Capital Equipment, R&D and Wage Inequality in the US and Germany*

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Very Preliminary

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Abstract

In this paper we investigate the importance of R&D and capital investment for the evolution of wage inequality across educational groups in the US and Germany. Constructing an industry panel from the 1970s until the end of the 1990s, we find substantial differences in investment in equipment capital, R&D and the evolution of wage inequality across sectors as well as across the two countries. Investment in capital equipment and R&D are associated with more compressed wages in Germany than in the US suggesting that R&D and investment are more complementary to unskilled workers in Germany. This is consistent with the hypothesis that innovation and investment incentives can be distorted towards unskilled labor if labor market institutions raise the wage of unskilled workers above the *laissez-faire* productivity level in Germany but less so in the US.

Keywords: Induced technology change, Capital deepening, Skill-wage differential, R&D.

JEL Nos: E22, J31, O3

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1 Introduction

Many authors have emphasized the differences in the evolution of wage inequality across developed countries, and in particular between Germany and the US (see for example, Blau and Kahn, 1996; Acemoglu, 2003b, and Abraham and Houseman, 1995). These differences have been partly attributed to differences in labor demand and supply but also to differences in labor market institutions (see for example Koeniger, Leonardi and Nunziata, 2004, and their references).

Whereas the focus of the literature mostly has been on the direct static effect of labor market institutions on wage inequality, in this paper we focus on their indirect effect resulting from distorted incentives to innovate and to invest. If labor market institutions increase the relative price of unskilled labor compared to the *laissez-faire*, firms might have an incentive to make these workers more productive in order to mitigate the institutional constraints. In imperfect labor markets firms can either invest in capital complementary to unskilled workers or train these workers (Acemoglu and Pischke, 1999), or employ different technologies which make unskilled workers more productive or are less intensive in unskilled workers to alleviate the hold-up problem (Blanchard, 1997; Caballero and Hammour, 1998; Acemoglu 2003a).

In this paper we provide some suggestive evidence on the relevance of this dynamic effect of labor market institutions. We document that the evolution of the wage differential, capital investment and R&D expenditure varies substantially across sectors and between two countries with very different labor market institutions, the US and Germany. Whereas labor market institutions such as unions or the social benefit system provide considerable implicit minimum wages for unskilled workers in Germany, the US is much closer to a *laissez-faire* economy.

Constructing a panel of two-digit industries in the US (1973-2001) and West Germany (1975-1995), we find evidence that suggests more complementarity of R&D expenditure or capital equipment and unskilled labor in Germany than in the US. Stronger labor market institutions in Germany seem to distort prices not only statically but also dynamically by changing the incentives for investment and technology change. This evidence is consistent with a simple theoretical model in which innovation and investment incentives are distorted if labor market institutions raise the wage of unskilled workers above their *laissez-faire* productivity level. In a simple model with imperfections in product markets this can foster innovations that decrease the price of those capital goods which are specific to unskilled labor. The capital-labor complementarities increase the productivity of unskilled workers and allow firms to dynamically re-appropriate the rents lost due to the wage constraints imposed by institutions.

Our paper relates both to the literature on wage inequality and skill-biased technology change (Berman et al., 1998) or capital-skill complementarities (Krusell et al., 2000). Krusell et al. argue that cheaper capital equipment together with capital-skill complementarities have been responsible for a large part of the increase in the wage differential in the US. Berman et al. claim instead that skill-biased technology change has been the major determinant and this technology change is common across industries and developed countries. In this paper we argue that the bias in technology change is likely to be different in countries with different institutional environments and might induce capital deepening for capital goods that differ in terms of their complementarity to specific types of labor. For example, a conveyor belt seems particularly useful for unskilled workers whereas a high-tech machine for a chemical laboratory is more likely to be combined with skilled labor.

The focus on only two countries in our empirical work allows us to construct more detailed data on three factors of production –capital equipment, skilled and unskilled labor– at the industry level compared with the literature on TFP or labor productivity growth across industries in developed countries (see Bernard and Jones, 1996; Beaudry and Green, 2003; van Ark et al., 2003). Most closely related is the work of Beaudry and Green (2003) and Pischke (2005). Pischke provides evidence that changes in investment between the 1990s and 1980s have been more pronounced in those industries in OECD countries that have been more unskilled-labor intensive in the 1980s. Moreover, the changes in capital investment are associated with less wage inequality in these countries. Beaudry and Green (2003) draw a similar conclusion using aggregate data on the US and Germany. They show that wage inequality between skilled and unskilled workers would have been smaller in the US if the capital accumulation in the US had matched the German pattern. Assuming that the newer technologies are *both* more skill complementary and more capital efficient, they show that the latter assumption implies that a higher capital intensity induces a flatter wage-education profile. In our paper we build on these analyses using more disaggregated and detailed data for two important economies. In particular, we are able to use data on capital equipment by industry which seems most relevant to study complementarities with different types of labor.

The rest of the paper is structured as follows. In the next subsection we motivate our paper further with some descriptive evidence for the US and Germany. In Section 2 we present a simple model to derive the wage differential as a function of R&D expenditure and capital investment. In particular, we mention how a minimum wage distorts the incentive to innovate. In Section 3 we present the data and discuss our econometric specification. In Section 4 we present our results before we conclude in Section 5.

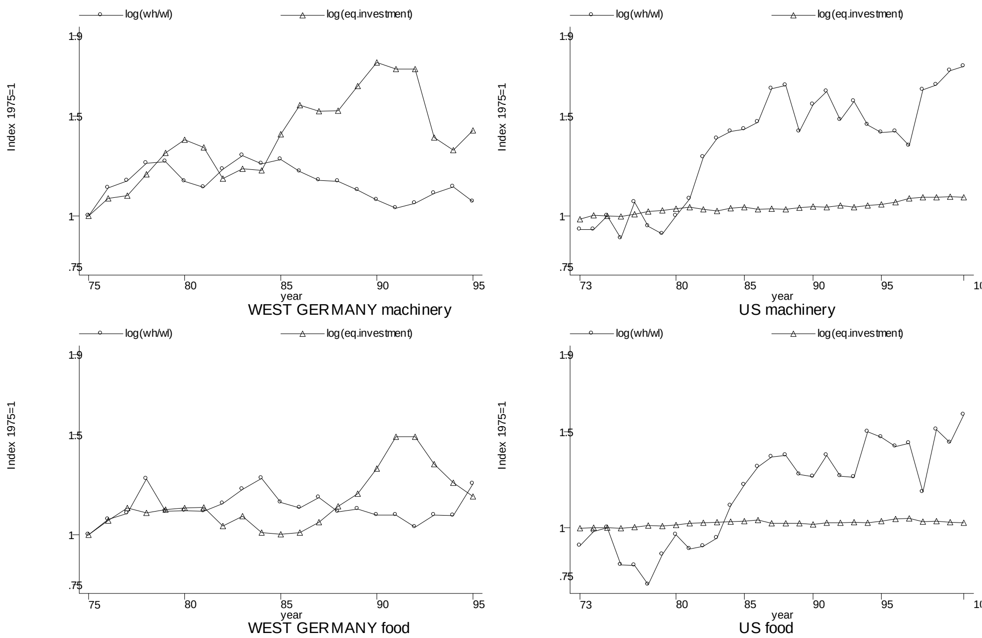

Figure 1: Wage differentials by skill and investment in equipment capital in the machinery and food industry in the US and West Germany 1970s-1990s. Source: Authors' calculations based on CPS, IAB, and national accounts data.

1.1 Some descriptive evidence

To motivate our analysis further, we illustrate the evolution of the main variables of interest in our sample period for some important industries. We choose three manufacturing industries with the chemical industry as the most skill intensive, the machinery industry with medium skill intensity and the food industry with low skill intensity. Finally, we also choose the retail industry as an important low-skill intensive service industry. To make the figures comparable we normalize all variables to one in 1975.

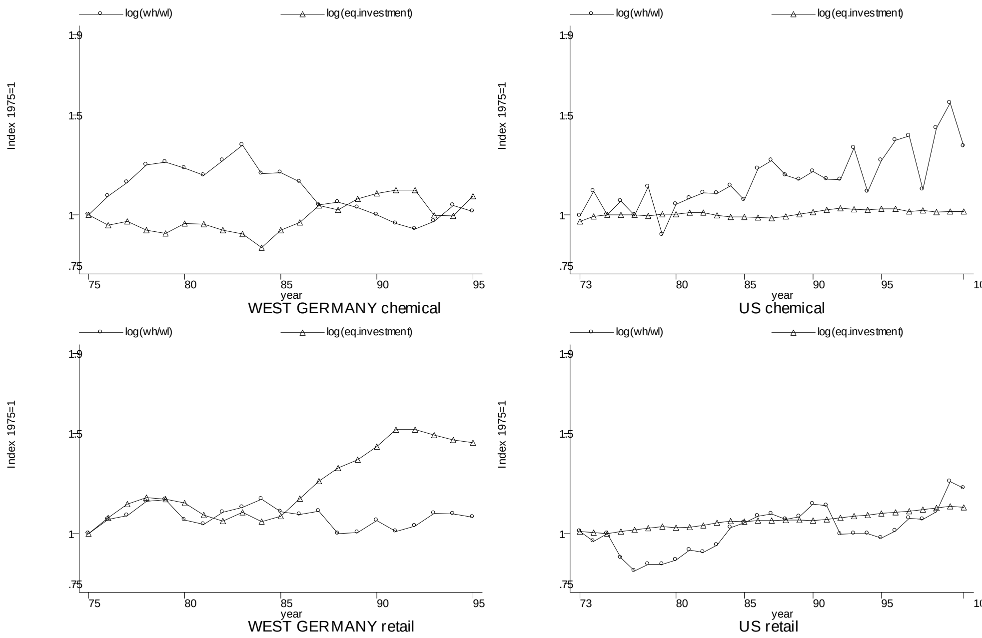

Figure 2: Wage differentials by skill and investment in equipment capital in the chemical and retail industry in the US and West Germany 1970s-1990s. Source: Authors' calculations based on CPS, IAB, and national accounts data.

