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ABSTRACT

The Shelf Life of Incumbent Workers during Accelerating Technological Change: Evidence from a Training Regulation Reform*

In periods of accelerating technological change, incumbent workers must continuously update their skills to remain productive. In contrast, high school or college graduates recently entering the labor market often have the most up-to-date skills. We investigate how incumbent workers' careers respond to the increasing labor supply of graduates with more technologically advanced IT skills during a period of accelerating technological change. We identify a supply shock of more technologically advanced IT-skilled graduates by exploiting a reform of a German training regulation, a reform mandating all new apprentices in a large manufacturing occupation to acquire in-depth IT skills. We use a difference-in-differences approach to analyze how this supply shock of IT-skilled workers affected the careers of incumbent workers. The results show that even young incumbents experienced long-lasting earnings losses in the form of lower wage growth after the IT-skilled graduates entered the labor market. A detailed analysis of the mechanisms suggests that incumbents on average forwent promotions and technologically advanced IT-skilled graduates crowded incumbents out of their occupation. However, despite losing their occupation, incumbents experienced relatively little unemployment during the transition period following the supply shock and on average resumed stable careers in other occupations and sectors.

JEL Classification: J24, J64, O30

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

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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 life-long learning for ensuring 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 technologically obsolete (NYT, Feb. 13, 2016).[2]

Yet incumbent workers incur high opportunity costs for continuously updating their skills—particularly those who work full-time and have a high earnings capacity.[3] In contrast, high school and college students can not only invest in human capital at low opportunity costs but also commonly learn how to handle new technologies according to the most recent curricula. Therefore, when technologies fundamentally change, are incumbent workers at a disadvantage relative to recent graduates? And, if so, does this disadvantage manifest in negative consequences for their careers?

Our paper investigates these empirical questions with a unique quasi-experimental setting. To do so, we exploit a large German training reform that led to a shock in the relative supply of graduates with modern IT skills complementing a fundamental technological innovation that substantially changed the demand for skills in the German manufacturing sector. To provide micro-evidence about whether and, if so, how incumbent workers responded to the market entry of these IT-skilled graduates, we use highly precise register data that allows us to follow the careers of incumbent workers for more than 25 years.

As micro-evidence on the long-term dynamics of workers' careers during periods of fundamental technological change is very scarce, our results provide important new insights into how technological change affects the labor market in the long term. While the general relationship between the wage distribution, job tasks, and workers' skills is relatively well

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

[2] A number of scientific studies have also shown that firms invest more in training their workers after they have adopted new technologies (Bresnahan et al., 2002; Sieben et al., 2009).

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

understood,[4] only two recent papers have analyzed the relationship between changing technologies and workers' careers. First, Cortes (2016) has studied how the careers of individual workers in routine and non-routine jobs have evolved over the last four decades. Second, El-Sahli and Upward (2017) have analyzed how the technology of containerization affected the employment patterns of UK dockworkers. We contribute to this literature by analyzing how incumbent workers' careers respond to the increasing supply of more technologically advanced skilled recent graduates.

The labor supply shock of graduates with more technologically advanced skills may influence the careers of incumbent workers through at least three channels: First, incumbent workers may not participate in continuous training programs to compete with technologically advanced skilled graduates, because the high opportunity costs associated with extensive training programs simply exceed their expected benefits. Second, firms may become less likely to (financially) support the training of incumbent workers if the external supply of workers with more advanced technological skills raises enough that hiring young graduates becomes cheaper than training incumbent workers.[5] Third, the increasing supply of up-to-date skills may directly impact firms' decisions to adopt newer technologies. As the theory of endogenous technological change argues, firms become more likely to adopt newer technologies if workers whose skills complement the new technology are cheap and available. As a result, the supply of more technologically advanced 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. We exploit a reform of a mandatory apprenticeship training regulation in a large manufacturing occupation in Germany, a reform that led to a substantial shock in the 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.

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

[5] Some studies have shown that firms that adopt new technologies hire more skilled workers (e.g., Akerman et al., 2015; Bresnahan et al., 2002; Brynjolfsson and Hitt, 2000; Brynjolfsson and Hitt, 2003), while others show that they become more likely to train their incumbent workers (e.g., Bartel and Sicherman, 1998; Sieben et al., 2009)

In contrast to most other industrialized countries, apprenticeship training is the main school-to-work route in Germany, with about two thirds of the German workforce participating. Because apprenticeship-training programs last between three and three and a half years, apprenticeship graduates are skilled workers who are comparable to U.S. workers with a medium level of college education. Apprenticeship training is regulated at the federal level, and mandatory training curricula define the requisite skills for more than 350 training occupations. Independent institutions monitor apprenticeship training programs and enforce these curricula through occupation-specific final exams (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 have, at the very least, the skills 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 were trained *before* the reform, respond to the reform-induced supply shock of workers who possess more technologically advanced IT-skills, because they were trained *after* the reform.[6]

We analyze a particular reform in the occupation of machining metal operators, who 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 prospects in Germany, many young men with a medium level of general education choose to become machining metal operators. Until the mid-1980s, machining metal operators performed processes such as drilling, turning, and milling on several specific manual machines. At that point, computer numerical control machines (CNC), a groundbreaking new technology, spread across the industry (see figure 1). CNC technology integrated most manual machining processes into one machine that workers could control via a computer system. Therefore, CNC machines substantially changed both the nature of work and the necessary skills in the occupation (Bartel et al., 2007; Lewis, 2011).

—Figure 1 about here—

In the late 1980s, German policy makers 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 were trained before the reform with those who were trained thereafter. Instead, our interest is in understanding how incumbent workers respond to the increasing competition of more technologically advanced skilled workers.

operators had to learn how to use one of several traditional manual machines during apprenticeship training. After the reform, all machining metal operators throughout Germany 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. Although CNC technology was available before the reform, the reform accelerated the supply of workers with sophisticated CNC skills within a very narrow window of time. In contrast, apprentices who had graduated (and later became workers) before the reform did not receive extensive CNC training in their apprenticeship training. Therefore, these incumbent workers were, on average, less proficient in the use of CNC technology than post-reform apprenticeship graduates.

Using a difference-in-differences approach to identify the effect of the reform-induced supply shock, we analyze how the careers of incumbent machining metal operators[7] *without* CNC skills responded to the increasing supply of CNC-trained graduates. 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 a part of their apprenticeship training.

The comparison group consists of incumbent workers from a similar occupation that was not exposed to a groundbreaking technological innovation. This 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 but do not use CNC technology. Otherwise, non-machining metal mechanics are very similar to machining metal operators, because both groups have studied and worked in the same vocational schools and firms, produced similar final goods, and have representation by the same unions. As a result, both groups were exposed to exactly the same labor market institutions and macroeconomic conditions, and their employers applied similar selection criteria when hiring.

Our analysis relies on register data from the Federal Employment Agency of Germany. This data allows us to follow our treatment and comparison groups for more than 25 years, i.e., both before and after the supply shock. The data contains highly accurate information about workers' wages, employment status, and common demographic characteristics (e.g., age, nationality, and education). Moreover, the data allows us to link the worker to the firm, so that we can account for the unobserved heterogeneity in training quality by matching workers from the two groups who have been trained in the same firms at the same time.

[7] The term "incumbent workers" refers to those who graduated before the apprenticeship training reform and thus did not receive CNC training as a mandatory part of their apprenticeship training.

Our results show that incumbent workers experienced long-lasting earnings losses in response to the market entry of graduates with CNC skills. Over the observation period of more than 25 years, total earnings losses amounted to about 70% of an average worker's 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 experienced only transitory unemployment during a short period immediately after the first 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, who incur high opportunity costs for learning CNC skills, forwent crucial promotions after they had to compete with technologically advanced graduates, i.e., the incumbents' lower wage growth appears to be partly the consequence of a less favorable career path within firms. Moreover, incumbent workers 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, on average, incumbent machining metal operators also 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. Nonetheless, our results suggest that most incumbent workers remained in the metal working industry. One possible reason is that employment in German manufacturing has evolved in a more stable way than, for example, that of U.S. manufacturing, after the East-European trade integration (Dauth et al., 2014). Thus affected workers in Germany potentially had many opportunities for remaining in the metal working industry.

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. Consequently, our results contribute to at least four strands of the literature. First, previous studies showed that the adverse consequences of routine-biased technological change were most substantial for medium-educated workers, particularly for medium-educated production workers (Goos et al., 2014). While our paper supports these findings—and shows that wage losses persist over workers' entire careers—our evidence also shows that workers adjust to the consequences of technological change by, for example, 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 findings 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, with only few data sources providing micro-level information about workers' careers and skills, and the changing nature of individual jobs. Therefore, most studies had to rely on aggregate measures that only allow them to infer time trends of descriptive associations between changes in the content of job tasks, computer usage, employment, and wage rates. However, as these descriptive associations often do not allow the inference of precise mechanisms, a number of researchers have criticized the results for merely reflecting other institutional and macroeconomic changes that 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 technologically advanced IT skills for a narrowly defined treatment occupation in response to a fundamental technological innovation. Thus we are able to provide causal micro-level evidence on a specific mechanism that explains how technological changes influence the 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 have analyzed whether older workers decide to take early retirement after their firms 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] for explaining occupational mobility, college wage premiums, or 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 studies have analyzed the effects of labor market programs, training, and schooling reforms for those who benefit from them (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 those labor market programs (Crépon et al., 2013). Our study shows the long-term consequences from such a displacement effect.

The remainder of the paper is organized as follows. Section II describes the CNC technology and the institutional details of the apprenticeship system in Germany. Section III

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

describes the training reform and the identification strategy. Section IV presents the data and descriptive statistics. Section V gives our empirical approach. Section VI presents the main results, and section VII gives the mechanisms underlying incumbent workers' wage losses. Section VIII contains the robustness checks, and section IX concludes.

II. CNC TECHNOLOGY AND TRAINING IN THE MANUFACTURING SECTOR

This chapter describes both 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 that 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 and be able to use new tools and handle different manufacturing processes simultaneously. Thus CNC technology increased the demand for both computer programming and problem-solving skills (Bartel et al., 2007) and is a strong complement to medium and high skills (Lewis, 2011).

