Are Technological and Organizational Change Still Skill Biased? Evidence from German Linked Employer-Employee Data

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October 29, 2008

Abstract

Much theoretical and empirical work suggests that skill-biased technological change explains the increasing income disparity observed in much of the world since the 1980s. However, some recent work has suggested that this increase is an episodic event unrelated to technological change. In this paper, I use matched employer-employee data from Germany to study whether two types of "technologies" display a persistent skill bias. I study group work and equipment upgrades introduced at various times from 1993-2000. I find that group work implemented in 1993-1995 leads to a decrease in the wage bill share of the least-educated workers, but group work introduced in later years has, if anything, a positive effect. I find no effect of equipment upgrades on the wage bill share at any time. Controlling for worker fixed effects, I also find that these two technology changes have a weakly negative effect on residual wages after 1995, depending on the time period observed.

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1 Introduction

For decades, economists have tried to explain the widening wage gap observed in most developed countries. Their explanations are of great interest to policy makers. The redistributive systems in many European nations are founded on the belief that extreme wealth disparities lead to social instability. Understanding the causes of such disparities is therefore an important input into the decision of whether and how public policy should seek to influence these outcomes. Even in the United States, the recent financial crisis has opened the door for a more interventionist state. While this intervention is currently limited to the financial sector, one should not forget that it was a similar crisis that provided the impetus for Franklin D. Roosevelt's New Deal. Some observers have called for the current round of bank bailouts to be tied to caps on executive pay, indicating a latent concern with "inequitable" pay distributions that might be "corrected" by government intervention.

Perhaps the most widely accepted explanation for widening income inequality is that technological change increases the demand for, and returns to, skill. However, translating this explanation into policy is complicated by two factors. The first is ambiguity about operational definitions of "technology" and "skill". How good are our empirical proxies for these broad concepts and, moreover, are these proxies stable over time? Evidence of technology-skill complementarity can be found at least as far back as the beginning of the 20th Century (Goldin and Katz 1998), but the meaning of "technology" has clearly evolved since then. Furthermore, some authors have recently suggested that the rise in U.S. wage inequality in the 1980s was an episodic event rather than part of a longer-term trend (Card and DiNardo 2002, Lemieux 2006).

The second factor clouding the policy implications is whether the phenomenon of skill-biased technological change is a universal one, or whether it appears to different degrees in different national and institutional contexts. For example, as its name suggests, the supply-demand-institution explanation for wage structure changes (Katz and Autor 1999) incorporates a role for wage setting institutions that are much more prevalent in some countries than in others.

In this paper, I use matched employer-employee data from Germany to examine whether skill-biased technological change is a persistent characteristic of that labor market. The data span the years 1993-2005, allowing me to compare the effects of organizational changes implemented at various points throughout the 1990s. The data are also extensive, covering over one thousand plants and hundreds of thousands of employees – approximately 3.5 percent of employment in the sectors studied. I examine two measures of "technology" change at the plant level: upgrading of the plant's equipment and introduction of self-directed work teams. The latter encompasses the view that the organization of work is also a form of productive technology (Ichniowski et al. 1997) that is potentially skill biased (Caroli and Van Reenen 2001). My measures of the skill impact of these changes are (a) the wage bill share of employees with a middle school education and (b) an individual's wage residual from a regression of log wages on a battery of personal characteristics.

I find little to suggest that either group work or equipment upgrades have been skill biased since the mid-1990s in western Germany. While group work introduced between 1993 and 1995 did lead to a subsequent reduction in the wage bill share of middle-school employees by 2000, this is not so for group work introduced between 1996 and 1998 or between 1998 and 2000. Furthermore, group work and technology upgrades introduced after 1996 led either to a decrease in workers' residual wages (controlling for individual fixed effects) or no change, depending on the year under observation.

The rest of the paper proceeds as follows. In Section 2, I discuss related literature. Section 3 describes the data and Section 4 the analytical methods. Section 5 presents the results and Section 6 the discussion and conclusions.

2 Literature Overview

Since 1980, the gap between 90th and 10th percentile wages has been growing in the United States and most other OECD countries (Katz and Autor 1999). One leading explanation for this phenomenon is that technology and skill are complements. Technological advances therefore increase the returns to skill and earnings differences between more- and less-skilled workers.

