNC training became a mandatory element of their apprenticeship training program, i.e., they were exclusively trained according to the old curriculum. As depicted in Figure 2, the last cohort of apprentices who were exclusively trained according to the old curriculum had begun their apprenticeship training in 1986 and had graduated in the summer of 1989.[9] We follow all of these six graduation cohorts from the first year after the year of their apprenticeship graduation until 2010. Thus, we follow the same incumbent machining metal operators in the pre-treatment period before 1991 and the post-treatment period after 1991. Figure 4 presents a graphical example for the graduation cohort of 1986 (solid line).

—Figure 4 about here—

(III) The comparison group includes six graduation cohorts of non-machining metal operators who also graduated between 1984 and 1989. As with our treatment group of machining metal operators, we follow all cohorts from our comparison group from the first year after the year of their apprenticeship graduation until 2010 (dashed line in Figure 4). Incumbent non-machining metal mechanics form an ideal comparison group, because they are very similar to machining metal operators, but their curriculum has not been updated to match the skill demand of a path-breaking technological innovation.[10] In contrast to machining metal operators who produce metal parts, non-machining metal mechanics assemble metal parts to a machine, a gearbox, or a motor. Thus, non-machining metal mechanics neither use manual drilling machines nor CNC technology. However, machining metal operators and non-machining metal

[9] As a consequence of the grace period, some apprentices who were still trained according to the old curriculum graduated in 1990. We excluded this cohort, because the training reform was already implemented and other firms have already started to train their apprentices according to the new curriculum.

[10] Importantly, the training curriculum of metal mechanics was also updated and extended in 1987, but the curriculum was not adapted to a fundamental technological innovation.

mechanics are otherwise very similar. First, both training programs are similar. More specifically, they have the same training duration and even share the first training year when apprentices learn basic metal working techniques. Second, both occupations are frequently trained in the same training firms, and employers apply similar criteria to select their potential apprentices for both occupations. Third, both occupations are represented by one union and governed by the same collective bargaining agreement. Fourth, both occupations experienced the same macroeconomic shocks, because both groups work in the same industry and often in the same firms.

Although German apprenticeship programs are specifically designed to ensure that all apprenticeship graduates within a given occupation possess the same baseline level of occupation-specific skills, firm-specific differences of training quality may exist. More specifically, some firms may have better instructors than others, have better training centers, or provide additional on-the-job training beyond the required training program (Dustmann and Schönberg, 2009). For example, Mohrenweiser and Zwick (2017) have investigated whether training firms of metal working apprentices train skills beyond the respective training curricula. They show that about 50% of firms train additional skills that are not part of the training curricula. These additional skills contain mostly soft and language skills that are transferable across firms. The results suggest that only very few firms might train additional firm-specific skills that are directly related to the technology that firms use. However, to account for the unobserved heterogeneity of the quality of training, we restricting the comparison group to non-machining metal mechanics trained in the same firms as the incumbent machining metal operators of the treatment group. Doing so, allows us to remove unobserved heterogeneity of training quality on the cohort-by-training firm level.

To avoid confusion, we will, from now on, refer to workers of the treatment group as *incumbent* machining metal operators and to workers of the comparison group as *incumbent* non-machining metal mechanics. In contrast, we use the term *CNC-skilled* apprenticeship graduates or *CNC-skilled* machining metal operators for those machining metal operators who graduated after the reform and, therefore, underwent the structured apprenticeship CNC training program. As described in this subsection, these CNC-skilled workers are neither included in the treatment nor in the comparison group of our main regression analyses. In contrast, the supply shock of CNC-skilled workers is the treatment itself.[11]

[11]A number of robustness checks in Section III and IV also include CNC-skilled workers.

IV. DATA AND DESCRIPTIVE STATISTICS

IV.A. Data source

We use the Employee History Panel (BEH, Beschäftigtenhistorik Panel) provided by the German Federal Employment Agency. The BEH contains the universe of social security records form Germany from 1975 throughout 2010. It covers all employees subject to social security contributions, but excludes civil servants and self-employed. Unique person and establishment IDs identify all individuals and establishments, such that we can follow all workers and firms over time.

As German data protection legislations prohibit to use the entire universe of machining metal operators and non-machining metal mechanics, we have to use a sample of all individuals who had an apprenticeship spell of at least two years in one of the two metal-working occupations between 1983 and 1996. Thus, the data contains an 80% random sample of apprentices in the treatment group (machining metal operators) and a 50% sample of apprentices from the comparison group (non-machining metal mechanics). For each individual, we merge the Unemployment Insurance Records (LEH, Leistungsempfängerhistorik Panel) to the BEH information to obtain information about workers employment status.

As common in many register data sources the data contains precise information about the length of the apprenticeship training (due to their unique legal status), but the data contains no information about whether apprentices successfully graduated from their training program or not. Therefore, we follow an approach similar to Von Wachter and Bender (2006) or Dustmann and Meghir (2005) and define the graduation year as the year of the individuals' last apprenticeship spell.[12] Moreover, we remove apprentices with less than 725 consecutive days of documented apprenticeship training and require that they had real employment spells after their graduation to avoid identifying drop-outs as successful graduates. More specifically, we require that they have had at least one at least one real employment spell before and one after the supply shock in 1991.

For our main analysis, we focus on apprentices who have graduated between 1984 and 1989, i.e., the years before the supply shock, and follow all of them to 2010. Furthermore, we use only apprenticeship graduates in the treatment occupation for which we find a peer in the comparison group who has graduated in the same establishment and year, and vice versa (compare III.C). These restrictions reduce our initial sample from 15,641 to 9,075 individuals

[12] As reporting the transition from apprenticeship to work was not mandatory in the 1980's a number of firms report only once a year to the Social Security Administration. In these cases, establishments usually report the actual status of an employee (apprentice or skilled worker) at December 31st. We redefine those individuals with final apprenticeship spell on December 31st to the graduation cohort of the following year.

in the treatment occupation and from 51,979 to 10,846 in the control occupations (compare Table 2).

—Table 2 about here—

Our main dependent variables are annual and daily earning that we measure in Euros of 2010 by using the consumer price index from the national statistical office. Moreover, as in many register data sources, our earnings data is top coded. However, this is hardly a problem for our specific sample of apprenticeship graduates who seldom earn wages above the censor limit.[13] Finally, such as most previous studies that have been using this data, we remove earnings below the Social Security thresholds, because these appear to be rarely happened misreports.

Table 3 provides descriptive statistics for workers in the treatment and comparison group before the supply shock in 1991. We calculate averages for some key variables, on a sample of the workers' first observation after the apprenticeship training. Although neither the treatment nor the comparison group contain a large number of women and foreigners, the comparison group contains slightly fewer females and foreigners and is slightly older than the treatment group. Given the large number of observations these differences are significant at reasonable confidence levels. However, our main results persist if we control gender and nationality, and even if we remove all women and non-German workers.

—Table 3 about here—

IV.B. Descriptive results: Main regression sample

Figure 5a and 5b graphically present descriptive statistics for the key results of the paper. Figure 4a shows the results for the graduation cohort of 1986 on a large scale, and Figure 5b gives an overview for all graduation cohorts between 1984 and 1989 in smaller subfigures. The solid lines represent the earnings trajectories of workers from the treatment group, and the dashed lines represent those of the comparison group. Both figures follow all workers from the

[13] The BEH data top codes very high wages that lie above the margin for social security contributions. Although this top coding affects between 10 to 12% percent of all male fulltime workers and about one to three percent of all female fulltime workers (including University graduates), apprenticeship graduates are seldom affected. For example, Dustmann and Meghir (2005) calculate that the censoring limit affects less than 1% of all apprentices at late stages of their careers. Therefore, we did not impute high wages. Similarly, Card et al. (2017) and Dustmann and Meghir (2005) who also use the same data base refrain from the imputation of high wages when using only apprenticeship graduates.

first employment spell after the year of their apprenticeship graduation (vertical dashed line) until 2010. Thus, we do not report workers' wages during their apprenticeship training period, because apprentices only receive small training compensation that is less than 50% of common entry wage and mechanically very similar for all workers within an manufacturing sector. For example, the graduation cohort of 1986 experienced their first entire year on the labor market in 1987.

The solid vertical line indicates the supply shock, i.e., when the first cohort of machining metal operators with modern CNC programming skills entered the German labor market in response to the reform of the training curriculum.[14]

—Figure 5a and 5b about here —

Figure 5a shows that earnings trajectories of incumbent machining metal operators (treatment group) and incumbent non-machining metal mechanics (comparison group) were almost identical before the supply shock, i.e., from the year after their graduation in 1986 until the first cohort of CNC-skilled workers entered the labor market in 1991. After the supply shock, the earnings trajectories have started to diverge into long-lasting earnings gaps that persisted throughout the workers' entire careers. These results clearly indicate that the market entry of CNC-skilled graduates had a long lasting impact on the careers of incumbent machining metal operators. Figure 4b confirms the results of Figure 4a for all graduation cohorts between 1984 and 1989. In addition, Figure 4b suggests that the effect was larger for earlier graduation cohorts than for later ones.

The decline of the wage differential is consistent with our argumentation. As modern CNC technology became a common standard in German manufacturing only during the late 1980s, apprentices who graduated during the early 1980s were unlikely to have had any access to CNC technology. In contrast, some apprentices among those who graduated in the late 1980s may have had training in CNC technology. For example, some firms may have decided to provide on-the-job CNC training for some workers in addition to the mandatory pre-reform training program. Moreover, shortly before the CNC training became mandatory for all machining metal mechanics, the German government provided scholarship for a small number of outstanding apprenticeship graduates to learn CNC skills. As a result, those who graduated

[14] As we mentioned in the previous section, the market entry of CNC-skilled machining metal operators is the *treatment*, i.e. CNC-skilled graduates do neither belong to the treatment group nor to the control group.

in the late 1980s were on average better prepared to compete with the increasing supply of CNC-skilled workers than those who graduated in the early 1980s.

IV.C. Descriptive statistics: Post-reform cohorts

General macroeconomic developments are unlikely to have affected the treatment group differently from the comparison group, because both have been trained in the same firm and graduated at the same time. However, we cannot completely rule out that structural changes other than the reform of the training curriculum have had an adverse impact on the occupation of machining metal operators, such that their wage trajectories differed systematically from those of non-machining metal mechanics. To surmount such worries, we analyzed the earnings trends of the *CNC-skilled* machining metal operators, who underwent the new training program after the reform. The post-reform cohorts of CNC-skilled machining metal operators do neither belong to the treatment nor the comparison group of our main regression sample, but they are useful to support the validity of our argument.

More specifically, if the long-lasting effects presented in Figure 4a and 4b were indeed related to the CNC training after the reform, we should not find earnings gaps for post-reform cohorts of *CNC-skilled* machining metal operators, because they received the structured training. In contrast, structural changes that were unrelated to the CNC training should have a similar impact on all machining metal operators regardless of whether they possessed CNC skills or not—pre- and post-reform cohorts alike.

Figure 6 presents the earnings trajectories of the post-reform cohorts of *CNC-skilled* machining metal operators along with their counterparts from the occupation of non-machining metal mechanics. The solid lines represent the wage trajectories of *CNC-skilled* machining metal operators, and the dashed lines those of non-machining metal mechanics. For example, the solid line in the first subfigure represents the wage trajectory of CNC-skilled machining metal operators who graduated in 1991. The dashed line represents the wage trajectory of the corresponding graduation cohort of non-machining metal mechanics.[15] Subfigures two throughout six present the same results for the graduation cohorts between 1992 and 1996. In contrast to the results in Figure 5, we cannot find persistent earnings gaps in Figure 6. As the post-reform cohorts only differ in their training content from the pre-reform cohorts, the results do not support that structural changes other than the reform of training curriculum have adversely affected the treatment group of incumbent machining metal operators.