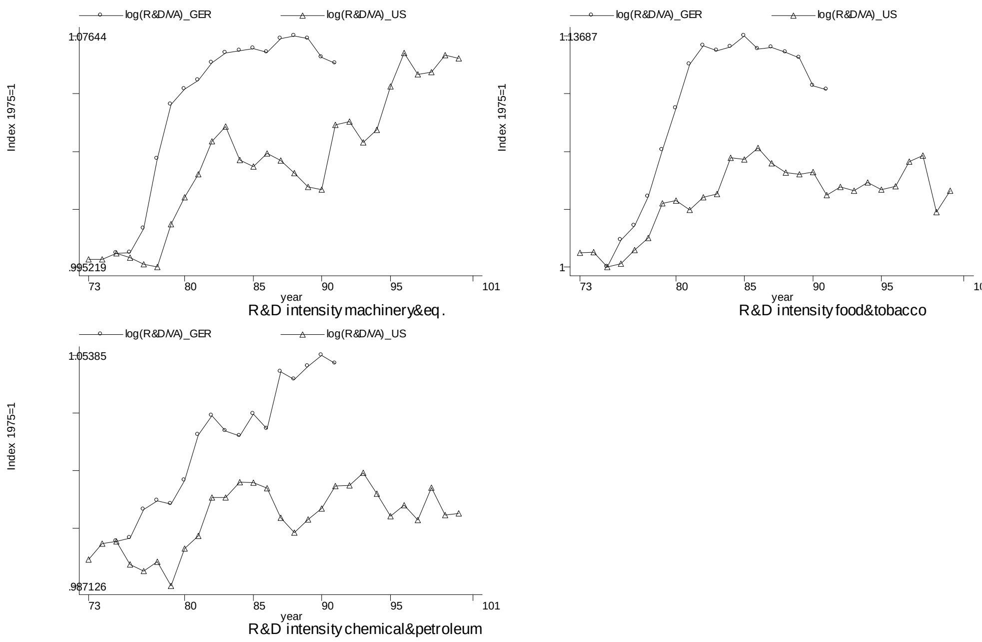

Figure 3: R&D intensity in selected manufacturing industries: US and Germany. Source: Authors' calculation based on OECD data.

Figures 1 to 3 display the main patterns for the evolution of wage differentials by education (some college versus less than college) and investment into equipment capital in the US and Germany. Wage differentials increased substantially in the US especially in the 1980s whereas they remained relatively stable in West Germany. Investment into equipment capital as well as the R&D intensity increased much more in West Germany than in the US. This suggests that equipment capital or R&D might have been more complementary to unskilled workers in Germany than in US. Of course, these patterns are more or less pronounced depending on the respective industry. Whereas this patterns is quite strong in the machinery industry as well as in the food industry, the pattern is less clear for capital investment in the chemical industry in Germany and the retail industry in the US. However, these descriptive graphs sufficiently motivate a more detailed investigation in a regression framework after we have provided a brief theoretical perspective.

2 Theoretical background

In this section we set up a simple model to motivate the evolution of industry wage differentials as a function of R&D expenditure and capital investment. We first derive a simple expression of the wage differential as a function of the capital-good prices relevant for unskilled or skilled labor, respectively. We then mention how these prices depend on innovations in the production of each of these capital goods; and how in imperfect product markets with step-by-step innovations as in Aghion et al. (2001) minimum wages can induce more innovations for the capital good complementary to unskilled labor (the mechanism is also similar to the innovation incentives in imperfect labor markets in Acemoglu and Pischke, 1999).[1]

The model structure is stylized and shall motivate the specifications in the empirical part. We start with a brief overview of the main building blocks which are illustrated in Figure 4 and laid out in more detail in Appendix A. In the following we focus on the wage differential and how it depends on innovations and investment.

We assume that the economy consists of i industries in each of which two competitive subsectors produce final-goods with different technologies. One subsector uses unskilled labor L_i and a capital good $K_{l,i}$ specific to unskilled labor (for example, a conveyor belt) whereas the other

[1] This section draws on previous work in Koeniger (2005).

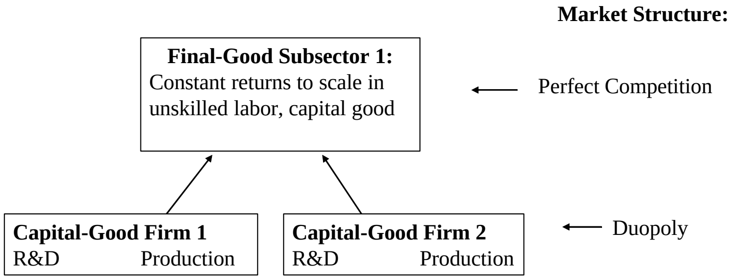

Figure 4: The production structure of the subsector using unskilled labor in industry i.

subsector uses skilled labor H_i and another specific capital good $K_{h,i}$ (for example, laboratory equipment; the subscript h denotes that the capital-good is used together with skilled labor). As a benchmark we assume that labor cannot move across industries so that wages differ across industries (as is empirically plausible to some extent, see Tables 2 and 3 below). This implies that all inputs are subsector-specific.

The capital good for each subsector is produced by two intermediate-good firms in the same subsector and both of these firms also innovate to produce the capital good more efficiently. The resource input to produce the capital-good and R&D is supplied fully elastically in the world market. This assumption is done for clarity since it prevents feedbacks from changes in the factor prices of labor or capital on the production of the capital-good or R&D.

2.1 Final-good production in the industry

Each subsector j in industry i has a production function $F_j(.)$, $j = 1, 2$, which is assumed to have constant returns to scale and to be strictly concave in each factor. For simplicity we assume that capital depreciates fully every period so that capital equals the investment flow.[2] Dropping

[2]Relaxing this assumption would slightly complicate the algebra since we would need to solve a Hamiltonian. In substance, the optimality condition for capital changes: agents take into account the depreciation of the current capital stock and the losses of the capital value due to the decreasing price of capital resulting from innovations.

the industry index i for convenience, in each industry the maximization problem of subsector 1 employing unskilled labor is

$$\max_{\{L(t),K_l(t)\}} J_1 = \int_0^\infty e^{-rt} \left[P_1(t)F_1(L(t),K_l(t)) - W_l(t)L(t) - \mathbf{p}_1(t)K_l(t)\right] dt \ .$$

Similarly, subsector 2 solves

$$\max_{\{H(t),K_h(t)\}} J_2 = \int_0^\infty e^{-rt} \left[P_2(t)F_2(H(t),K_h(t)) - W_h(t)H(t) - \mathbf{p}_2(t)K_h(t)\right] dt \ ,$$

where r is the exogenous market interest rate, W_l is the wage of the unskilled, W_h is the wage of the skilled, $\mathbf{p}_1$ is the price of capital good K_l, and P_i is the price of subsector j output. For concreteness we parametrize the production functions[3] as $F_1(L,X_1) = L^{\frac{1}{2}}(K_l)^{\frac{1}{2}}$ and $F_2(H,X_2) = H^{\frac{1}{2}}(K_h)^{\frac{1}{2}}$. Writing both production functions in intensive form, $f_1(l) = l^{\frac{1}{2}}$ and $f_2(h) = h^{\frac{1}{2}}$, where $l \equiv \frac{L}{K_l}$, $h \equiv \frac{H}{K_h}$, we get the static first order conditions omitting time indices for convenience:

$$W_l = \frac{P_1}{2\sqrt{l}},\ W_h = \frac{P_2}{2\sqrt{h}}\ ,\ \mathbf{p}_1 = \frac{P_1}{2}\sqrt{l}\ ,\ \mathbf{p}_2 = \frac{P_2}{2}\sqrt{h}\ . \tag{1}$$

We assume a small open economy so that the relative price of the final goods of the two subsectors in each industry $P \equiv \frac{P_2}{P_1}$ is taken as given where P_1 is the numeraire. The prices of the capital goods $\mathbf{p}_i$ are determined in the intermediate-good sector. Hence, the four conditions (1) fully determine the remaining four unknowns $W_l(\mathbf{p}_1,P)$, $W_h(\mathbf{p}_2,P)$, $l(\mathbf{p}_1,P)$ and $h(\mathbf{p}_2,P)$.

We refer to Appendix A for further details on the modeling structure concerning the production of the capital good and innovation of the capital-good firms. Since this is not novel in this paper, we immediately mention how industry-wage differentials depend on capital-good prices and R&D which is our focus of interest.

Since this however does not affect the expression for the *changes* of the wage differential as long as prices decrease at a constant rate (and the interest as well as the depreciation rate are assumed to be constant), we prefer to simplify the problem as much as possible.

[3] In these specifications skilled labor is more productive than unskilled labor because we will assume that the price of the final good produced with skilled labor is larger than the price of the final good produced with unskilled labor. Note also that we assume the same capital intensity for simplicity.

2.2 Wage differential, investment and innovation

Using (1), substituting out l and h, and defining[4] $w_l \equiv \frac{W_l}{P_1}$, $w_h \equiv \frac{W_h}{P_1}$, $r_2 \equiv \frac{\mathbf{p}_2}{P_1}$, $r_1 \equiv \frac{\mathbf{p}_1}{P_1}$, $P \equiv \frac{P_2}{P_1}$, the wage differential is

$$\ln\left(\frac{w_h}{w_l}\right) = \ln\left(\frac{r_1}{r_2}\right) + 2\ln P. \tag{2}$$

Not surprisingly, the wage differential positively depends on the relative price P of the final good using skilled labor. More interestingly, the wage differential also increases if the relative price of the intermediate capital good used with unskilled labor is higher. A higher price of the capital good induces substitution towards labor in the final-good subsector. If $r_1 > r_2$, the labor intensity is higher in the final-good subsector using unskilled labor so that the marginal productivity and wage of unskilled labor is relatively smaller.

As firms innovate in the capital-good sector they completely pass-on efficiency gains to prices. This results from the unit elasticity of the factor demand function in the final-good production so that revenues and profits do not depend on the marginal cost for capital-good production in each subsector j. Thus, over long time intervals

$$\lim_{\Delta t\to\infty} \frac{\Delta \ln \mathbf{p}_j}{\Delta t} = -g_j \ , \tag{3}$$

where g_j is the growth rate of capital-good production in each subsector j.