Until the late 1990s, 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 substantially interrupt 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 for guaranteeing a smooth and fast production process. By the late 1990s and early 2000s, advances in software, fusion control technologies, and three-dimensional computer-aided designs (3D CAD) made CNC programming simpler to complete and execute (Bartel et al., 2007).

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 countries such as the U.S., 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-a-half years, and apprentices are commonly high school graduates in their late teens who apply immediately for an apprenticeship in training firms. Firms that fulfill the training requirements stated in the Vocational Training Act are free to decide whether to hire and train apprentices and, if so, how many.

Each training occupation has a specific training curriculum that defines the precise training content for each training year, and independent institutions monitor apprenticeship training and administer and grade final exams. Thus all firms have to comply with the training regulations, with no leeway for designing their apprenticeship training to contain mostly firm-specific skills. As a result, apprenticeship graduates in each occupation acquire comparable levels of both 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., 2018).

For two reasons, the German apprenticeship system is ideal for identifying curriculum-induced skill shocks between cohorts. First, training curricula are closely aligned to technological developments. 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 in providing 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 one day after the final exam, which commonly takes place on the same day for each occupation and region in the first half of a calendar year. 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 excellent setting for identifying the skills of recent graduates and for inferring when cohorts of graduates enter the labor market with new skills.

III. TRAINING REFORM AND IDENTIFICATION STRATEGY

The goal of this paper is to analyze how the careers of incumbent machining metal operators without CNC skills responded to the increasing labor supply of graduates with those skills. We exploit a reform of an apprenticeship-training curriculum, a reform that led to a substantial labor supply shock of graduates with CNC skills in the labor market of machining metal operators. The following two 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, such as metal cogs, screws, or threads. Before the reform, apprentices in machining metal operations were trained for three years. During this period they had to choose among three training programs, each of which specialized in one of three different manual machines: drilling, turning, or milling (see figure 1 for an example of a turning machine). To use those machines, apprentices had to learn manual precision skills but not any IT or programming skills.

In 1987 policy makers implemented an entirely new training curriculum, which combined several machining metal occupations into one and introduced in-depth CNC training (first red vertical line in figure 2). As a result, to obtain their apprenticeship degree, all machining metal operators who started their apprenticeship training under the new curriculum had to become proficient in using CNC machines. Specifically, the new curriculum required all apprentices to spend at least eight weeks of training on CNC programming. Throughout this period, they had to learn how to write and code new programs, to debug and change existing ones, and to produce their own parts on CNC machines. They also had to work for at least 26 weeks on non-manual machines. For example, they learned to change and adjust tools to guarantee a smooth production process and to quickly prepare the machines for new lines of production. Moreover, during their final examination they had to produce a metal part on a CNC machine. As the second red line in Figure 2 shows, the new training curriculum extended the training duration from three to three-and-a-half years, meaning that the last cohort of manual machining metal operators graduated in the summer of 1989 and that the first cohort of CNC-skilled machining metal operators graduated at the start of 1991.

—Figure 2 about here—

Previous evidence suggests that the sophisticated CNC training under the new curriculum has affected the organization of work in Germany. For example, Backes-Gellner (1996) shows that, in the 1990s, many German firms programmed their CNC machines in-house, while firms in countries without a comparable apprenticeship system largely contracted with external specialists to program theirs. While 66% of German firms programmed their CNC machines in-house, only about 8% of French or UK firms did so (Backes-Gellner (1996). Moreover, evidence from the U.S. suggests that formal CNC training is productivity enhancing. 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 running times of CNC machines by about 50% more than firms with comparable CNC technology but that did not provide that formal training.

As CNC technology was available even before the reform, firms might already have trained their workers on CNC machines, thereby making the reform merely a legal manifestation of a process that had occurred long before the actual reform. However, the reform required very extensive, structured CNC training—demanding specialized instructors and spare CNC machines—for fulfilling the new curriculum's training requirements. As many firms were unable to provide such an extensive training program, the government subsidized and set up special programs to help firms cope with the change and cooperate in the training of machining metal operators (Freding, 1992). Moreover, many firms started to send their apprentices to specialized CNC training centers or to larger firms that ran their own training centers. Thus, even if some apprentices had already received CNC training before the reform, the reform itself substantially changed the average level of CNC skills that apprentices had to reach.

Table 1 and Figure 3 further 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. During this period, policy makers implemented a grace period for facilitating the transition from the old to the new training curriculum, giving firms the option of still following the old training curriculum instead of applying the new one (see figure 2 for the detailed timing of the grace period).

As row 1 of Table 1 shows, only about 45% of the apprentices who started their apprenticeship training in 1987 had been enrolled under the new curriculum. If most firms had extensively trained their workers on CNC machines even before the reform, almost all firms would have immediately applied the new curriculum. However, throughout the grace period, the percentage of apprentices trained according to the new curriculum increased to 89% within only one year—and virtually all training firms applied the new training curriculum for the starting cohort of 1989. Although these results cannot rule out the possibility that some firms provided CNC training before the reform, the results substantiate that most firms introduced CNC training only in response to the reform.

—Table 1 about here—

Figure 3 presents descriptive statistics about the relative number and size of training firms for all graduation cohorts between 1984 and 1996. The figure shows a sharp decline in the number of training firms between 1989 and 1991, and an increase in their median size. Although a part of these effects arises because the training period was extended from three to three-and-half years, these results nonetheless suggest that smaller firms took a short break from apprenticeship training—most likely because they faced problems in quickly implementing the new curriculum, particularly the CNC training requirements. However, when the new training curriculum became mandatory at the end of the grace period, the median size of training firms decreased, and the number of training firms rose again, showing that small firms quickly resumed apprenticeship training with the new curriculum. Overall, Figure 3 thus provides additional evidence that the reform of the training curriculum indeed changed the way that firms trained their apprentices. Nevertheless, the number of apprenticeship graduates declined again for the graduation cohorts of 1995 and 1996, because of a severe recession in the manufacturing sector (with unemployment reaching about 12% in 1996).

—Figure 3 about here—

III.B. Identification strategy

We exploit the training reform to estimate how the supply shock of CNC-skilled workers impacted the careers of incumbent manual machining metal operators. We do so by using a difference-in-differences approach comparing the careers of incumbent machining metal operators to those of incumbent non-machining metal mechanics, who were not exposed to the supply shock of CNC-skilled workers. We define the treatment, the treatment group, and the comparison group as follows (see figure 2 for a graphical overview):

The treatment is the supply shock of CNC-skilled workers. The supply shock started in 1991 with the market entry of the first cohort of machining metal operators who were trained with the new curriculum. Thus the treatment indicator simply divides the observation period in the pre-treatment period before 1991 and the post-treatment period after 1991.

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 trained exclusively according to the old curriculum. As Figure 2 shows, the last cohort of those apprentices began their apprenticeship training in 1986 and graduated in the summer of 1989.[9] We follow all six graduation cohorts from the first year after the year of their apprenticeship graduation through 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 (solid line) presents a graphical example of the graduation cohort of 1986.

—Figure 4 about here—

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 through 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—except that no training for a new technology was implemented in the non-machining metal mechanics' curriculum.[10] In contrast to machining metal operators (who *produce* precision metal parts), non-machining metal mechanics *assemble* all type of metal parts of a machine, gearbox, or motor. Thus non-machining metal mechanics use neither manual machines nor CNC technology.

Otherwise, machining metal operators and non-machining metal mechanics are almost identical, for the following four reasons: First, they both have similar training programs, because they not only have the same training duration but also spend their first training year learning basic metal-working techniques. Second, both groups frequently receive their training in the same training firms, and employers apply similar criteria to selecting apprentices for both

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

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

occupations. Third, both occupations are represented by the same union and governed by the same collective bargaining agreement. Fourth, both groups experience 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 in training quality may exist. Some firms may have better instructors or better training centers, or provide more on-the-job training than the training program requires (Dustmann and Schönberg, 2009). For example, Mohrenweiser and Zwick (2017) have investigated whether the training firms of metal-working apprentices train skills beyond those required by the training curricula. They show that about 50% of firms train apprentices in additional skills, such as English and soft skills, which are transferable across firms. Their results suggest that only very few firms train additional firm-specific skills directly related to the technology that the firms actually use.

Nevertheless, to account for the unobserved heterogeneity of the quality of training, we restrict the comparison group to non-machining metal mechanics who were 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 at the cohort-by-training firm level.

To avoid confusion, we hereafter 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 terms "*CNC-skilled* apprenticeship graduates" and "*CNC-skilled* machining metal operators" for those machining metal operators who graduated after the reform and who had undergone the structured CNC training apprenticeship program.[11] As mentioned earlier, these CNC-skilled workers do not appear in either the treatment or comparison group in our main regression analyses.

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 entire population of German social security records from 1975 through 2010. It covers all employees subject to social security contributions except civil servants and the self-employed. Unique person and

[11] A number of robustness checks in sections VII and VIII also include CNC-skilled workers.

establishment identifiers identify all individuals and establishments, allowing us to follow all workers and firms over time.

As German data protection legislation prohibits using the entire population of machining metal operators and non-machining metal mechanics, we have to use a sample of all individuals with 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) with the BEH information to obtain information about the workers' unemployment status.

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

For our main analysis, we focus on apprentices who graduated between 1984 and 1989, i.e., the years before the supply shock, and follow all of them through 2010. Furthermore, we use only apprenticeship graduates in the treatment occupation for which we find a peer in the comparison group, i.e. who graduated in the same establishment and year, and vice versa (see III.C for more details). Doing so allows us to account for the unobserved heterogeneity of the training quality by incorporating cohort-by-training firm fixed effects. Our restrictions reduce our initial sample from 15,641 to 9,075 individuals in the treatment group and from 51,979 to 10,846 in the comparison group (table 2). However, when we conduct robustness checks on the full sample, the results do not change (section V.III.C)

[12] In the 1980s, despite having to report the employment status of an individual at the end of the year, firms were not forced to report the transition from apprenticeship to regular employment within the year. Therefore, a number of firms report only once a year to the German social security administration. Such firms usually report the actual status of an employee (apprentice or skilled worker) on December 31st. Therefore, we plausibly assume that individuals whose last apprenticeship spell was registered on December 31st of a given year graduated in the following year.