[15] Such as for our main regression sample, we require that machining metal operators and non-machining mechanics were trained in the same firms.

—Figure 6 about here—

V. ESTIMATION APPROACH

We use different versions of the following difference-in-differences equation:

$$lnw_{ist} = \alpha + \tau_t + \theta_i + \delta SupplyShock[1(s = m) \times 1(\tau_t \geq 1991)]_{st} + X\beta + \varepsilon_{ist} \quad (1)$$

where lnw_{ist} denotes the log real daily wage of a worker *i* at time *t* who either belongs to the treatment group of incumbent machining metal operators ($s = m$) or the comparison group of incumbent non-machining metal mechanics ($s = nm$). ε_{ist} is a normally distributed error term with $E(\varepsilon_{ist}) = 0$, and τ_t denotes time fixed effect. θ_i captures the unobserved time-constant heterogeneity on the worker level. X_i captures observable worker characteristics that we have restricted to four age categories,[16] because all other observable characteristics are either time-constant or endogenous to the treatment. However, we perform a number of regressions on a sparser model without individual fixed-effects. These specifications also include the workers' gender, nationality, cohort effects, and a set of cohort-by-training firm effects to account for unobserved differences in the quality of the apprenticeship training.

Supplyshock is a dummy variable that indicates when the incumbent worker of the treatment group is exposed to the supply shock of CNC-skilled graduates, i.e., the variable is one for workers of the treatment group of incumbent machining metal operators (s = m) after 1991 and zero otherwise. As the time dummies and worker fixed effects absorb all unobserved heterogeneity on the time and worker level, the isolated dummy to account for differences between the treatment and comparison group ($1(s = m)$) is implicitly included. Again, our sparser specifications without individual fixed effects explicitly include the isolated dummy for the treatment group.

δ is the effect of main interest and describes how the careers of incumbent machining metal operators are influenced by the market entry of CNC-skilled graduates. Thus, we expect the coefficient estimate to be negative if incumbent machining metal operators are indeed affected by the increased completion of CNC-skilled graduates.

[16] We have used age categories, because we cannot identify a continuous function of age in a model with time and worker fixed effects (see, for example, Davis and von Wachter (2011)).

We emphasize here that our estimation approach differs in two important aspects from more commonly used *population* difference-in-differences approaches that have, for example, been used to analyze how education influences labor market outcomes.[17] First, we do *not* compare those who graduated before the reform with those who graduated after the reform. Instead, we follow the pre-reform cohorts of treatment and comparison workers for their entire careers, both *before* (pre-treatment period) and *after* the reform (post-treatment period), to evaluate how the reform-induced supply shock of CNC-skilled graduates influenced the careers of incumbent workers. Thus, the treatment–*not the treatment group*–is the labor market entry of CNC-skilled graduates, who neither belong to the treatment group (incumbent machining metal operators without CNC skills) nor to the comparison group (incumbent non-machining metal mechanics). In other words, our treatment is the market entry of a group of workers in response to the training reform and not the reform itself. Second, unlike population difference-in-differences approaches, we use panel data to follow the careers of the *same* workers, both before and after the treatment occurred. This allows us to account for time-constant unobserved heterogeneity on the worker level that may bias the effect downwards if, for example, low-ability workers of the treatment group self-select out of the labor market in response to the treatment.

Our difference-in-difference approach relies on three identifying assumptions. First, *the common trends assumption* (key identification assumption) requires that trends in the outcome variable would have been parallel in the absence of the supply shock (treatment). Thus, we need to assume that the wage profiles of incumbent machining metal operators and incumbent non-machining metal mechanics would have been parallel in the absence of the supply shock. Although we cannot test this assumption, the graphical evidence in Figures 5a and 5b strongly supports the *common trends assumption,* because the pre-treatment wage profile trends are almost identical.

Second, *the no effect on pre-treatment population* assumption requires that firms and individuals do not change their behavior in anticipation of the treatment. On one hand, some firms may anticipate the reform of the training program and start training their apprentices before the reform. As we have already discussed in section III, this bias results in an underestimation of the effect, specially, for the later graduation cohorts. On the other hand, more able individuals may have anticipated the reform-induced supply shock and, thus, might

[17] For example, Meghir and Palme (2005) have used difference-in-differences approach that compares pre- and post-reform cohorts to evaluate an education reform in Sweden. Many others have used instrumental variable regressions that use the variation from compliers among the post-reform cohorts to evaluate educational reforms (for example, Pischke and von Wachter (2008).

have chosen another training occupation. However, that 16 year old individuals were able to foresee the technological development of many years is unlikely, in particular, for those who have started their apprenticeship training in the early 1980s when CNC-technology barely existed.

Third, *the stable unit treatment value assumption (SUTVA)* requiring that the outcome of the comparison group after the treatment is the same in a world with and without the treatment (Rubin, 1977). As most field studies that use approaches similar to ours, we are unable to access parallel worlds. In other words, we derive our model within a partial equilibrium framework to highlight a specific individual adjustment process to a labor market shock. In contrast, our data and empirical methods do not allow to estimate how technology and training affects wages and employment for the entire German economy.

However, as general equilibrium effects are likely to violate the SUTVA in many empirical studies, it is in principle the most critical identification assumption.[18] Moreover, a trade-off between the common trends assumption and SUTVA is very common. While the common trends assumption usually requires that the treatment and comparison group are as similar as possible, such that treatment and comparison groups face the same external conditions, the SUTVA is more likely to hold if the treatment and comparison group live in parallel worlds, such that the comparison group itself is unaffected by the treatment. Therefore, we discuss the SUTVA here in more detail.

In our case, the SUTVA may not hold, because the market entry of CNC-skilled graduates may have disproportionally increased the demand for the non-machining metal mechanics of the comparison group. More specifically, technology and training commonly increase the productivity of firms and the economic growth of the entire country. As a result, the overall demand for manufacturing workers, including those of the comparison group, may have increased in response to the treatment. In this scenario, $\hat{\delta}$ may not only capture the displacement (substitution) effect that arises if incumbent machining metal operators are displaced by young CNC-skilled graduates. In contrast, $\hat{\delta}$ might partly capture the net productivity (scale) effects (the difference between the scale effects for incumbent workers of the treatment and comparison group) that arises because the demand for all manufacturing workers increases in response to the market entry of CNC-skilled workers.

[18] For example, Crépon *et al.* (2013) analyze the effect of a job placement assistance program and find that the program had negative effects on the control group, i.e., non-participants had worse labor market prospects in response to the program.

If returns to scale were constant, we would still be able to isolate the displacement effect, because the scale effect would influence incumbent workers of the treatment and comparison group in the same way and would, therefore, be removed through the difference-in-differences approach. However, incumbent non-machining metal mechanics of the comparison group may benefit relatively more from scale effects than our treatment group of incumbent machining metal operators, such that $\hat{\delta}$ may not capture the pure displacement effect. Thus we emphasize here that the reader must bare this possibility in mind when interpreting the results. However, even if the coefficients would not identify the isolated displacement effect, our results still highlight important distributional consequences that may arise if labor markets adjust to the consequences of technological change. Subsection VII.C provides suggestive evidence from an alternative comparison group contradicting that scale effects have a big impact on our main results.

V. MAIN RESULTS

V.A. Un-adjusted difference-in-difference estimates

Table 4 shows the earnings of machining metal operators (row one and three), and the earnings gaps compared to non-machining metal mechanics (row two and four) for each graduation cohort before and after the market entry of CNC-skilled graduates. The fifth row shows the unadjusted difference-in-differences estimates. Rows one and two show that, before the market entry of CNC-skilled graduates, average earnings differences between incumbent machining metal operators and incumbent non-machining mechanics were close to zero, i.e., wage differences between both groups of incumbent workers were very small and either not or only marginally significant at conventional levels. In contrast, rows three and four show large and significant wage differences after the market entry of CNC-skilled graduates.

—Table 4 about here—

The unadjusted difference-in-differences estimates in row five are significantly negative for each cohort and, thus, confirm the results of Figure 5b. Again, we find that wage losses were larger for workers who graduated in the early 1980s than for workers who graduated in the late 1980s. For example, incumbent machining metal operators who graduated in 1984 forwent annual earnings of about five percentage points, whereas those who graduated in 1989 forwent on average only about two percentage points of annual earnings.

V.B. Regression-adjusted difference-in-differences estimates

Table 5 shows our regression adjusted difference-in-differences estimates according to regression equation (1). The first specification contains year and cohort fixed effects. The second specification adds control variables for age, gender, German nationality, and a set of cohort-by-training firm dummies to account for unobserved differences in initial selection and quality of training. The third specification includes individual worker fixed effects to account for time-constant unobserved heterogeneity on the worker level. Of course, the third specification excludes all time-constant variables, such as gender, nationality, cohort, and cohort-by-training firm fixed effects.

—Table 5 about here—

The simple OLS estimate of the supply shock effect amounts to about three percentage points and is highly significant at the one percent level (specification (I)). Including observable worker and cohort-by-training firm effects (II) or individual fixed effects (III) leads to slightly larger effects than the simple OLS approach (I). The increase of the coefficient estimates between columns (I) and (III) indicates that composition effects result in a downward bias in specification (I). More specifically, incumbent machining metal operators with lower ability may have left the labor market in response to the supply shock. However, the results do not suggest that composition effects are large as the differences between specifications (I) and (III) remain small.

Table 6 presents estimation results separately for each graduation cohort of incumbent workers. All coefficient estimates are negative and precisely estimated at the one percent level. As the unadjusted results of Table 4 have suggested, incumbent machining metal operators who graduated in the early 1980s appear to have experienced larger wage losses than those who graduated in the late 1980s.

—Table 6 about here—

We present a number of additional robustness checks to support the credibility of these main results at the end of the paper (Section VII). This section includes the following robustness checks. First, we present placebo analyses. Second, we analyze the unaffected graduation cohorts within a regression framework. Third, we take into account that standard errors in difference-in-differences estimates may be serially correlated. Fourth, we present estimations that account for group-specific trends, and six, we present specifications that rely on a different comparison group. The results proof to be robust for all these speciation changes.

VI. MECHANISMS

This section analyses the underlying mechanisms that account for incumbent workers' wage losses. The first subsection presents long-term effects. The second subsection investigates the extensive margin by analyzing workers' unemployment pattern, and the third subsection analyses workers' occupational mobility. The fourth subsection analyzes their upward mobility, and the fifth subsection quantifies the overall effects as total earnings losses over the workers' course of life.

V.I.A. Long-term effects: daily wages

The average effects that we have presented in the previous section may be a consequence of a transitory wage reduction or a persistent and long-lasting reduction of incumbent workers' wage growth. To analyze the longevity of the effect, Figure 7 investigates the long-term development of incumbent machining metal operators' wage losses. Therefore, we estimate the following adjusted version of regression equation (1).

$$lnw_{ist} = \alpha + \lambda_t + \theta_i + \sum_{k=-2}^{19} \delta_k \, RT_k + X\beta + \varepsilon_{ist} \qquad (2)$$

where $\sum_{\tau=-2}^{19} \delta_\tau \, RT_\tau$ represents a set of dummy variables equal to one in the *k*th period before or after the supply shock.. For example, RT_{-2} equals one for an incumbent machining metal operator two years before the supply shock, and RT_2 equals one for an incumbent machining metal operator in the second year after the supply shock. This approach allows us to capture not only the long-term dynamics of the wage effects, specification (2) is also more flexible than specification (1), i.e., RT_k is a set of dummy variables that capture the wage trajectory of the treatment group without imposing a functional structure for the pre- and post-treatment period.