Since $\lim_{t\to\infty} \mathbf{p}_j = 0$ as long as $g_j > 0$, the equations in (1) imply for our parametric specification that $\lim_{t\to\infty} h = \lim_{t\to\infty} l = 0$: the capital-labor ratio grows over time in each subsector; and this relatively faster the larger is the innovation effort. It follows that $\lim_{t\to\infty} w_l = \infty$ and $\lim_{t\to\infty} w_h = \infty$. Using L'Hôpital's rule, it follows that

$$\lim_{t\to\infty} \ln\left(\frac{w_h}{w_l}\right) = g_2 - g_1 \ . \tag{4}$$

In the limit the wage differential in each industry depends on the relative growth rates of the two subsectors j in each industry i, where the wage of labor used in the faster-growing final-good subsector is higher. Together with equations (2) and (3), this also implies

$$\lim_{\Delta t\to\infty} \frac{\Delta \ln(\frac{w_h}{w_l})}{\Delta t} = g_2 - g_1 \ . \tag{5}$$

[4] The choice of the numeraire is irrelevant for the results.

For our purposes it is important to note that changes in the wage differential depend on the growth rate of the produced capital-good in each subsector j in industry i. If the output of the capital-good combined with unskilled labor grows more, then the wage differential becomes more compressed. Higher growth is associated with larger R&D expenditures and "capital deepening through capital cheapening" of the respective capital good. The effect on the wage differential, however, depends on whether the capital good combined with unskilled or skilled labor becomes cheaper. We now mention how the incentives to innovate are distorted by labor market institutions such as the minimum wage.

Minimum wages, innovation incentives and the wage differential We assume that the minimum wage is binding only for unskilled labor. Skilled workers are more productive and earn a higher wage because the price of the skill-intensive good is larger, $P_2 > P_1$. Since final-good prices are given in the small open economy, a minimum wage implies a maximum price for the capital good combined with unskilled labor. Formally, it follows from equation (1) that

$$\mathbf{p}_1^{\max} = \frac{(P_1)^2}{4w^{\min}} \tag{6}$$

for the final-good sector to break even. We assume that $w^{\min}$ is sufficiently low so that the unskilled-labor intensive sector does not have to close down: the asset value of firms in the intermediate-good sector remains non-negative. As shown in Koeniger (2005), for the firm producing capital for the unskilled-intensive subsector, a minimum wage can temporarily increase innovation (see Appendix B).

The intuition is that minimum wages strengthen the incentive to innovate so that the price constraint is relaxed. Since product markets are imperfect in the intermediate-good sector, this constraint temporarily redistributes rents from capital-good firms to unskilled workers. Firms become the residual claimant of productivity increases, however, and are able to reverse this redistribution by producing the capital good more efficiently (the mechanism is similar to models with imperfect labor markets and rents in Acemoglu and Pischke, 1999). The higher efficiency is passed on to lower prices and induces substitution towards the capital good combined with unskilled labor in industry i. This makes unskilled workers more productive and the minimum wage less binding. Note that here it is important that the capital good indeed is specific to the subsector so that the firm does not have alternative opportunities to sell the good, for example in countries in which minimum wages do not apply.

We now want to investigate empirically whether labor market institutions which compress the wage differential statically, induce innovations and capital investment which compress the wage differential dynamically compared with a *laissez-faire* economy.[5]

3 Data and econometric specification

The model above argued that labor market institutions affect capital and R&D investment of firms and thus also the wage structure. In this section we try to find evidence in support of the hypothesis that wage-compressing labor market institutions in Germany have induced investment into capital equipment or R&D which has been more complementary to low-skill jobs in Germany than in the US.

To test this hypothesis we investigate how the changes in capital equipment and R&D intensity are associated with the wage differential. We now mention how we construct the data used for the analysis and briefly describe some of its interesting patterns before we provide the results of the estimations.

3.1 Data

Our evidence is based on an industry panel for Germany and the US, combining industry-level data on capital investment and R&D expenditure with micro data on wages and employment by education level. We describe the data only briefly and refer to the data appendix for further details on variable construction and industry classification in the various data sources (Tables 4 and 5).

We use data on value added and capital equipment from the national accounts (Bureau of Economic Analysis and *Statistisches Bundesamt*, respectively) and the 60-Industry Database available online at the Groningen Growth and Development Centre. We construct the stock of capital equipment for Germany using the series on gross capital equipment formation and applying the perpetual inventory method. Capital equipment in both countries is deflated

[5] Our model also implies that for this effect to be present, the minimum wages cannot be prohibitively high so that industries close down.

with the chain-price indices provided by the respective statistical office. Although these price deflators have been criticized for their accuracy, we are not aware of any better price index to deflate capital equipment at the industry level. Thus, we check whether our results below are robust to the choice of the deflator in each country.

The data on R&D expenditure are from the Stan-Anberd database provided by the OECD. Wages and employment by skill and industry are constructed using the CPS May/ORG for the US and the dataset on the social-security records from the *Institut für Arbeits- und Berufsforschung* (IAB) for Germany. Our sample includes employees in full-time employment, age 20-60 with potential labor market experience up to 39 years. We only use the information on West-Germany in the IAB dataset and drop all East-German observations after 1990. Whereas the CPS is a representative sample of all employees, the IAB dataset is a 1% random sample of employees with a social-security record. This leaves us with a industry panel in the time period 1973-2001 for the US and 1975-1995 for West Germany.[6]

We define skilled workers as those with some college or college degree in the US and with Abitur (high-school degree) in Germany. Since 13 years of schooling imply a high-school degree in Germany and some college in the US, this educational skill measure achieves some comparability (if imperfect) across the two countries. All those with less education in the respective country are classified as unskilled. We now describe some of the main patterns of interest in the data.

Tables 2 and 3 display the patterns in the sample period for the main variables of interest: the skill intensity, the wage differential, the investment in equipment per unskilled worker, R&D intensity and their respective changes across decades. We also report the changes in hours worked per industry as a measure for the intensive margin of the labor input.

Tables 2 and 3 show that if industries in the 1970s were more skill intensive and R&D intensive in the US, the same held true for West Germany. The (rank) correlations are larger than 0.75 and highly significant. Moreover, R&D is highly positively correlated with the skill intensity across sectors in both countries. Instead, investment in capital equipment per unskilled worker in the 1970s is less clearly related across countries and to the skill intensity and R&D within countries.

[6] Although we manage to extend our sample period for West Germany to 1995 since some series are available until then, we prefer to omit these years in our estimations since disentangling East and West German data is not straightforward for all variables. Thus, in the estimations the West-German sample period is 1975-1991.

Tables 2 and 3 further show that the skill-intensity increased across decades in all industries and in both countries. This also holds true for the changes in the R&D intensity between the 1970s and 1980s in the US and Germany but less so for changes between the 1980s and 1990s. Instead, changes in the equipment investment per unskilled worker have different signs across industries and countries, although investment in capital equipment has increased in most industries. Interestingly, hours worked have increased slightly in most industries in the US since the 1970s whereas they have decreased in all industries in West Germany. Since hours worked influence the total amount of labor supplied we control for these differences in hours by industry in some of the regressions below.

Finally, Tables 2 and 3 show the well-known differences in the evolution of wage differentials in Germany and the US. Whereas wage inequality has increased in nearly all industries in the US and up to 13.5% within a decade in some industries, wage differentials have remained constant or even have fallen in West Germany. Overall there is substantial variation in the data across industries as well as across countries which we will exploit in our empirical estimation.

3.2 Econometric specification

In our estimations we investigate whether investment in capital equipment and R&D are differently associated to the evolution of wage differentials in the US and Germany. Our simple model predicts that the stronger wage-compressing institutions in Germany can induce relatively more investment complementary to unskilled workers than in the US.

As in Machin and van Reenen (1998) we assume a simple translog cost function C for industry i in country c and year t: $C[\log(w_h)_{ict,} \log(w_l)_{ict,} \log(k_{ict}), \log(y_{ict}), A_{ict})]$, where A_{ict} is an indicator for technological differences and capital k_{ict}, output y_{ict} and technology A_{ict} are quasi-fixed factors. It follows that

$$\log(\frac{w_h}{w_l})_{ict} = \alpha_{ic} + \beta_c \log(k_{ict}) + \gamma_c \log(y_{ict}) + \delta_c A_{ict} + \zeta_c \left(\frac{w_h H}{w_h H + w_l L}\right)_{ict} \tag{7}$$

where as before w_h, w_l is the wage of the skilled and unskilled and $(w_h H/(w_h H + w_l L))_{ict}$ is the wage bill share of educated workers. Since the wage-bill share is highly endogenous and we do not have a good instrument, we assume that the wage-bill share evolves as a industry-specific time trend in each country. Taking first differences to eliminate the industry-specific fixed effect

α_{ic}, it follows that the wage differentials evolve according to

$$\Delta \log(\frac{w_h}{w_l})_{ict} = \beta_c \Delta \log(k_{ict}) + \gamma_c \Delta \log(y_{ict}) + \delta_c \log\left(R\&D/y\right)_{ict} + \eta_c D_{ci} + u_{ict}. \tag{8}$$

This is the specification we will estimate where the changes in the wage-bill share of educated workers have been replaced by country-specific industry dummies $\eta_c D_{ci}$ since the wage-bill share is highly endogenous.[7] Note that as in Machin and van Reenen (1998), we proxy changes in technology by the ratio of R&D expenditure to value added. R&D is an imperfect measure since it is an input for technology changes but it has been shown to be strongly correlated with technological progress in a series of papers.

The hypothesis that wage-compressing labor market institutions in Germany induce investment in capital equipment or R&D which is more complementary to unskilled labor than in the US, corresponds to a test of

$$\beta_{Ger} < \beta_{US} \text{ and/or } \delta_{Ger} < \delta_{US}$$

in equation (8).

4 Results

Our estimation results for a specification as in equation (8) are summarized in Table 1. The estimations use the data of twelve manufacturing sectors for which both data on the equipment capital and R&D are available. To account for the different importance of industries in the economy, we weight each observation by the size of real value added in the respective industry (although this weighting does not affect the results much at all). Since measures of changes over time are typically more vulnerable to measurement error, we experiment with data on annual changes and changes of three-year averages.