A number of empirical studies have documented a relationship between various measures of technology and demand for skills. Bartel and Lichtenberg (1987) find that relative demand for educated workers declines as the age of plant and equipment increases. Their interpretation is that educated workers have a comparative advantage in the implementation of new technologies. Bound and Johnson (1992) find that inferred measures of industry-level productivity growth are correlated with more rapid wage growth for workers with more years of schooling. Krueger (1993) is perhaps the first to introduce a direct technology measure into the analysis. He finds a 10-15 percent wage premium for people who use computers at work. Berman et al. (1994) and Machin and Van Reenen (1998) find that investment in computers and R&D is correlated with increased demand for nonproduction workers. In a recent contribution, Bartel et al. (2007) found that IT adoption in one manufacturing industry is associated with increases in skill requirements for machine operators.

This evidence is not without dissenting voices. DiNardo and Pischke (1997) note that German workers who use pencils or sit down at work also earn wage premia, leading them to question whether the computer-use wage premium reflects true returns to skill. Bartel and Sicherman (1999) find that the correlation between returns to education and the rate of technological change is substantially weakened when they control for individual fixed effects, suggesting that sorting drives observed effects of industry-level measures of technical change on the wage structure. Finally, Card and DiNardo (2002) and Lemieux (2006) have questioned the whole premise of a long-run increase in U.S. wage inequality, arguing that the increase observed in the 1980s was merely an episodic event.

Recognizing that technology is not merely the physical tools but also the way production is organized, several authors have investigated the link between organizational change and returns to skill. Ichniowski et al. (1997) show that innovative work practices such as incentive pay, team production, and flexible job assignments raise productivity in one industry. Caroli and Van Reenen (2001) propose that some of these practices – those giving more decision-making autonomy to workers – are inherently skill-biased. They show that organizational delayering is associated with reduced demand for unskilled manual workers in a broad sample of British and French establishments. Bresnahan et al. (2002) show that the apparent complementarity between organizational change and skills is more pronounced when combined with IT.

Although most evidence for the skill-biased technological change hypothesis comes from the U.S., some authors have looked at the international dimensions. Berman et al. (1998) find that within-sector shifts away from skilled labor are concentrated in the same industries around the world. They argue that, in an open economy with trade, this can only be due to pervasive technological change. Falk (2002) finds in a sample of German establishments that organizational change has a positive effect on expected employment for all skill groups except unskilled labor. Bauer and Bender (2004) find in a different German sample that organizational change is skill-biased because it leads to higher job destruction and separation rates among un- and medium-skilled employees.

Another international aspect of the debate is whether skill-biased technological change has a uniform impact across different countries with different institutions. The statistics from Katz and Autor (1999) cited above show that the 90-10 wage gap grew much more in the U.S. and U.K. than in any of the other OECD nations. Krugman (1994) has suggested that rigid labor market institutions in many of the non-Anglo-Saxon countries cause skill-biased technological change to be reflected in unemployment gaps rather than wage gaps. Pischke (2005) has disputed the "Krugman hypothesis," noting that unemployment in Germany seems to affect all skill groups. The mediating effects of institutions are not limited to the labor market. For example, Guadalupe (2007) shows that product market competition increases returns to skill in the UK.

Autor et al. (2008) show that the growth in wage inequality in the U.S. slowed in the 1990s. However, they also note that this average masks a divergence in "upper-tail" and "lower-tail" trends. 90-50 wage inequality continued to increase, while 50-10 wage inequality flattened or decreased after the mid-1980s. They suggest that these patterns are consistent with a modified version of the skill-biased technological change hypothesis in which information technology substitutes for routine tasks and complements cognitively demanding tasks – a hypothesis first articulated by Bresnahan (1999). Using French data, Maurin and Thesmar (2004) find evidence consistent with this model, showing that new technologies increase the demand for "nonprogrammable cognitive activities," such as design and marketing.

My contribution to this literature is to examine two potentially skill-biased technologies at different points in time in the same country, using a consistent sample, skill and technology definitions and methodology. This allows me to state whether there is any persistent skill bias embedded in these technologies. In addition, the matched employer-employee data permit controls for fixed individual characteristics in some specifications, which is not possible in much of the work cited above. Finally, the German setting complements work in other national contexts.

3 Data[1]

I use the Linked Employer-Employee Data from the German Federal Employment Agency's Institute for Labor Market Research. The data are commonly known under the acronym LIAB. They merge information from two sources: (a) an ongoing panel survey of German establishments, conducted annually since 1993 and (b) information on employees in those establishments, drawn from mandatory reporting within the social security system (health, pension and unemployment insurance). The data used in this study come from the survey years 1993-2005.