—Table 2 about here—

Our main dependent variables are the annual and daily earnings that we measure in 2010 Euros by using the consumer price index from the national statistical office. As in many register data sources, our earnings data is top coded. However, top coding is not a problem for our specific sample of apprenticeship graduates, who seldom earn wages above the social security contribution threshold.[13] Finally, as with most studies that have used this data, we remove the few observations with earnings below the social security thresholds, because these observations are very likely to be incorrect data entries.

Table 3 provides descriptive statistics for workers in the treatment and comparison groups 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 contains a large number of women or non-German nationals, the comparison group contains slightly fewer females and non-German nationals and is slightly older than the treatment group. Given the large number of observations, these differences are significant at reasonable confidence levels. Moreover, although balanced characteristics are not an identification assumption of a difference-in-differences approach, our main results persist when we control for gender and nationality, and even when we remove all women and non-German nationals.

—Table 3 about here—

IV.B. Descriptive results: Main regression sample

Figures 5a and 5b graphically present descriptive statistics for the key results of the paper. Figure 5a shows the results for the graduation cohort of 1986 on a large scale, and Figure 5b gives an overview of 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 first employment spell after the year of their apprenticeship graduation (vertical dashed line)

[13] The BEH data censors very high wages that lie above the threshold for social security contributions. Although this top coding affects from 10 to 12% percent of all male full-time workers and about one to three percent of all female full-time 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 do not impute high wages. Similarly, Card et al. (2017) and Dustmann and Meghir (2005), who also use the same data base, refrain from imputing high wages when using only apprenticeship graduates.

through 2010 (e.g., when the graduation cohort of 1986 experienced their first entire year on the labor market in 1987). We do not report workers' wages during their apprenticeship training period, because apprentices receive only a small training compensation (worth less than 50% of a skilled worker' entry wage), and the training compensation is very similar for all apprentices within the manufacturing sector (Ryan, 2001; Ryan et al., 2013).

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

—Figures 5a and 5b about here —

Figure 5a shows that the 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 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 5b confirms the results in Figure 5a for all graduation cohorts between 1984 and 1989. In other words, each graduation cohort of machining metal operators experienced lower wage growth in response to the supply shock of CNC-skilled machining metal operators.

However, Figure 5b suggests that the effect was larger for earlier graduation cohorts than for later ones. The decline of the wage differential is consistent with our main argument. As 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 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 operators, the German government provided scholarships for a small number of outstanding apprenticeship graduates to learn CNC skills. As a result, those who graduated in the late 1980s

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

were on average better prepared to compete with the increasing supply of CNC-skilled workers than those who had 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 were trained in the same firms and graduated at the same time. However, we cannot completely rule out the possibility that structural changes other than the supply shock have had an adverse impact on the occupation of machining metal operators, enough so to make their wage trajectories differ systematically from those of non-machining metal mechanics. To resolve such a concern, we analyzed the earnings trends of the *CNC-skilled* machining metal operators, who underwent the new training program after the reform. While the post-reform cohorts of CNC-skilled machining metal operators belong neither to the treatment nor the comparison group of our main regression sample, they are useful for supporting the validity of our argument.

Specifically, if the long-lasting effects presented in Figure 5a and 5b were indeed related to the CNC training after the reform, we should find no 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—i.e., 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 non-machining metal mechanic counterparts, i.e., non-machining metal mechanics who graduated after 1991. 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 lines in the first subfigure of Figure 6 represent the wage trajectory of the 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 differ only from the pre-reform cohorts in their training content, the results do not show that structural changes other

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

than the supply shock adversely affected the treatment group of incumbent machining metal operators.

—Figure 6 about here—

V. ESTIMATION APPROACH

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

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

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_{ist} 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 at the time and worker level, the isolated dummy to account for differences between the treatment and comparison group ($D(s = m)$) 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. It describes how the careers of incumbent machining metal operators are influenced by the market entry of CNC-skilled graduates. Thus we expect the

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

coefficient estimate to be negative if incumbent machining metal operators are indeed affected by the increased competition of CNC-skilled graduates.

We reiterate that our estimation approach differs from the more commonly used *population* difference-in-differences approaches, which have, for example, been used for analyzing how education influences labor market outcomes.[17] Our approach differs because 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* (post-treatment period) the supply shock to evaluate how the reform-induced supply shock of CNC-skilled graduates influenced the careers of incumbent workers. In other words, the treatment—*not the treatment group*—is the labor market entry of CNC-skilled graduates.

Our difference-in-differences 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 this assumption is not testable, 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 did not change their behavior in anticipation of the treatment. On one hand, some firms might have started to train their apprentices in anticipation of the reform. As previously discussed (section III), such anticipation might explain why the effects declined for later graduation cohorts that were closer to the reform. Thus, if this bias drives our results, our estimates represent a lower bound. On the other hand, more able individuals might have chosen other training occupations before the reform, because they might have anticipated its consequences. However, as it is unlikely that individuals can foresee technological developments over many decades, we should expect larger, not smaller, effects for those who graduated in the late 1980s (shortly before the reform) than for those who graduated in the early 1980s. Moreover, as our estimation approach accounts for all unobserved time-constant heterogeneity at the worker level, this effect is unlikely to bias our results.

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[17] For example, Meghir and Palme (2005) have used a difference-in-differences approach that compares pre- and post-reform cohorts for evaluating 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 (e.g., Pischke and von Wachter (2008)).

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

Nonetheless, 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 (so that the treatment and comparison groups face the same external conditions), the SUTVA is more likely to hold if the treatment and comparison groups live in parallel worlds (so that the comparison group itself is unaffected by the treatment). Therefore, we now discuss the SUTVA 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. Specifically, technology and training commonly increase the productivity of firms and the economic growth of an 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 capture not only the displacement (substitution) effect (which arises if incumbent machining metal operators are crowded out by young CNC-skilled graduates) but also the net scale effect (which arises because the demand for manufacturing workers in CNC firms increases in response to the market entry of CNC-skilled workers).

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 groups in the same way and would, therefore, be removed through the difference-in-differences approach. However, incumbent non-machining metal mechanics in the comparison group may benefit relatively more from scale effects than our treatment group of incumbent machining metal operators, so that $\hat{\delta}$ may not capture the pure displacement effect. Thus we emphasize

[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.

here that the reader must bear this possibility in mind when interpreting the results. Nonetheless, Section VI.C. provides a robustness check with a comparison group of workers who work in non-CNC firms and are therefore less likely to be directly affected by the scale effects of CNC firms—and the results remain the same.

VI. MAIN RESULTS

VI.A. Un-adjusted difference-in-differences estimates

Table 4 compares the earnings of machining metal operators (rows one and three) and the earnings gaps between machining metal operators and non-machining metal mechanics (rows two and four) for each graduation cohort before and after the supply shock of CNC-skilled graduates.

—Table 4 about here—

Row five shows the unadjusted difference-in-differences estimates. Rows one and two show that, before the supply shock of CNC-skilled graduates, the 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.

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 daily wages of about five percentage points, whereas those who graduated in 1989 forwent on average only about two percentage points of daily wages.

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

Table 5 shows our regression-adjusted difference-in-differences estimates according to regression equation (1).

—Table 5 about here—

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 at the worker level, while excluding all time-constant variables.

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

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 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—

VII. MECHANISMS

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

VII.A. Long-term effects: daily wages

The average effects 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 distributed-lag version of regression equation (1).

$$lnw_{ist} = \alpha + \lambda_t + \theta_i + \sum_{k=-2}^{19} \delta_k RT_k + X_{ist}\beta + \varepsilon_{ist} \tag{2}$$

where $\sum_{k=-2}^{19} \delta_k RT_k$ 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. We emphasize here that specification (2) is more flexible than specification (1), because 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 but 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 the daily wages of incumbent machining metal operators.

If incumbent machining metal operators had 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 retraining period. However, the evidence reveals that the effect is persistent in the long run. This finding may appear counterintuitive, because the workers in our study are relatively young, with a long career ahead of them for reaping the benefits of further training. However, a likely reason for our finding is the high opportunity costs associated with extensive training in an entirely new technology. In our case, CNC training is costly, because it often takes place in specialized training centers and requires a lot of time to practice on CNC machines. On one hand, incumbent machining metal operators may have decided not to undertake CNC training on their own, because the opportunity costs for CNC training simply exceeded its expected benefits. Incumbent workers might have high opportunity costs because they earn high wages and are likely to have families, and therefore substitute time for home production. On the other hand, the young incumbent workers may have been too credit-constrained to invest in CNC skills without the financial support of their firms, while their firms may have profited from hiring fresh graduates instead of training incumbent workers.

VII.B. The extensive margin: unemployment

Thus far, the results have shown that the supply shock of CNC-skilled graduates was related to effects on the intensive margin in the 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 the likelihood of incumbent workers of becoming unemployed. Therefore, Figure 8 shows the results for incumbent machining metal operators' likelihood of becoming unemployed. The results stem from a linear probability version of regression equation (2), for which we have replaced the lnw_{ist} with a dummy variable indicating whether a worker had at least one spell of unemployment in a 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—and, 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 workers performing routine and non-routine tasks 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 strong employment protection regulations comparable to those of German manufacturing workers.

We emphasize here that the increased likelihood of incumbent machining metal operators becoming unemployed occurred during a period of economic prosperity, i.e., before a severe recession hit the German metal working sector in 1995 (see grey dashed line). Thus the results in Figure 8 validate that our estimated effects are indeed related to the supply shock of CNC-skilled graduates, not a consequence of unrelated macro-economic conditions.

VII.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 analyzes 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.