Table 1 presents the estimation results for equation (8) for the US and West Germany, respectively. In columns (1) and (2) we present results of the simplest specification. In columns

[7] Note that equation (8) is written as a pooled country regression. For presentation purposes we estimate it separately for each country. Furthermore, note that our specification allows for industry-specific time trends in the level equation (7). Allowing for an aggregate time trend in equation (8), leaves the coefficient of $\Delta \log(k_{ict})$ unchanged and significant. If we allow for time dummies instead, the limited remaining sample variation implies that the coefficients of $\Delta \log(k_{ict})$ and $\log\left(R\&D/y\right)_{ict}$ are no longer significant.

		Dependent Variable: First-difference log(wh/wl)					
		Raw differential		Raw differential		Residual differential	
		US	Germany	US	Germany	US	Germany
	Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
One-year changes	First difference log(equipment capital)	0.089	-0.077	0.05	-0.072	0.13	-0.083
		(0.116)	(0.018)**	(0.118)	(0.019)**	(0.081)	(0.019)**
	log(R&D / value added)	-0.007	-0.018	-0.009	-0.017	-0.01	-0.017
		(0.012)	(0.004)**	(0.012)	(0.004)**	(0.009)	(0.004)**
	First difference log(real value added)	-0.032	0.045	-0.04	0.045	-0.023	0.01
		(0.038)	(0.034)	(0.038)	(0.035)	(0.019)	(0.034)
	First difference log(skill intensity)			-0.086	-0.416	-0.092	-0.578
				(0.042)*	(0.164)*	(0.031)**	(0.168)**
	First difference log(hours)			-0.071	-0.055	0.093	-0.015
				(0.261)	(0.12)	(0.19)	(0.12)
	Observations	251	192	251	192	251	192
Changes of three-year averages	First difference log(equipment capital)	0.091	-0.069	0.1	-0.062	0.21	-0.065
		(0.049)	(0.014)**	(0.042)*	(0.014)**	(0.040)**	(0.016)**
	log(R&D / value added)	-0.014	-0.08	-0.017	-0.077	0.001	-0.059
		(0.011)	(0.008)**	(0.012)	(0.009)**	(0.011)	(0.010)**
	First difference log(real value added)	0.007	0.026	-0.004	0.024	-0.004	-0.053
		(0.01)	(0.039)	(0.01)	(0.038)	(0.009)	(0.043)
	First difference log(skill intensity)			-0.049	-1.366	-0.06	-0.766
				(0.036)	(0.358)**	(0.035)	(0.497)
	First difference log(hours)			-0.465	0.258	0.023	0.409
				(0.285)	(0.131)*	(0.249)	(0.169)*
	Observations	84	60	84	60	84	60
	Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
	Year Dummies	No	No	No	No	No	No
	Number of Industries	12	12	12	12	12	12

Notes: Estimated with generalized least squares accounting for industry-level heteroscedasticity and weighted by real value-added in each industry. Each estimation includes a constant. Standard errors in parentheses. *: 5% significance level;**: 1% significance level. The residual wage differential is obtained by regressing log wages on education and experience, experience squared, gender and their interactions for each industry and year in the CPS and IAB data, respectively. We then keep the coefficients of the education dummy as a measure of the residual education wage differential after controlling for the other variables. We use the inverse of the standard errors to weight each obtained estimate. The twelve industries are Wood, Stone and Clay, Primary Metals, Machinery, Electrical Machinery, Transport Equipment, Professional Goods, Food and Tobacco, Textiles, Paper and Printing, Chemicals and Petroleum, Plastic and Leather. See the Data Appendix for further details.

Table 1: Estimation results for changes in the wage differential as a function of changes in capital equipment and R&D intensity with additional controls

(3) and (4) we add the skill intensity and hours worked as further controls. Finally, in columns (5) and (6) we use the residual wage differential after controlling for observable heterogeneity across industries such as gender and experience.

The results in Table 1 show that a 1 percentage-point (pp) increase in the change of capital equipment or a 1 percent increase in R&D in West Germany is associated with a 0.07-0.08 pp or 0.02 pp decrease in the change of the wage differential, respectively. The corresponding numbers for changes of the three-year averages are 0.06-0.07 pp and 0.06-0.08 pp for capital equipment and R&D, respectively. For the US we only find significant effects in the regressions using changes of three-year averages: in this case a 1 percentage-point (pp) increase in the change of capital equipment implies a 0.1-0.2 pp increase in the change of the wage differential (see columns 3 and 5).

As for the additional controls, not surprisingly a higher skill-intensity is negatively associated with a change in the wage differential. If the skill-intensity increases by 1 pp, the change of the wage differential is 0.086 pp smaller in the US and 0.416 pp smaller in Germany (in the estimations based on annual changes). Changes in hours worked are not significant but for the estimation with changes of three-year averages in Germany. The positive coefficient implies that industries with stronger working-time reductions in Germany also have less growth in wage differentials. This correlation might be spurious if union power changed over time and relatively stronger unions decreased working time on the one hand and further compressed wages on the other hand.

The results in Table 1 suggest that capital investment and R&D are positively associated with wage differentials in the US, if anything, whereas the association is negative for West Germany. Although the coefficients are not always estimated precisely enough to allow us to formally reject the hypothesis that the coefficients are the same in the US and Germany at standard significance levels, our evidence suggests that capital equipment is more complementary to unskilled workers in Germany than in the US. Consistently with our hypothesis we find that the point estimates $\beta_{Ger} < \beta_{US}$ and $\delta_{Ger} < \delta_{US}$.

The theory suggests further that a change of capital equipment or R&D is more negatively associated with the evolution of the wage differential in industries in which the initial wage differential was more compressed. Interacting $\Delta \log(k_{it})$ and $\log{(R\&D/y)}_{it}$ with $(w_h/w_l)_{i,1975}$, we find evidence for such an effect in West Germany but only significantly so for R&D.

One further indication that capital equipment in West Germany might have been more complementary to unskilled labor is that the results vanish if we use the series on office machinery and computers for Germany constructed by Falk and Koebel (2004): the coefficient of $\Delta \log(k_{ict})$ and the corresponding standard error changes to -0.005 (0.015) in the specification for annual changes in Table 1, column (4). Arguably, office machinery and computers are more complementary to skilled workers and thus we should be less likely to find differences between Germany and the US.[8]

To gauge the quantitative impact of capital investment and R&D on wage differentials in West Germany, we use the fitted values of the wage differential obtained from the specification for annual changes in Table 1, column (4). We then also compute the fitted values holding capital equipment and R&D constant at their initial level in 1975. Comparing the differences in the fitted wage differential at the beginning of the 1990s, we find that the wage differential would have been about 13% higher in industries such as chemicals and petroleum, food and tobacco or machinery, if capital equipment and R&D had remained constant at their level of 1975 in West Germany.

4.1 Robustness

We check the robustness of our results with respect to the chosen deflator of capital equipment. Deflating the West German series with the US prices for capital equipment leaves the results nearly unchanged: the coefficient of $\Delta \log(k_{ict})$ and the corresponding standard error changes to -0.065 (0.021) in the specification for annual changes in Table 1, column (4). Moreover, it is important to note that none of our significant coefficient estimates depends on a specific industry. All coefficients remain robust if we drop one industry at a time.

Finally, we improve our measure of the wage differential exploiting the information in the CPS and IAB to control for differences in observables such as gender and experience across industries. The residual wage differential is obtained by regressing log wages on a dummy for at least some college education controlling for experience, experience squared, gender and their interactions. The regression is run for each industry and year in the CPS and IAB data, respectively. We then keep the coefficients of the education dummy as a measure of the residual

[8] Since the series on office machinery and computers also reduces our sample size by two years and one industry, we adjust the sample of our previous regressions to check that the change of the coefficient estimate is not due to the different sample.

education wage differential. We use the inverse of the standard errors to weight each obtained estimate. Columns (5) and (6) in Table 1 show that the results for the variables of interest remain qualitatively unchanged if we control for some observed worker heterogeneity across industries. Quantitatively the results become even stronger.

Of course, the data we have do not allow us to interpret the different coefficient estimates as causal.[9] For example, if R&D and investment in equipment increased for other reasons and labor market institutions compressed wages in Germany but not in the US, we would get the same qualitative pattern of the estimates. However, in absence of plausible instruments the industry-specific time trends will also capture the heterogenous effect of institution across industries.

Some firm-level evidence In order to get further insights on whether our hypothesis is plausible, we use firm-level data for the US to measure more precisely R&D, capital investment and value-added. Unfortunately the Compustat Germany is only available for 1992-2001 with scarce information on R&D and capital investment so that we cannot use this dataset to compare results with our West-German sample 1975-1991.

We use the Compustat dataset for the US as described in Hall et al. (2000). We include all firms in the manufacturing sector between 1973 and 1995 according to the industry classification in Table 4. This results in a large unbalanced panel of approximately 3,000 firms which are all publicly traded on the NYSE. The total number of observations is 22,784 where each firm on average stays in the panel for 7.5 years and has 8,800 employees.

The Compustat dataset contains firm-level information on R&D expenditure, net sales and the current value of capital equipment (net of depreciation). We construct the R&D intensity as R&D expenditure over sales and the percentage change of capital equipment as the first difference of the log net capital equipment deflated by the industry-level price of capital equipment. We use sales net of operating costs at the firm level instead of the previously used value-added at the industry level. Net sales are deflated with the industry-specific price of value added. Since there is no information on wages by education and workforce skills in the Compustat, we merge in the respective industry-level data for the US.

[9] We experimented with using public R&D expenditure as instrument for private R&D. Unfortunately, the industry data on public R&D provided by the OECD are very noisy. Although the correlation between both R&D measures is significant at the 5% level in the first stage, the standard errors in the second-stage regression increase so that we do not find any significant results.

We estimate specifications as in Table 1, column (5). The results (which are not reported) remain qualitatively the same compared with the previous industry level regressions for the US. Thus, the results in Table 1 are robust to using different measures for capital equipment and R&D expenditures at the firm level. This result is robust if we only keep firms which are present in the whole sample period (the balanced panel) or if we include also those firms entering and exiting (the unbalanced panel).

5 Conclusion

Investment in capital equipment and R&D may affect the evolution of the wage differential between skilled and unskilled workers because of labor market institutions. In Germany where labor market institutions raise the relative wage of unskilled workers, firms tend to invest relatively more into capital equipment and R&D complementary to unskilled workers. Instead, in the US where wage-compressing institutions are weaker, firms invest more in high-skilled workers.