The establishment data are from the IAB Establishment Panel. Establishments with at least one employee in the German social security system are interviewed annually at mid-year. The first survey wave in 1993 encompassed 4265 establishments in western Germany. In 1996, over 4700 establishments in eastern Germany were added (although I drop eastern German establishments from the analysis). Since 2001, the net sample contains over 15,000 establishments. The response rate of repeat participants in the survey is over 80 percent. The sample is continually refreshed to account for establishment births and deaths and also to replace establishments who refuse to continue participating. The data include extensive information on the size and composition of the workforce, hiring and separations, training, organizational restructuring and technological status of the

[1] This discussion draws extensively from Alda et al. (2005) and Jacobebbinghaus (2008). The former is available in English.

plant. I restrict the sample to establishments in western Germany and exclude those in agriculture, forestry, mining, education, and quasi-public organizations such as trade associations. I also exclude all establishments where sales revenue is not the primary income measure – primarily banks and insurance companies. For further background on the Establishment Panel, see Fischer et al. (2008).

The basis for the employee data is the integrated notification procedure for the social security system. Employers must file notifications for each employee covered by social security at the end of the employment relationship and at the end of each year for ongoing employment relationships. Approximately 80 percent of all German employees are covered by social security, the chief exceptions being civil servants and the self-employed. Therefore, the coverage in the broad private sector that I study is higher. Data collected on each employee include: start and end of the reporting period, daily wages, age, sex, nationality, education, three-digit occupation code, industry, and the employer's location (county). Data from periods of employment are augmented with each employee's benefits receipt history during periods of unemployment. The unit of observation in the employee data is a "spell." Employment spells are at most one year long, due to the mandatory year-end reporting. Unemployment spells may be longer, but these are not relevant to the present analysis. I restrict the sample to full-time workers (not including apprentices).

In theory, the data permit the researcher to see the complete employment and unemployment history of anyone who has ever passed through a surveyed establishment (subject to the requirement that they be in the social security system). Because such a data set would be impractically large, the Institute for Labor Market Research offers two different versions of the LIAB, each of limited scope. I use both versions in this paper.

The first version is the cross-sectional model. This version includes all establishments participating in the survey, but limits the employment data to a single record for each person who was employed on June 30 of the respective year (the reference date of the establishment survey). Work histories can therefore only be constructed for employees who remain continuously employed at the same establishment, or who move from one surveyed establishment to another.

The other version of the data, the longitudinal model, contains the full work history for each employee passing through surveyed establishment, but limits the number of observations in two ways.[2] First, only establishments responding to the survey in one of the years 2000-2002 are included. Second, only individuals employed for at least one day from 1997-2003 at one of these establishments are retained.

The data appendix defines the main variables used in the analysis. Tables 1 and 2 provide summary statistics.

4 Methods

4.1 Wage Imputation

In the raw data, wages are the average daily wage over the employment spell. I impute values for the top-coded wages using the method in Gartner (2005). This method replaces the top-coded wages with draws from a lognormal distribution truncated at the social security contribution limit. Controls in the imputation are quartics in age and experience, and categorical variables indicating gender, nationality (German or foreign), education (6 categories), branch of industry (24 categories), occupational status (8 categories), occupation (88 categories), and year.

[2] Technically, the Institute for Labor Market Research offers several different longitudinal models that differ in the filtering rules for inclusion of establishments and employees. The version used here is version 2.

Because of the wage imputation, wages and wage bill shares are measured with error. Since these are dependent variables in the regressions, this error will tend to bias against finding statistically significant effects of organizational changes. Because top coding and, therefore, imputation is correlated with observable and unobservable measures of skill, the variance in the error term will be larger for such observations. Therefore, all inference is based on robust standard errors.