—Table 7 about here—

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 CNC-skilled graduates. As occupation-specific skills are a 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 observed in subsection *VI.A.*

However, as employment protection regulations are relatively strict in Germany, firms face obstacles to laying off workers without cause. Thus many firms may have reallocated incumbent workers to other jobs. For example, firms may have reallocated them to jobs with inferior career perspectives, either to minimize the firms' long-term costs for those workers or to encourage them to leave the firm on their own.[19] For a more detailed analysis of this argument, the second specification analyzes workers' occupational mobility within firms. Specifically, the second specification estimates the same linear probability model as the first one on a restricted sample of incumbent workers who have remained with their training firm. The 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. However, as we include individual fixed effects in the regression model, we remove all time-invariant unobserved heterogeneity. The second column reveals that even those incumbent machining metal operators who remained with their training firms became about seven percentage points less likely to remain in their training occupation. This result is consistent with the argument that firms have reallocated incumbent workers in response to the market entry of CNC-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 the service sector (Autor, 2013; Autor, 2015; Autor et al., 2006;

[19] German law commonly forbids the demoting of workers to jobs with lower earnings or less responsibility. However, the law does not protect the prospect of future earnings.

Goos et al., 2009; Goos et al., 2014; Gregory et al., 2016). Therefore, in Table 8 we analyze whether incumbent machining metal operators became more likely to leave the manufacturing sector. The table contains three specifications. The first analyzes whether incumbent workers became less likely to remain in the metal working sector (column 1). The second analyzes whether incumbent workers became more likely to enter low-wage service jobs (e.g., waiters or nurses) (column 2), and the third analyzes whether they became more likely to enter high-wage service jobs (e.g., in finance or law) (column 3).

—Table 8 about here—

The results reveal that incumbent machining metal operators became less likely to remain in the manufacturing sector and more likely to enter the service sector, primarily the low-wage service sector. These 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 other occupations within the manufacturing sector. This result is in contrast to recent evidence from the U.S. showing a large outflow from the manufacturing sector. One potential reason for this difference 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), whereas international trade has substantially reduced employment in U.S. manufacturing over the recent three decades (Autor et al., 2013).

VII.D. Upward mobility

One potential reason for incumbent machining metal operators forgoing wage growth, even without leaving their occupation or firm, is that their career prospects may have deteriorated as a result of the supply shock. Many employers implement promotion tournaments to provide incentives for their workers to exert more effort. Tournaments commonly reward workers' relative performance, which is a function of skills, ability, and effort (Gibbons and Waldman, 1999; Lazear and Rosen, 1981; Waldman, 2016). 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 have impacted incumbent workers' likelihood of receiving promotions. In comparison to the CNC-skilled graduates, incumbent machining metal operators on average have a skills disadvantage, because they did not receive structured CNC training. As a result, they may have become less likely to win promotion tournaments after the supply shock of CNC-skilled workers. The reduced possibility of winning may have further distorted their incentives for exerting effort (Chan, 1996).

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

Although we cannot identify precise job hierarchies in the register data, the German occupational-based career system offers a unique opportunity for analyzing promotions of blue-collar workers to the managerial level. If an apprenticeship graduate wants to become a foreman (i.e., move up to a managerial position) he or she needs an additional degree—that of technician or master craftsman. Most candidates for both degrees work a few years after apprenticeship completion before they join a part- or full-time technician or master craftsman training course for one (full-time) or two years (part-time). These courses are organized by local chambers of industry and commerce, follow a standardized curriculum, and give their graduates a recognized certificate. Both degrees are categorized as level 5 degrees in ISCED 97, an international standardization of educational degrees, and thus are equivalent to a MSc degree in the U.S. (Schneider, 2008). Due to the high standardization of occupational labor markets in Germany, employers commonly urge talented workers to obtain a master craftsman/technician degree for promotion eligibility for the managerial level. Therefore, holding a master craftsman or technician degree is a valid proxy for a worker's upward mobility within firms.

Table 9 gives the results of a linear probability version of equation (1) with the dependent dummy variable that indicates whether a worker holds a master craftsman or technician degree at time t. The results reveal that the supply shock reduced the likelihood of incumbent machining metal operators becoming master craftsmen or technicians by about five percentage points. This effect is substantial, 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 CNC-skilled graduates had a substantial negative impact on the upward mobility of incumbent machining metal operators.

—Table 9 about here—

VII.E. Benchmarking the overall effects: annual earnings

We now 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 the independent variable of regression equation (2) to calculate $\hat{\delta}_k$ (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:

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

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

The three columns of Table 10 present three specifications of the results. The first column presents the results of a specification that includes only 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 to zero all observations that have missing annual earnings and that occur before the workers' last observed spell. As mentioned in section IV, our data includes only workers who contribute to German social security. We therefore cannot observe self-employed workers, certain types of civil servants, or non-employed workers who leave the sample without claiming unemployment benefits or joining some type of state-provided program.[20] Thus, while the first specification may underestimate the true effect, the second specification may overstate it.

The third column presents the 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

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

us to disentangle the wage effect (price effect) from the employment effect (quantity effect). As in the first specification, we ignore missing annual earnings in the third specification.

—Table 10 about here—

Columns one and two show that the incumbent machining metal operators' total earnings losses amounted to about 70% of their average pre-treatment annual earnings if we exclude zero earnings and about 90% if we include them. Thus, missing earnings appear to increase the total effect. However, column three reveals that the largest share of earnings losses is related to reductions in real daily wages not to spells of non- or unemployment, because the price effect amounts to about 50% of incumbent workers' annual pre-treatment earnings.[21]

To assess the magnitude of the overall effect, we benchmark our results to existing evidence about the effect of other shocks on workers careers. A natural candidate for comparing our results is 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 layoffs at between 171% and 250% of annual pre-displacement earnings. These estimated lifetime displacement losses are much larger than our effects for the following two reasons. First, many workers remain in their training firms but change their occupations in response to the treatment. Thus incumbent machining metal operators incur lower wage growth rather than real earnings 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, 2018).

Another natural candidate for comparing our results to is Walker (2013), who estimated the long-term wage effects of the clean air act for U.S. manufacturing workers. 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 where average industry wages may not fully reflect shifts in the labor demand curve. Whereas 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. In contrast to the workers in his study, the affected incumbent workers in ours do not fully recover from the labor market shock: Many were crowded out of their occupation and

[21] As we cannot measure working hours, the price effect may partly reflect reductions in working hours. However, our sample contains predominantly male blue-collar workers, among whom part-time employment is very rare in Germany. Therefore, that reductions in working hours account for much of price effect is unlikely.

potentially lost a large share of their occupation-specific human capital, making their earnings losses more persistent than those in Walker's study.

VIII SENSITIVITY ANALYSIS

VIII.A. Placebo treatments

This subsection analyzes the robustness of our results by benchmarking the goodness-of-fit from our preferred specification equation (1) against the goodness-of-fit 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 9 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, thereby providing the best fit for the observed data.

—Figure 9 about here—

VII.B. Post-reform cohorts

As mentioned in subsection IV.C., we should not find wage losses for the post-reform cohorts of *CNC-skilled* machining metal operators if the effects we present were indeed related to the treatment and not to general macroeconomic shocks. The descriptive results in Figure 6 have already suggested that CNC-skilled graduates did not experience wage losses relative to the post-treatment cohorts from the counterfactual occupation. In Figure 10, we estimate a distributed lag model similar to the one in regression equation (2) but for a sample that only includes workers who graduated after the 1991 supply shock. The figure, which clearly supports the finding in Figure 5, 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 10 about here—

VIII.C. Alternative comparison group

As discussed in subsection V, disentangling the displacement from the scale effect might be challenging. This subsection provides suggestive evidence for further exploring this issue by analyzing an alternative comparison group. Our original comparison group of non-machining metal-operators 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 at the cohort-by-training firm level, this group may benefit from scale effects when the more productive CNC-skilled machining metal workers enter their firms. Such a scenario is likely to occur for an alternative comparison group of incumbent non-machining metal mechanics who have been trained in firms that do not train machining metal operators.

Non-machining metal mechanics also work in firms that produce large metal parts for ships, large machines, or vehicles. Producing such large metal parts requires welding and riveting metal parts but not using CNC technology (commonly used for small precision parts). Some firms specializing in large metal parts employ non-machining metal mechanics to assemble and connect these large metal parts but—because these firms do not use CNC technology—they do not employ 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 their peers who work in *CNC-firms*.[22] As a result, the SUTVA may be more likely to apply for this comparison group.

Table 11 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 available to us (see rows one and three of table 2 in section IV for a detailed definition of the sample). 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. Moreover, the results of the second specification suggest that the potential unobserved heterogeneity at the training-firm level does not have a big influence on our results.

—Table 11 about here—

VIII.D. Group-specific trends

A common robustness check to access the validity of difference-in-differences estimators is to include “state-specific” trends in the regression equation (Angrist and Pischke, 2008). Thus we include different trends between the treatment and comparison group, using a

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

quadratic function of a group-specific trend in regression equation (1). The first specification of Table 12 shows that the coefficient is somewhat smaller than the coefficient of our preferred specification but that the effect remains highly significant at conventional levels.

—Table 12 about here—

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

VIII.E. Autocorrelation of standard errors

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

The second specification of Table 12 presents results from this *collapsing method*. As expected, these more conservative standard errors are almost twice the size of the standard errors in our main regression. Nonetheless, the coefficient estimates remain precisely estimated at the one percent level.

IX. CONCLUSION

This paper shows that, when technologies fundamentally change, the increasing labor supply of more technologically advanced graduates has a long-lasting impact on the careers of young incumbent workers. Overall, incumbent workers with outdated skills experienced discounted earnings losses of about 70% of an average pre-treatment earnings year in response to the increasing supply of more technologically advanced graduates. Furthermore, as incumbent workers experienced only little unemployment during a transition period after the supply shock, our results suggest that the overall earnings losses of incumbent workers were mainly related to lower wage growth.