This mechanism is borne out in a model with imperfections in the product market. In such a framework firms have incentives to recover the rents accruing to unskilled workers because of wage compression. Initial wage compression induces innovation incentives to increase the productivity of unskilled labor and thus affects the evolution of the wage differential.

We construct an industry panel for West Germany and the US between the 1970s to 1990s merging industry-level data on capital equipment, value added and R&D to data on skill intensity and the wage differential from micro datasets. We find evidence that changes in capital equipment and R&D are negatively associated with changes in the wage differential in West Germany while the relationship is positive for changes in capital equipment in the US but mostly insignificant. Our estimates imply that changes in capital equipment and R&D in Germany in the 1980s are associated with a reduction in the wage differential of about 13% in important manufacturing industries such as chemicals and petroleum, food and tobacco or machinery.

This evidence suggests that labor market institutions may affect wage differentials through the investment behavior of firms. Clearly, more detailed firm-level data is needed to shed further light on the mechanism of how and why firms invest in unskilled workers in countries with stronger wage-compressing institutions. Finally, although wage compression might induce firms to increase the productivity of employed unskilled workers if wages are compressed by institutions, we have neglected the possible adverse employment effects for this group of workers.

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Appendix A: Background material for the model

I. Further background material on the final-good sector

First let us determine the demand for the capital good. The parametrization of the production functions implies that each subsector spends

$$\Lambda_j \equiv \mathbf{p}_j K_n = P_j/2$$

on the capital good per unit of output. We assume that in each industry the capital goods are produced by two firms in the intermediate-good sector (specifically for one final-good subsector j in the industry i). Both capital goods are imperfect substitutes in the production of the final good so that the composite intermediate good K_n, $n = h, l$, is given by

$$K_n \equiv \phi_j(k_j^*, k_j) = \left(\left(k_j^*\right)^{\alpha_j} + k_j^{\alpha_j} \right)^{\frac{1}{\alpha_j}},$$

where $\alpha_j \in (0;1)$, $j = 1, 2$, and k_j^* and k_j is the capital good produced by each of the two firms in industry j, respectively. The problem's structure allows two-stage budgeting so that minimizing cost $p_j^* k_j^* + p_j k_j$ s.t. $\phi_j(\cdot)$ results in the factor demand

$$k_j = \frac{p_j^{\frac{1}{\alpha_j - 1}}}{p_j^{\frac{\alpha_j}{\alpha_j - 1}} + \left(p_j^*\right)^{\frac{\alpha_j}{\alpha_j - 1}}} \Lambda_j \tag{A1}$$

and

$$k_j^* = \frac{\left(p_j^*\right)^{\frac{1}{\alpha_j - 1}}}{p_j^{\frac{\alpha_j}{\alpha_j - 1}} + \left(p_j^*\right)^{\frac{\alpha_j}{\alpha_j - 1}}} \Lambda_j, \tag{A2}$$

$j = 1, 2$, where p_j^* and p_j denote the price of the capital good produced by the two firms for the subsector j, respectively, and

$$\mathbf{p}_j = \left[\left(p_j\right)^{\frac{\alpha_j}{\alpha_j - 1}} + \left(p_j^*\right)^{\frac{\alpha_j}{\alpha_j - 1}} \right]^{\frac{\alpha_j - 1}{\alpha_j}} \tag{A3}$$

is the price index of the capital good for final-good subsector j.

II. Capital-good production

In this section we characterize the intermediate capital-good production in more detail to show how prices p_j and profits are determined (the intermediate good's market and R&D activity is modelled very similarly to Aghion et al., 2001). In both intermediate-good markets two firms engage in an infinitely repeated duopoly game in which they perform R&D to increase efficiency of production and then set prices in Bertrand competition. We first characterize production of the capital good before we analyze how innovation effort is determined.

To simplify the analysis considerably, we assume that the capital good is produced with resources that are supplied fully elastically on the world market. The production function is assumed to have constant returns. The cost of every production unit ρ_j varies according to how many resources are necessary to produce the intermediate good.

We now derive revenues, prices and profits for firms producing for final-good subsector j (the results for the other subsector are symmetric). Using equations (A1) and (A2), total revenue of each firm, $\widetilde{\lambda}_j \equiv p_j x_j$, can be written as

$$\widetilde{\lambda}_j = \frac{p_j^{\frac{\alpha_j}{\alpha_j - 1}}}{p_j^{\frac{\alpha_j}{\alpha_j - 1}} + \left(p_j^*\right)^{\frac{\alpha_j}{\alpha_j - 1}}} \Lambda_j \ , \tag{A4}$$

where $\widetilde{\lambda}_j + \widetilde{\lambda}_j^* = \Lambda_j$ and the asterisk denotes the respective other firm. Defining the fraction of revenues

$$\lambda_j \equiv \frac{\widetilde{\lambda}_j}{\Lambda_j} \ , \tag{A5}$$

with $\lambda_j + \lambda_j^* = 1$, and assuming that firms in the intermediate-good sector compete in prices, the elasticity of demand (defined as a positive number) for the intermediate good is

$$\eta_j = \frac{1 - \alpha_j \lambda_j}{1 - \alpha_j} \ . \tag{A6}$$

Note that the price setting of firms does not influence the total expenditure for the intermediate good in the final-good subsector because the elasticity of demand in the final-good sector is unity.

Equation (A6) implies that the revenue-maximizing price at which a capital-good firm sells to the final-good subsector j is

$$p_j = \frac{\eta_j}{\eta_j - 1} \rho_j = \frac{1 - \alpha_j \lambda_j}{\alpha_j \left(1 - \lambda_j\right)} \rho_j \tag{A7}$$

and profits are

$$\pi_j = \frac{\widetilde{\lambda}_j}{\eta_j} = \frac{\lambda_j (1 - \alpha_j)}{(1 - \alpha_j \lambda_j)} \Lambda_j \ , \tag{A8}$$

where we use equations (A5) and (A6) for the second equality.

Equations (A5), (A7) and (A8) can be used to solve for unique equilibrium prices, revenues and profits in the two capital-good firms which depend on the relative cost (see Appendix A IV below for the derivations)

$$z_j \equiv \frac{\rho_j}{\rho_j^*}. \tag{A9}$$

For later reference it is interesting to note that equilibrium profits of firms negatively depend on the relative cost z_i. The absolute cost level does not matter for profits since the demand for the intermediate good is unit-elastic (the production functions in the final-good sectors are Cobb-Douglas). Moreover,

$$\lim_{z_i \to 0} \pi_i(z_i) = \Lambda_i \ .$$

If one firm is not competitive at all, the other firm's profit equals total revenue. In this case the firm sells the intermediate good at a finite but very high price and extracts all revenues at infinitesimal cost.

III. R&D

Both firms in each intermediate-good market engage in an infinitely repeated duopoly game in which they perform R&D and then set prices in Bertrand competition. Innovations are step-by-step: a technology laggard first has to catch up with the technology leader before he can take the lead. Step-by-step innovations are an important ingredient of the model because innovation incentives do not depend on the absolute asset value of the firm, as in Schumpeterian models with leapfrogging, but on the increase of the asset value as firms proceed on the technology frontier. Hence, incentives to innovate can be higher even if the absolute asset value of the firm falls. For the analysis below this is important because minimum wages make firms worse off that are producing for the unskilled-labor intensive sector. With step-by-step innovations this does not necessarily imply less innovation complementary to unskilled labor.

For tractability, we assume that the R&D effort depends only on the firm's current state of technology so that we search for symmetric stationary equilibria in Markov strategies. Furthermore, we focus on the case of very large innovations because the model can be solved analytically in this case. The results are more general, however, as shown by Aghion et al. (2001). In the case of very large innovations, the technology leader does not exert any research effort q_s so that firms in the intermediate-good sector are in either of the three states $s \in \{1, 0, -1\}$ which denote the technology leader being one step ahead, neck-and-neck firms and the technology laggard, respectively.

Employing $\beta q_s^2/2$ units of resources, $s \in \{1, 0, -1\}$, $\beta > 0$, a firm moves one step forward with the endogenous Poisson hazard rate q_s. In this case the input requirement for the production of the intermediate good falls by the factor γ^{-1}, $\gamma > 1$, which is also the relative cost advantage of the technological leader, $z = \gamma^{-1}$. Since the technology leader does not exert any research effort, $q_1 = 0$, the technology laggard catches up with the leader at rate q_{-1}. If the laggard catches up with the leader, firms are neck-and-neck. Neck-and-neck competition is defined as $z = 1$. Both firms supply the intermediate good at the same price. Firms in neck-and-neck competition exert research effort q_0 which is also the Poisson hazard of each firm to become a technology leader.

Using subscripts j, s to denote the relative position s on the technology frontier of the two firms producing the capital good for final-good subsector j, the asset value of the firm $V_{j,s}$ satisfies the following Bellman equation (for small time intervals):

$$rV_{j,1} = \pi_{j,1} + q_{j,-1}(V_{j,0} - V_{j,1}) \ , \tag{A10}$$

$$rV_{j,0} = \pi_{j,0} + q_{j,0}(V_{j,1} - V_{j,0}) + \overset{\substack{\text{rival's R\&D} \\ \downarrow}}{q_{j,0}} (V_{j,-1} - V_{j,0}) - \frac{\beta(q_{j,0})^2}{2} \tag{A11}$$

and

$$rV_{j,-1} = \pi_{j,-1} + q_{j,-1}(V_{j,0} - V_{j,-1}) - \frac{\beta(q_{j,-1})^2}{2} \ . \tag{A12}$$

The rate of return of the firm has to equal the rate of return available in the market, r. For example, the technology laggard in equation (A12) earns profit flows $\pi_{j,-1}$ and has an option value of moving one step ahead on the technology frontier, $V_{j,0} - V_{j,-1}$, which happens with probability $q_{j,-1}$. Exerting R&D effort $q_{j,-1}$ implies a flow cost $\beta(q_{j,-1})^2/2$ for the used capital input.