—Figure 7 about here—

The results show that wage differences were insignificant for the years prior to the market entry of CNC-skilled workers and significantly increased immediately after the treatment. The insignificant effects throughout the pre-treatment period support the validity of the parallel trends assumption. The significant and persistent increase of wage losses after the supply shock shows that the market entry of CNC-skilled graduates had a long-lasting impact on incumbent machining metal operators' daily wages.

If incumbent machining metal operators would have been able to respond to the market entry of CNC-skilled graduates, by accumulating sufficient CNC skills, they should have experienced only transitory wage losses—i.e., through their re-training period. However, the evidence reveals that the effect is persistent in the long run. This may appear counterintuitive as the workers in our study are relatively young, such that they have a long career ahead of them to collect the benefit of further training. However, a likely reason is that incumbent workers were unable to accumulate sufficient CNC skills are the high opportunity costs associated with extensive training for an entirely new technology. CNC-training is costly and often takes place in specialized training centers, such that incumbent machining metal operators may face difficulties to accumulate CNC-skills without the (financial) support of their firms.

V.I.B. The extensive margin: unemployment

So far, the results have shown that the supply shock of modern skilled graduates was related to effects on the intensive margin in form of forgone real daily wage growth for the employed workers. However, the supply shock may also have had effects on the extensive margin, particularly, for incumbent workers' likelihood to become unemployment. Therefore, Figure 8 shows the results for incumbent machining metal operators' likelihood to become unemployed. The results stem from a linear probability version of regression equation (2) for which we have replaced the lnw_{ist} by a dummy variable indicating whether a worker had at least one spell of unemployment in the given year.

—Figure 8 about here—

The results show that incumbent machining metal operators were up to two percentage points more likely to have experienced at least one spell of unemployment in a given year. However, unemployment effects were only transitory and occurred immediately after the market entry of CNC-skilled graduates. In the longer run, incumbent machining metal operators appear to have resumed a stable employment path. These small transitory unemployment periods after the supply shock are similar in magnitude to recent evidence by Cortes (2016) who compares the unemployment incidences of routine and non-routine workers in the U.S.. Similarly, El-Sahli and Upward (2017) find that containerization had only low or even positive employment effects for UK dockworkers who benefited from comparably strong employment protection regulations as German manufacturing workers.

It is worth to emphasize that the increased likelihood of incumbent machining metal operators to become unemployed occurred during a period of economic prosperity, i.e., before the recession hit the Germen metal working sector in 1995. This pattern further supports that our estimated effects are indeed related to the supply shock of CNC-skilled graduates and not a consequence of unrelated macro-economic conditions.

V.I.C. Lateral mobility.

If modern-skilled graduates enter the labor market, firms have an incentive to replace incumbent machining metal operators with relatively more productive graduates. Thus, incumbent machining metal operators may be crowded out of their occupation and lose occupation-specific human capital. Table 7 analyses this argument in detail. The table presents two linear probability versions of equation (1). The depended variable for the first specification is a dummy variable indicating whether incumbent workers have remained in their training occupation or not. The results show that incumbent machining metal operators became about 10 percentage points less likely to remain in their training occupation in response to the market entry of modern-skilled graduates. As occupation-specific skills are very important determinant for workers' wages in the German labor market (Ryan, 2001; Ryan et al., 2013), the observed occupational mobility is consistent with the persistent wage losses that we have observed in Subsection *VI.A.*

—Table 7 about here—

However, as employment protection regulations are relatively strict in Germany, firms face hurdles to lay-off workers without a cause. Thus, many firm may have reallocated incumbent workers to other jobs. For example, firms may have reallocated workers to jobs with inferior career perspectives to minimize the long-term costs for those workers, or to encourage them to leave the firm on their own.[19] To analyze this argument in more detail, the second specification analyses workers' occupational mobility within firms. More specifically, the second specification estimates the same linear probability model as the first one on a restricted sample of incumbent workers who have remained in their training firm. We emphasize here that inference from the second specification is more challenging than from the first one, because workers who manage to remain in their training firms are likely to be positively selected. Yet, as we include individual fixed effects into the regression model, we at least remove all time-

[19] German law commonly forbids to demote workers to jobs with lower earnings or less responsibility. In contrast, future earnings perspectives are not protected by the law.

invariant unobserved heterogeneity. The result of specification two reveals that even those incumbent machining metal operators who have remained in their training firms became about seven percentage points less likely to remain in their training occupation and continue to work in other occupations within the same firm. Thus, this result is consistent with the argument that firms have reallocated incumbent workers in response to the market entry of modern-skilled graduates.

A number of recent studies from the U.S. and Europe have shown that technological change was associated with a reallocation of employment from the manufacturing sector into other sectors—particularly, into the service sector (Autor, 2013; Autor, 2015; Autor *et al.*, 2006; Goos *et al.*, 2009; Goos *et al.*, 2014; Gregory *et al.*, 2016). Therefore, we have analyzed whether incumbent machining metal operators became more likely to leave the manufacturing sector in Table 8. The table contains three specifications. The first specification analyses whether incumbent workers became less likely to remain in the metal working sector (column 1). The second specification analyses whether incumbent workers became more likely to enter low-wage service jobs (e.g., waiters in restaurants or jobs in health care; column 2), and the third specification analyzes whether they became more likely to enter high-wage service jobs (e.g., jobs in the financial industry or in the law sector; column 3).

—Table 8 about here—

The results reveal that incumbent machining metal operator became less likely to remain in the manufacturing sector and more likely to enter the service sector, specifically the low-wage service sector. The results are consistent with the existing evidence.

However, that the sector-specific coefficient estimates from Table 8 are much smaller than the occupation-specific effects from Table 7 shows that many workers have moved to occupations within the manufacturing sector. This result stays in contrast to recent evidence from the U.S. showing a larger outflow from manufacturing sector. One potential reasons may be that overall employment in the German manufacturing sector has remained relatively stable as a result of East European trade integration (Dauth *et al.*, 2014), while international trade has substantially reduced the employment in U.S. manufacturing over the recent decades (Autor *et al.*, 2013).

V.I.D. Upward mobility

One potential reason for incumbent machining metal operators to forgo wage growth, even without leaving their occupation and firm, is that their career perspectives may have deteriorated in response to the supply shock. Many employers implement promotion tournaments to provide incentives for their workers to exert effort. Tournaments commonly reward workers' relative performance, which is a function of skills, ability and effort. As the increasing supply of CNC-skilled graduates had a direct impact on the relative skill distribution of machining metal operators in the labor market, the supply shock of CNC-skilled graduates may impact incumbent workers' likelihood to receive promotions (Gibbons and Waldman, 1999; Lazear and Rosen, 1981; Waldman, 2016). More specifically, in comparison to the CNC-skilled graduates, incumbent machining metal operators have on average a disadvantage in skills, because they have not received a structural CNC training. As a result, they may become less likely to win promotion tournaments after the supply shock of CNC-skilled workers. This effect may have been further magnified, because the reduced chances for incumbent workers to win promotion tournaments may have distorted their incentives to exert effort (Chan, 1996).

Promotion tournaments may also provide another explanation for why even younger workers, who commonly have a long career ahead of them to efficiently undertake large investments in modern skills, experience long-lasting earnings losses during periods of technological change. Young incumbents are commonly those who work with the technology while more experienced workers are more likely to have moved up the hierarchy and perform managerial tasks. As a result, young incumbents may be more likely to be exposed to the direct competition of CNC-skilled graduates with their technical skills than older ones.

Although we cannot identify precise job hierarchies in the register data, the German occupational-based career system offers a unique opportunity to analyze promotions for blue-collar workers to the managerial-level. If an apprenticeship graduate wants to move-up the career ladder to become a foreman, i.e. move up to a managerial position, he needs an additional degree: the technician or master craftsman degree. Typical candidates for both degrees work a few years after apprenticeship completion before they join a part-time or full-time technician or master craftsman training course for two (part-time) or one year (full-time). The training courses are organized by local chambers, follow a standardized curriculum and end with a recognized certificate from the chambers. Both degrees are categorized as level 5 degrees in ISCED 97, an international standardization of educational degrees, and thus equivalent to a MSc degree (Schneider, 2008). Due to the high standardization of occupational labor markets in Germany, employers commonly suggest workers to undertake a master craftsman/technician degree to be able to get a promotion to the managerial-level. Therefore, holding a degree as master craftsmen/technician is a valid proxy for a workers' upward mobility within firms.

Table 9 provides the results of a linear probability version of equation (1) with the dependent dummy variable that indicates whether a worker holds a degree as master craftsman or technician at time t. The results reveal that the supply shock reduced the likelihood of incumbent machining metal mechanics to become master craftsman or technician by about five percentage points. This is a substantial effect given that about 16% of all incumbent machining metal operators in the sample ever received such a degree. Thus, the results clearly suggest that the market entry of modern-skilled graduates had a substantial impact on the upward mobility of incumbent machining metal operators.

—Table 9 about here—

V.I.E. Benchmarking the overall effects: annual earnings

In the following, we quantify the total treatment effect as the discounted present value (DPV) of incumbent workers' total earnings losses. We calculate the DPV by summing up the earnings of all employment spells in a given year and use this measure as independent variable of regression equation (2) to calculate $\hat{\delta}_k$ (see Walker (2013); and Davis and von Wachter (2011) for similar approaches). Second, we calculate the DPVs from the estimated $\hat{\delta}_k$ according to the following formula:

$$DPV = \sum_{k=1}^{19} \hat{\delta}_k \frac{1}{(1+r)^{k-1}} \tag{3}$$

where $\hat{\delta}_k$ represent the estimated coefficient from our estimation of equation (2) on workers annual earnings and *r* is the annual discount rate that we assume to be five percent, following Davis and von Wachter (2011). We scale the DPVs by incumbent workers' mean annual earnings in the year before the market entry of CNC-skilled graduates. This approach expresses the earnings losses as the number of earnings years lost at the pre-treatment level of earnings.

Unfortunately, our data only covers the period between 1985 and 2010, such that we cannot observe workers' entire careers. Nevertheless, we did *back-of-the-envelope* calculations for workers' life-time earnings losses following Davis and von Wachter (2011) and have estimated two versions of DPVs. The first one only includes the results from our observation period. The second one extrapolates beyond our observation period by using the existing data to predict workers' earnings losses for 21 more years, i.e., until the year 2031, when most workers of our sample will have reached their legal retirement age. To predict unobserved future earnings losses, we use a cubic function of time in a regression on estimated earnings losses from equation (2).

The first row of Table 9 presents the results from observed earnings losses. The second row presents the extrapolated earnings losses. The three columns of Table 9 present three specifications. The first column presents the results of a specification that only includes observations with positive earnings. However, workers who are non- or unemployed may not receive any earnings in a given year, and such earnings losses may clearly be part of the treatment effect. Therefore, the second specification sets observations to zero that have missing annual earnings and occur before the workers' last observed spell in the data. As mentioned in section IV, our data only includes workers who pay social security contributions, such that we cannot observe self-employed workers, certain types of civil servants, and non-employed workers who leave the sample without claiming unemployment benefits or joining some type of state-provided program.[20] Thus, while specification one may underestimate the true effect, specification two may overstate it. The third column presents results for the total price effect by assuming that all workers were employed for 365 days of a given year. Comparing columns one and three allows us to disentangle the wage effect (price effect) from the employment effect (quantity effect). Such as in specification one, we ignore missing annual earnings in the third specification.