Consistent with these patterns of wage losses and unemployment, we find that incumbent workers forwent promotions and that they became more likely to switch their occupation after the supply shock. Although we find that incumbent workers became less likely to remain in the metal working industry, most incumbent workers appear to have changed their occupations within that industry and even within the same firms. Those who left the metal working industry were most likely to switch to the service sector—particularly to low-wage service jobs. Although previous research has largely analyzed how technological change influences aggregate measures for employment and wage structures, we provide micro-evidence that highlights the individual adjustment processes of incumbent workers to the impact of fundamental technological changes.

Our findings suggest that opportunity costs for and access to continuous training determine the ability of incumbent workers to compete with more technologically advanced graduates throughout periods of accelerating technological change. On one hand, incumbent workers may not participate in continuous training programs, because the high opportunity costs associated with extensive training programs simply exceed their expected benefits. Such high opportunity costs are likely because these workers earn high wages and might have families, so that they therefore substitute training time for home production. On the other hand, incumbent workers may be credit constrained and depend on the financial support of their firms to access high-quality training programs (in our specific case, because high-quality training requires access expensive machines). Moreover, when the supply of more technologically advanced workers increases, firms have incentives to hire more technologically advanced graduates instead of training incumbent workers. Indeed, firms may even have incentives to invest more in modern technology as hiring more technologically proficient workers becomes cheaper. As a result, even young incumbent workers with sufficiently long return periods of potential training investments may not perfectly adjust their skills so as to operate fundamentally new technologies, and may thus experience negative long-term consequences for their careers.

Although this paper studies a specific group of manufacturing workers who were affected by a specific technological innovation, our results have external validity for the following three reasons. First, CNC technology was one of the major technological developments in manufacturing throughout the 1990s, changing the nature of work and the demand for skill in this industry worldwide. Thus CNC technology is comparable to other technologies that have substantially changed the demand for skills and the nature of work in recent decades (e.g., personal computers or the internet). Second, our analysis focuses on medium-skilled manufacturing workers, 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, similar adjustment processes will doubtless take place when many industries are exposed to the consequences of new technological developments, such as cyber-physical systems and artificial intelligence. As with CNC technology, these new technologies will change the nature of work, including the skill requirements and educational curricula—not only for apprenticeship-training programs but also for schools and universities all over the world. Thus this paper provides an important case study for better understanding how labor markets adjust to technological change.

Technological innovation and human capital investments have been shown to foster overall economic growth and prosperity (Colecchia and Schreyer, 2002; Hanushek and Wößmann, 2007). While in no way challenging this view, our results shed light on a distributional consequence that arises when labor markets adjust to technological developments. These results are important for assessing all long-term labor market consequences of technological change.

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TABLES IN THE TEXT

TABLE 1:
REGISTERED 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 for facilitating the transition between the old and the new training curricula. Source: Berufsbildungsbericht 1991

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 groups who have graduated while working 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	0.048	0.015	-0.033***
Foreigner	0.091	0.067	-0.023***
Age	20.900	21.397	0.497***

Notes. The table presents descriptive statistics for the baseline characteristics of the treatment and comparison groups. The baseline period is the first observation per individual after graduation but 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 in the treatment and comparison groups before and after the supply shock of CNC-skilled graduates. Daily earnings are deflated with the consumer price index (CPI) and measured in 2010 Euros. 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***	-0.034***	-0.037***
	(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-squared	0.137	0.275	0.672
Number of observations	379717	379717	379717

Notes. The table presents the results from regression equation (1). The dependent variable measures log daily wages that are deflated by the CPI and measured in 2010 EUROS. The standard errors (in parentheses) are clustered at the individual level. Individual control variables contain four age categories, a dummy for being female, and a dummy for being a foreign national. 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	-0.059***	-0.035***	-0.031***	-0.028***	-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-squared	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 measures log daily wages that are deflated by the CPI and measured in 2010 EUROS. The standard errors (in parentheses) 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 OF REMAINING 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-squared	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 with 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 relies only on individuals who have remained in their training establishment. The standard errors (in parentheses) 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 OF REMAINING IN THE 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-squared	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 with a dummy indicating whether a worker remains in the metal working industry (column one), moves to the low-wage service sector (column two), or moves to the high-wage service sector (column three). Low-wage service jobs include, for example, waiters, office clerks, and 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 relies only on individuals who have remained in their training establishment. The standard errors (in parentheses) 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 OF BECOMING A MASTER/TECHNICIAN

	Master craftsman/technician
Treatment effect	-0.046***
	(0.004)
Individual f.e.	Yes
Time f.e.	Yes
R-squared	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 with a dummy indicating whether a worker has become a master craftsman or technician. The standard errors (in parentheses) 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 EARNINGS EFFECT

	Total effect (excl. zeros)	Total effect (incl. zeros)	Price effect
Observation period	-0.682	-0.911	-0.516
Number of obs.(1st stage)	379717	427481	379717

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 used this measure as dependent variable of regression equation (2) to, first, calculate $\hat{\delta}_k$. Second, we calculate the DPVs according to equation (3). Column one includes only positive wage observations, column two replaces 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 controls	Yes	Yes
Individual fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
R-squared	0.675	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. In other words, the sample is not restricted to workers in the treatment and comparison groups who have been trained in the same firms. The dependent variable measures log daily wages that are deflated by the CPI and measured in 2010 EUROS. The standard errors (in parentheses) 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	-0.014***	-0.038***
	(0.003)	(0.005)
Individual controls	Yes	Yes
Individual f.e.	Yes	Yes
Time f.e.	Yes	Yes
R-squared	0.673	0.762
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 groups, 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 measures log daily wages that are deflated by the CPI and measured in 2010 EUROS. The standard errors (in parentheses) in the first specification are clustered at the individual level. Individual control variables contain four age categories in the first specification. The second specification does not allow us 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

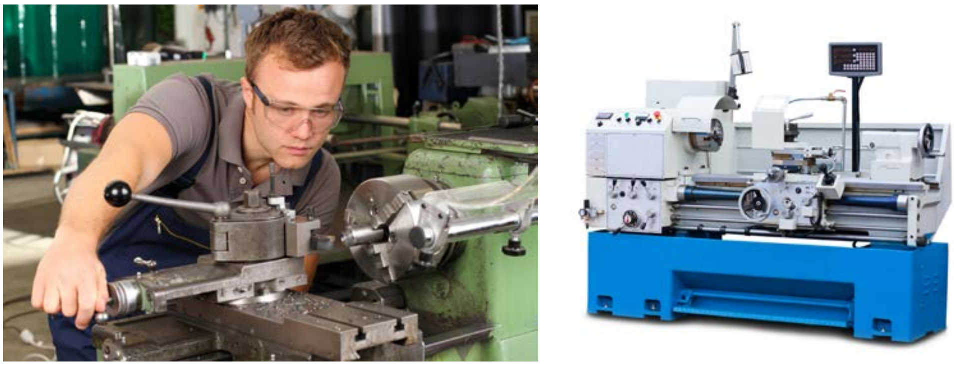

FIGURE 1:

Manual drilling machine and CNC-machine

The left panel shows a manually operated drilling machine most commonly used by machining metal operators until the late 1980s. The right panel shows a computer numerical control (CNC) machine that has become the common standard in German manufacturing since the late 1980s. Under the new training curriculum, all German apprentices in the occupation of machining metal operators had to undergo a structured training program to acquire CNC skills.

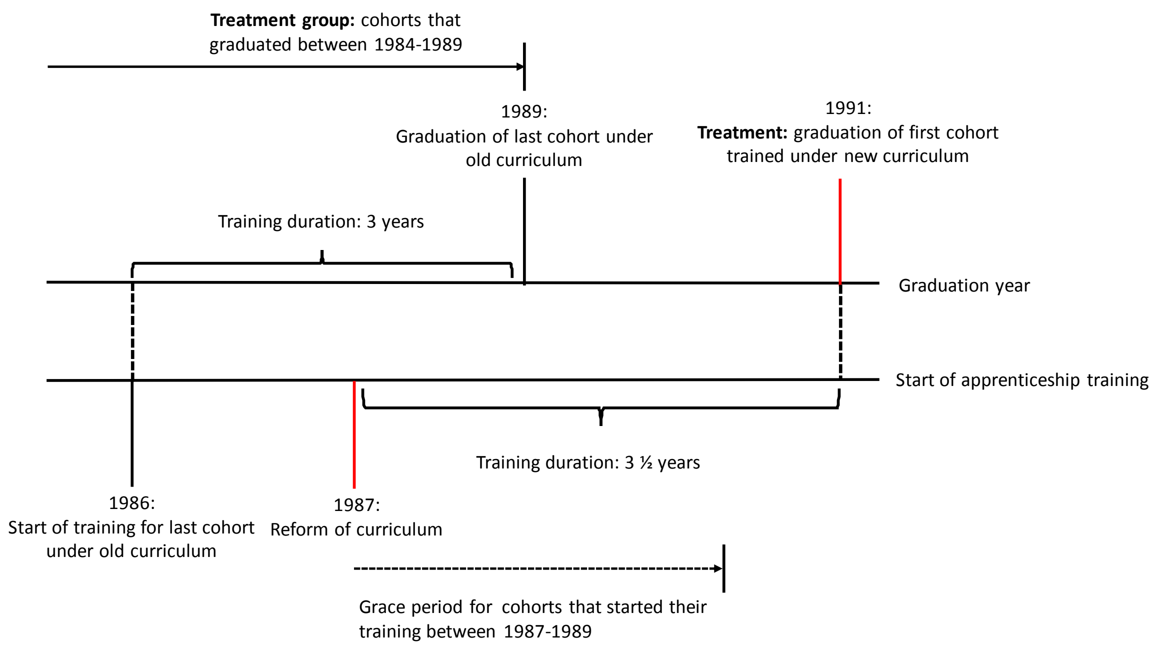

FIGURE 2:

The reform of the training curriculum

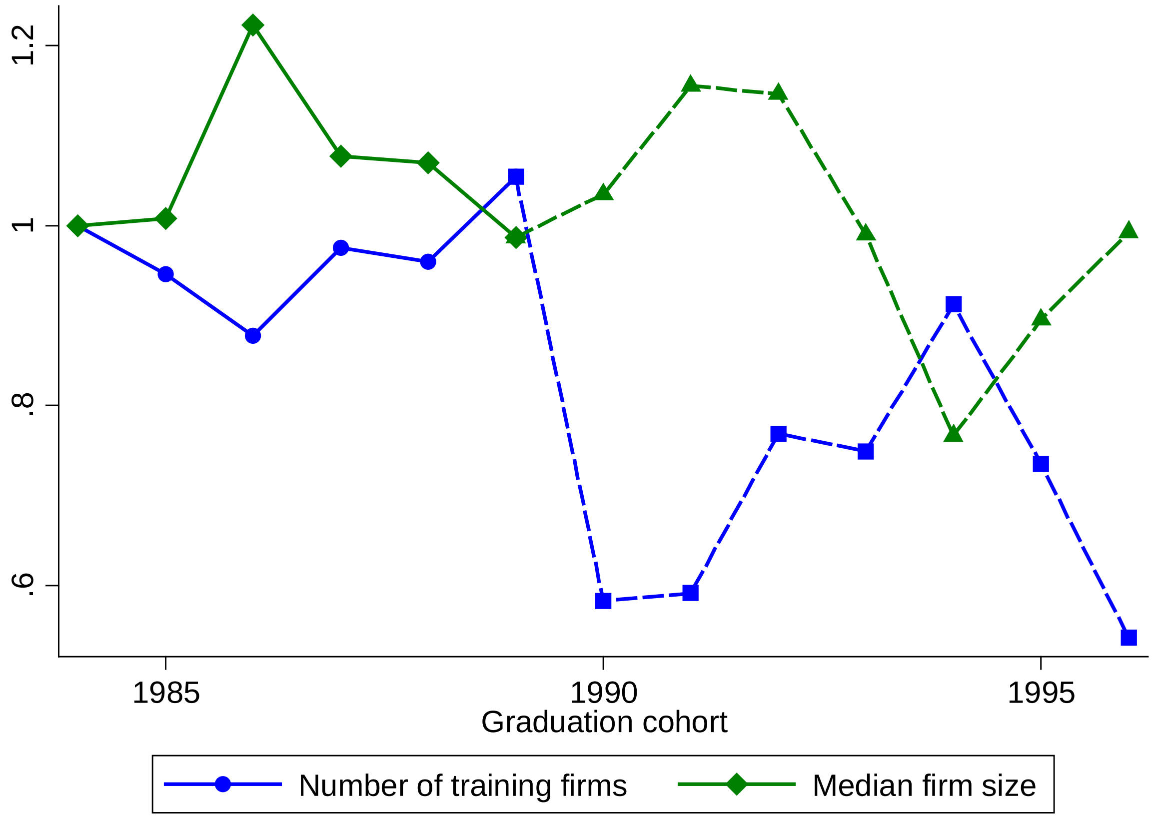

FIGURE 3:

Number and median size of training firms

The blue line shows the average growth rate of the number of training firms between 1984 and 1996. The green line shows the growth rate of median firm size of training firms between 1984 and 1996. The solid lines mark the graduation cohorts before the reform of the training curriculum, and the dashed line shows those that came afterwards.

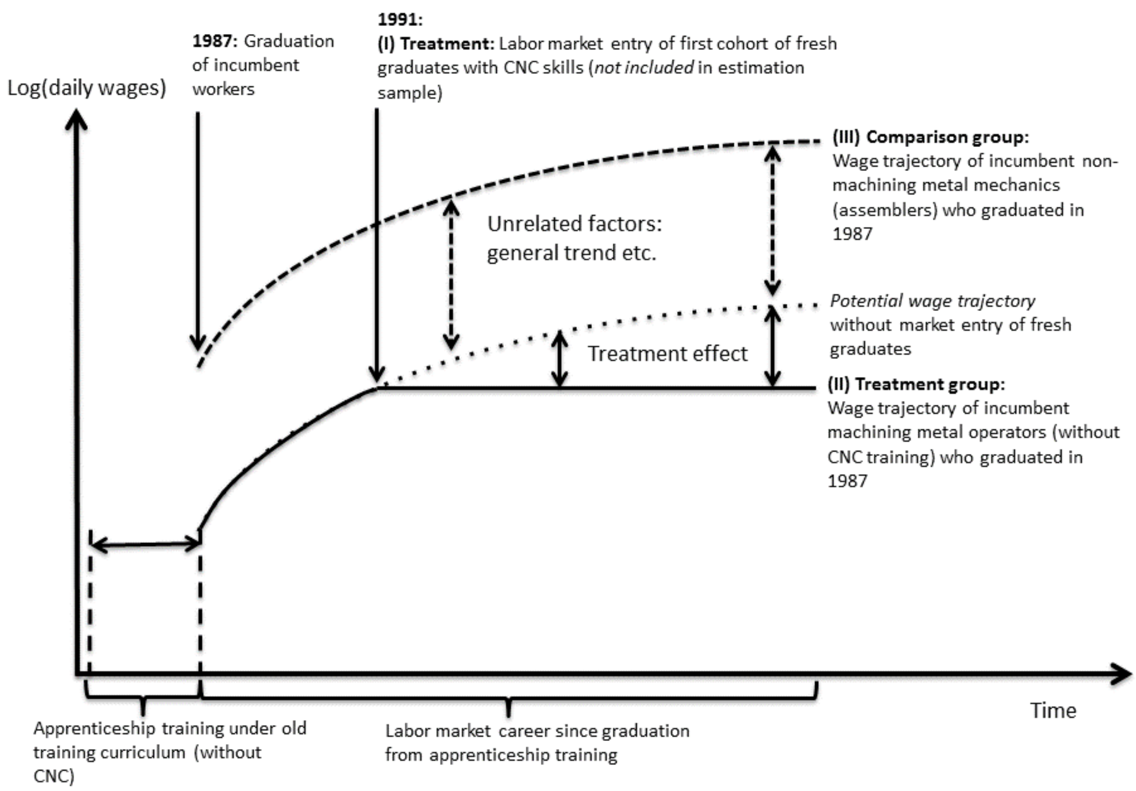

FIGURE 4:

Identification strategy (example for graduation cohort of 1986)

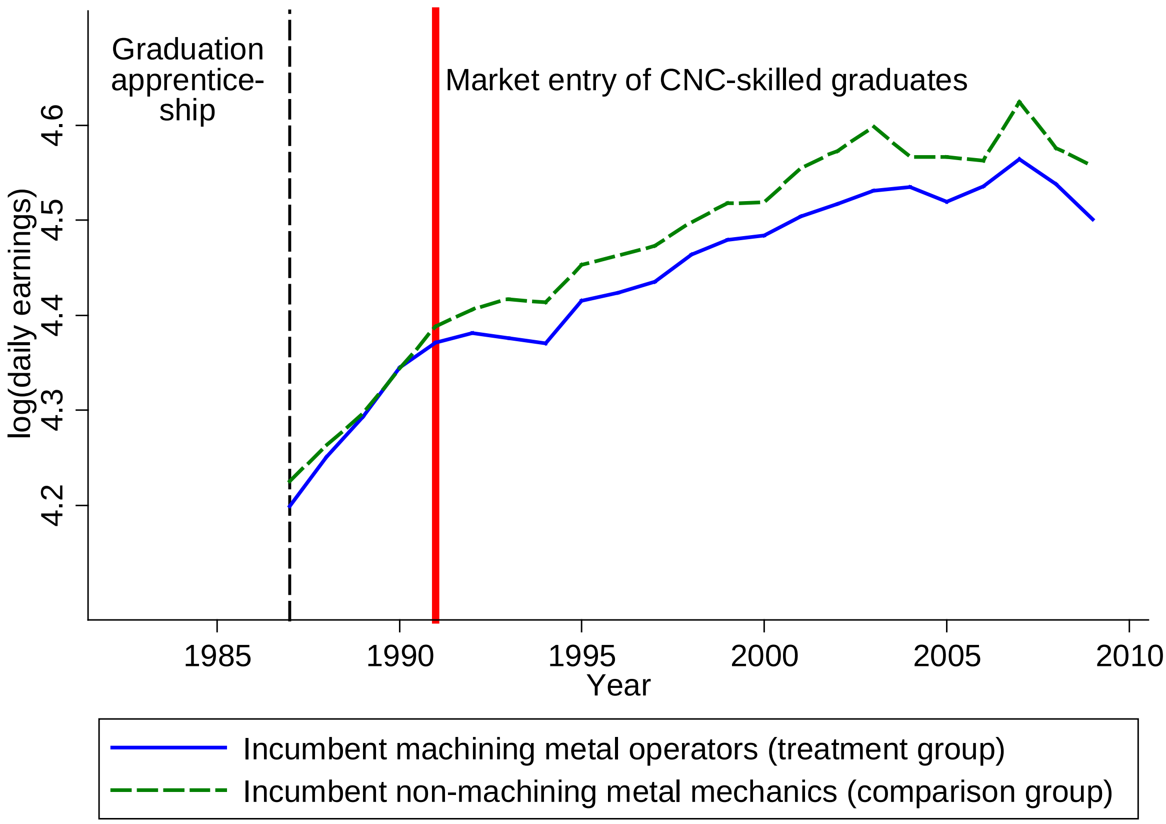

FIGURE 5a:

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 graduates (solid vertical line). The cohort of the treatment group consists 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 mandatory element of apprenticeship training in the occupation of machining metal operators. The cohort of the comparison group consists of incumbent non-machining metal mechanics who graduated from the same training firms and at the same time as the individuals in the treatment group. Non-machining metal mechanics do not use CNC technology and were not exposed to a supply shock of more technologically advanced 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 measured in logs and deflated by the CPI. Source: BEH 1984-2010