4.2 Wage Bill Shares

To facilitate comparison with the results in Caroli and Van Reenen (2001), the estimation follows the approach laid down there. For the reader's convenience, I will summarize the main elements here, adopting their notation. The firm has a translog cost function with heterogeneous labor the only variable input. Labor is differentiated by skill, indexed f (for factor). In addition.there is a factor, K, that is interpreted as "organizational capital" assumed fixed in the short run. For the present analysis, K corresponds with the presence of self-directed work groups ("group work"). For each class of labor, there is a variable cost share equation of the form

$$S_f = \beta_f + \beta_{ff} \ln W_f + \sum_{g,f\neq g} \beta_{fg} \ln W_g + \beta_{fK} \ln K + \beta_{fY} \ln Y + \omega_{f.} \quad (1)$$

S_f is the wage bill share, Y indicates value added, W_f is the wage rate of each class of labor, and ω is an error term. $\beta_{fK} > 0$ corresponds to the hypothesis that group work is complementary with labor class f. In this analysis, I focus on workers whose maximum educational attainment is middle school (e.g., German *Hauptschule*, *Realschule* or similar). The reason is that these are the wages least frequently affected by top coding. Therefore, the wage bill share measure will be most accurate within this group.

I estimate the cost share equation in long differences, which controls for any fixed components of ω_f that might be correlated with the presence of group work. The data do not provide good measures of other forms of capital besides group work that might affect the wage bill share. As Caroli and Van Reenen (2001) do for Britain, I assume that other variables are adequate proxies – in my case, sales per employee, industry dummies and the change in employment. Finally, concerns about correlation between organizational change and unobserved determinants of changes in the wage bill share are partially mitigated by using lagged organization changes. The basic regression equation is therefore

$$\Delta S_{fit} = \beta_{fo} OC_{t-1} + \beta_{fK} \Delta \ln L_{it} + \beta_{fY} \Delta(\frac{Y}{L}) + \alpha' x_{it-1} + \gamma_1' IND_j + \gamma_2' REG_k + u_{fit}, \tag{2}$$

where OC is organizational change (introduction of group work), L is total employment, $\frac{Y}{L}$ is sales per employee, x is other establishment characteristics, IND is a vector of over 30 industry dummies, and REG is a vector of over 100 local labor market dummies.[3] The labor market dummies replace the wage terms in equation 1.

4.3 Residual Wages

I compute residual wages from an OLS regression of log wages (including imputed wages) on the same controls listed above for the wage imputation. Rather than use the predicted values from the tobit regression which gives the imputed wages, I use coefficients from a separate OLS regression so that the mean residual is zero.

I perform the wage imputation and calculation of residuals separately for each year. Therefore, the returns to observable characteristics are not assumed to be

[3] The exact number of industry and labor market dummies varies with the specification due to missing observations of some variables and different representation in the panel in different years.

fixed throughout the sample period. Were these returns assumed to be fixed, any secular changes in returns to observable skills would be registered as changes in residuals.

I estimate the effect of organizational change on residual wages using the analogue of equation 2:

$$\Delta(w-\widehat{w})_{it} = \beta_{fo}OC_{t-1}+\beta_{fK}\Delta\ln L_{it}+\beta_{fY}\Delta(\frac{Y}{L})+\alpha' x_{it-1}+\gamma_1' IND_j+\gamma_2' REG_k+u_{fit},$$

where i now indexes individuals rather than establishments, and OC can be either the introduction of group work or the upgrading of the establishment's production equipment.

5 Results

Table 3 contains the results for the effect of group work on the middle school wage bill share. The introduction of group work in 1995 led to a reduction of 2.4 percentage points in the wage bill share of the least-educated workers by 2000. Although I am using an education-based skill definition, it is still worthwhile comparing this result to the results for "unskilled manuals" in Caroli and Van Reenen (2001), simply to determine if this value is in a plausible range. The reduction in the wage bill share I find lies between the value they report for Britain from 1984-1990 (ca. 0.8 points per year) and that for France from 1992-1996 (ca. 0.4 points per year).

However, for the 1998-2003 and 2000-2005 time periods, I find no reduction in the wage bill share associated with the introduction of group work. In 1998-2003, the reduction is 0.9 percentage points, but with a large standard error. In 2000-2005, I find an *increase* of 1.3 percentage points. While this estimate is not significant by conventional standards, it is not far off, having a p value of approximately 0.11.

Collectively, these results suggest that any skill bias in the introduction of self-managed work teams in Germany was present only in the mid-1990s. The point estimates for the wage bill share change suggest a time trend away from skill bias in this organizational practice, although this is not clear-cut due to the marginal significance of the 2000-2005 estimate.