—Table 10 about here—

Columns one and two of row one show that incumbent machining metal operators' total earnings losses amounted to about 70% of their average pre-treatment annual earnings throughout the observation period—irrespective of whether we include or exclude zero annual earnings. Thus, missing data cannot have a big impact on the results. Column three reveals that the largest share of earnings losses is related to reductions in real daily wages and not to spells of non- or unemployment, because the price effect amounts to about 50 percent of incumbent workers' annual pre-treatment earnings.[21] The second row shows that extrapolated life-time earnings losses amount to about 117 % of the workers' annual pre-treatment earnings. Again,

[20] This is a common problem in most register data sources. See, for example, Card *et al.* (2013).

[21] We emphasize here that we cannot measure working hours, such that the wage effect may partly be related to reductions in working hours. However, our sample contains predominately male blue-collar workers and part-time employment is very rare among this group in Germany. Therefore, it is unlikely that reductions in workings hours account for much of the daily wage loss.

including zeros earnings does not change the results (column two), and the largest share of the earnings effect is related to reductions of real daily wages.

To assess the magnitude of the overall effect, it is useful to benchmark our results to existing evidence about the effect of shocks on workers careers. A natural candidate to compare our results to displaced workers' earnings losses. For example, Davis and von Wachter (2011) estimate average earnings losses of U.S. workers who lost their jobs during mass layoff between about 171% and 250% of annual pre-displacement earnings. The estimated life-time displacement losses are much larger than our effects for two reasons. First, many workers remain in their training firms but change the occupation in response to the treatment. Thus, incumbent machining metal operators incur lower wage growth rather than real earning losses. The supply shock may lead to much smaller wage effects than a shock that leads workers to leave their firms. Second, the German wage bargaining system is relatively rigid—particularly, in the manufacturing sector, and previous evidence has shown that displaced workers' earnings losses are smaller under rigid wage bargaining systems (Janssen, 2017).

Another natural candidate to compare our results to is Walker (2013) who estimated the long-term wage effects of the clean air act for U.S. manufacturing workers. More specifically, he analyzed the long-term consequences of a labor market shock that specifically affected workers in the manufacturing sector where labor is often not instantly reallocated and average industry wages may not fully reflect shifts in the labor demand curve. As Walker (2013) estimated discounted earnings losses of about 20%, our total earnings losses are somewhat larger. The main difference between Walker's and our results is that our estimated wage losses persist in the long run. More specifically, in contrast to the workers in his study, the affected incumbent workers in our study do not fully recover from the labor market shock. The main reason for this result is that many of the affected workers in our study were crowded out of their occupation and potentially lost a large share of their occupation-specific human capital, such that their earnings losses were more persistent than in Reed's study.

VII SENSITIVITY ANALYSIS

VII.A. Placebo treatments

This subsection analyses the robustness of our results by benchmarking the goodness-of-fit from our preferred specification equation (1) against the goodness-of-fits from a series of 21 placebo regressions. Each regression includes a dummy variable that indicates a potential treatment between 1987 and 2009 instead of the true treatment in 1991. Figure 8 depicts the F-statistics from each of those regression models—including the one from the true specification (vertical line). The results demonstrate that the regression with the true treatment effect leads to the largest F-statistic and, thus, provides the best fit for the observed data. [22]

—Figure 8 about here—

VII.B. Post-reform cohorts

As already mentioned in subsection IV.C., we should not find wage losses for the post-reform cohorts of *CNC-skilled* machining metal operators, if the presented effects were indeed related to the treatment and not to general macroeconomic shocks. The descriptive results in Figure 5 have already suggested that CNC-skilled graduates have not experienced wage losses relative to the post-treatment cohorts from the counterfactual occupation. Figure 9 summarizes the coefficients and confidence intervals of a series of multivariate regressions. More specifically, we estimate a distributed lag model similar to the one in regression equation (2) but for a sample that only includes workers who have graduated after the reform of the training curriculum in 1991. The figure clearly supports the finding in Figure 5 and reveals no significant wage gaps for the post-reform cohorts of CNC-skilled machining metal operators. Thus, general macroeconomic effects cannot explain our main finding.

—Figure 9 about here—

VII.C. Alternative comparison group

As discussed in subsection VI.D, disentangling the displacement from the scale effect might be challenging. This subsection provides suggestive evidence to further explore this issue by analyzing an alternative comparison group. The comparison group of non-machining metal-operators that we have used so far works in the same plants and produces the same final products as our treatment group of incumbent machining metal operators. Although this comparison group allows us to account for unobserved effects on the cohort-by-training firm level, this comparison group may benefit productivity gains from scale effects when the more productive CNC-skilled machining metal workers enter their firms. This is less likely to occur for an alternative comparison group of incumbent non-machining metal mechanics who have been

[22] We emphasize here that a number placebo treatments yield to significant coefficient estimates, because our treatment response is dynamic and increases over time. Moreover, as each placebo regression includes exactly the same number of covariates, we don't need to rely on goodness-of-fit measures that are more sensitive to the inclusion of additional covariates, such as BIC or AIC. However, BIC and AIC lead to the same conclusions as the presented F-statistics.

trained in firms that do not train machining metal operators. Non-machining metal mechanics also assemble metal parts in plants that produce joint large metal parts for ships, large machines or vehicles. Producing such large metal parts requires welding and riveting metal parts but no CNC-technology, which is commonly used for small precision parts. Some firms specializing in those types of metal working processes employ non-machining metal mechanics but no machining metal operators. We argue that non-machining metal mechanics who work in such *non-CNC firms* are less likely to directly benefit from the productivity gains of CNC-skilled graduates than non-machining metal mechanics who work in *CNC-firms*.[23] As a result, the SUTVA may be more likely to hold for this comparison group. Table 10 presents the results. The first specification relies on a comparison group that only contains incumbent non-machining metal mechanics who have been trained in non-CNC firms, and the second specification relies on the entire sample of incumbent machining metal operators and non-machining metal mechanics that is available to us (see rows one and three of Table 2). More specifically, the second specification does not restrict our sample to include only incumbent workers of the treatment and comparison group who have been trained in the same firms. The results remain very similar to the main effect of our preferred specification. Thus, the results suggest that a possible violation of the SUTVA does not invalidate our results. Additionally, the results of the second specification suggest that the potential unobserved heterogeneity on the level of the training firm does not influence our results.

—Table 10 about here—

VII.D. Group-specific trends

A common robustness check to access the validity of difference-in-differences estimators is to include “state-specific” trends into the regression equation (Angrist and Pischke, 2008). Thus, we included different trends between the treatment and comparison group using a quadratic function of a group-specific trend in regression equation (1). The first specification of Table 11 shows that the coefficient estimate is somewhat smaller than the coefficient estimate of our preferred specification, but the effect remains highly significant at conventional levels.

—Table 11 about here—

[23] Indirect effects may still arise if the overall demand for non-machining metal operators rises in the response to the increasing supply of CNC-skilled graduates.

However, separating group-specific trends from the treatment effect becomes challenging if the treatment response is dynamic (see Wolfers (2006): pp. 1807 for a detailed discussion of this problem). In our specific case, it is very plausible that the treatment response is dynamic, because incumbent workers who have to switch their occupation or forwent promotion are likely to be on a lower wage trajectory in response to the treatment. Yet, this response is part of the effect. Thus, the group-specific trends are likely to capture a fraction of the gradually increasing treatment effect, such that we regard this result merely as a proof of robustness and not as our preferred specification.

VII.E. Autocorrelation of standard errors

Autocorrelation in fixed-effects panel data models may result in downward biased standard errors, and Bertrand *et al.* (2004) have shown that this problem is particularly severe in difference-in-differences estimations with many years of data. Therefore, Bertrand *et al.* (2004) proposed a method that collapses the time series information into a pre- and post-treatment period to account for the autocorrelation of standard errors. Their Monte Carlo simulations revealed that this collapsing method works particularly well if the number of treated and non-treated group is small, such as in our case.

The second specification of Table 11 presents results from this *collapsing method* according to (Bertrand *et al.* (2004)). As expected these more conservative standard errors are almost twice the size of the standard errors in our main regression. However, the coefficient estimates are still precisely estimated at the one percent level.

VIII. CONCLUSION

This article provides two major results. First, we show that the increasing labor supply of modern-skilled graduates has a significant and long-lasting impact on incumbent workers' careers when technologies change fundamentally. Overall, our results reveal that incumbent workers with outdated skills experienced present discounted earnings losses of about 70% of an average earnings year. Thus, while previous research has largely analyzed how technological change influences aggregate measures for employment and for wage structures, we provide micro evidence for an important adjustment process on the individual level. Moreover, this paper is the first to show that even relatively young workers can experience indirect long-term consequences in response to accelerating technological change because they are more likely to use the technology at work than older workers who are more likely to have moved on in their careers. This highlights that young workers are exposed to technology change driven supply shocks.

Second, our estimates shed light on how incumbent workers adjust to the competition of modern-skilled workers. The results show that incumbent workers experienced real wage losses in form of lower wage growth. They are more likely to adjust to the increasing supply of modern skills by missing promotions and changing occupations and the sector—specifically, to lower wage service jobs. The largest share of incumbent workers changed occupations within the metal working industry and even within firms. In addition, the results reveal that incumbent workers only experienced little unemployment in response to the supply shock of modern-skilled workers—specifically, directly after the supply shock. This finding highlights that analyzing individual careers in the long run is important to assess the labor market costs and consequences of technological change.

Although this paper studies a specific group of manufacturing workers who were affected by a specific technological innovation, our results have external validity for at least three reasons. First, CNC technology was one of the major technological developments in manufacturing throughout the 1990s and has changed the nature of work and skill requirements in this industry all over the world. Second, our analysis focuses on medium-skilled manufacturing workers who happen to be the group of workers who have experienced the most severe adverse consequences in response to changing technologies in many developed countries since the mid-1980s (Goos *et al.*, 2009; Goos *et al.*, 2014). Third, we strongly believe that similar adjustment processes may take place in the future when many sectors will be exposed to the consequences of new technological developments, such as cyber-physical systems and artificial intelligence. Thus, this paper provides an important case study to better understand how labor markets adjust to technological changes.

We derive our estimates in a partial equilibrium framework, and focus on a particularly salient aspect of the indirect consequences from technological change for workers' careers. In contrast, our data and research design does not allow to estimate the overall economic effects that resulted from the introduction of CNC technology or the change in the apprenticeship training curriculum. Therefore, we emphasize that our results do not challenge the common view that technological innovation and human capital investments foster overall economic growth and prosperity (Colecchia and Schreyer, 2002; Hanushek and Wößmann, 2007). In contrast, our results shed light on a distributional consequence that arises when labor markets adjust to technological developments.