Maximizing the respective right-hand side of equations (A10) to (A12) results in the optimal research effort

$$q_{j,1} = 0 \ , \ q_{j,0} = \frac{V_{j,1} - V_{j,0}}{\beta}, \ q_{j,-1} = \frac{V_{j,0} - V_{j,-1}}{\beta}, \text{ respectively.} \tag{A13}$$

Equations (A10) to (A13) can be solved for $q_{j,1}, q_{j,0}, q_{j,-1}, V_{j,1}, V_{j,0}$ and $V_{j,-1}$. Subtracting equation (A11) from equation (A10), equation (A12) from equation (A11), using equations (A13) results in two quadratic equations in $q_{j,0}$ and $q_{j,-1}$ that have the solution:

$$q_{j,0} = -r + \sqrt{r^2 + \frac{2(\pi_{j,1} - \pi_{j,0})}{\beta}} \tag{A14}$$

and

$$q_{j,-1} = -(r + q_{j,0}) + \sqrt{r^2 + 2rq_{j,0} + 2q_{j,0}^2 + \frac{2(\pi_{j,0} - \pi_{j,-1})}{\beta}} \ . \tag{A15}$$

Research effort positively depends on relative and not on absolute profit. From Aghion et al. (2001), Proposition 1, we know that $\pi_{j,1} > \pi_{j,0} > \pi_{j,-1}$ and $\pi_{j,1} - \pi_{j,0} > \pi_{j,0} - \pi_{j,-1}$, where the latter implies that $q_{j,0} > q_{j,-1}$ (see Appendix A IV below). Research effort is largest, if firms are neck-and-neck. We now demonstrate how these innovation efforts translate into growth rates of each firm and determine the evolution of wage differentials in each industry.

The model's structure implies a steady-state distribution across technology states as is shown by Aghion et al. (2001). Over long time intervals, the growth rate in capital-good production for subsector j is (see Appendix A IV)

$$g_j = \frac{2q_{j,0}q_{j,-1}}{2q_{j,0} + q_{j,-1}} \ln \gamma \ , \tag{A16}$$

where γ is the efficiency gain after an innovation. The growth rate unambiguously increases in the research effort of either technology laggards ($q_{j,-1}$) or neck-and-neck firms ($q_{j,0}$).

IV. Further derivations of equations

Revenues λ as a function of z We repeat or sketch the following derivations contained in Aghion et al., 2001, to facilitate the reading of the paper. We drop the firm index j for notational convenience.

Equations (A4) and (A5) imply that

$$\lambda = \frac{1}{1 + \left(\frac{p}{p^*}\right)^{\frac{\alpha}{1-\alpha}}}. \tag{A17}$$

Equation (A7), and $\lambda + \lambda^* = 1$ imply

$$\frac{p}{p^*} = \frac{(1 - \alpha\lambda)\,\lambda z}{(1 - \alpha(1 - \lambda))\,(1 - \lambda)}.$$

Substituting $\frac{p}{p^*}$ into equation (A17) and rearranging, we get

$$(1 - \alpha\lambda)^\alpha \lambda z^\alpha = (1 - \alpha(1 - \lambda))^\alpha (1 - \lambda)$$

which is an implicit function of λ in z. Aghion et al. (2001) apply the implicit function theorem to show that $\lambda(z)$ is strictly decreasing in z. The more efficient firm (with a smaller z) obtains a higher fraction of the revenues λ.

Relative profits $\pi_s - \pi_{s-1}$ as a function of z We now show that relative profits increase as firms proceed on the technology frontier. Plugging $\lambda(z,\alpha)$ into the profit function as defined by equation (A8) we get

$$\pi(z,\alpha) = \frac{\lambda(z,\alpha)(1-\alpha)}{(1-\alpha\lambda(z,\alpha))}\Lambda \ .$$

To simplify let us divide by the constant Λ and redefine

$$\Pi(z,\alpha) \equiv \frac{\pi(z,\alpha)}{\Lambda} = \frac{\lambda(z,\alpha)(1-\alpha)}{1-\alpha\lambda(z,\alpha)} \ . \tag{A18}$$

If firms are neck-and-neck, by symmetry

$$\lambda(z,\alpha) = \lambda(1,\alpha) = 1/2 \ .$$

Suppose without loss of generality that $z < 1$ so that $\lambda > 1/2$ (the fraction of the revenue of the domestic firm that is technology leader). We want to show that

$$\Pi(z,\alpha) - \Pi(1,\alpha) > \Pi(1,\alpha) - \Pi(1/z,\alpha).$$

Using equation (A18) we get

$$\Pi(z,\alpha) + \Pi(1/z,\alpha) - 2\Pi(1,\alpha) = (1-\alpha)\left(H(\lambda)) - H(1/2)\right) \ ,$$

where

$$H(\lambda) \equiv \frac{\lambda}{1-\alpha\lambda} + \frac{1-\lambda}{1-\alpha(1-\lambda)} \ .$$

It follows that

$$H'(\lambda) = \frac{1}{(1-\alpha\lambda)^2} - \frac{1}{(1-\alpha(1-\lambda))^2} > 0$$

for $\lambda > 1/2$. Hence,

$$\Pi(z,\alpha) + \Pi(1/z,\alpha) - 2\Pi(1,\alpha) > 0$$

which implies the result we wanted to show.

Derivation of the growth rate g We use the same notation as in Aghion et al. (2001) and adapt their argument to our model. First note that in steady state as many firms have to exit a state on the relative technology frontier as enter the same very state. Let μ_s be the fraction of firms in state $s \in \{\iota, n\}$, where ι denotes the state in which there is a technology laggard and leader and n denotes the state in which both firms are neck-and-neck. This implies that over a long enough time interval ($\Delta t \to \infty$)

$$2\mu_n q_0 = \mu_\iota q_{-1} \ .$$

In state n both neck-and-neck firms engage in process innovation and they are successful with probability q_0. In state ι only the technology laggard potentially innovates with probability q_{-1}. Given that $\mu_n + \mu_\iota = 1$, the equation simplifies to

$$2\mu_n q_0 = (1-\mu_n) q_{-1} \ . \tag{A19}$$

Output of each intermediate-good sector, K, is exposed to independent and identically distributed shocks (innovations occur with Poisson hazard) so that the growth rate equals

$$g = \lim_{\Delta t \to \infty} \frac{\Delta \ln K}{\Delta t} \ .$$

This growth rate is determined by the asymptotic frequency of firms that advance the industry's frontier technology. Every time this happens the value of $\ln K$ increases by $\ln \gamma$. In the case of very large innovations only the firms which are neck-and-neck advance the industry's frontier technology. The asymptotic fraction of firms in this state is μ_n and the probability that the technology frontier is advanced is $2q_0$ so that

$$g = 2\mu_n q_0 \ln \gamma = \frac{2q_0 q_{-1}}{2q_0 + q_{-1}} \ln \gamma$$

where the last equality uses equation (A19).

Appendix B: Minimum wages and innovation

We repeat the argument contained in Koeniger (2005) for completeness. We assume $P > 1$ so that the minimum wage affects only the first final-good sector which uses unskilled labor. With $P > 1$ and $r_1 = r_2$, equation (2) implies that the productivity and wage of the skilled is larger than of the unskilled.

We want to show that a minimum wage can increase the research effort in the sector producing the intermediate good used with unskilled labor. Both firms engage in step-by-step innovations. It follows from equations (A14) and (A15), that all we need to show is that the relative profits $\pi_{1,0} - \pi_{1,-1}$ and $\pi_{1,1} - \pi_{1,0}$ increase.

If there is a binding minimum wage, the final-good sector using unskilled labor can pay a maximum price $\mathbf{p}_1^{\max}$ for the intermediate good:

$$\mathbf{p}_1^{\max} = \frac{(P_1)^2}{4w^{\min}} \ ,$$

where $w^{\min}$ is defined in terms of good 1, i.e., $w^{\min} = \frac{W^{\min}}{P_1}$ (the choice of the numeraire is not crucial for the results). Thus, the maximization problem of the firm in the intermediate-good sector 1 has an additional constraint $\mathbf{p}_1 \leq \mathbf{p}_1^{\max}$. Technologically more advanced firms with smaller marginal cost are relatively less affected by this constraint because they set lower prices: equation (A7) implies that in the unconstrained case $p_{1,1}^u < p_{1,0}^u < p_{1,-1}^u$, where $p_{1,k}^u$ is the price of an unconstrained firm in sector 1 with technology status k. This would increase relative profits and thus innovation effort. Since the relevant constraint involves the price index $\mathbf{p}_1$, however, the constraint can be less binding for the technology laggard in the special case in which the low price set by the technology leader implies that the price index is not binding whereas it is binding for neck-and-neck firms.

We have to distinguish three cases to characterize profits and revenues:

a) the minimum-wage constraint is binding for all firms in sector 1.

b) the minimum-wage constraint is binding for the technology laggard and the neck-and-neck firms in sector 1.

c) the minimum-wage constraint is binding only for the neck-and-neck firms in sector 1.

to a): From equation (A4) it follows that $\widetilde{\lambda}_{1,k} = \frac{1}{2}\Lambda_1$, $k \in \{1, 0, -1\}$. Profits change to

$$\pi_{i,k} = \left(1 - \frac{\rho_{1,k}}{\mathbf{p}_1^{\max}}\right)\frac{\Lambda_1}{2}. \tag{A20}$$

If the constraint is binding for all firms, $p_{1,k} = \mathbf{p}_1^{\max}, k \in \{1, 0, -1\}$. The constraint is most binding for the laggard and least binding for the leader. I.e., $p_{1,1}^u - \mathbf{p}_1^{\max} < p_{1,0}^u - \mathbf{p}_1^{\max} < p_{1,-1}^u - \mathbf{p}_1^{\max}$. Hence, relative profits $\pi_{1,0} - \pi_{1,-1}$ and $\pi_{1,1} - \pi_{1,0}$ increase although absolute profits fall. Note that for marginal changes the envelope theorem implies that we can neglect the changes in revenues. For discrete changes of the minimum wage there is an additional effect since $\widetilde{\lambda}_{1,-1}$ increases and $\widetilde{\lambda}_{1,1}$ decreases to $\frac{\Lambda_1}{2}$. Moreover, note that we still assume $q_{1,1} = 0$ although with binding minimum wages there is an incentive for the technology leader to innovate in order to mitigate the constraint. Allowing $q_{1,1} > 0$ would further increase R&D efforts and growth in the subsector using unskilled labor.