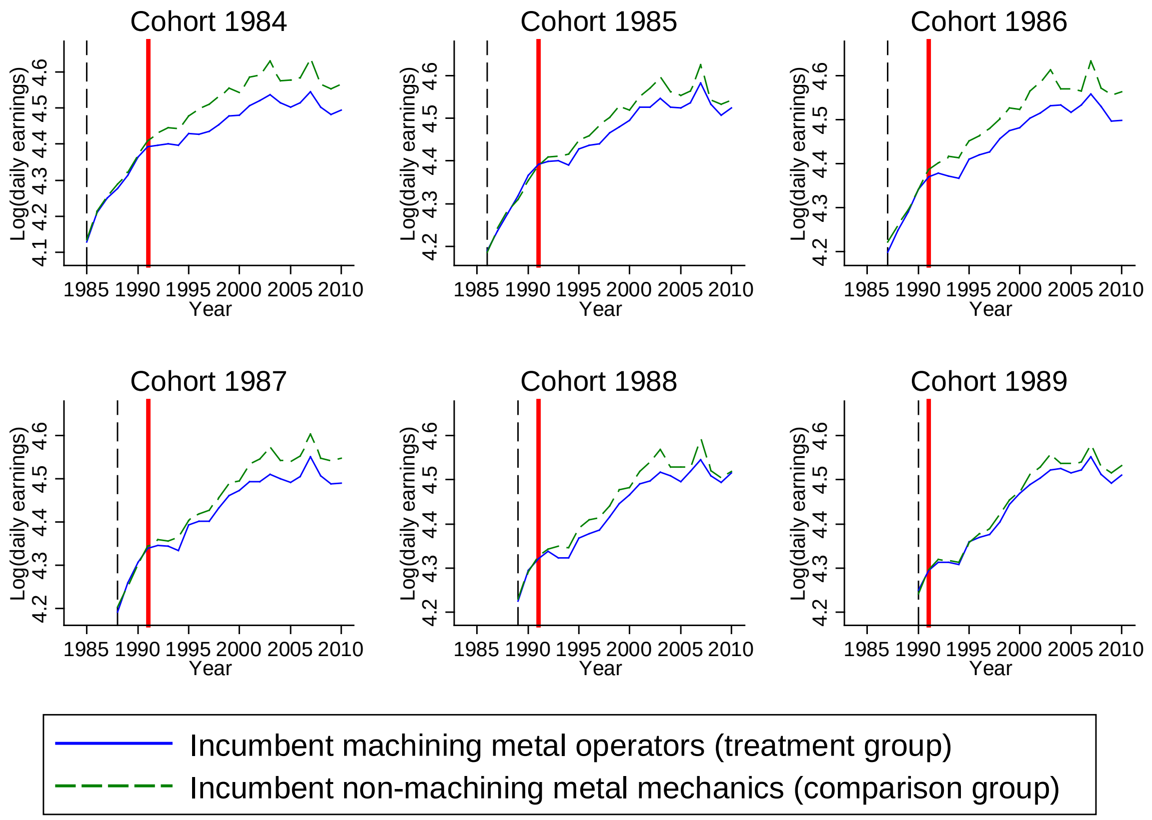

FIGURE 5b:

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

The figure shows the development of log real daily wages for all graduation cohorts 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 graduates (solid vertical line). The cohorts of the treatment group consist of incumbent machining metal operators who graduated between 1984 and 1989, respectively. These cohorts were trained before CNC technology became a mandatory element of apprenticeship 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 comparison group consist of incumbent non-machining metal mechanics who graduated from the same training firms and in the same graduation years as the cohorts in the treatmet group, i.e., between 1984 and1989, respectively. Non-machining metal mechanics do not use CNC technology and were not exposed to a supply shock of more technologically advanced 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 measured in logs and deflated by the CPI. Source: BEH 1984-2010

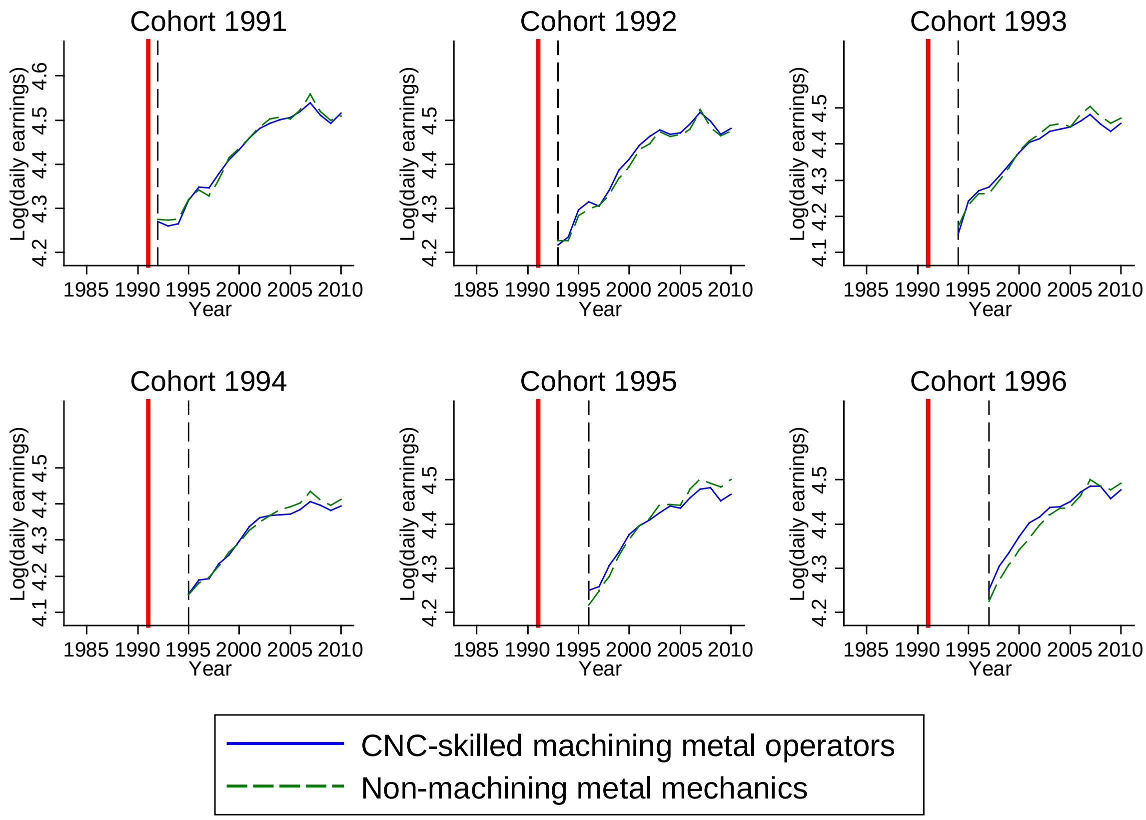

FIGURE 6:

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 unaffected cohorts who graduated after CNC training became a mandatory element of the apprenticeship training of machining metal operators. The solid lines indicate the wage development for CNC-skilled machining metal operators 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 while working in the same firms and during the same graduation years between 1991 and 1996. The solid vertical lines indicate the treatment. Source: BEH 1984-2010