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Tables in the text

TABLE 1:
RESGISTERED APPRENTICES UNDER THE OLD AND NEW TRAINING CURRICULUM DURING THE GRACE PERIOD

Beginning of training	without CNC (old curriculum)	With CNC (new curriculum)
1987	55%	45%
1988	11%	89%
1989	5%	95%

Notes. The Table presents descriptive statistics for the registered training contracts of machining metal operators who started their apprenticeship training between 1987 and 1989. During this period, policy makers implemented a grace period to facilitate the transition between the old and the new training curriculum. Source:

TABLE 2:
NUMBER OF OBSERVATIONS FOR TREATMENT AND COMPARISON GROUP

	Machining metal operators (TG)		Non-machining metal mechanics (CT)	
	80% sample	Estimation sample	50% sample	Estimation sample
1984	2616	1654	7897	2001
1985	2471	1505	8138	1804
1986	2407	1452	8840	1741
1987	2545	1484	9038	1777
1988	2623	1454	8964	1807
1989	2960	1526	8988	1716
Total	15622	9075	51865	10846

Notes. The Table shows the number of individuals in each graduation cohort for the entire sample (columns two and four) and the estimation sample (columns three and five) that we have restricted to apprentices of the treatment and comparison group who have graduated in the same establishments. Source BEH 1984-2010.

TABLE 3:
BASELINE CHARACTERISTICS OF TREATMENT AND COMPARISON GROUP BEFORE MARKET ENTRY OF CNC-SKILLED GRADUATES

	Machining metal operators	Non-machining metal mechanics	Difference
Female	0.047	0.014	-0.032***
Foreigner	0.090	0.064	-0.025***
Age	20.980	21.525	0.546***

Notes. The Table presents descriptive statistics for the baseline characteristics of the treatment and comparison group. The baseline period is the first observation per individual after graduation before the treatment. *** p<0.01. Source BEH 1984-2010.

TABLE 4:
LOG DAILY WAGE DIFFERENCES BETWEEN TREATMENT AND COMPARISON GROUP

	All	1984	1985	1986	1987	1988	1989
	Before market entry of CNC-skilled graduates						
Non-machining mechanics	4.272	4.273	4.279	4.284	4.255	4.261	4.245
Machining operators (difference)	-0.005*	-0.010*	0.001	-0.011*	-0.000	-0.002	0.007
	After market entry of CNC-skilled graduates						
Non-machining mechanics	4.492	4.532	4.506	4.513	4.476	4.465	4.455
Machining operators (difference)	-0.032***	-0.062***	-0.026***	-0.042***	-0.024***	-0.019***	-0.012*
	After - Before						
Unadjusted diff.-in-diff. estimator	-0.026***	-0.052***	-0.026***	-0.030***	-0.023***	-0.016**	-0.017**
Number of observations	379717	76548	67132	61979	60705	58150	55203

Notes. The Table presents descriptive statistics for average wage differences between individuals of the treatment and comparison group before and after the supply shock of CNC-skilled graduates. Daily earnings are deflated with the consumer price index and measured in Euros of 2010. Standard errors are clustered at the individual level. * p<0.1; ** p<0.05; *** p<0.01. Source BEH 1984-2010.

TABLE 5:
EFFECT OF CNC-SKILLED GRADUATES ON INCUMBENT WORKERS' DAILY WAGES

	No controls	Full controls	Individual Fixed effects
Machining metal operator#	-0.004*	-0.001	—
	(0.003)	(0.003)	
Treatment effect	-0.029***	-0.033***	-0.036***
	(0.003)	(0.003)	(0.003)
Individual controls	No	Yes	Yes
Cohort-by-training-firm f.e.	No	Yes	No
Individual f.e.	No	No	Yes
Cohort f.e.	Yes	Yes	No
Time f.e.	Yes	Yes	Yes
R-square	0.137	0.274	0.672
Number of observations	379717	379717	379717

Notes. The Table presents the results from regression equation (1). The dependent variable are log daily wages that are deflated by the CPI and measured in EUROS of 2010. The standard errors (in parenthesis) are clustered on the individual level. Individual control variables contain four age categories, a dummy for being female, and a dummy for holding a foreign nationality. Column three only contains the age categories as individual controls, because the remainder individual variables are time-constant. # dummy for training occupation * $p<0.1$; *** $p<0.01$; Source: BEH 1984-2010.

TABLE 6:
EFFECT OF CNC-SKILLED GRADUATES ON INCUMBENT WORKERS' DAILY WAGES (BY GRADUATION COHORT)

	1984	1985	1986	1987	1988	1989
Treatment effect	-0.057***	-0.034***	-0.030***	-0.027***	-0.020***	-0.024***
	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
Individual f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Time f.e.	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.688	0.674	0.670	0.677	0.665	0.656
Number of observations	76548	67132	61979	60705	58150	55203

Notes. The Table presents the results from regression equation (1), separately for each graduation cohort. The dependent variable are log daily wages that are deflated by the CPI and measured in EUROS of 2010. The standard errors (in parenthesis) are clustered at the individual level. Individual control variables contain four age categories. *** p<0.01; Source: BEH 1984-2010.

TABLE 7:
EFFECT OF CNC-SKILLED GRADUATES ON INCUMBENT WORKERS' PROBABILITY TO REMAIN IN TRAINING OCCUPATION

	Occ. stayer	Occ. stayer within establishment
Treatment effect	-0.104***	-0.077***
	(0.006)	(0.008)
Individual controls	Yes	Yes
Individual f.e.	Yes	Yes
Time f.e.	Yes	Yes
R-square	0.680	0.789
Number of observations	379717	140894

Notes. The Table presents the results of a version of regression equation (1) for which we have replaced the dependent variable by a dummy indicating whether a worker remains in his or her training occupation or not. The first column presents a specification that relies on the entire sample. The second column presents a specification that only relies on individuals who have remained in their training establishment. The standard errors (in parenthesis) are clustered at the individual level. Individual control variables contain four age categories. *** $p<0.01$; Source: BEH 1984-2010.

TABLE 8:
EFFECT OF CNC-SKILLED GRADUATES ON INCUMBENT WORKERS' PROBABILITY TO REMAIN IN METAL WORKING SECTOR

	Stay in metal ind.	Move to service sector	
		Low wage	High wage
Treatment effect	-0.037***	0.020***	0.001
	(0.006)	(0.004)	(0.002)
Individual controls	Yes	Yes	Yes
Individual f.e.	Yes	Yes	Yes
Time f.e.	Yes	Yes	Yes
R-square	0.658	0.624	0.541
Number of observations	379717	379717	379717

Notes. The Table presents the results of a version of regression equation (1) for which we have replaced the dependent variable by a dummy indicating whether a worker remains in the metal working industry (column one), move to the low wage service sector (column two), or moves to the high wage service sector (column three). Low wage service jobs include jobs, such as, for example, waiters, office clerks, cleaning and sales personnel. High wage service jobs include, for example, teachers, lawyers, and physicians. The first column presents a specification that relies on the entire sample. The second column presents a specification that only relies on individuals who have remained in their training establishment. The standard errors (in parenthesis) are clustered at the individual level. Individual control variables contain four age categories. *** $p<0.01$; Source: BEH 1984-2010.

TABLE 9:
EFFECT OF CNC-SKILLED GRADUATES ON INCUMBENT WORKERS' PROBABILITY TO BECOME A MASTER/TECHNICIAN.

	Master craftsman/technician
Treatment effect	-0.045***
	(0.004)
Individual f.e.	Yes
Time f.e.	Yes
R-square	0.576
Number of observations	379717

Notes. The Table presents the results of a version of regression equation (1) for which we have replaced the dependent variable by a dummy indicating whether a worker has become a master craftsman or technician. The first column presents a specification that relies on the entire sample. The second column presents a specification that only relies on individuals who have remained in their training establishment. The standard errors (in parenthesis) are clustered at the individual level. Individual control variables contain four age categories. *** p<0.01; Source: BEH 1984-2010.

TABLE 10:
DISCOUNTED PRESENT VALUE OF TOTAL EARNING EFFECT

	Total effect (excl. zeros)	Total effect (incl. zeros)	Price effect
Observation period	-0.684	-0.707	-0.517
Lifetime (extrapolated)	-1.157	-1.195	-0.847
Number of obs.(1st stage)	379,717		379,717

Notes. The Table presents discounted present values (DPV) of incumbent workers' total earnings losses. We have calculated the DPVs by summing up the earnings of all employment spells in a given year and use this measure as independent variable of regression equation (2) to calculate $\hat{\delta}_k$ in a first step. In a second step, we calculate the DPVs according to equation (3). Row one presents results for the entire observation period until 2010. Row two extrapolates the effects until 2031. To predict unobserved future earnings losses, we have used a cubic function of time in a regression on estimated earnings losses from equation (2). Column one includes only positive wage observations, column one replace missing wage observations by zeros, and column three estimates the DPVs under the assumption that each worker had been employed for each day throughout the observation period.

TABLE 11:
ALTERNATIVE COMPARISON GROUP OF NON-MACHINING METAL OPERATORS IN NON-CNC FIRMS.

	Non-CNC firms	All
Treatment effect	-0.040***	-0.031***
	(0.003)	(0.002)
Individual fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
R-square	0.674	0.679
Number of observations	831373	1145140

Notes. The Table presents the results from regression equation (1) for two alternative samples. The first column presents results that are estimated with a comparison group of non-machining metal mechanics who have been trained in firms that do not employ machining metal operators. The second column presents results that are estimated on a sample that contains the entire universe of observable machining metal operators and non-machining metal mechanics from the affected graduation cohorts between 1984 and 1989, i.e., the sample is not restricted on workers of the treatment and comparison group who have been trained in the same firms. The dependent variable are log daily wages that are deflated by the CPI and measured in EUROS of 2010. The standard errors (in parenthesis) are clustered on the individual level. Individual control variables contain four age categories. *** p<0.01; Source: BEH 1984-2010.

TABLE 12:
FURTHER ROBUSTNESS CHECKS

	Trends	Collapsing method
Treatment effect	-0.018***	-0.038***
	(0.003)	(0.007)
Individual controls	Yes	No
Individual f.e.	Yes	Yes
Time f.e.	Yes	Yes
R-square	0.673	0.307
Number of observations	379717	39824

Notes. This Table presents further robustness checks. The first column presents results from a specification that allows for different trends between the treatment and comparison group using a quadratic function of a group-specific trend in regression equation (1). The second column presents results from an approach that collapses the time series information into a pre- and post-treatment period to account for the autocorrelation of standard errors. The dependent variable are log daily wages that are deflated by the CPI and measured in EUROS of 2010. The standard errors (in parenthesis) are clustered at the individual level. Individual control variables contain four age categories in the first specification. The second specification does not allow to account for age, because the observations are collapsed into a pre- and post-treatment period. Instead of the year dummies, the time fixed effect of the second specification is a dummy that accounts for the pre- vs post-treatment period.*** p<0.01; Source: BEH 1984-2010.

Figures in the text

FIGURE 1:

Manual drilling machine and CNC-machine

The left panel shows a manual drilling machine as most commonly used by machining metal operators until the late 1980’s. The right panel shows computer numerical control (CNC) machine such as it became a common standard in Germen manufacturing since the late 1980s. Under the new training curriculum all Germen apprentices in the occupation of machining metal operators had to undergo a structured training program to acquire modern CNC-skills.