Another measure of returns to skill comes from residual wages. In this analysis, the residual wage is the difference between the actual log daily wage and the value predicted based purely on a battery of individual characteristics. A positive residual therefore indicates one or both of the following: (a) the worker has high levels of unobservable skill, or (b) the establishment pays for observable skills at a higher-than-average rate. The residual wage is therefore a compact description of how much a particular establishment values skill.

In Table 4, I report the effect of the introduction of group work on individuals' residual log wages. The regression includes workers entering or leaving the establishment since the year in which group work was introduced. Because the "longitudinal model" of the LIAB data is needed to track all movers to and from these establishments, the analysis must be confined to the years 1998-2003. The 1995 organization changes cannot be studied. Furthermore, the long difference for the 2000 organization change can only be computed over three years. Therefore, I take three-year long differences for both the 1998 and 2000 subsamples.

Table 4 shows that group work introduced in 1998 is associated with a 1.4 percent decrease in residual wages. This estimate is essentially unaffected by the inclusion of controls for collective bargaining and works councils at the establishment. Group work introduced in 2000 has no statistically significant impact on residual wages.

One might be concerned about selection effects in these results, since the analysis incorporates only a rudimentary control for worker selection. The coefficients on the group work indicator correspond to workers staying in the establishment. Even if the negative point estimates are biased by selection effects, it is hard to conclude that group work increases the returns to skill. First, whatever skills the retained workers have are being rewarded at a lower rate after group work is introduced – the long differencing has already removed the levels effects of any individual skill differences. Second, if group work increases returns to skill, we should expect the most skilled workers to be retained and show the highest wage growth, meaning the results for the retained workers should be an upper bound. Finally, we should expect to see workers joining establishments who implement group work having higher residual wage growth than those joining establishments not implementing group work. This is not true for the 1998-2001 sample, but it is true for the 2000-2003 sample. The large estimated effects for the group work-arriving employee interaction may or may not indicate some element of positive skill bias for group work. First, less than 0.2 percent of the sample consists of movers to establishments who have implemented group work. Second, if new arrivals are more likely to come from low-wage firms, then they could show an increase in their residual wages for this reason alone. Therefore, the results for stayers are perhaps the best indication of the effects of group work, since they simultaneously control for unobserved worker and match characteristics.

In Table 5, I report results for the effect of an upgrade in manufacturing technology on residual wages. (The analysis of wage bill shares revealed no statistically significant impact of a technology upgrade in any year, and so those results are not reported here.) The sample is restricted to the years 1998-2003 for the reasons cited above. The table indicates no effect in the 1998-2001 time window, but a negative effect in the 2000-2003 window.[4] The 2000-2003 results show a 2.0 percent

[4]The reader will note that the coefficient for the technology upgrade-arriving employee interaction is not estimated. This variable was automatically dropped in Stata's estimation. This

decline in wages for workers retained by establishments upgrading their technology. They also show some evidence of an increase in residual wages for leavers. However, this latter result is not robust to controls for collective bargaining and works council status. Furthermore, even if it were, it is hard to reconcile the pattern of results with increasing returns to skills from a manufacturing technology upgrade.

6 Discussion

Overall, there is some evidence that organizational change was skill biased in my western German sample in the mid-1990s. Group work introduced in 1995 led to an average annual decline in the wage bill share of 0.5 percentage points. This matches well with the 0.4 point annual decline reported in Caroli and Van Reenen (2001) for a similar time period and organization change (delayering) in France. It should be noted however, that their skill definition is based on an occupational category (unskilled manual labor), while mine is based on educational attainment (middle school).

It is interesting to note that the wage bill share reduction Caroli and Van Reenen (2001) find for Britain is double that for France. One possible interpretation is related to the Krugman hypothesis – differences in labor market institutions. While Table 3 does not include collective bargaining and works council controls (an oversight that will be corrected in the next version of this paper), the results in the other tables are scarcely affected by the inclusion of these controls.

Another difference between the British and French results in Caroli and Van Reenen (2001) is that the British organization changes precede the French ones by eight years. This opens the possibility that the skill bias in organizational change is

is possibly due to the very small number of employees in this category; this will be investigated in the next version of this paper.

similar in both countries but declining over time. My results for organization changes in Germany in 1998 and 2000 suggest that this might be the case. The point estimates increase steadily, and the positive 2000 estimate, while of only borderline significance, is clearly significantly greater than the 1995 estimate.