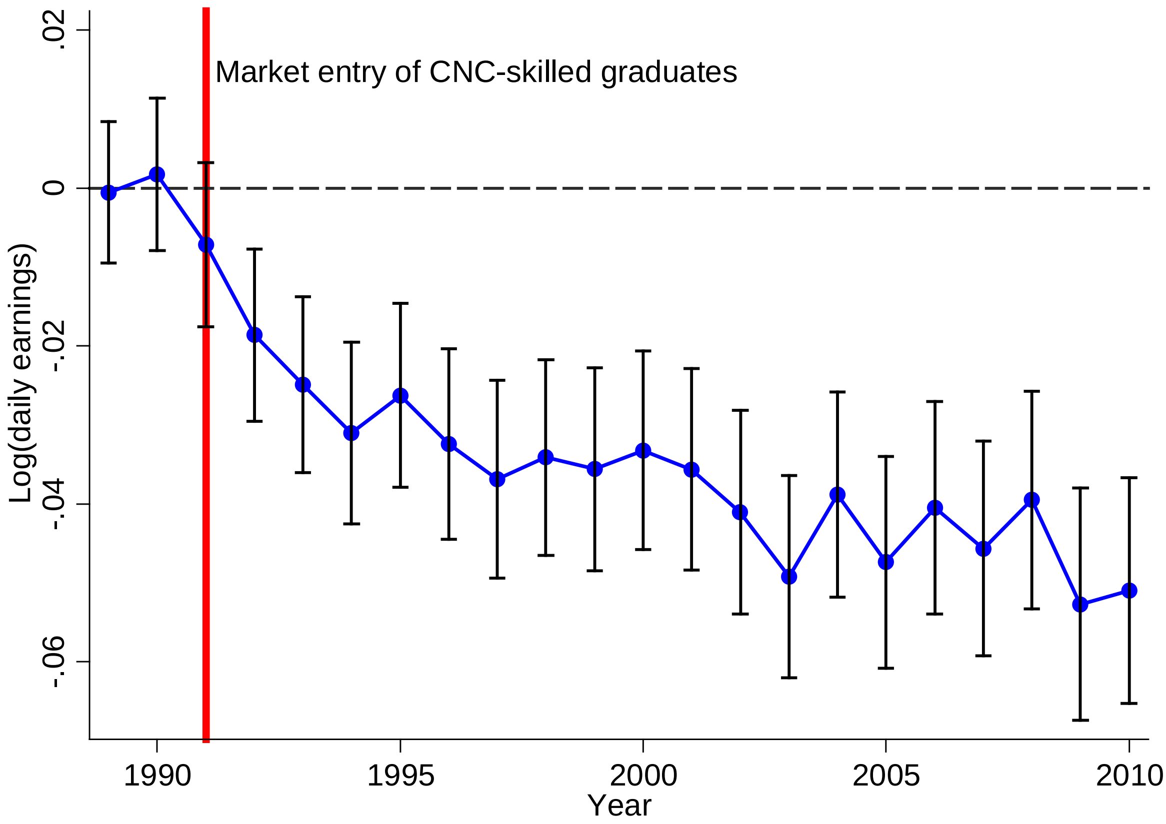

FIGURE 7:
Long-term effect of supply shock on incumbent workers' daily wages

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

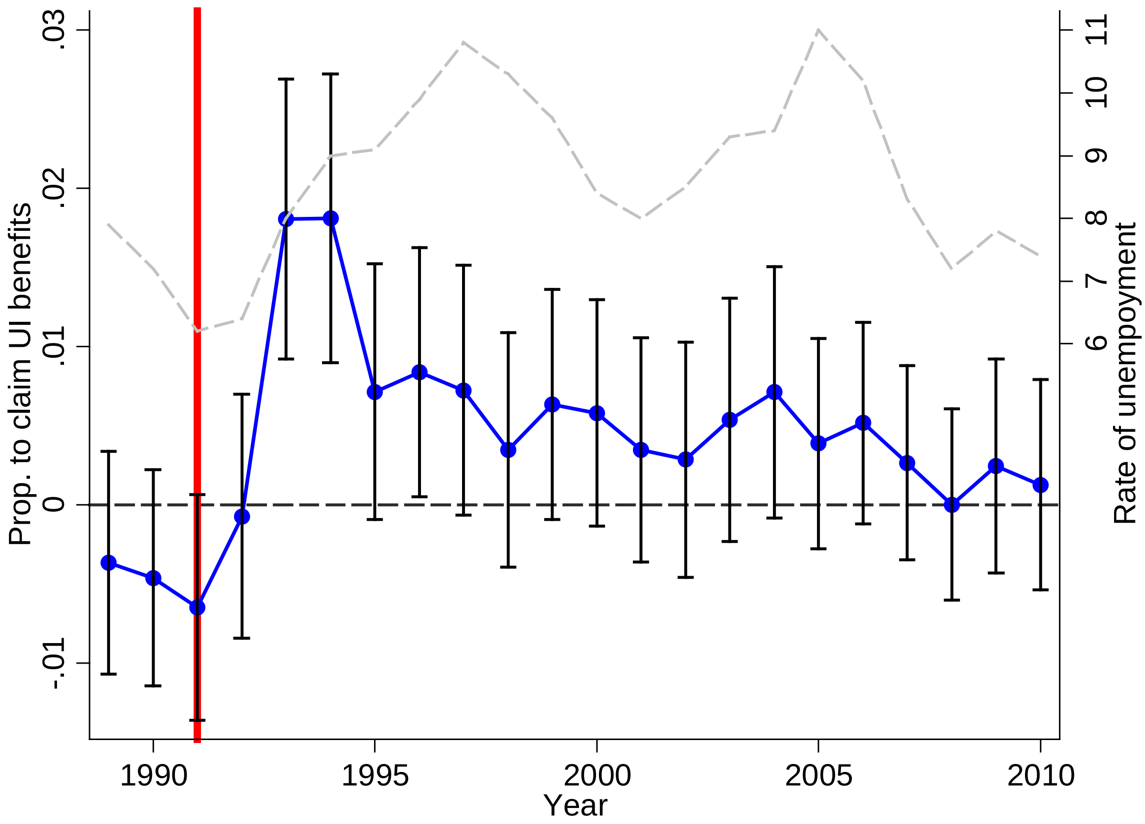

FIGURE 8:

Long-term effect of supply shock on unemplyoment.

The figure shows the long-term effects of the supply shock of CNC-skilled graduates on the unemployment probability of incumbent machining metal operators. The dots indicate the coefficient estimates of a distributed lag model according 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 unemployment in the ongoing year. Standard errors are clustered at the individual level. The capped spikes indicate confidence bands at the 5% level. Control variables include four age categories, year dummies, and individual fixed effects. The dashed line indicates the rate of unemployment in West Germany. Source: BEH 1984-2011

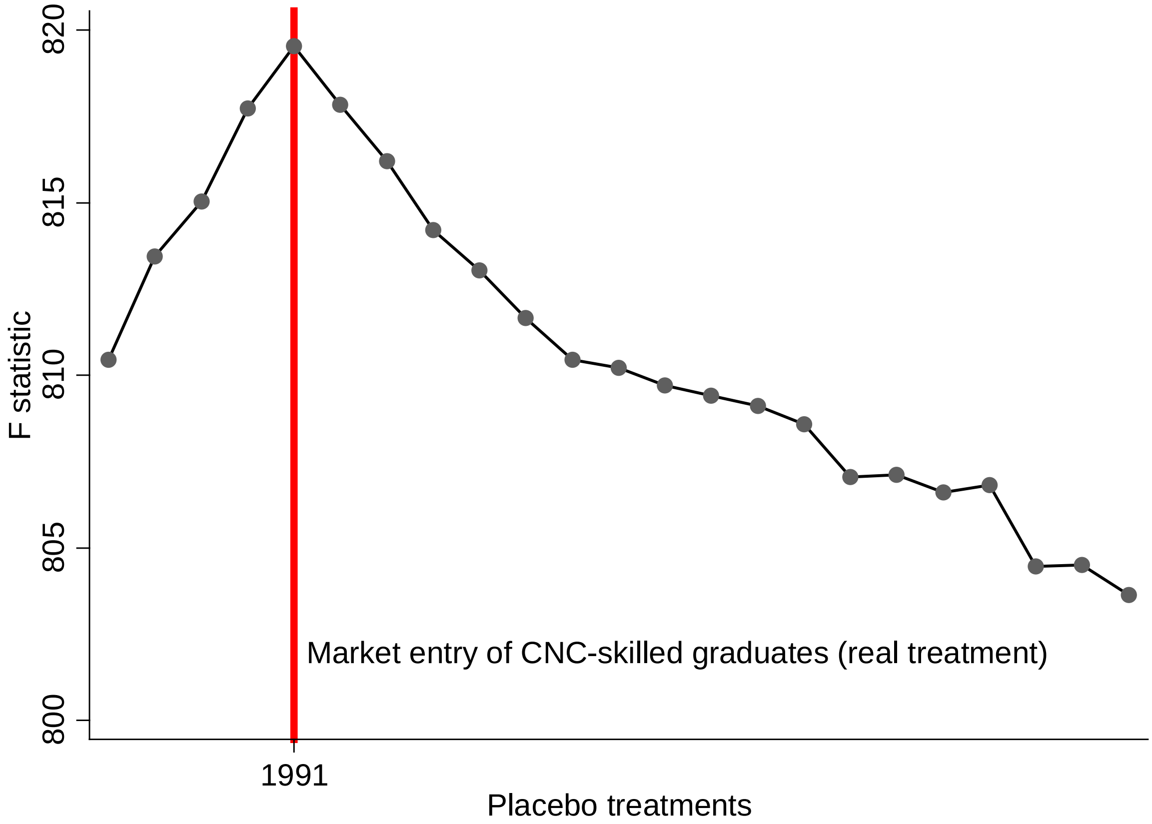

FIGURE 9:

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

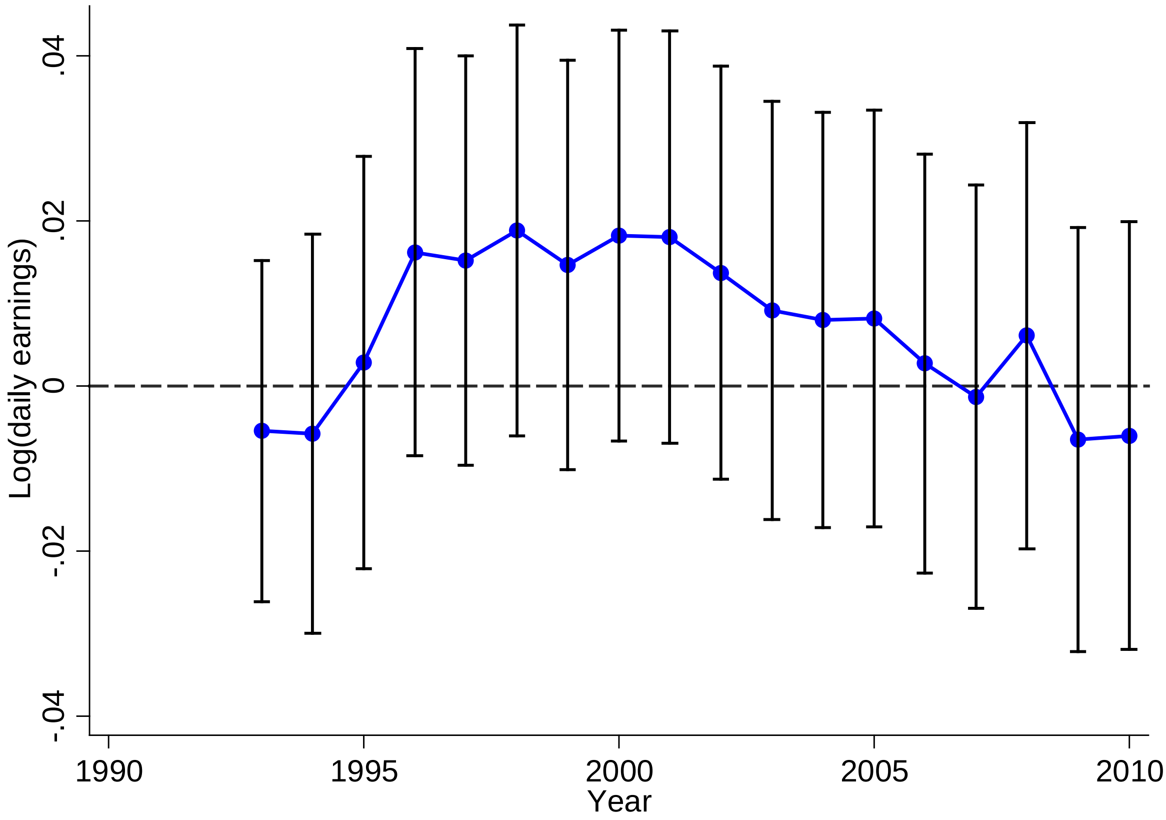

FIGURE 10:

Wage effects for CNC-skilled graduates relative to counterfactual cohorts from comparison 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 their respective comparison cohorts of non-machining metal mechanics who graduated while working in the same firms and during the same period. All post-treatment cohorts underwent the structured CNC training. Source: BEH 1984-2010