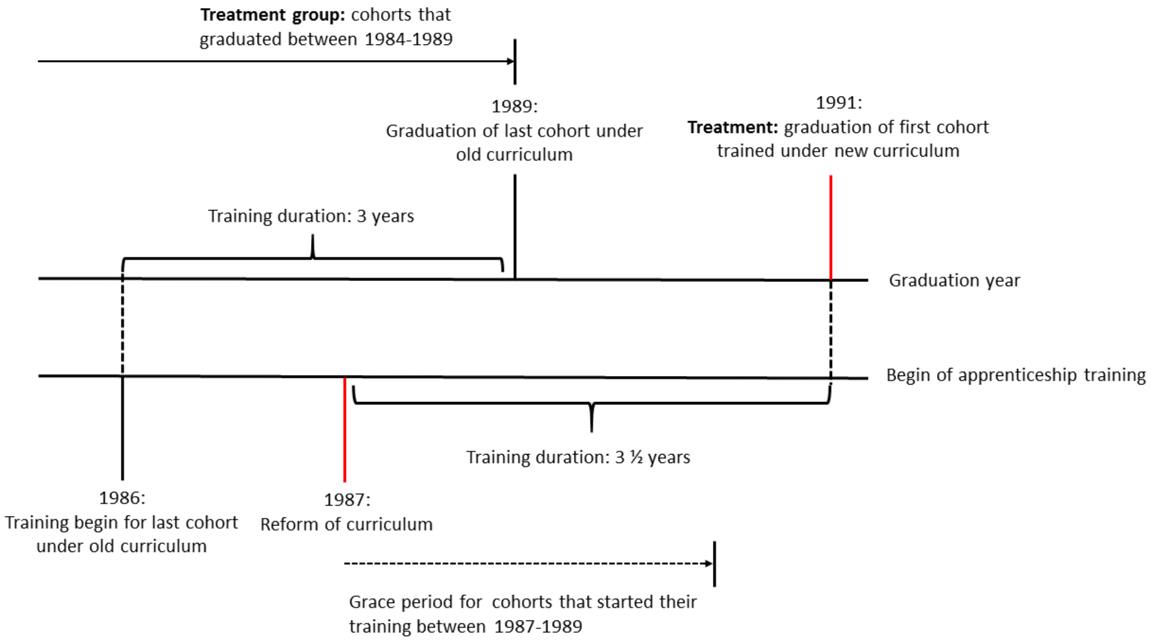

FIGURE 2:

The reform of the training curriculum

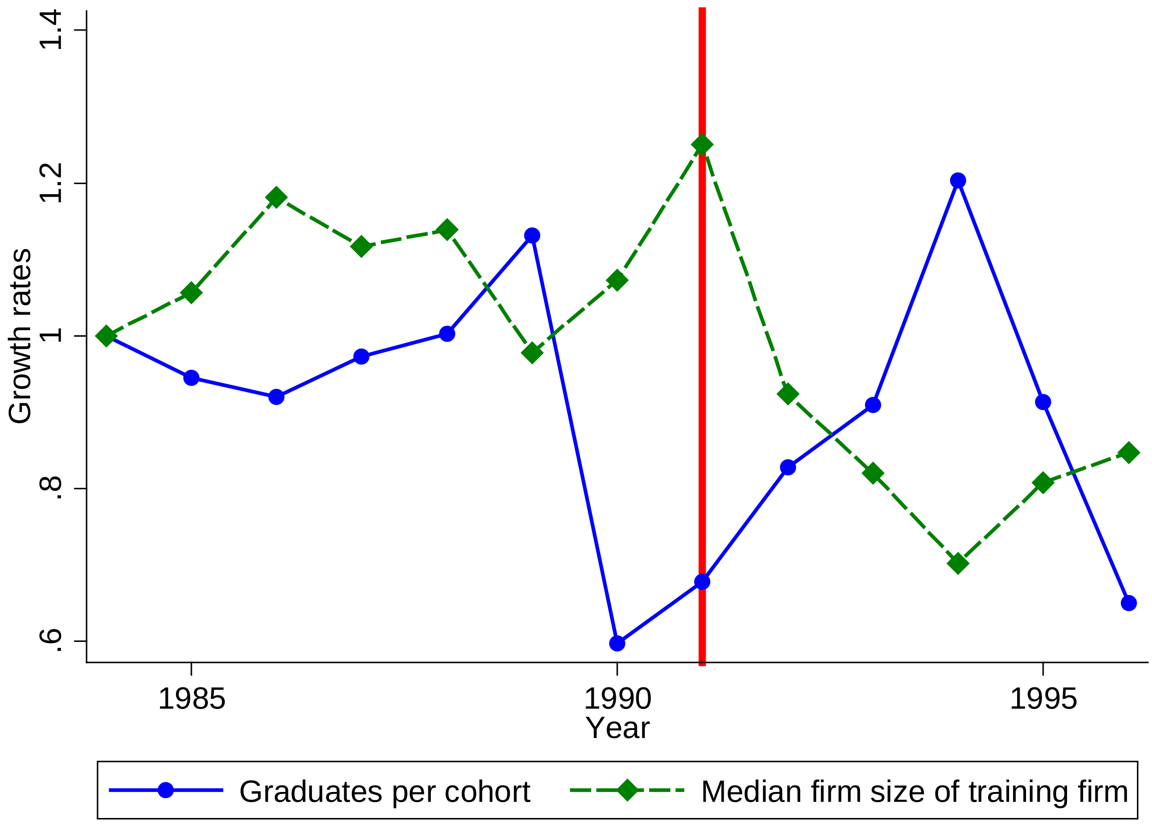

FIGURE 3:

Apprenticeship graduation cohorts and median size of training firms

The dashed line shows the growth rate of median firm size of training firms between 1984 and 1996. The solid line shows the average growth rate of graduation cohorts between 1984 and 1996.

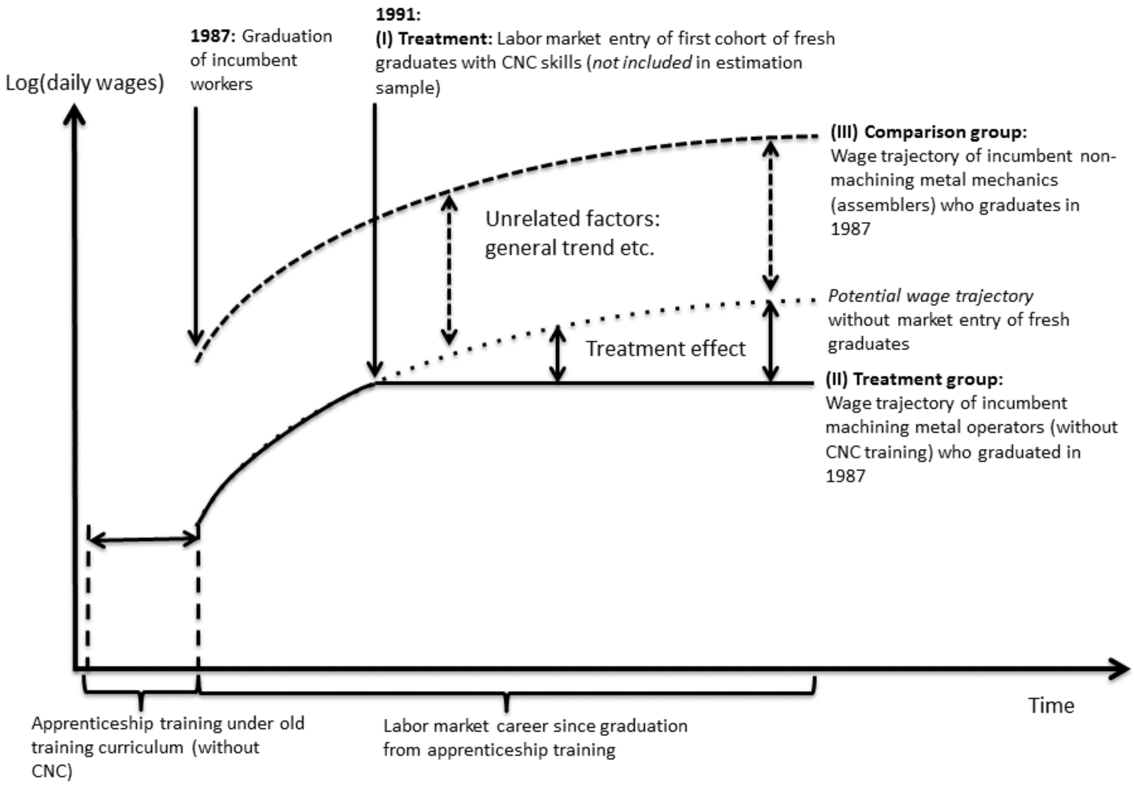

FIGURE 4:

Identification strategy (Example for graduation cohort of 1986)

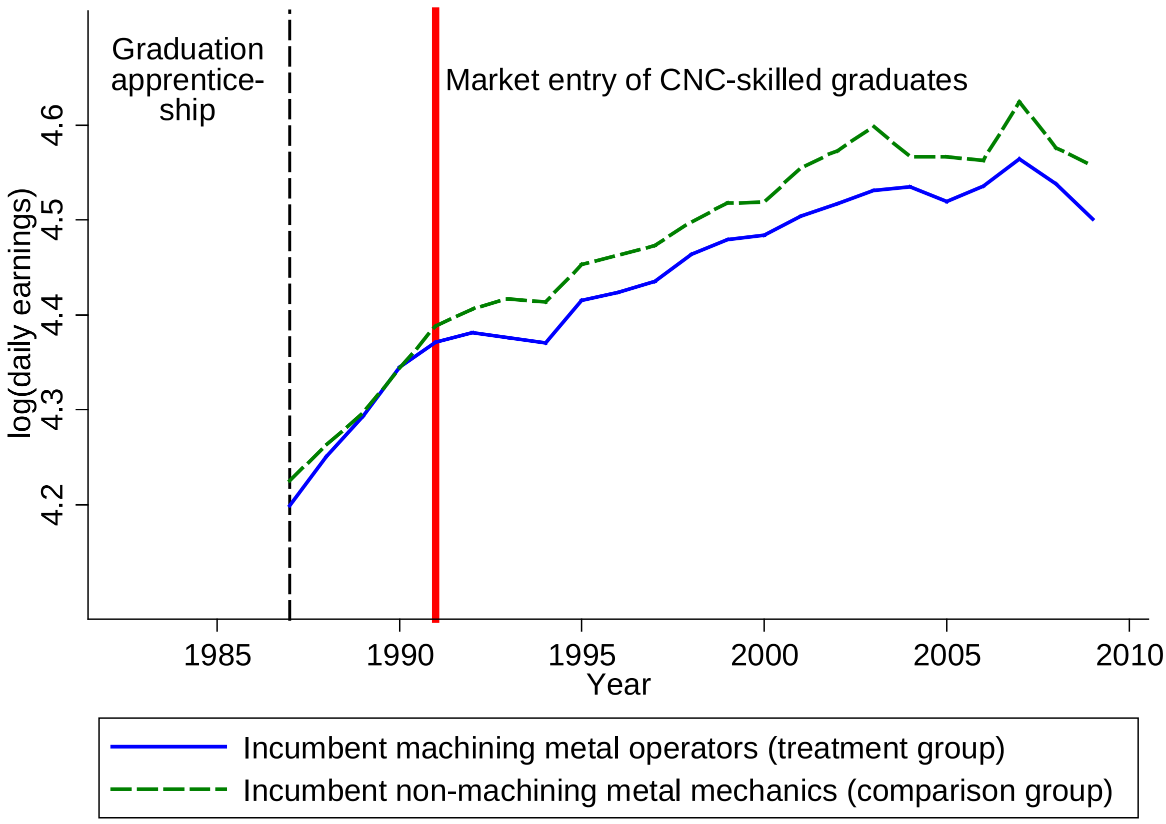

FIGURE 5a:

Daily wage trajectories for treatment and comparison group (1986 cohort)