to b): Neck-and-neck firms are characterized as in a). The technological leader's price and profit are determined by equations (A7) and (A8) whereas the profits of the technology laggard are

$$\pi_{i,-1} = \left(1 - \frac{\rho_{1,-1}}{\mathbf{p}_1^{\max}}\right) \widetilde{\lambda}_{1,-1},$$

where $\widetilde{\lambda}_{1,-1} = \Lambda_1 - \widetilde{\lambda}_{1,1}$. It remains to determine $\lambda_{1,1}$ with the following implicit equation:

$$\widetilde{\lambda}_{1,1} = \frac{p_{1,1}(\lambda_{1,1})^{\frac{\alpha_1}{\alpha_1 - 1}}}{(\mathbf{p}_1^{\max})^{\frac{\alpha_1}{\alpha_1 - 1}} + p_{1,1}(\lambda_{1,1})^{\frac{\alpha_1}{\alpha_1 - 1}}} \Lambda_1 > \frac{\Lambda_1}{2}.$$

As in a) relative profits increase compared with the unconstrained case. Indeed, $\pi_{1,0} - \pi_{1,-1}$ and $\pi_{1,1} - \pi_{1,0}$ increase even more compared with a) because the technology leader now solves an unconstrained maximization problem and the technology laggard is constrained.

to c): Neck-and-neck firms' profits and revenues are as in a). The technology laggard's and leader's revenues and profits are determined as in the unconstrained case. It follows that relative profits $\pi_{1,1} - \pi_{1,0}$ increase but $\pi_{1,0} - \pi_{1,-1}$ decreases compared with the unconstrained case. Which of the two effects dominates depends on the parameter values.■

Data appendix

Industry classifications of the data series are summarized in Tables 5 and 4.

Data for the US

We use the Current Population Survey May in the period 1973-78 and May/ORG in the period 1979-2002 for data on wages and employment by skill and sector for each year. Our sample includes "wage-and-salary" workers in full-time employment, age 20-60 with potential labor market experience up to 39 years.

Skill measure

We define skilled workers as those with some college or college degree and all those with less education as unskilled.

Wages

Hourly wages are the logarithm of hourly earnings for those paid by the hour and the logarithm of usual weekly earnings divided by hours worked last week for workers not paid by the hour. Topcoded earnings are multiplied by 1.5. Full-time earnings below \$67/week in 1982\$ and hourly earnings below \$1.675/hour in 1982\$ are dropped as are hourly wages exceeding 1/35th of the topcoded value of weekly earnings. All earnings are deflated by the CPI. Allocated earnings are excluded in all years. Our final measure are yearly wages which are comparable with the stock of capital computed on a yearly basis. Annual wages are obtained by multiplying hourly wages with hours worked last week times 52. For more details see Autor, Katz and Kearney (2004).

Hours

The data on hours by industry is taken from the 60-Industry Database, Groningen Growth and Development Centre, February 2005, http://www.ggdc.net. Since the data are only available 1979-2002, we extrapolate the early years 1973-78 in the sample based on the industry-specific linear time trend.

Value added in current prices

Since the BEA changed its industry-classification in 1998 in a way that makes it impossible to construct a consistent time series, we use the data on value added by industry from the 60-Industry Database, Groningen Growth and Development Centre, February 2005, http://www.ggdc.net for the time period 1979-2002. For the time period 1973-78 we use the data of the national accounts provided by the BEA.

Employment

Employment by skill in each sector and year is given by the sum of employed persons using the frequency weights to retrieve the total number in the population. We multiply both skilled and unskilled employment with the total numbers of hours worked per industry and year.

Capital stock and gross capital formation

We use the current cost net stock of private equipment and software and the historical-cost investment in private capital equipment by industry provided by the BEA. Both series can be deflated using the respective chain-type quantity index which is provided for each series.

Depreciation

We use the current-cost depreciation provided by the BEA, divided by the net capital stock in current cost.

Risk-free rate

We use the US treasury bond with a maturity of 10 years.

Returns to capital

We compute the gross return to capital as the sum of the risk-free rate and depreciation rate.

R&D expenditure

We use R&D expenditure by industry for the period 1965-95 from the database based on Compustat data provided by Browyn Hall at www.econ.berkeley.edu. Alternatively, we also use the R&D data provided in the STAN-Anberd database for the years 1973-2000.

Data for West-Germany

We use a 1% random sample of the social security records provided by the Institut für Arbeits- und Berufsforschung (IAB) in the period 1975-95 for data on wages and employment by skill and sector for each year. Our sample includes employees in full-time employment, age 20-60 with potential labor market experience up to 39 years.

Skill measure

We define skilled workers as those with Abitur (high-school degree) and more education. Unskilled workers are those with less education than Abitur. An Abitur-degree implies usually 13 years of schooling which is comparable with some college in the US.(which implies 13 or more years of schooling).

Wages

We only use the information on West-Germany in IAB and drop all East-German observations after 1990. The IAB data do not contain information on weeks or hours worked. Thus, we construct yearly wages multiplying the daily wage measure by an average of 260 working days.

Hours

The data on hours by industry is taken from the 60-Industry Database, Groningen Growth and Development Centre, February 2005, http://www.ggdc.net. Since the data for West Germany are only available 1979-2002, we extrapolate the early years 1975-78 in the sample based on the industry-specific linear time trend. For the years after German reunification, 1992-95, we readjust the mean of the series after 1992 and extrapolate with its time trend.

Value added

We use the gross valued added in current prices (Bruttowertschöpfung) by industry and year from the Statistisches Bundesamt for Germany until 1995. Because this series has a break after German reunification and we are only interested in West-German value added, we adjust the mean of the series after 1992 and extrapolate with its time trend.

Employment

We compute the fraction of skilled and unskilled workers by industry in year in the IAB. Since the IAB only contains employees with social security records, we scale up the number of employees to the total population using the series on total employment by industry and year provided by the *Statisches Bundesamt* (German Statistical Office). Because this series has a break after German reunification and we are only interested in West-German employees, we adjust the mean of the series after 1992 and extrapolate with its time trend.

Capital stock and gross capital formation

We use the gross capital formation on equipment (Anlagevermögen) by industry and year from the *Statistisches Bundesamt* for Germany until 1995. The series exist for West Germany only until 1991. We adjust the mean of the series after 1992 and extrapolate with its time trend. The real formation is in prices of 1991 deflated by a chain-type price index. We accumulate this series using a perpetual inventory method. We assume a depreciation rate of 8.4 % for all industries as in Machin and van Reenen (1998). Alternatively, we use the series on depreciation rates of equipment by industry. All our results reported in the paper are robust to using the latter series.

Depreciation

We use the current-cost depreciation for equipment provided by the *Statistisches Bundesamt* for West Germany until 1995, divided by the net capital stock in current cost.

Risk-free rate

We use the German BUND with a maturity of 10 years.

Returns to capital

We compute the gross return to capital as the sum of the risk-free rate and depreciation rate.

R&D expenditure

We use the R&D data for West Germany provided in the STAN-Anberd database for the years 1973-1993. We extrapolate this series for the years 1994-95.

US

Sector name	*H/L* 1970s	*1st diff. ln(H/L)* 1980s-1970s	*1st diff. ln(H/L)* 1990s-1980s	*wh/wl* 1970s	*1st diff. ln(wh/wl)* 1980s-1970s	*1st diff. ln(wh/wl)* 1990s-1980s	*1st diff. ln(hours)* 1980s-1970s	*1st diff. ln(hours)* 1990s-1980s
Agriculture and Mining	0.478	0.337	0.228	1.300	0.065	0.028	-0.051	-0.030
Construction	0.338	0.192	0.399	1.163	0.069	0.032	-0.004	0.022
Wood	0.210	0.224	0.419	1.413	0.060	-0.012	0.004	0.017
Stone, Clay etc.	0.272	0.286	0.443	1.407	0.061	-0.015	0.013	0.025
Primary Metals	0.323	0.125	0.546	1.282	0.064	0.065	0.010	0.055
Machinery	0.521	0.342	0.455	1.349	0.135	0.053	-0.002	0.026
Electrical Machinery	0.507	0.340	0.639	1.592	0.096	0.081	0.001	0.016
Transport Equipment	0.446	0.387	0.507	1.324	0.073	0.070	0.020	0.020
Professional Goods	0.656	0.322	0.608	1.661	0.025	0.050	0.000	0.011
Food and Tobacco	0.330	0.128	0.379	1.348	0.095	0.087	0.000	0.029
Textiles	0.141	0.336	0.611	1.922	0.009	0.008	0.006	0.016
Paper and Printing	0.534	0.232	0.513	1.301	0.000	0.090	0.007	0.015
Chemicals and Petroleum	0.779	0.244	0.528	1.510	0.045	0.060	-0.019	0.026
Plastic and Leather	0.231	0.314	0.604	1.540	0.090	-0.013	0.009	0.017
Transport Communication	0.497	0.337	0.561	1.127	0.054	0.061	-0.019	0.028
Utilities	0.518	0.391	0.519	1.240	0.060	0.013	0.001	0.024
Wholesale Retail	0.543	0.184	0.396	1.384	0.035	0.028	-0.039	-0.020
Banking, Insurance	1.089	0.186	0.591	1.600	0.035	0.010	-0.003	0.012
Business, Personal Services	0.564	0.339	0.449	1.543	0.042	0.058	0.040	0.027
Health Services	0.928	0.406	0.533	1.666	-0.006	0.123	0.009	0.015

Sector name	*ln(equipment investment/L)* 1970s	*1st diff. ln(equipment investment/L)* 1980s-1970s	*1st diff. ln(equipment investment/L)* 1990s-1980s	*R&D/value added* 1970s	*1st diff. ln(R&D/va)* 1980s-1970s	*1st diff. ln(R&D/va)* 1990s-1980s
Agriculture and Mining	4.188	-1.014	3.300			
Construction	0.805	-0.393	0.462			
Wood	1.925	-0.316	0.961	0.005	-0.421	0.277
Stone, Clay etc.	3.817	-0.137	3.598	0.019	0.530	-0.536
Primary Metals	1.863	0.211	1.827	0.014	0.421	-0.371
Machinery	0.514	0.263	1.579	0.023	0.398	0.288
Electrical Machinery	0.424	0.517	2.662	0.245	0.265	-0.178
Transport Equipment	0.565	0.263	0.829	0.204	0.332	-0.260
Professional Goods	1.150	0.997	5.592	0.120	0.095	0.496
Food and Tobacco	0.803	0.334	0.385	0.009	0.461	-0.045
Textiles	0.894	0.022	1.239	0.003	0.440	0.421
Paper and Printing	0.623	0.141	0.970	0.008	-0.022	0.571
Chemicals and Petroleum	1.162	-0.045	1.483	0.100	0.207	0.038
Plastic and Leather	2.247	-0.093	2.144	0.032	-0.168	0.085
Transport Communication	0.501	-0.076	0.651			
Utilities	1.150	0.508	1.095			
Wholesale Retail	0.084	0.039	0.207			
Banking, Insurance	0.205	0.161	1.212			
Business, Personal Services	0.448	-0.173	0.295			
Health Services	0.204	0.101	0.687			

Notes: Author's calculations based on the data further described in the Data Appendix.