After the mid-1990s, the results are hard to reconcile with increasing returns to skill associated with group work or manufacturing technology upgrades. Furthermore, the effect on residual wages is sensitive to the time period under observation. For group work, the effect on residual wages is negative from 1998-2001 but not statistically different from zero from 2000-2003, while for manufacturing technology upgrades, the pattern is reversed.

Why might organization change become less skill biased over time? The Bresnahan (1999) and Autor et al. (2008) hypotheses (that new technologies are substitutes for routine tasks) would seem not to apply to self-directed work groups, since those hypotheses are explicitly about information technology. However, an analogous argument may apply. The idea behind those hypotheses is that information technology embeds easily routinized information. Bresnahan (1999) observes that the boundary of what routines can be encoded is constantly advancing. This recalls Bartel and Lichtenberg's (1987) hypothesis that the skill bias in technological change is due to its novelty – figuring out how to use a new technology most efficiently is cognitively demanding. Once the "best practices" for a specific technology are established and widely disseminated, the skill requirement to implement it drops. Lloyd-Ellis (1999) suggests something similar: even if a technology is not inherently skill biased, if it is introduced faster than it can be absorbed, returns to skill will increase. Casual observation suggests two ways in which the spread of new knowledge might have become more efficient in the 1990s. The first is the growth of the management consulting industry and the second is the rise of the Internet. One promising avenue for future research is to examine whether these affected returns to skill by more rapidly routinizing new methods of production.

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Table 1: Summary Statistics: Analysis of Wage Bill Shares

Variable	Obs	Mean	Std. Dev.	Min	Max
			1995		
Group work indicator	1051	0.247	0.432	0	1
Change in middle school wage bill share	1062	-0.023	0.097	-0.907	0.715
Change in log employment	1092	-0.072	0.555	-4.683	4.143
Sales per employee (euro)	972	240783	950518	5723	1.99E+07
Log total employment	1092	4.352	2.215	0	10.833
			1998		
Group work indicator	1058	0.213	0.409	0	1
Change in middle school wage bill share	1024	-0.035	0.132	-0.806	0.689
Change in log employment	1074	-0.048	0.451	-4.522	2.457
Sales per employee (euro)	968	218937	775940	5013	2.07E+07
Log total employment	1075	3.853	2.256	0	10.696
			2000		
Group work indicator	1795	0.148	0.355	0	1
Change in middle school wage bill share	1686	-0.027	0.131	-0.947	0.790
Change in log employment	1801	-0.113	0.458	-5.920	2.404
Sales per employee (euro)	1598	205600	697707	7572	2.38E+07
Log total employment	1803	3.686	2.033	0	10.624

Notes: The unit of observation is an establishment. Variables measured as changes are from the indicated year to the fifth year following.

Table 2: Summary Statistics: Analysis of Residual Wages

Variable	Obs	Mean	Std. Dev.	Min	Max
			1998		
Change in log residual wage	920581	0.062	0.269	-3.477	3.668
Group work indicator	434987	0.599	0.490	0	1
Technology upgrade indicator	440915	0.251	0.434	0	1
Change in log employment	439929	-0.016	0.225	-5.643	4.500
Sales per employee (euro)	358064	241002	264367	5013	2.07E+07
Log employment	440912	7.740	1.624	0	10.696
			2000		
Change in log residual wage	933037	0.015	0.272	-2.939	3.828
Group work indicator	627524	0.418	0.493	0	1
Technology upgrade indicator	628391	0.166	0.372	0	1
Change in log employment	503307	-0.028	0.238	-4.644	2.848
Sales per employee (euro)	517943	203860	225942	4024	2.38E+07
Log employment	628390	7.300	1.764	0	10.624

Notes: The unit of observation is an employee. Variables measured as changes are from the indicated year to the third year following.

Table 3: Effect of Group Work on Middle School Wage Bill Shares

	Dependent Variable: Change in Middle School Wage Bill Share		
	1995-2000	1998-2003	2000-2005
Group work	-0.024**	-0.009	0.013
	(0.010)	(0.011)	(0.008)
Change in log employment	0.003	-0.011	-0.021
	(0.008)	(0.019)	(0.018)
Sales per employee t=0	0.000	0.000***	0.000
	(0.000)	(0.000)	(0.000)
Log total employment t=0	-0.002	0.004	-0.002
	(0.002)	(0.003)	(0.002)
N	901	903	1488

Notes: The dependent variable is the change in the middle school wage bill share from t=0. Explanatory variables entering as changes are over the corresponding time period; those entering as levels are the values at t=0. Basic controls include indicators for labor market and industry. Robust standard errors in parentheses. *Statstically significant at the .10 level; ** at the .05 level; *** at the .01 level.