The Figure shows the development of log real daily wages for a cohort of the treatment group (solid line) and a cohort of the comparison group (dashed line), before and after the supply shock of CNC-skilled graudates (solid vertical line). The cohort of the treatment group consits of incumbent machining metal operators who graduated in 1986 and experienced their first entire year on the labor market in 1987 (vertical dashed line). This cohort was trained before CNC-technology became a manadatory element of CNC-training in the occupation of machining metal operators. The cohort of the comparaison group consists of incumbent non-machining metal mechanics who graduated from the same training firms and at the same time as the indiviudals of the treatment group. Non-machining metal mechanics do not use CNC-technology and were not exposed to a supply shock of modern-skilled graduates in 1991. The red vertical line indicates the supply shock of CNC-skilled graduates who entered the labor market for the first time in 1991 (treatment). Daily earnings are meassured in logs and delfated by the CPI. Source BEH 1984-2010

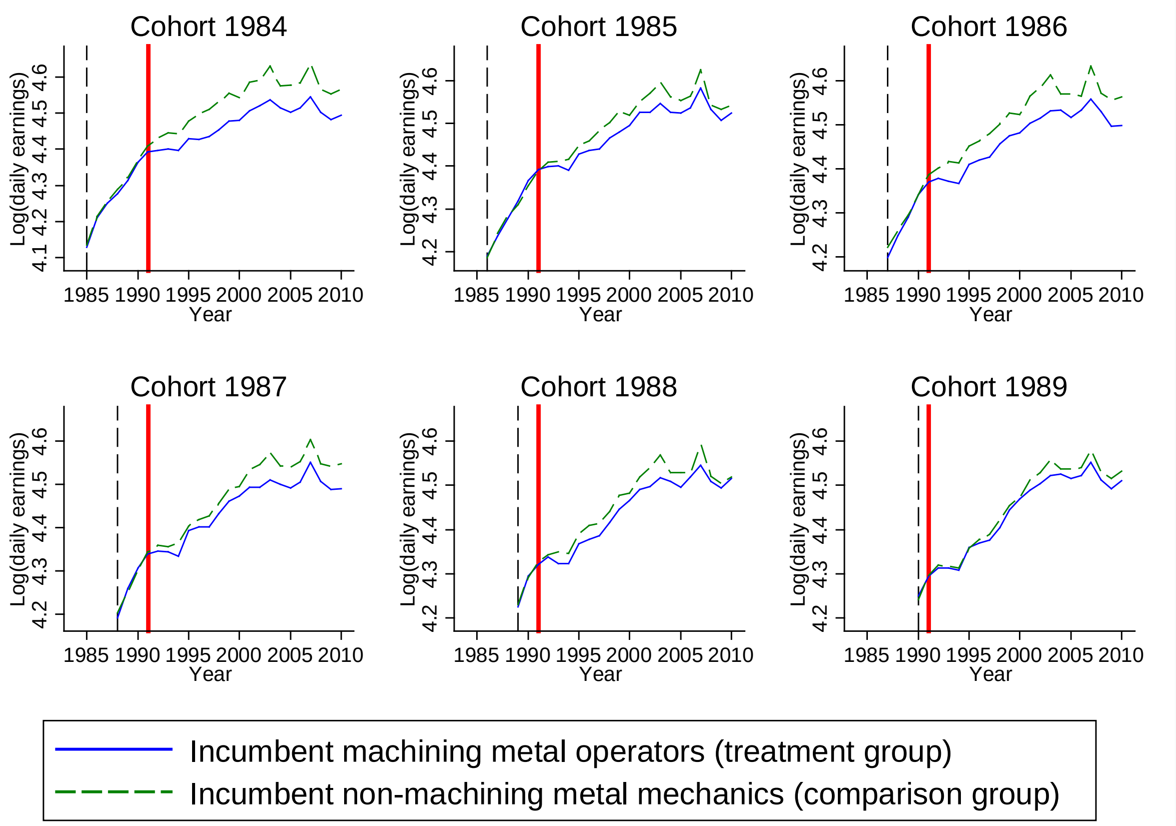

FIGURE 5b:

Daily wage trajectories for treatment and comparison groups (all affected cohorts)

The Figure shows the development of log real daily wages for all graduation kohorts of the treatment group (solid lines) and all graduation cohorts of the comparison group (dashed lines), before and after the supply shock of CNC-skilled graudates (solid vertical line). The cohorts of the treatment group consits of incumbent machining metal operators who graduated between 1984 and 1989, respectively. These cohorts were trained before CNC-technology became a manadatory element of CNC-training in the occupation of machining metal operators. The dashed vertical lines indicate their first entire year on the labor market. The cohorts of the comparaison group consists of incumbent non-machining metal mechanics who graduated from the same training firms and at the same graduation years as the cohorts of the treatmet group, i.e., between 1984 and1989, repspectively. Non-machining metal mechanics do not use CNC-technology and were not exposed to a supply shock of modern-skilled graduates in 1991. The red vertical lines indicate the supply shock of CNC-skilled graduates who entered the labor market for the first time in 1991 (treatment). Daily earnings are meassured in logs and delfated by the CPI. Source: BEH 1984-2010

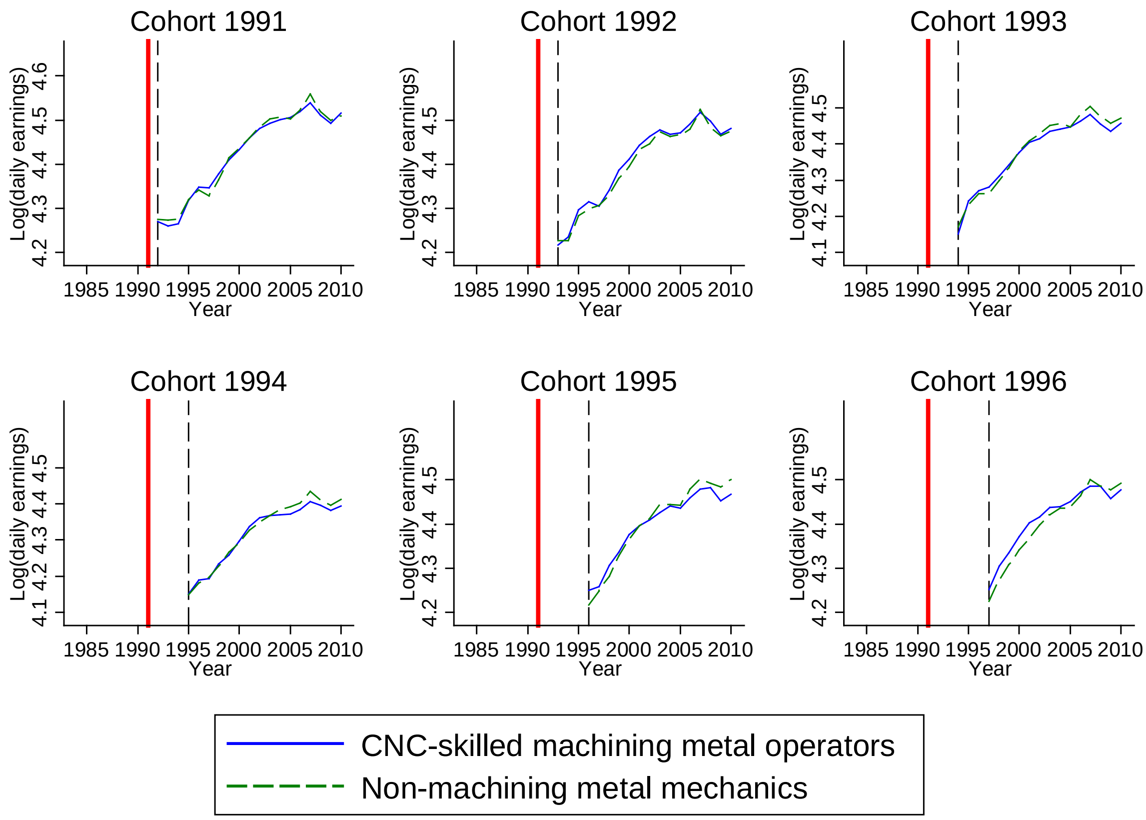

FIGURE 6:

Daily wage trajectories for CNC-skilled graduates and comparison groups (all unaffected post-treatment cohorts)

The Figure shows the development of log daily wages for all unafected cohorts who graduated after CNC-training became a mandatory element of the apprenticeship training of machining metal operators. The solid lines indicates the wage development for CNC-skilled machining metal opereators who graduated between 1991 and 1996. The vertical dashed line indicates their first entire year on the labor market. All members of theses cohorts underwent the structured CNC-training program. The dashed lines indicate the wage developments of non-machining metal mechanics who graduated at the same firms and during the same graduation years between 1991 and 1996. The solid vertical lines indicates the treatment. Source: BEH 1984-2010

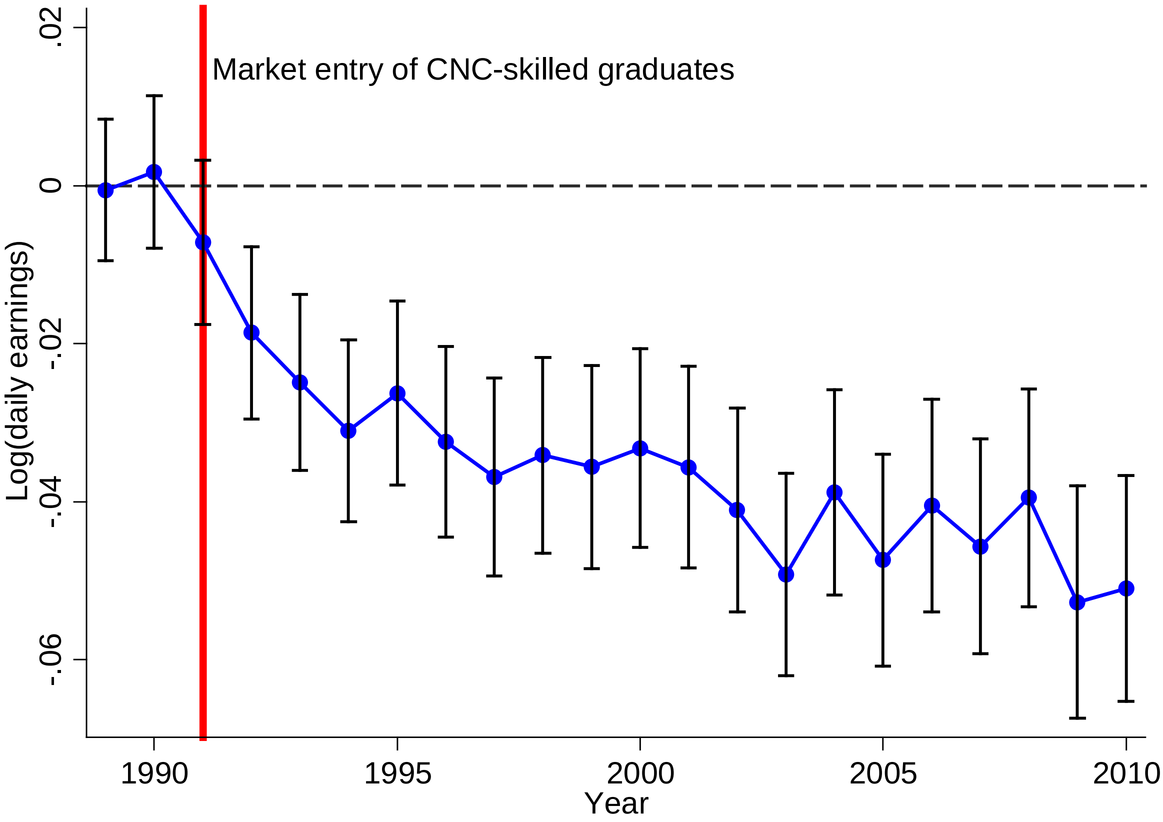

FIGURE 7:
Long-term effect of supply shock on incumbent workers' daily wages

The Figure shows the long-term effects of the supply shock of CNC-skiled graduates on the log real daily wages of incumbent machining metal operators. The dots indicate the coefficient estimates of a distrubuted lag model accourding to equation (2). The red solid vertical line indicates the supply shock of CNC-skilled graduates in the labor market. Standard errors are clustered on the individual level. The capped spikes indicate confidence bands at the 5% level. Control variables include four age categiories, year dummies, and individual fixed effects. Source: BEH 1984-2011