Table 2: Summary statistics for the US

Germany

Sector name	*H/L* 1970s	*1st diff. ln(H/L)* 1980s-1970s	*1st diff. ln(H/L)* 1990s-1980s	*wh/wl* 1970s	*1st diff. ln(wh/wl)* 1980s-1970s	*1st diff. ln(wh/wl)* 1990s-1980s	*1st diff. ln(hours)* 1980s-1970s	*1st diff. ln(hours)* 1990s-1980s
Agriculture and Mining	0.028	0.320	0.383	1.386	-0.067	0.046	-0.055	-0.039
Construction	0.025	0.242	0.241	1.385	-0.011	-0.023	0.007	0.059
Wood	0.015	0.297	0.534	1.347	-0.059	0.005	-0.052	-0.041
Stone, Clay etc.	0.031	0.197	0.384	1.373	0.017	-0.066	-0.056	-0.030
Primary Metals	0.040	0.181	0.325	1.396	0.006	-0.035	-0.055	-0.052
Machinery	0.054	0.301	0.518	1.305	0.009	-0.028	-0.066	-0.060
Electrical Machinery	0.100	0.466	0.316	1.451	-0.001	-0.022	-0.040	-0.043
Transport Equipment	0.046	0.340	0.366	1.314	0.029	-0.012	-0.060	-0.054
Professional Goods	0.043	0.478	0.368	1.414	0.016	-0.011	-0.051	-0.047
Food and Tobacco	0.019	0.272	0.464	1.486	0.016	-0.017	-0.033	-0.047
Textiles	0.017	0.252	0.540	1.585	-0.003	-0.059	-0.030	-0.057
Paper and Printing	0.029	0.375	0.538	1.313	0.002	-0.051	-0.051	-0.070
Chemicals and Petroleum	0.084	0.296	0.456	1.338	0.006	-0.049	-0.045	-0.044
Plastic and Leather	0.019	0.618	0.570	1.572	-0.050	-0.049	-0.034	-0.048
Transport Communication	0.029	0.404	0.410	1.226	0.017	-0.010	-0.054	-0.072
Utilities	0.082	0.210	0.328	1.243	0.001	-0.049	-0.027	-0.063
Wholesale Retail	0.040	0.271	0.426	1.366	-0.004	-0.005	-0.053	-0.085
Banking, Insurance	0.095	0.556	0.599	1.199	-0.076	-0.017	-0.123	-0.051
Business, Personal Services	0.170	0.216	0.296	1.519	0.010	-0.017	-0.072	-0.066
Health Services	0.092	0.322	0.229	1.491	0.067	-0.082	-0.045	-0.062

Sector name	*ln(equipment investment/L)* 1970s	*1st diff. ln(equipment investment/L)* 1980s-1970s	*1st diff. ln(equipment investment/L)* 1990s-1980s	*R&D/value added* 1970s	*1st diff. ln(R&D/va)* 1980s-1970s	*1st diff. ln(R&D/va)* 1990s-1980s
Agriculture and Mining	3.864	0.456	0.735			
Construction	1.953	-0.233	0.715			
Wood	2.828	-0.204	1.422	0.003	1.659	-0.362
Stone, Clay etc.	4.787	0.982	2.778	0.006	1.022	-0.105
Primary Metals	4.110	0.110	1.027	0.005	0.511	-0.414
Machinery	2.591	0.837	0.963	0.025	0.590	-0.050
Electrical Machinery	5.447	2.351	1.977	0.085	0.426	0.226
Transport Equipment	4.988	2.433	2.437	0.057	0.540	0.352
Professional Goods	2.772	0.069	1.217	0.018	0.421	0.157
Food and Tobacco	4.076	0.213	2.115	0.003	0.913	-0.110
Textiles	1.681	0.466	1.088	0.002	0.923	0.207
Paper and Printing	4.331	1.369	2.181	0.001	0.744	-0.201
Chemicals and Petroleum	8.250	0.467	2.881	0.072	0.405	0.169
Plastic and Leather	2.883	1.098	1.760	0.009	0.798	-0.145
Transport Communication	6.321	0.866	1.427			
Utilities	23.708	3.486	-4.738			
Wholesale Retail	1.662	0.072	0.811			
Banking, Insurance	5.486	2.428	4.073			
Business, Personal Services	2.707	0.130	0.450			
Health Services	3.507	-0.275	0.429			

Notes: Author's calculations based on the data further described in the Data Appendix.

Table 3: Summary statistics for West Germany

US Sector ID	Sector name	Capital stock	*Gross capital formation*	*Depreciation*	*Value added (BEA)*	*Hours, Value added (van Ark)*	*R&D STAN-Anberd*	*R&D (Hall)*	*CPS 1973-78 (indciv)*	*CPS 1979-83 (ind70)*	*CPS 1983-93 (inddt)*	*CPS 1994-2002 (inddt)*
1	Agriculture and Mining	2, 5	2, 7	2, 7	3, 6	1 to 4			1 to 3	17 to 58	1 to 3	1 to 3
3	Construction	10	12	12	11	33			4	67 to 78	4	4
4	Wood	13, 14	15, 16	15, 16	14, 15	9, 31	103	3, 4	6, 7	107 to 118	5, 6	5, 6
6	Stone, Clay etc.	15	17	17	16	15	110	10	8	119 to 138	7	7
7	Primary Metals	16	18, 19	18, 19	17	16	111	11	9	139 to 149	8	8
10	Machinery	18	20	20	19	18	116	13	11	177 to 198	11	11
11	Electrical Machinery	19	21	21	20	19 to 22	117 to 119	14 to 16	12	199 to 209	12	12
12	Transport Equipment	20, 21	22, 23	22, 23	21, 22	27 to 30	120 to 123	17, 18, 23	13 to 15	219 to 238	13 to 15	13 to 15
15	Professional Goods	22	24	24	23, 24	25 to 26	124	19	16	239 to 258	16	16
18	Food and Tobacco	25, 26	27, 28	27, 28	26, 27	5	101	1	18, 19	268 to 299	19, 20	19, 20
20	Textiles	27, 28	29, 30	29, 30	28, 29	6, 7	102	2	20, 21	307 to 327	21, 22	21, 22
22	Paper and Printing	29, 30	31, 32	31, 32	30, 31	10, 11	104	5, 6	22, 23	328 to 339	23, 24	23, 24
24	Chemicals and Petroleum	31, 32	33, 34	33, 34	32, 33	12, 13	105	7, 8, 20	24, 25	347 to 378	25, 26	25, 26
26	Plastic and Leather	33, 34	35, 36	35, 36	34, 35	8, 14	109	9	26, 27	379 to 398	27, 28	27, 28
28	Transport Communication	36, 44	38, 46	38, 46	37, 45	38 to 42			28 to 30	407 to 449	29, 30	29, 30
30	Utilities	47	49	49	48	32			31	467 to 479	31	31
31	Wholesale Retail	51, 52	53, 54	53, 54	49, 50	34 to 36			32 to 34	507 to 698	32, 33	32 to 34
33	Banking, Insurance	53	55	55	51	43 to 46			35, 36	707 to 718	34, 35	35, 36
35	Business, Personal Services	64 to 71, 73 to 7	69 to 75	69 to 75	62 to 64, 67, 68	37, 47, 48, 49			37 to 41	727 to 817	36, 40	37 to 41
40	Health Services	72	77	77	69	54			42, 43	828 to 848	41, 42	42, 43

Table 4: Industry classification for US data series

Germany Sector ID	Sector name	Capital stock	*Gross cap. form.*	*Depreciation*	*Employment, Value added*	*Hours (van Ark)*	*R&D STAN-Anberd*	*IAB*
1	Agriculture and Mining	1, 10	1, 6	1, 9	1, 9, 13	1 to 4		0 to 3, 5 to 8
3	Construction	46	25	50	50	33		59 to 61, 25
4	Wood	35, 36	13	24	24	9, 31	103	40, 42 and 41
6	Stone, Clay etc.	18 to 20	18	13	31	15	110	14 to 16
7	Primary Metals	21, 22	19	33	32	16	111	17 to 18
10	Machinery	26	20	35	35	18	116	26
11	Electrical Machinery	27, 31	21	37 to 39	37, 38, 39	19 to 22	117 to 119	33 to 34
12	Transport Equipment	28 to 30	22	41	41	27 to 30	120 to 123	27 to 32
15	Professional Goods	32	23	40	40	23 to 25	124	35 to 36
18	Food and Tobacco	43 to 45	10	17	17	5	101	54 to 57
20	Textiles	41, 42	11	20	20	6, 7	102	47 to 53
22	Paper and Printing	37 to 39	14	25	25	10, 11	104	43 to 44
24	Chemicals and Petroleum	14, 15	15, 16	28, 29	28, 29	12, 13	105	9 to 11
26	Plastic and Leather	16, 17, 40	12, 17	30	23, 30	8, 14	109	12 to 13, 45 to 46
28	Transport Communication	53	29	58	58	38 to 42		63 to 68
30	Utilities	5	24	47	47	32		4
31	Wholesale Retail	50	27	53	53	34 to 36		62
33	Banking, Insurance	59, 62	30	64	64	43 to 46		69, 81
35	Business, Personal Services	64, 65	37, 28	79	57, 79	37, 47, 48		70 to 77, 79 to 80, 82 to 83, 85 to 86
40	Health Services	66	36	78	78	54		78, 84

Table 5: Industry classification for West German data series