Table 4: Effect of Group Work on Residual Wages

	Dependent Variable: Change in Residual Log Daily Wage 1998-2001		2000-2003	
Group work introduction	-0.014***	-0.013***	-0.004	-0.005
	(0.005)	(0.004)	(0.008)	(0.007)
Arriving employee	0.017	0.017	-0.143*	-0.129***
	(0.121)	(0.125)	(0.079)	(0.022)
Departing employee	-0.014	-0.014	0.008	0.003
	(0.016)	(0.016)	(0.016)	(0.017)
Group work X arriving employee	-0.034	-0.034	0.149*	0.139***
	(0.125)	(0.129)	(0.081)	(0.034)
Group work X departing employee	0.006	0.006	0.024	0.028
	(0.024)	(0.025)	(0.026)	(0.027)
Change in log employment	0.002	0.002	0.009	0.017
	(0.007)	(0.007)	(0.012)	(0.012)
Sales per employee t=0	0.000***	0.000***	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Log total employment t=0	0.004***	0.002	0.008***	0.005
	(0.002)	(0.002)	(0.002)	(0.003)
Collective bargaining, works council controls	No	Yes	No	Yes
N individuals	351010	340383	426791	413460
N establishments	1297	1283	2248	2117

Notes: The dependent variable is the change in residual log wages from t=0. Explanatory variables entering as changes are over the corresponding time period; those entering as levels are the values at t=0. Basic controls include indicators for labor market and industry. Robust standard errors in parentheses. *Statstically significant at the .10 level; ** at the .05 level; *** at the .01 level.

Table 5: Effect of Technology Upgrade on Residual Wages

	Dependent Variable			
	Change in Residual Log Daily Wage			
	1998-2001		2000-2003	
Technology upgrade	0.004	0.005	-0.020*	-0.020**
	(0.005)	(0.005)	(0.011)	(0.01)
Arriving employee	-0.015	-0.023	0.052	0.052
	(0.029)	(0.033)	(0.037)	(0.037)
Departing employee	-0.003	-0.001	0.022*	0.020
	(0.015)	(0.015)	(0.013)	(0.014)
Technology upgrade X arriving employee	–	–	–	–
Technology upgrade X departing employee	-0.032	-0.036	-0.059	-0.059
	(0.027)	(0.028)	(0.045)	(0.047)
Change in log employment	0.004	0.004	0.006	0.014
	(0.007)	(0.007)	(0.012)	(0.012)
Sales per employee t=0	0.000***	0.000***	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Log total employment t=0	0.002	0.000	0.008***	0.005*
	(0.002)	(0.002)	(0.002)	(0.003)
Collective bargaining, works council controls	No	Yes	No	Yes
N individuals	356238	345611	427108	413770
N establishments	1319	1304	2252	2120

Notes: The dependent variable is the change in residual log wages from t=0. Explanatory variables entering as changes are over the corresponding time period; those entering as levels are the values at t=0. Basic controls include indicators for labor market and industry. Robust standard errors in parentheses. *Statstically significant at the .10 level; ** at the .05 level; *** at the .01 level.

A Description of the Data

Wages: sum of all wages and bonus payments, divided by the number of days in the employment spell. Wages are top-coded at the limit of income subject to social security contributions. This affects mainly workers with higher levels of experience and educational attainment [**add statistics on top coding]. I deflate the wages using the consumer price index (annual average national value for the respective year). I further impute values to the top-coded wages as described below.

Wage bill share: share of full-time wages by skill group. Part-time employees and apprentices are omitted from the calculation.

Group work: indicator if the establishment introduced self-managed work groups or similar work practices in the two years preceding the survey.

Technology upgrade: year-on-year increase in the establishment's evaluation of its technology. Each year, surveyed establishments are asked to rate the technical level of their plant and equipment relative to others in their industry on a five-point scale. If an establishment's evaluation improves by at least one point in consecutive calendar years, I measure this as a technology upgrade.

Employment: total number of employees subject to social security reporting.

Sales: establishment sales in euros. This figure is self-reported; many establishments decline to report it, as can be seen in comparing the sample sizes in the summary statistics reported in tables 1 and 2.

Sales per employee: sales divided by employment.