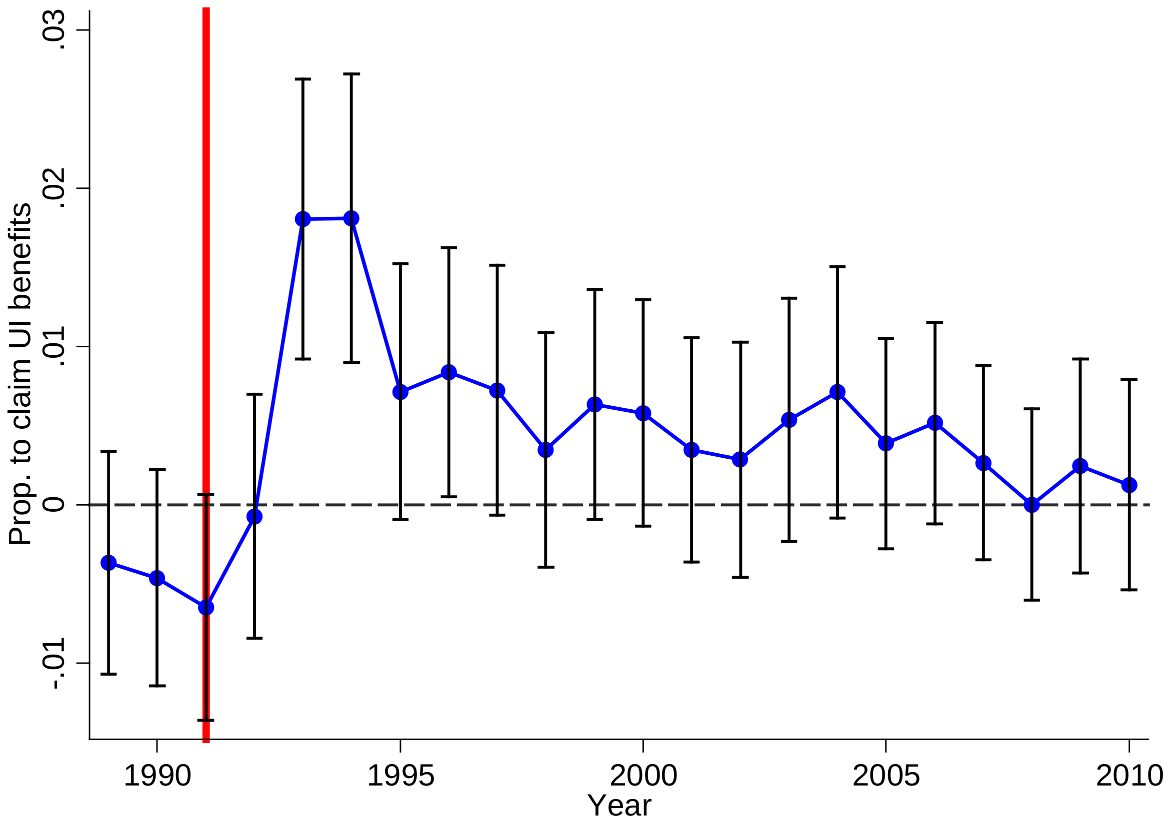

FIGURE 8:

Long-term effect of supply shock on unemplyoment.

The Figure shows the long-term effects of the supply shock of CNC-skiled graduates on the unemplyoment probability of incumbent machining metal operators. The dots indicate the coefficient estimates of a distrubuted lag model accourding to equation (2). The red solid vertical line indicates the supply shock of CNC-skilled graduates in the labor market. The dependent variable is a dummy that is one if the worker had experienced at least one spell of unemplyoment in the ongoing year. Standard errors are clustered on the individual level. The capped spikes indicate confidence bands at the 5% level. Control variables include four age categiories, year dummies, and individual fixed effects. Source: BEH 1984-2011

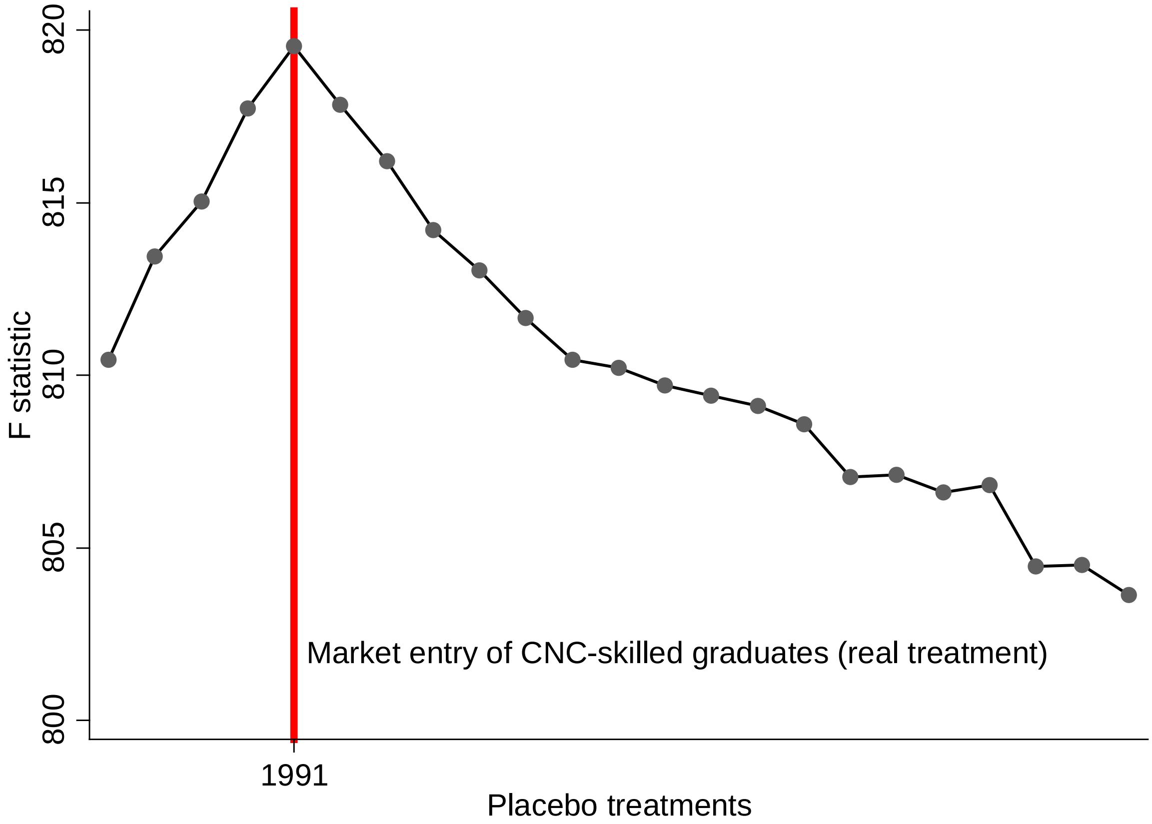

FIGURE 9:

Goodness of fit from placebo regressions vs. goodness of fit from regression with real treatment.

The Figure shows the F-statistics for a set of regressions with placebo treatments. Each of these placebo regressions includes a treatment dummy that is one in another placebo year. The solid vertical line indicates the F-statistic for the regression with the real treatment in 1991. Source BEH 1984-2010

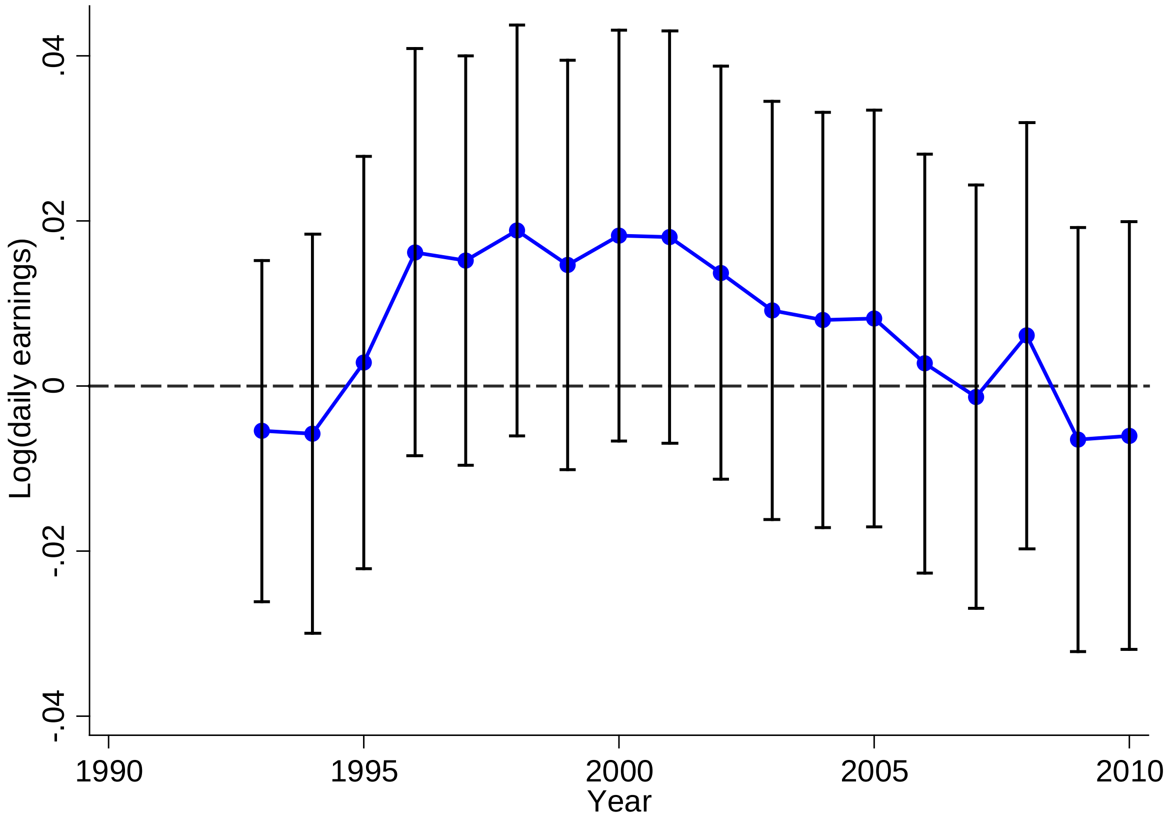

FIGURE 10:

Wage effects for CNC-skilled graduates relative to counterfactual cohorts from comparsion occupation (all unaffected post-treatment cohorts)

The Figure present the results of a distributed-lag model according to equation (2) for the post-treatment cohorts of CNC-skilled graduates and the their respective comparison cohorts of non-machining metal operators who graduated in the same firms and during the same preriod. All post-treatment cohorts underwent the structured CNC-training. Source BEH 1984-2010